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Research Note

Social network analysis: Characteristics of online social networks after a disaster

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ABSTRACT

Social media, such as Twitter and Facebook, plays a critical role in disaster management by propagating emergency information to a disaster-affected community. It ranks as the fourth most popular source for accessing emergency information. Many studies have explored social media data to understand the networks and extract critical information to develop a pre- and post-disaster mitigation plan.

The 2016 flood in Louisiana damaged more than 60,000 homes and was the worst U.S. disaster after Hurricane Sandy in 2012. Parishes in Louisiana actively used their social media to share information with the disaster-affected community – e.g., flood inundation map, locations of emergency shelters, medical services, and debris removal operation. This study applies social network analysis to convert emergency social network data into knowledge. We explore patterns created by the aggregated interactions of online users on Facebook during disaster responses. It provides insights to understand the critical role of social media use for emergency information propagation. The study results show social networks consist of three entities: individuals, emergency agencies, and organizations. The core of a social network consists of numerous individuals. They are actively engaged to share information, communicate with the city of Baton Rouge, and update information. Emergency agencies and organizations are on the periphery of the social network, connecting a community with other communities. The results of this study will help emergency agencies develop their social media operation strategies for a disaster mitigation plan.

1. Introduction

Social media, such as Twitter and Facebook, plays a critical role in disaster management. It is ranked as the fourth most popular source for accessing emergency information (Lindsay, 2011). Mickoleit (2014) identified that government institutions are using platforms such as Twitter, Facebook, and blogs to communicate with their communities. Twitter accounts have been created in 24 out of 34 OECD member countries, which can be compared to 21 out of 34 for Facebook. Many studies have explored the systematic use of social media during emergency responses by extracting social media data to identify needs of a disaster-affected community (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013; Yin et al., 2015). For example, social media data was used to develop a GIS-based real-time map during 2012 Hurricane Sandy in NYC. It shared emergency information and community needs with emergency agencies and NGOs (Middleton, Middleton, & Modafferi, 2014). Furthermore, real-time data from social media has been used to develop an early warning system for a tornado (Knox et al., 2013; Tyshchuk, Hui, Grabowski, & Wallace, 2011). Social media is used to communicate emergency information and urgent requests between emergency agencies and disaster-affected people (Feldman et al., 2016; Lindsay, 2011). These approaches support emergency agencies in understanding emerging situations rapidly after a disaster.

More than 60,000 homes were damaged in the 2016 flood in Louisiana (Han, 2016). It was the worst disaster after Hurricane Sandy in 2012 (Yan & Flores, 2016). A couple of parishes in Louisiana used their social media to share emergency information with people affected by the disaster. The city of Baton Rouge in Louisiana actively used its social media, such as Facebook and Twitter, to deliver real-time emergency information to the affected people in a timely manner. Few studies have analyzed social network structures and roles during disaster responses. This study applied social network analysis (SNA) to understand the characteristics of social media networks in Louisiana during emergency responses.

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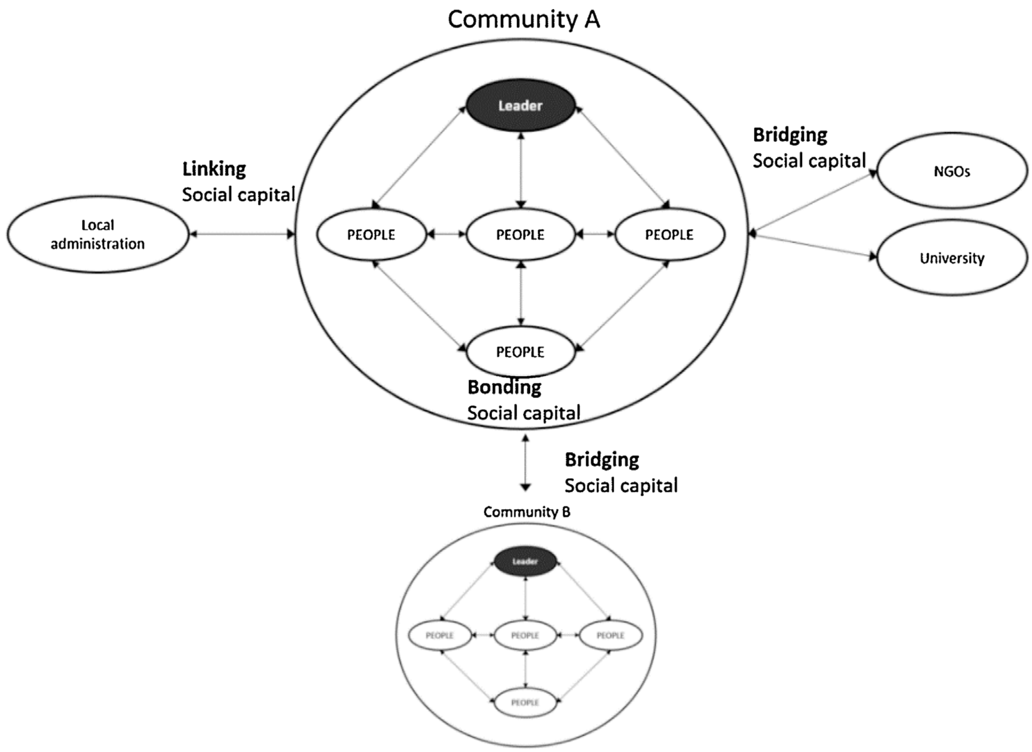


Fig. 1. Conceptual diagram of social capital (Nakagawa & Shaw, 2004).

