Evolution of Communities on Twitter and the Role of their Leaders during Emergencies

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Abstract—Twitter is presently utilized as a channel of communication and information dissemination. At present, government and non-government emergency management organizations utilize Twitter to disseminate emergency relevant information. However, these organizations have limited ability to evaluate the Twitter communication in order to discover communication patterns, key players, and messages that are being propagated through Twitter regarding the event. More importantly there is a general lack of knowledge of who are the individuals or organizations that disseminate warning information, provide confirmations of an event and associated actions, and urge others to take action. This paper presents a methodology that shows how Natural Language Processing (NLP) and Social Network Analysis (SNA) can aid in addressing these issues. The methodology, in addition to qualitative data collected during on-site interviews and publicly available information, was successfully applied to a Twitter data set collected during 2011 Japan tsunami. NLP techniques were applied to extract actionable messages. Based on the messages extracted by NLP, SNA was used to construct a network of actionable messages. While SNA discovered communities and extracted the community leaders, NLP was used to determine the behavior of the community members and the role of the community leaders. Therefore, the proposed methodology automatically finds communities, evaluates its members’ behaviors, and authenticates cohesive behaviors of the community members during emergencies. Moreover, the methodology efficiently finds the leaders of the communities, while also identifying their role in communities.

I. INTRODUCTION

Twitter is an important channel of information dissemination. It is particularly useful when current and relevant information is required. The format of Twitter messages allows people to exchange information about any occurrence. This capability is very useful during emergencies, events that pose a significant threat to one’s well-being. In our work we focused on one type of emergencies - natural disasters. Twitter messages, interview data, and electronic alerts concerning the 2011 Japan tsunami provided the data for the research reported on in this paper. During emergencies such as a tsunami, when the impact is significant and proximity is low, people engage in information milling - obtaining and exchanging information and/or confirmation. The process requires rapid access to the most current information. Twitter has the capability to provide this functionality. Additionally, Twitter provides people with a way to connect with others affected by the same emergency, which can provide emotional support [1].

One of the significant challenges in studying Twitter is a sheer volume of data and lack of ability to efficiently read the data. In this paper Natural Language Processing (NLP) techniques were used to extract three types of actionable events from 2011 Japan tsunami dataset: receive the warning, seek information or confirmation, and take prescribed action. NLP techniques were also used to associate tweets with following attributes - modality and polarity. These attributes provide further insight into the information being shared on Twitter.

The paper begins with an evaluation of existing methods employed in Natural Language Processing (NLP) and Social Network Analysis (SNA). The paper then describes a proposed methodology that incorporates NLP findings with SNA. The paper proceeds to describe the data set used in applying the proposed methodology. The results are then described in detail in the following section. The paper concludes with a discussion of contributions and suggestions for future research.

II. RELATED WORK

A. Warning Response Process during Emergencies

During emergencies affected individual participates in the warning response process, which includes obtaining and sharing information, the evidence of which can be discovered on Twitter during an emergency. In general, the warning response process for an individual has been segmented into six stages [2]: (1) obtaining/hearing the warning; (2) understanding the contents of the warning; (3) trusting the warning; (4) personalizing the warning; (5) seeking information/confirmation; and (5) taking action.

An individual starts the warning response process by receiving notification of the emergency and ends the process by taking action, where doing nothing is a valid action. However, how and when each stage is accomplished may vary across individuals and emergencies [3]. The first stage of the warning response process for individuals is to obtain the warning from one or many sources. The second stage of the warning response process requires assigning a specific meaning to the warning message, which can vary from individual to individual. This meaning can also be different from that intended by the issuing source. The third stage is trusting the warning message, which is influenced by many factors such as the source of the message, contents, and the channel. The fourth stage requires personalization of the warning to one’s situation. This requires
an individual to assess her or his willingness to assume the necessary personal risk. The fifth stage of warning response process is to seek additional information or attempt to obtain confirmations about the information already obtained [2]. This process is often referred to as warning confirmation process. The final stage of warning response process is taking action. People engage in the action they believe is the best for them, which may be at odds with a prescribed action. Three stages of the warning response process - obtaining/hearing the warning, seeking information/confirmation, and taking action can be inferred from communication between individuals unlike the other three stages, which are cognitive processes.