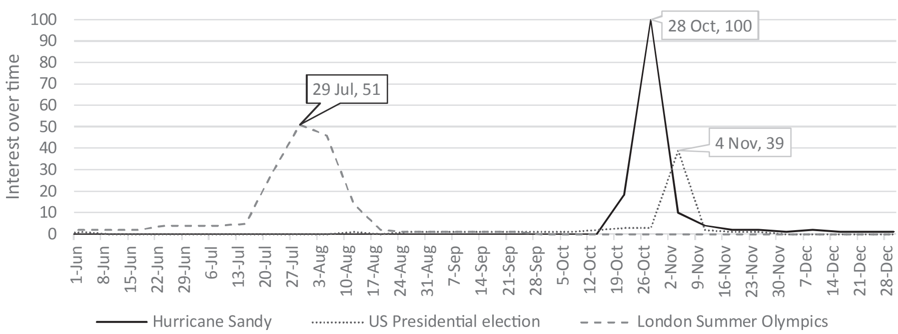


Fig. 2. Search-term comparison during 2012 Hurricane Sandy in the U.S. (Google Trends, 2017a).

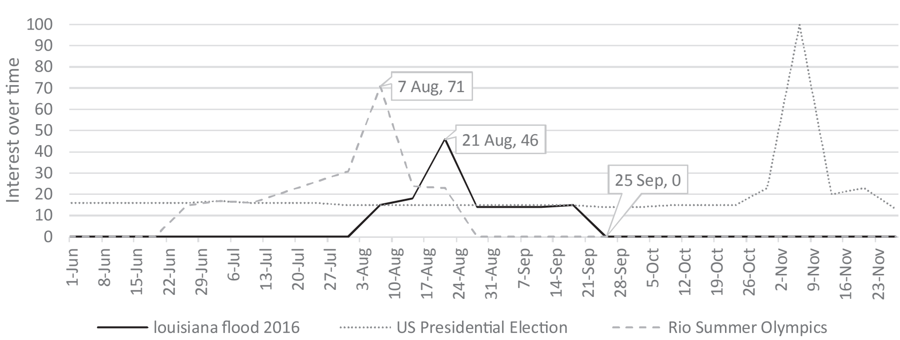


Fig. 3. Search-term comparison during 2016 Louisiana flood in the city of Baton Rouge, Louisiana, USA (Google Trends, 2017b).

2. Literature review

2.1. Social capital for disaster recovery

Social capital can be defined as “the resources accumulated through the relationships among people” (Coleman, 1988). Positive social outcomes from social capital have been identified through public health, lower crime rates, and financial markets (Adler & Kwon, 2002). In general, social capital brings a positive effect of interaction among participants in a social network (Helliwell & Putnam, 2004). Ellison, Steinfield, and Lampe (2007) identified that greater social capital

Table 1
Social media demographics and frequency (Duggan, 2015).

Facebook		Twitter
18–29	82%	32%
30–49	79%	29%
50–64	64%	13%
65 +	48%	6%
Daily	70%	38%
Weekly	21%	21%
Less often	9%	40%

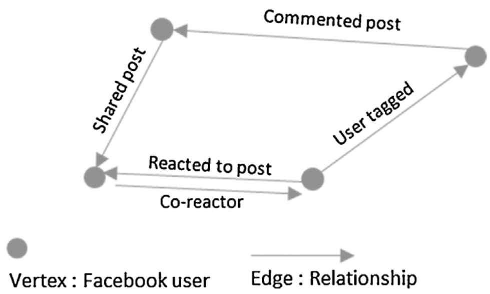


Fig. 4. Illustration of users and relationship.

Table 2
Overall Metrics.

Graph Metric	Value
Graph Type	Directed
Vertices	1171
Unique Edges	21,115
Edges with Duplicates	6400
Total Edges	27,515
Self-Loops	671
Reciprocated Vertex Pair Ratio	0.024
Reciprocated Edge Ratio	0.047
Connected Components	18
Single-Vertex Connected Components	16
Maximum Vertices in a Connected Component	1153
Maximum Edges in a Connected Component	27,510
Maximum Geodesic Distance (Diameter)	5
Average Geodesic Distance	2.41
Graph Density	0.02

increased commitment to a community and the ability to mobilize collective actions.

Many scholars have emphasized that social capital plays a critical role in responses to disasters. Nakagawa and Shaw (2004) examined the post-earthquake rehabilitation and reconstruction programs in two cases: Kobe in Japan and Gujarat in India. They identified that social capital and leadership in the community are the basic attributes for rapid disaster recovery. They described three aspects of social capital: *bonding*, *bridging* and *linking (see* Fig. 1). By investigating disaster recovery after the 1995 Kobe earthquake in Japan, Aldrich (2011) emphasized that the power of people (social capital) is the strongest and most robust predictor of population recovery after a catastrophe. Aldrich and Meyer (2014) examined recent literature and evidence to investigate the critical role of social capital and networks in disaster recovery. They highlighted that disaster agencies, governmental decision makers, and NGOs need to strengthen social infrastructures at the community level to increase disaster resilience. Joshi and Aoki (2014) investigated two districts affected by the tsunami in India. They concluded that the strength of social networks, the commitment of residents to the community, popularity of leaders, and various social factors influenced the disaster recovery. Grube and Storr (2014) studied how pre-disaster systems of self-governance support post-disaster recovery. They concluded that local knowledge and knowledge transfer are important in the recovery of disaster-affected communities. To increase community resilience after a catastrophe, the role of social media is substantial.

2.2. The role of social media in a disaster

The importance of social media engagements after a disaster has been identified by many scholars (Kim & Hastak, 2017; Middleton et al., 2014; Poorazizi, Hunter, & Steiniger, 2015; Reuter, Heger, & Pipek, 2013; Yin et al., 2015; Yoo, Rand, Eftekhar, & Rabinovich, 2016). Social media has a range of roles, from preparing and receiving disaster preparedness information and warnings, and signaling and detecting disasters prior to an event, to linking community members following a disaster (Houston et al., 2015).

After the 2010 Haiti earthquake, people shared numerous texts and photos via social media. Within 48 h, the Red Cross had received US$8 million in donations, and this exemplified one benefit of the powerful information propagation capability of social media sites (Gao, Barbier, & Goolsby, 2011; Keim & Noji, 2011; Yates & Paquette,2011). Graham, Avery, and Park (2015) surveyed more than 300 local government officials from municipalities across the U.S. Their study identified that the extent of social media use is related with assessments of the local city's ability to control a crisis. It is also related to their overall evaluations of the strength of their responses. The Federal Emergency Management Agency (FEMA) utilizes various social media, including Facebook, Twitter, Instagram, LinkedIn and YouTube, to provide the public with emergency information related to a catastrophe (FEMA, 2016).

Yoo et al. (2016) collected Twitter data during Hurricane Sandy and applied information diffusion theory to characterize diffusion rates. The variables are (1) information cascade's diffusion speed, (2) cascade originator's influence and cascade content's contribution to situational awareness, (3) lateness in the launch of the cascade during the disaster, (4) incidence of cascade boosts by the originator, and (5) misleading cascade. They identified that internal diffusion through social media networks advances at a higher speed than information in these networks coming from external sources.

Furthermore, uses of social media as an information diffuser should be calibrated to expedite the effectiveness in an emergency. Keim and Noji (2011) emphasized that P2P communications could spread misinformation and rumor as well as privacy rights violations. An extremely high volume of messages via social media makes it hard for disaster-affected communities and professional emergency responders/agencies to process and analyze the information. Imran et al. (2013) proposed a system integrated with machine learning techniques to provide actionable information from social media. Liu et al. (2014) studied disaster information forms (social media vs. traditional media) and sources (national agencies and media vs. local agencies and media) to generate desired public outcomes such as intentions to seek and share emergency information.

2.3. Social network analysis and tools

Software and tools have been developed to fulfill the increasing need for social network data mining and visualization technology. Researchers created toolkits from sets of network analysis components

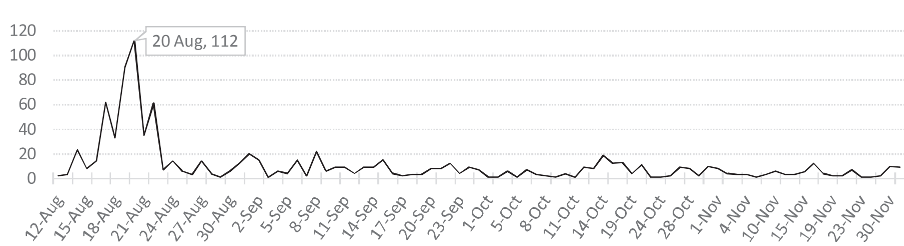


Fig. 5. Numbers of reactions on the Facebook page of the city of Baton Rouge.

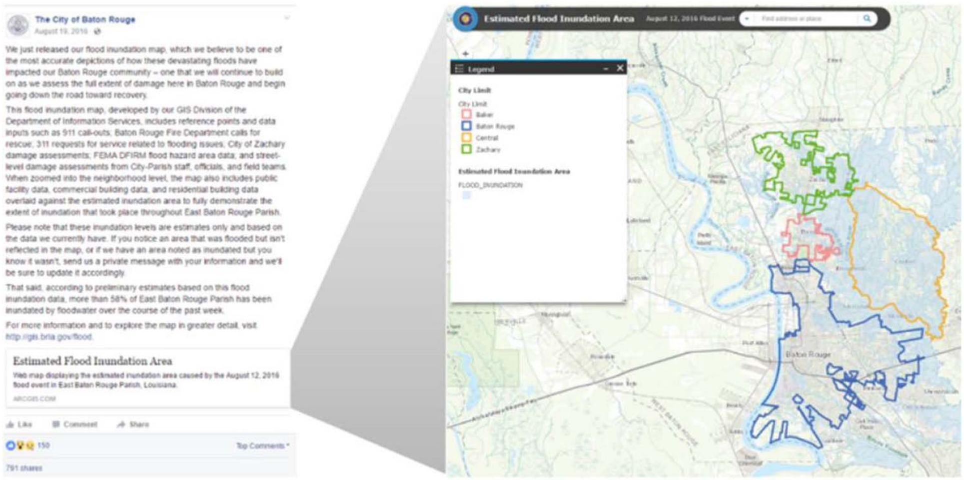


Fig. 6. Most shared and commented information on Facebook after the flood (eBRGIS, 2016).
(150 likes, 791 shares and 61 comments retrieved from the Facebook page of the city of Baton Rouge).