B. Social Media during Emergencies

Social media has been used by the public as well as governmental and non-governmental organizations during emergencies. Some examples of the use include rapid information dissemination of one’s well-being as it was demonstrated by the researchers in [4]. In Haiti, U.S. government was able to utilize social media, such as Wikipedias and workspace sharing media, as a knowledge based system [5]. The researchers in [6] were able to develop a unique annotation, which facilitated the emergence of the digital volunteers. Social media provides a natural environment for facilitating decentralized coordination for onsite field response teams [7]. During 2011 Japan Tsunami, people utilized Twitter for information milling, warning propagation, providing information about recovery efforts, and emotional support [1].

C. Social Network Analysis (SNA) and Twitter

Social network analysis facilitates the determination of the communication patterns among users. In [1], the researchers showed that social network analysis is a useful tool in identifying information sources. It was demonstrated that there are various techniques rooted in social network analysis to study emergent communities on Twitter [1]. The Twitter communication networks were analyzed to find the structural phenomena related to directed closure and its role in link formation [8]. In [9], researchers studied the Twitter hashtag adoption based on the structural properties of the network. The research showed that Twitter communication networks that drive the daily interactions among people are sparse and are based on existing friends and followers [10].

D. Open-domain Event Discovery

Traditional event extraction work focused on supervised learning for pre-defined event types in formal genres such as newswire [11], [12]. However, these methods are not appropriate for social media, which covers a wide range of diverse topics and lacks labeled data. Early work of event discovery exploited the word distribution differences across instances. For example, Yang et al [13] detected events by clustering documents based on the semantic distance between documents, while Kleinberg et al. [14] used word distributions to discover events by grouping words together. Some recent work attempted to rapidly and automatically adapt an event extraction system to new event types. For example, Li et al. [15] automatically acquired verb clusters from parallel corpora and discovered novel events based on semantic role labeling and active learning.

Unlike formal genres, social media stream is characterized by short messages with heavily colloquial speech. To handle such data stream, He et al. [16] analyzed signals in the frequency domain. They applied Discrete Fourier Transformation (DFT) to convert the signals from the time domain into the frequency domain. A spike in the frequency domain corresponded to trending event. Weng and Lee [17] tackled event discovery task for Twitter by detecting important word tokens and clustering them to represent novel events. They analyzed word-specific signals in the time domain. The advantage was that signals for individual words were built by applying wavelet analysis on the frequency-based raw signals of the words, hence important words were identified based on corresponding signal auto-correlations. The researchers in [18] developed a graphical model to extract event records from Twitter by learning a latent set of records and a record-message alignment simultaneously.

To conclude, our event extraction approach is most related to the research explored in [15] and [17]. Given some event clusters as seeds, we obtained new relevant keywords to expand each event keyword cluster and use these clusters to represent events. In addition, we utilized semantic attributes to declaratively discriminate specific and affirmed events from others. To the best of our knowledge, this is the first work to incorporate semantic attributes into novel event discovery in an open domain.

III. METHODOLOGY

A. Overview

An overview of the approach taken in this paper is illustrated in Fig. 1. First, data was collected via streaming Twitter API during the time of an emergency. Then the data was processed using the Support Vector Machines (SVMs) based binary classifier to extract tweets related to the emergency. Next, a selected set of search terms was used to annotate the tweets with actionable events - 'propagate the warning', 'seek information or confirmation', and 'take prescribed action'. To overcome the unstructured format of the tweets' text an appropriate set of NLP techniques was used. The annotation was further enriched through assignment of attributes for each tweet - polarity and modality. This was accomplished via SVMs based event attribute classification.

A timeline was constructed utilizing data collected from on-site interviews and publicly available information on the Internet. The timeline was used to construct communication networks for each time slice. A random walk algorithm was employed to discover communities in Twitter communication networks by time slice. SNA was used to identify the leaders of these communities. The knowledge obtained from NLP about the tweet content - actions and attributes, enabled us to make inferences about the behaviors of community members and roles of their leaders.

B. NLP Approach

1) Terminology: We defined the following terminology for a series of NLP approaches.

On-topic/Off-topic Tweets: We defined the tweets that were related to the topic of our interests as “on-topic” and the
rest as “off-topic”. In our case study, all tweets related to Japan tsunami were on-topic. An on-topic tweet example is as follows: RT @CBCAlerts: 7.2 magnitude earthquake hits Northern Japan. Tsunami alert has been issued.#Japan #Quake

**Actionable Events**: Events that belonged to the following categories: receive the warning; seek information or confirmation; and take prescribed action. The categories were selected from the six stages of warning response process previously described in Section II Related Work.