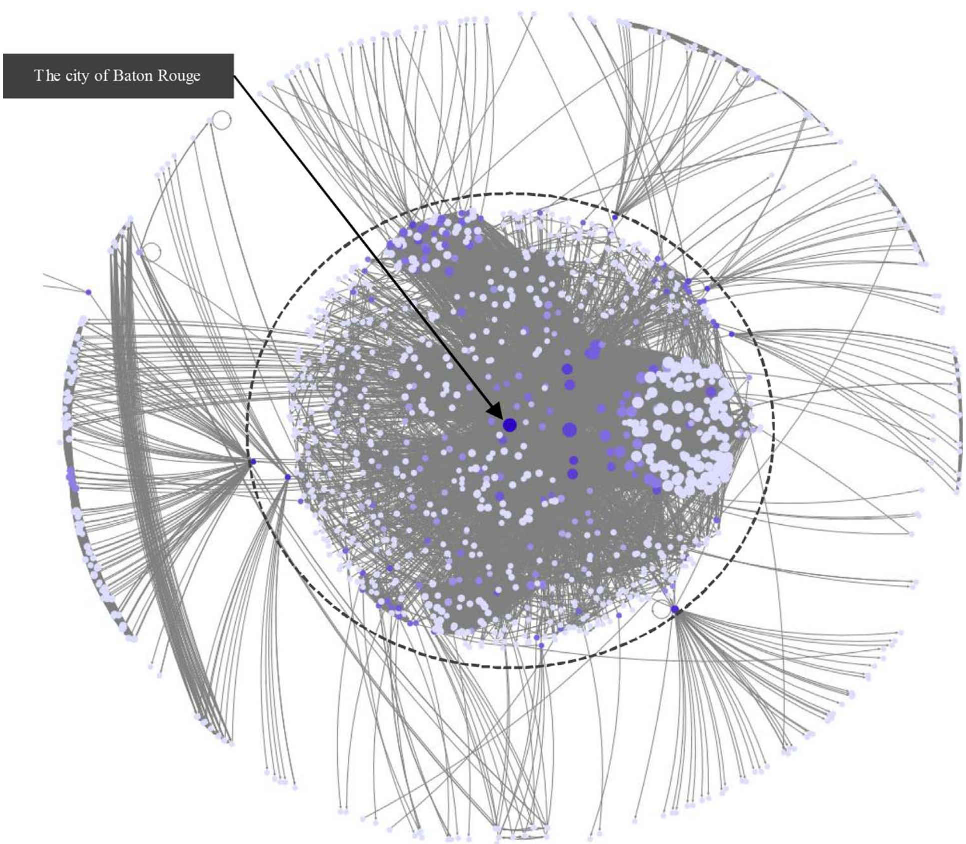


Fig. 7. Network graph during the 2016 Louisiana flood.
(Harel–Karen layout is used. Vertex size is based on out-degree. Bluer vertices represent higher betweenness)

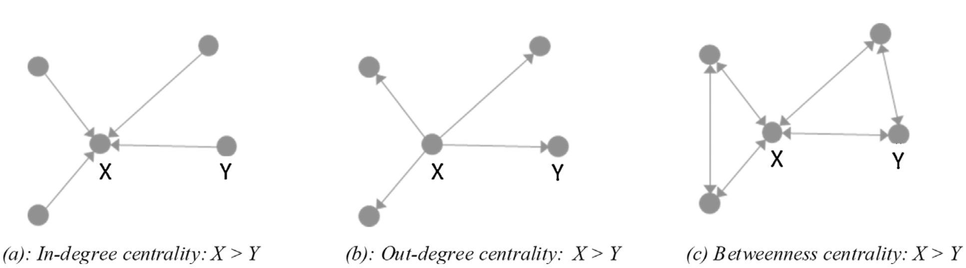
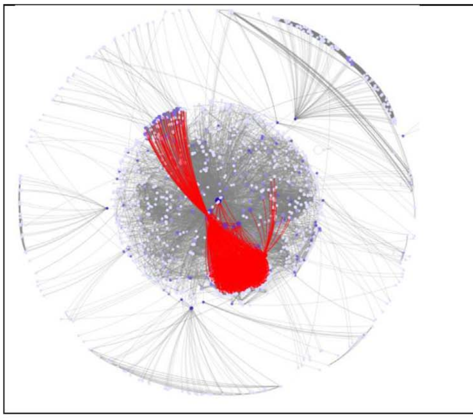


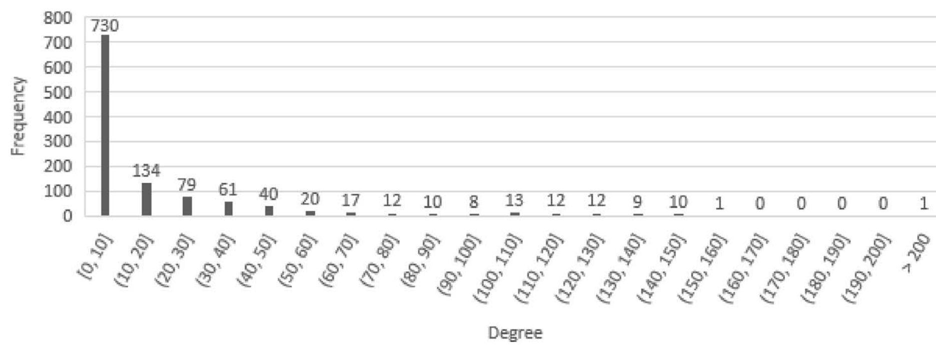
Fig. 8. Illustration of degree centrality.

not limited to R and the SNA library, JUNG, Guess, and Prefuse including NodeXL and Gephi (Adar, 2006; Heer, Card, & Landay, 2005; Smith et al., 2009; White, 2005). These tools have different characteristics, but most of them allow (1) computation of metrics that provide a local (actor level) and global (network level) description of the network, (2) graphical visualization of the network, and (3) community detection (Combe, Largeron, Egyed-Zsigmond, & Géry, 2010; Oliveira & Gama, 2012).

Table 3
Top 10 out-degree centrality and degree distribution.
Red-colored lines are all edges linked with top 10 out-degree vertices excluding CBR.



Users	Out-degree
CBR	228
User#1	153
User#2	150
User#3	149
User#4	147
User#5	147
User#6	146
User#7	145
User#8	144
User#9	143



(minimum 0, maximum 228, average 19, median 5).

3. Research objectives

Many studies have explored social media data to understand social networks and extract critical information to develop a pre- and post-disaster mitigation plan. This study explored disaster responses in social media after the 2016 Louisiana flood. The prolonged rainfall in southern parts of Louisiana resulted in catastrophic flooding that submerged thousands of houses and businesses. It was recorded as the worst disaster in the U.S. after Hurricane Sandy in 2012, and it damaged more than 60,000 homes (Ball, 2016; Brown et al., 2016; May & Bowerman, 2016; Yan & Flores,2016). This study applies SNA to convert social media data into knowledge. It provides insights to understand the critical role of social media for emergency information propagation. Objectives of this study are as follows:

1) Collect social media data from the Facebook page of the city of Baton Rouge during the period of the 2016 Louisiana flood, August 12–December 1, 2016.
2) Explore connections and patterns created by the aggregated interactions in the Facebook page during disaster responses.
3) Identify and analyze social roles and key players in the social network.
4) Analyze the posts during the disaster, such as discussions, top words and word pairs.
5) Suggest further actions to improve the effectiveness of information diffusion via social media.

4. Louisiana flood and social media

4.1. Search-term trends: 2012 Hurricane Sandy vs. 2016 Louisiana flood

The major media has been criticized by many leaders in Louisiana for the lack of coverage of the 2016 Louisiana flood, especially compared to the other major natural disasters in the U.S. (Berman, 2016; May & Bowerman, 2016; Pallotta, 2016; Scott, 2016). During the period, the media mainly covered the 2016 U.S. presidential election and the 2016 Rio Summer Olympics. Craig Fugate, the administrator for the FEMA, stated: “You have Olympics, you got the election. If you look at the national news, you’re probably on the third or fourth page. … We think it is a national headline disaster” (O’Donoghue, 2016). For instance, the *New York Times* published its first story on the evening of August 14 (Hersher, 2016).

Thus, we explored Google Trends to identify 2012 and 2016 trending stories in the U.S. near two disasters: Hurricane Sandy and the Louisiana flood. The trend data, *interest over time*, are scaled on a range of 0–100 based on a topic’s proportion to searches for all topics (Google, 2017).

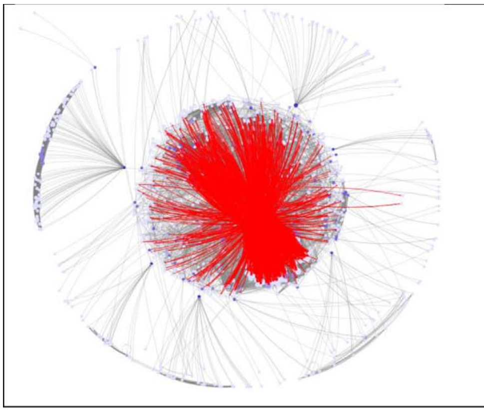
4.1.1. Trends at a national level

It was hard to observe the search-term trend (or interest over time) for *Louisiana flood 2016* compared to *2016 presidential election* and *2016 Rio Summer Olympics* at a national level. However, search-term trends in 2012 were different in similar circumstances when Hurricane Sandy struck. Despite the 2012 London Summer Olympics and the 2012 presidential election occurring in the year of Hurricane Sandy, media interest in Hurricane Sandy was significantly higher than in these other events. Hurricane Sandy hit New York City on Oct 29, 2012. Interest peaked during the week of October 28–November 3 (Fig. 2).

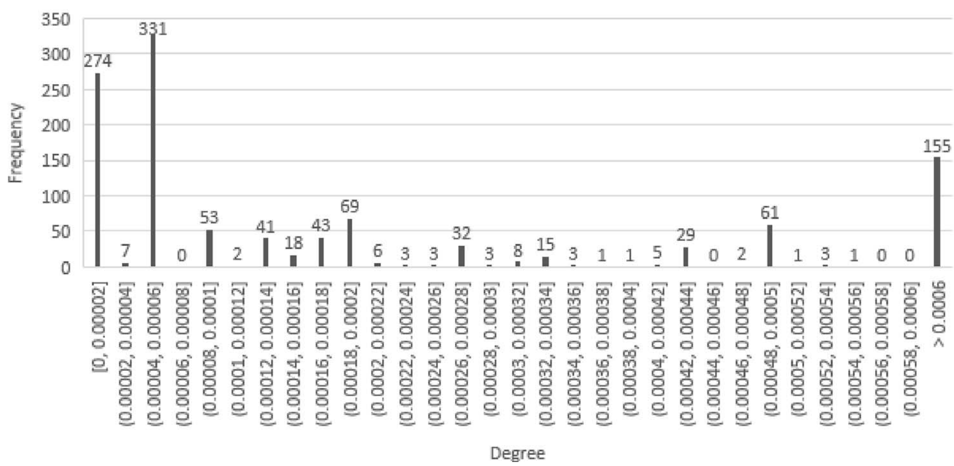
4.1.2. Trends at a local level

Google search-term trends in Louisiana are shown in Fig. 3. *Louisiana flood 2016* reached a peak during the week of Aug 17–21, 2016. Compared to Hurricane Sandy in 2012, the peak of interest on the topic, *2016 Louisiana flood*, was not higher than *2016 Rio Olympics* and

Table 4
Top 10 Eigenvector centrality and degree distribution.
Red-colored lines are all edges linked with top 10 in-degree vertices excluding CBR. User#5 is in both the top 10 out-degree and eigenvector centralities.



Users	Eigenvector
CBR	0.006628
User#10	0.006238
User#11	0.006149
User#12	0.006122
User#13	0.006084
User#14	0.00606
User#15	0.006042
User#16	0.006006
User#5	0.005995
User#18	0.005995



(minimum 0, maximum 0.00663, average 0.00085, median 0.00005)

2016 presidential election in Louisiana. Also, it reached the peak after the flood occurred in Aug 12, 2016.

4.2. Comparison of social media platforms: Facebook and Twitter

According to Social Times, Facebook has 1.59 billion monthly active users (as of Dec 2015), while Twitter has 320 million (as of March 2016) (Social Times, 2016). Duggan (2015) examined Facebook and Twitter users among internet users in the survey and identified Facebook as having a broader range of generation than Twitter. In addition, 70% of Facebook users are on the platform on a daily basis, compared with 38% of Twitter users (see Table 1). The Pew Research Center (2017) reported Facebook as the most widely used of the major social media platforms, and its user base is broadly representative of the population as a whole. In January 2016, 68% of U.S. adults were Facebook users.

The city of Baton Rouge has been using two social media platforms, Facebook and Twitter, since 2011. As of December 1, 2016, the number of Twitter followers was higher than Facebook followers, at 13,500 and 9936, respectively. However, Facebook user engagement was apparently higher than Twitter during the 2016 Louisiana flood. For example, a single post on the Facebook page was, on average, shared by 792 users and liked by 150 users, compared to posts on Twitter receiving 4–5 retweets and 1–2 likes.