**Event Attributes**: Event attributes were used to measure user intention to participate in actionable event. Two semantic attributes were adapted from [19] to describe each actionable event: (1) modality, where an event was “asserted” when the author or speaker made reference to it as though it were a real occurrence; and (2) polarity, where an event was “positive” when it was explicitly indicated that the event occurred.

**Actionable Tweets**: Tweets that belonged to an actionable event (receive the warning, seek confirmation, and take prescribed action).

2) **On-topic Tweet Detection**: According to the hashtag definition from Twitter, the hashtag symbol, #, together with a relevant keyword or a phrase in the tweet is used to categorize the tweets and allow them to be displayed more easily in Twitter Search. Also, popular hashtagged words are often characterized as trending topics.

Inspired by the hashtag definition, we developed a novel annotation scheme based on the assumption that tweets with the same hashtag are on the same topic. First, we extracted hashtags with high frequency $^1$ that indicate trending topics. Then we manually annotated each trending hashtag as either on-topic or off-topic hashtag. After annotating hashtags, we propagated the on-topic/off-topic label of each hashtag to all tweets with each hashtag. We trained an on-topic/off-topic tweet classifier, based on Support Vector Machines (SVMs) [20], using the following features: (1) unigrams (all unique unigrams of a tweet); (2) userID (the ID of the user who posted the tweet); (3) replyID (the ID of the user to whom the tweet is replying); and (4) mentionID (the ID of users who the tweet has mentioned). All hashtags were removed from tweets during training and testing process, so the trained classifier was able to process all of the genetic tweets without any hashtags.

3) **Actionable Event Extraction**: After filtering out irrelevant tweets, we developed a bootstrapping framework to predict actionable events. To expand the key word seeds, we followed the cross-lingual event trigger clustering approach described in [15] to discover words with similar meanings. The algorithm exploited the idea that if two words - $w_1$ and $w_2$ on the source side of bi-lingual parallel corpora were aligned with the same word on the target side with high confidence, then they should be have similar meanings. For each English key word seed, the search was to find other English words that shared the same frequently as aligned Chinese terms and vice versa. The word alignment information between each bilingual sentence pair was obtained by running Giza++ [21]. To eliminate the noise introduced by automatic alignment, we filtered out stop words and those English-Chinese word alignment pairs with frequency (in parallel corpora) less than a threshold$^2$. Finally, we used each expanded keyword set as keywords to retrieve actionable events.

4) **Event Attribute Labeling**: In addition to identifying actionable events, we also labeled semantic attributes including modality and polarity for each event. We learned a separate SVMs based classifier for each attribute from Automatic Content Extraction 2005 Evaluation (ACE2005) training data. The learnt classifier was applied to predict modality and polarity values for each actionable event. Because the training data set, ACE2005, was mostly news and our target domain was tweets, we explored the following genre-independent features to bridge the genre gap between news and tweets: (1) lexical features, which are unique full words, lowercase words, lemmatized words and part-of-speech tags; (2) N-gram features, where an n-gram ng (n=1, 2, 3) was selected as an indicative context feature if it matched one of the following two conditions - (i) ng appeared only in one class, and with frequency higher than a threshold; and (ii) the probability that ng occurring in one class was higher than a threshold; where both thresholds were optimized from a small development set including 30 events; and (3) dictionary features, such as expression, consideration, subjective, intention, condition, and negation, were used.

C. **SNA Methodology**

1) **Network Construction**: The communication network of Twitter data was constructed using the communication directional identifiers - @ for directed and mention tweets and RT for the re-tweets. Two relationships were incorporated into the communication network – the directed/mention and the re-tweet relationships. For directed/mention relationship an edge existed if one user tweeted and/or mentioned another user. The user doing the tweeter was at the head of the edge and the user who was mentioned or the tweet was directed at was at the tail of the relationship. For re-tweet relationship the

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$^1$we treat hashtags appear more than 50 times as high frequency ones

$^2$we set the frequency threshold as 4
A user re-tweeted another user’s tweet. The user who was doing the re-tweeting was at the tail of the edge and user sending the original message was at the head of the relationship. The network was constructed for each of the time slices of the event timeline previously discussed. This allowed for investigation of the evolution and the dynamics of the network. The research evaluated actionable behaviors on Twitter, therefore, only actionable tweets were utilized to construct the network. The constructed network is referred to as Twitter communication network in the following sections.