5. Data collection and pre-processing

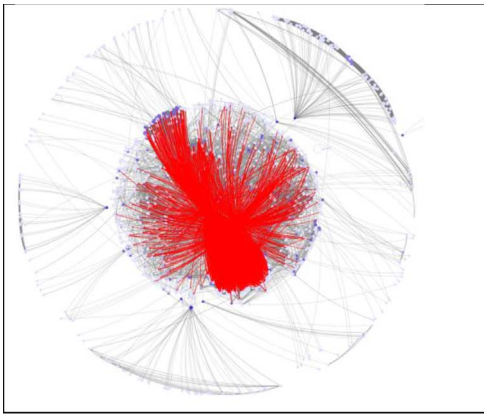
We collected data from the Facebook page of the city of Baton Rouge (www.facebook.com/cityofbatonrouge) that were created during August 12–December 1, 2016. There were 1171 users and 21,115 activities or responses on the page. To represent the collected data on a network graph, a vertex is defined as an engaged user and an edge is defined as a connection between users created by their interactions (see Fig. 4). We assumed any link between two vertices, regardless of direction, to be an indication of their similarity (Clauset, Newman, & Moore, 2004).

We filtered the collected data to ensure they were strictly related to the 2016 Louisiana flood before analyzing and visualizing the network. There were repeated vertex pairs on the edges, and 6400 edges with duplicates out of 27,515 edges (see Table 2) These duplicate vertex pairs may occur when user A replies to user B on multiple occasions. These duplicates can cause some metrics, such as *degree*, to be inaccurate (Smith et al., 2009). Thus, the 6400 edges were combined into a single weighted edge. Finally, edges that connect a vertex with itself − self-loops, of which there were 671–were deleted.

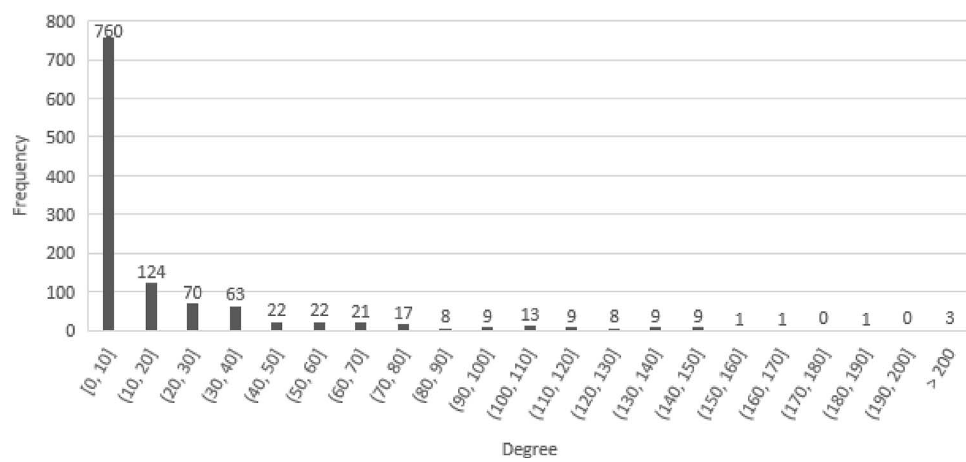
6. Results

The number of user engagements (e.g., comments, commented comments and user tagged) on the Facebook posts is described in Fig. 5. The number of user engagements exponentially increased and then declined after August 20. From August 24, the numbers were less than

Table 5
Top 10 in-degree centrality and degree distribution.
Red-colored lines are all edges linked with top 10 in-degree vertices excluding CBR.



Users	In-degree
CBR	829
User#19	296
User#20	254
User#21	252
User#22	184
User#23	169
User#24	159
User#25	148
User#26	146
User#27	145



(minimum 0, maximum 829, average 19.99, median 4.00).

20 (the trend is similar to that observed in the local search-term trend in Fig. 3).

The most shared and commented post was the estimated flood inundation map developed by the GIS division of the Department of Information Services in the city of Baton Rouge (see Fig. 6). The estimated flood inundation map was powered by a compilation of various data inputs including 911 call-outs, Baton Rouge Fire Department search-and-rescue data, City-Parish staff and other public officials, NOAA imagery, Civil Air Patrol imagery and FEMA DRIRM flood hazard areas (eBRGIS, 2016). The post consisted of text information with a link to the GIS map. Facebook users commented on the post to inform of incorrect information on the flood inundation map. Compared to the post on the city's Facebook page, there were 39 retweets and 18 likes on the Twitter post.

6.1. Network graph and structure

In social network analysis, graph-theoretic concepts are used to understand and analyze social phenomena (Ackland, 2010; Borgatti, Everett, & Johnson, 2013; Brandes, 2001; Wasseman & Faust, 1994). In Fig. 7, the graph is directed and laid out using the Harel–Koren fast multiscale layout algorithm (Harel & Koren, 2000). There are 1171 vertices, 21,115 edges, and 18 connected components. The vertex color is betweenness centrality and the size is scaled out-degree centrality. Maximum geodesic distance (diameter) is 5.00 and the average is 2.40 (see Table 2) The city of Baton Rouge is in the center of the network. The center of the network in the black-dashed circle is very dense with numerous vertices and edges. There are several vertices near the black-dashed circle that connect with other vertices at the outside of the network.

6.2. Degree centrality

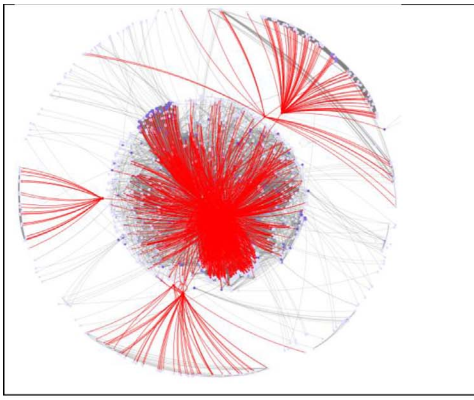
Degree centrality refers to the number of edges a vertex has to other vertices. As shown in Fig. 8, in-degree is the number of incoming edges incident to the vertex and out-degree is the number of outgoing edges incident to the vertex. Betweenness quantifies the number of times a vertex acts as a bridge along the shortest path between two other vertices (Freeman, 1977).