2) Attribute Setup: The NLP analysis assigned specific attributes to each actionable tweet - modality and polarity. These attributes were initially assigned as edge attributes in the Twitter communication network. However, when the Twitter network was constructed multiple and self-loop edges were discovered. Multiple edges represent multiple tweets between same two users. The self-loop edges represent edges from the user to itself. The presence of such edges precluded the use of community finding algorithms. In order to address this problem the graph was simplified and edge attributes were automatically collapsed into the node attributes to preserve all of the extracted information. Each node’s attribute was the sum of all respective tweet attributes sent or received by the user.

3) Community Finding: Currently, most of the algorithms can not handle the directedness of the edges when detecting the communities [22]. In order to overcome this issue, the graphs are often converted into undirected graph for the purposes of community detection [23]. When Twitter users communicate among each other and direct their messages to other users the evidence of communication (tweets) is displayed in the profiles of both users. This dichotomy allowed us to justify the modification of the graph from directed to undirected graph for community detection purposes. The community finding approach utilized in the research was a random walk community detection algorithm. The foundation of the approach lies with the assumption that there are only a few edges that leave communities. Therefore, the algorithm uses a number of random walks on the network and then uses those walks to merge the separate communities in a bottom up manner [24]. This particular algorithm is most appropriate to find communities in the large sparse networks, which commonly occur in the Twitter data.

The social science literature informs the research on the properties of cohesive groups. It suggests that the people in the same community tend to have similar and redundant information. Moreover, there is an ease of information transfer in cohesive groups [25], [26]. In this research, this concept was evaluated in the context of Twitter communication network during emergencies. In order to ascertain if this theory of group behavior applies to the communications and behaviors on Twitter the correlation between the community members based on behaviors derived from the Twitter users’ behavioral attributes was evaluated. The size of the communities found in the data enabled us to determine how many people obtained similar information and shared similar intents. The ten largest communities for each time slice were evaluated by examining the similarity (correlation) of behavior among the community members to discover the prevalent behavior.

4) Centrality and Prestige: Once the communities were identified the task was to find the community leaders. Each community was taken separately and a community leaders were identified as the most central/prestigious actors. The centrality/prestige measures that were utilized in this research were outDegree, inDegree, betweenness, and eigenvalue centrality (power). An outDegree centrality measure is simply the number of messages sent by a Twitter user to other users in the network. An outDegree measure is associated with faster information diffusion as it reaches more people. In [1], the researchers showed that people with high outDegree engage in information propagation. An inDegree measure represents a number of incoming messages sent to a Twitter user by other users. Another measure of betweenness represents a level of control one user has over the communication between other users. The users with high betweenness values serve as information gatekeepers [1], the betweenness of a node is the number of the shortest paths between any two nodes in the network that have to pass through this node [27]. A power measure represents the node’s connectedness to other central nodes [28].

Each centrality measure is associated with a different kind of behavior, users scoring high on each of those measures can represent different types of leadership. Therefore, three types of leaders are defined - the diffuser, the gatekeeper, and the information broker. The diffuser leader is a leader which “diffuses” the information through the network. This type of leader is associated with an outDegree measure as it measures the number of tweets (edges) a node sends out. Another type of leader is a gatekeeper. A gatekeeper is a node that controls an information flow in the network. Measures associated with the role of a gatekeeper are betweenness [29], [30] and power [31]. There are two types of gatekeepers that emerge when betweenness and power measures are combined - critical gatekeeper and unique access gatekeeper [31]. A critical gatekeeper is associated with high betweenness and low power values whereas a unique access gatekeeper is tied to low betweenness and high power values [31]. We defined the final type of the leader as information broker, who has access to valuable information and brokers it to other nodes in the network upon request. An information broker is associated with high inDegree and high power measures. A high power measure suggests access to other central actors and information they are able to provide. A high inDegree measure suggests high frequency of inquiry from other users in the community. The frequency of inquiry for information can be inferred from the ‘action’ attribute - ‘seek and obtain confirmation’.