We analyze four types of degree centrality. The city of Baton Rouge has the highest out-degree, in-degree, eigenvector and betweenness centrality in the network. Most vertices at the core of the network are identified as individuals. There are no organizations or agencies in the top 10 centralities. The results below describe individual users actively involved in this emergency information propagation.

Out-degree, in-degree, and betweenness degree distribution are highly right-skewed. It represents a significant majority of vertices having a low degree, but a few vertices having a high degree as a hub in the network (Tables 3–5).

The six organizations/agencies including the city of Baton Rouge are ranked in the top 10 of betweenness centrality. The verticies with high betweenness play critical roles in the network structure. From the social network perspective, Wasseman and Faust (1994) described the importance of high betweenness: "interactions between two nonadjacent actors might depend on other actors in the set of actors, especially the actors who lie on the paths between the two." These are

Table 6
Top 10 betweenness centrality and degree distribution.
Red-colored lines are all edges linked with top 10 betweenness centrality vertices excluding CBR.



Users	Betweenness
CBR	1,082,218
Organization#1	166,500
Organization#2	81,549
Organization#3	49,982
User#19	31,711
User#20	29,937
User#21	26,838
Organization#4	22,838
Organization#5	20,572
User#22	13,791

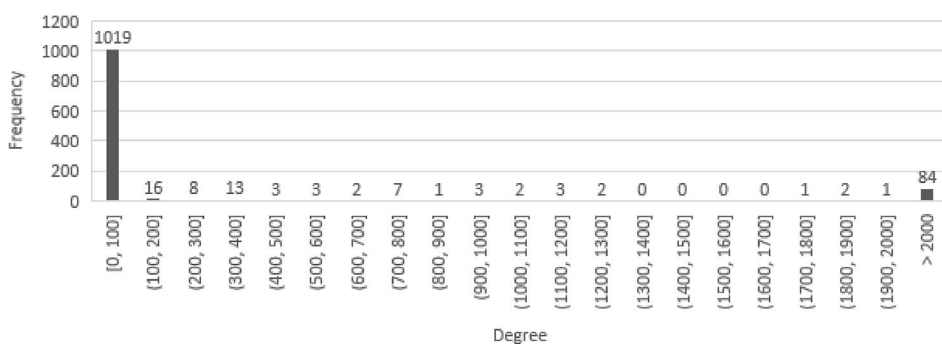


Table 7
Top 10 largest communities in the social network.

Rank	Size	Description
G1	144	Flood inundation map, information of debris separation, shelter locations
G2	63	Commenters on the flood inundation map – e.g., map update requests and sharing map information
G3	43	Donations and supports
G4	40	Road conditions (road closed/open)
G5	34	Locations of debris removal, debris collection status map
G6	33	Ordinances to help Baton Rouge residents; housing, noise ordinance waivers, waiving permit fees for structures damaged, policy changes
G7	30	Debris separation, Louisiana Department of Environmental Quality
G8	28	Reactors to hiring workers to help with debris removal efforts
G9	16	Commenters on the debris removal hiring event
G10	15	City events after final debris collection

also called *gatekeepers*, since they tend to control the information flow between communities (Oliveira & Gama, 2012). For example, a Facebook user in Texas shared a message to inform of the 2016 Louisiana flood via his Facebook page, encouraging people to help disaster recovery in the city of Baton Rouge. A network graph clearly describes a role of the vertices with highest betweenness centrality (see Table 6). Of the vertices in the network, 87% have betweenness centrality below 100. Thus, these high betweenness vertices played a role of gatekeepers in handling emergency information flow between the city of Baton Rouge and other communities.

6.3. Community structure

Most social networks tend to show *community structure*. This feature generally arises as a consequence of both global and local heterogeneity of edges distribution (Oliveira & Gama, 2012). We identified a community structure of the social network by the *Girvan–Newman algorithm* (Girvan & Newman, 2002; Newman & Girvan,2004). In Table 7, we provide an informal description of the 10 largest groups, which account for about 38% of the entire network. The remainder is generally divided into small, densely connected groups that represent highly specific co-interests of disaster-related information – e.g., flood inundation map, debris removal, road condition, donation and support. Interactions between groups are straightforwardly visualized in the graph (see Fig. 9). The interactions between groups have two types: (1) direct interactions and (2) indirect interactions. For example, G1 and G4 are directly connected, and the small groups (vertices in the red box) have a role as a bridge connecting G1 with G2.

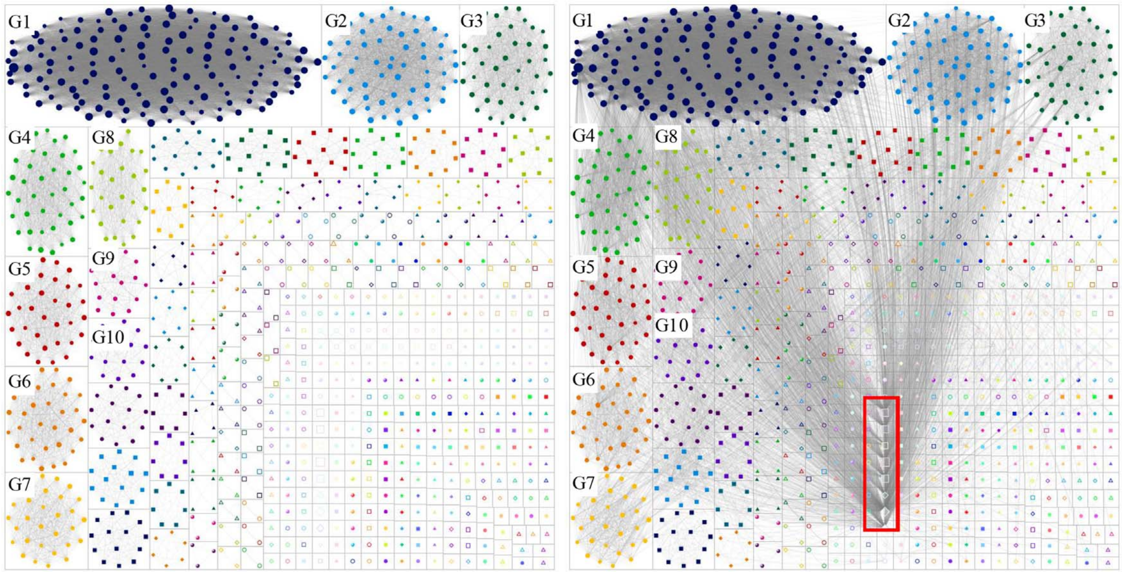
6.4. Top words and word pairs

Text analysis identified 77% of the posts during emergency responses as having positive words. The top five words during disaster responses are *map*, *water*, *thanks*, *GIS* and *flooded* (Table 8).