Once the community leaders were identified their behavior was evaluated based on the type of actionable tweets they sent out. That behavior was then compared to the overall behavior of the community members. For example, when a leader of the community sent out a warning to evacuate, which was accompanied by action attribute - ‘propagate the warning’ and polarity - ‘true’, the expected result was for the community to follow the lead and send out the tweets with action attributes - ‘propagate the warning’ and/or ‘take a prescribed action’ and polarity - ‘true’.

IV. DATA DESCRIPTION

The methodology presented in this work is generalizable to all emergencies. However, in order to facilitate the understanding of the methodology the 2011 Japan Tsunami was used. The
tsunami occurred on March 11th, 2011 and impacted the entire Pacific Coastline. There was over 15,000 people whose lives were lost due to the tsunami including one in Klamath River, CA, USA. It also produced between $12 and $16 millions of dollars worth of damage in California [32]. In Hawaii, the governor had made a disaster declaration [33]. Throughout the event the tsunami has triggered multiple warnings issued by the Tsunami Warning Centers and evacuation orders issued by the local emergency management organizations.

The qualitative data was collected via semi-structured interviews with the members of emergency community who were involved during the event - members of Tsunami Warning Centers, emergency managers at Hawaii Civil Defense and Del Norte County Emergency Management Services, and members of local broadcast media. The “After Action Reports” were collected during the interviews, which allowed the construction of the detailed timeline of the event summarized in Table I. Additional information, which was obtained from searching publicly available information, further enriched the knowledge about the event and details about human behavior during the event. Twitter data was obtained from Information Sciences Institute through collaborative work. Twitter data was collected via streaming Twitter API. The data set included all of the publicly available information, further enriched the knowledge of the detailed timeline of the event summarized in Table I.

<table>
<thead>
<tr>
<th>Time Slice</th>
<th>Time (UTC)</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5:46:28AM – 5:55:02AM</td>
<td>PTWC registers an earthquake 231 mi. from Tokyo, Japan of magnitude 7.9 and issues first bulletin – tsunami watch for HI</td>
</tr>
<tr>
<td>2</td>
<td>5:55:02AM – 6:41:22AM</td>
<td>PTWC issues second bulletins (international &amp; HI); EOC’s activated in HI</td>
</tr>
<tr>
<td>3</td>
<td>6:41:22AM – 7:31:00AM</td>
<td>PTWC issues third bulletin; tsunami warning is issued in HI</td>
</tr>
<tr>
<td>4</td>
<td>7:31:00AM – 9:01:00AM</td>
<td>Evacuation is ordered in HI; boat evacuations in HI and AK</td>
</tr>
<tr>
<td>5</td>
<td>9:01:00AM – 12:30:00AM</td>
<td>Evacuation travel is completed in HI. U of HI is closed; CA issues evacuation orders; tsunami arrives in King Cove, AK</td>
</tr>
<tr>
<td>6</td>
<td>12:30:00AM – 13:36:00AM</td>
<td>Tsunami arrives in HI; Hanaei, Kahului, Hilo</td>
</tr>
<tr>
<td>7</td>
<td>13:36:00AM – 17:31:00AM</td>
<td>Tsunami warning is downgraded to advisory in HI; all ports and evacuation zone are closed in HI; tsunami arrives in Crescent City, CA</td>
</tr>
<tr>
<td>8</td>
<td>17:31:00AM – 21:26:00AM</td>
<td>All clear is issued in HI</td>
</tr>
<tr>
<td>9</td>
<td>21:26:00AM – 6:36:00AM</td>
<td>Final all clear is issued by PTWC</td>
</tr>
</tbody>
</table>

10,622 tweets are used for blind test. The accuracy results were as follows: (1) for on-topic tweets classification - 81.93%; (2) for polarity - 96.8%; and (3) for modality 78.4%.

The actionable tweets were aggregated per time slice to evaluate the results and compare analyzed data and Twitter user behavior with the timeline of the events. In Table II, there is a great spike in the volume of tweets during the time slice 4. This is natural as that’s when most of the tsunami warnings were issued and evacuations were ordered along the affected coastline. Moreover, it is evident that the ‘receive the warning’ tweets are prevalent in earlier time slices and then gradually drops off as the event concludes. This is a natural progression and corresponds to the event timeline. The ‘take prescribed action’ tweets peak in time slices five, six, and seven after the evacuation orders have been issued. Finally, the confirmation tweets increase in the later time slices after the warnings and evacuation orders were issued. Additionally, during the later time slices people were confirming the well-being of their friends and relatives affected by the event. The evolution of behaviors extracted from the NLP action assignments to the tweets correspond to overall evolution of the event.

**V. Results**

**A. Natural Language Processing**

We were able to annotate 800 hashtags in a very short time period (1.5 hours) and gather a large number of human annotated tweets (311,735). As a result, 37 hashtags were annotated as on-topic and the rest were annotated as off-topic and thus 26,554 on-topic tweets and 285,181 off-topic tweets are gathered respectively. To balance the training and testing data, we randomly sampled the same amount of off-topic tweets as on-topic tweets to conduct the experiments. 42,486 tweets are randomly selected for training, and the remaining 10,622 tweets are used for blind test. The accuracy results were as follows: (1) for on-topic tweets classification - 81.93%; (2) for polarity - 96.8%; and (3) for modality 78.4%.

The actionable tweets were aggregated per time slice to evaluate the results and compare analyzed data and Twitter user behavior with the timeline of the events. In Table II, there is a great spike in the volume of tweets during the time slice 4. This is natural as that’s when most of the tsunami warnings were issued and evacuations were ordered along the affected coastline. Moreover, it is evident that the ‘receive the warning’ tweets are prevalent in earlier time slices and then gradually drops off as the event concludes. This is a natural progression and corresponds to the event timeline. The ‘take prescribed action’ tweets peak in time slices five, six, and seven after the evacuation orders have been issued. Finally, the confirmation tweets increase in the later time slices after the warnings and evacuation orders were issued. Additionally, during the later time slices people were confirming the well-being of their friends and relatives affected by the event. The evolution of behaviors extracted from the NLP action assignments to the tweets correspond to overall evolution of the event.

**B. Twitter Network Communities**

Table III shows the results produced by the random walk algorithm. Note that the time slice (TS) one was omitted from the results there were no communities discovered during that time slice. The range in the table represents the size range of the communities - i.e. for time slice the size of the smallest community was 2 and the size of the largest community was 11. A higher percentage of communities of size larger than four ('Percentage of > 4 com.') occur during time slices two, three, and four. This result is expected as the users are exchanging warning information recently issued and confirming prescribed action.

When the communities and its members were examined more closely there was significant correlation found in community members’ behaviors. Over all time slices, every community had 80 percent or greater of its members that had exactly the same behavior - i.e. same actionable event, modality, and polarity. For those communities, where there was a difference among the members’ behaviors, the difference
was in actionable events, and not in modality or polarity. The members usually split into two groups within the community, based on the actionable event - warning group, those who received and propagated the warning, and take action group, those who expressed intent to take the prescribed action. The finding suggests that people of a community tend to exhibit similar behaviors. It is important for all members of the community to share similar polarity for their behavior. For example, if the leader sends out a message urging people to evacuate - action 'propagate the warning' and polarity - 'true', the expected result for the rest of the community is to respond with either action of 'propagate the warning' or 'take prescribed action' with the same polarity. When the polarity was evaluated among the members of the communities only 5 per cent or less of all communities exhibited difference in polarity among its members. Additionally, the tweets with confirmation actionable event rarely occurred in the large communities and were more typical of communities of size less than 4. In order to visualize the results the network for time slice four was constructed to include top ten communities in color, and view different types of action using different shapes Fig. 2: square for 'receive the warning'; rectangle for 'seek and obtain confirmation'; and circle for 'the prescribed action'.

Time slice four was chosen because there was the most actionable information issued during that time - i.e. evacuation orders in HI and AK. Also this was the time slice which included the largest number of tweets. Moreover, when the communities were traced from time slice to time slice there was little overlap discovered between its members. This suggests that the communities formed on Twitter serve a purpose in each time slice such as propagate the warning, obtain information or confirmation, and exhibit an intent to take the prescribed action. Once the action is completed there is no longer a need to participate on Twitter.

C. Community Leaders

When community leaders were evaluated for all communities of size larger than four it was discovered that the roles of diffuser and gatekeeper were assumed by the same nodes. Additionally, it was confirmed that the action of 'seek information or confirmation' is a characteristic of communities of size smaller than four. Therefore, the information broker role was taken by a selected set of users in those communities. As shown in Table IV and V, ten largest communities for time slice four, when the critical warning information was issued, were selected for analysis, and diffuser and gatekeeper roles were combined and defined as community leaders.

The community leaders were the members of traditional media, and primarily focused on the diffusing the information - action attribute of 'propagate the warning', and the other community members were following the leaders by either taking the prescribed action or propagating the warning. When the leaders were issuing information to evacuate, actionable event - 'propagate the warning' and polarity - 'true', the rest of the community followed one of two actions - 'propagate the warning' or 'take the prescribed action', with the same polarity. When the lack of overlap between the communities across the timeline was discovered, a significant finding was the presence of the leaders in all time slices. As the members of communities participated in the communication only during a particular time slice, the leaders continued their participation throughout the event. This evidence suggests that Twitter users were gravitating towards the leaders who were sources of information and at the same time in control of the information, i.e. diffusers and gatekeepers.

VI. CONCLUSION AND FUTURE RESEARCH

The findings suggested that governmental emergency management organizations made limited use of Twitter during 2011 Japan tsunami. However, the traditional media outlets utilized Twitter extensively to disseminate warnings. In this paper the methodology was developed that combines natural language processing and social network analyses. The methodology was successfully applied to a data set collected from Twitter during 2011 Japan tsunami. The analysis was able to demonstrate that the behavior of the Twitter users was consistent with the issuance of actionable information based on warnings. It was also discovered that members of the same community demonstrate similar behaviors. The leaders of the communities, typically the traditional media, were propagating the warnings and urging the other community members to take the prescribed action. Moreover, it was discovered that the leaders

<p>| Table IV | Time Slice Four Community Results |</p>
<table>
<thead>
<tr>
<th>com</th>
<th>com size</th>
<th>Action</th>
<th>Modality</th>
<th>Polarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>32</td>
<td>receive</td>
<td>non-asserted</td>
<td>positive</td>
</tr>
<tr>
<td>4</td>
<td>114</td>
<td>receive</td>
<td>asserted</td>
<td>positive</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>receive</td>
<td>non-asserted</td>
<td>positive</td>
</tr>
<tr>
<td>6</td>
<td>77</td>
<td>receive</td>
<td>non-asserted</td>
<td>positive</td>
</tr>
<tr>
<td>10</td>
<td>325</td>
<td>receive</td>
<td>non-asserted</td>
<td>positive</td>
</tr>
<tr>
<td>11</td>
<td>42</td>
<td>receive</td>
<td>non-asserted</td>
<td>positive</td>
</tr>
<tr>
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<td>128</td>
<td>receive</td>
<td>non-asserted</td>
<td>positive</td>
</tr>
<tr>
<td>16</td>
<td>94</td>
<td>receive</td>
<td>asserted</td>
<td>positive</td>
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<td>17</td>
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</tr>
<tr>
<td>25</td>
<td>80</td>
<td>receive</td>
<td>asserted</td>
<td>positive</td>
</tr>
</tbody>
</table>

<p>| Table V | Time Slice Four Community Leadership Results |</p>
<table>
<thead>
<tr>
<th>Leaders</th>
<th>Action</th>
<th>Modality</th>
<th>Polarity</th>
<th>Tense</th>
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<td>non-asserted</td>
<td>positive</td>
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<td>present</td>
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</tr>
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</table>
maintained their role throughout the entire event, while the rest of the community members were present during a selected time slice. The communities formed around the information sources - i.e. the leaders.

To overcome a lack of knowledge of who are the individuals or organizations that disseminate warning information, provide confirmations of an event and associated actions, and urge others to take action the methodology employed was as follows: (1) assign actionable events to each on-topic tweet using NLP; (2) construct a communication network of tweets associated with actionable events; (3) use the network to discover communities with SNA; (4) extract the leaders of the communities and identify their roles with SNA; and (5) evaluate the behavior of the community members and their leaders using NLP. The key contributions in this research are the automatic discovery of the communities and community members behaviors during emergencies, authentication of the cohesive behaviors among the community members; and efficient extraction of their leaders, their roles and their behaviors.

In future research, the authors will attempt to include additional event attributes - i.e. location, to better understand the impact of emergencies on communities. In addition, this will allow us to study the co-evolution of the behavior of the community and its leaders and the structure of the network throughout an emergency. It will also provide the means to investigate the flow of actionable information and its distortion over time.

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