Top word pairs are listed in Table 9. The city of Baton Rouge operated a GIS flood map and shared the map with people. Most word pairs are related to flood, disaster recovery team and disaster debris removal in the city. There was a particular word pair, *private – message*, because people shared their home addresses via private messages to request rapid debris removal near their houses.

7. Conclusion

We investigated the Facebook social network in the city of Baton Rouge after the 2016 Louisiana flood. The data were collected from the city's Facebook page and analyzed for the emergent network after the flood. The city of Baton Rouge used both Twitter and Facebook to share



Community structure *Interactions between communities*

The primary divisions of community structure detected by the Girvan–Newman algorithm indicated by different vertex shapes and colors. Vertices in the red box played a role as a hub connecting G1 and G2.

Fig. 9. Community structure on the Facebook page of the city of Baton Rouge.

Table 8
Top Words in Tweets in Entire Graph.

Top Words in Tweets in Entire Graph	Count
Words in Sentiment List#1: Positive	4039
Words in Sentiment List#2: Negative	1206
Non-categorized Words	236,268
Total Words	241,513
Map	3395
Water	3265
Thanks	3090
GIS	2386
Flooded	2371

Table 9
Top word pairs.

Word Pairs	Count
GIS team	1698
private, message	462
water, house	456

emergency information. Facebook user engagement was higher than Twitter during the emergency responses. The trend of Facebook engagement significantly increased in the first two weeks, reached its peak on August 20, and then declined over time. We found that 47% of the engagements were generated within the first two weeks.

Statistical measures in the SNA provided insights about the structure of the network. We measured out-degree, in-degree, eigenvector and betweenness centrality in the emergent social network to identify the prominence or importance of vertices in the network. The degree distributions are very heterogeneous and highly right skewed (a large majority of vertices have a low degree but a small number of vertices have a high degree). Thus, we identified that there are certain vertices as a hub in the social network. We ranked top 10 out-degree, in-degree, eigenvector and betweenness centralities. The results suggested that individuals and agencies/organizations have different roles in social networks during emergency responses. The top 10 out-degree, in-degree and eigenvector centralities were individuals rather than emergency agencies/organizations, excluding the city of Baton Rouge. They actively shared emergency information with their online friends by either tagging their friends, posting a comment, or sharing information with their online community. Some vertices did not belong to either of the top 10 out-degree or in-degree centralities. Types of individual engagement in the social network are: (1) *like a post* (76.56%), (2) *write a comment* (15.55%) and (3) *share a post* (7.99%).

However, the top three betweenness centralities, with the exception of the city of Baton Rouge, were organizations/agencies, and six organizations were ranked in top 10 of betweenness centrality. We identified that organizations/agencies played a critical role in connecting a network of the city of Baton Rouge with external social groups or online communities.

The network graphs visualized the statistical analysis by the Harel–Koren fast multiscale algorithm in Section 6. The network graphs represented metrics to convey the result of the analysis. As shown in Fig. 7, the city of Baton Rouge was at the center of network as a hub and it is strongly linked with other vertices, i.e., individuals. It was the core of the entire network, as described in the graph. Organizations and agencies are at the periphery of the core network, but played a critical role in connecting external vertices with the core network. The social network graph has a similar structure to the conceptual diagram of social capital shown in Fig. 1; the core of a community consists of numerous individuals, while agencies and organizations link communities.

Text analysis from the Facebook posts identified that two-thirds of users left positive comments and feedback on the Facebook posts, with one-third leaving negative posts. Top word pairs were *GIS–team, flood–water* and *private–message.*

8. Discussion

We compared search-term trends about the 2016 Louisiana flood and Hurricane Sandy of 2012. There were summer Olympic Games and presidential elections around the time of both disasters, but the trends were significantly different. People's interest in the 2016 Louisiana flood was not significant and was lower than that shown for the summer Olympic Games and the presidential election, even though it was recorded as the worst disaster after Hurricane Sandy. As discussed in Section 4, there were articles criticizing the major media for a lack of coverage of the 2016 Louisiana flood. Further investigations are needed to answer how these events (Olympics and elections) affect information diffusion during disaster responses. Comparing the effectiveness of social media as early warning systems would be beneficial.

Contrary to previous studies, this case study showed that disaster-related information was diffused actively via Facebook rather than Twitter. There might be several reasons behind this. Firstly, Facebook has more functions for sharing numerous types of message via its interface, such as images, videos, and hyperlinks. This flexibility might help users understand information faster and trigger them to share multiple types of information with others. In addition, Facebook has 1.59 billion users (as of Dec 2015), which is about four times higher than Twitter (320 millions, as of March 2016) (Social Times, 2016). Duggan (2015) identified that of Facebook's total number of users, 70% visit the platform daily, while for Twitter this is 38%. Thus, more people might have a chance of being engaged in emergency information via Facebook rather than Twitter. Further investigations, using survey and interview, would identify their motivations and reasons for their engagements.

There was a limitation on data collection. Since we collected data from a Facebook fanpage of the city of Baton Rouge, we were not able to explore how the shared information on a user's Facebook page will be re-shared with other social networks, compared to a *retweet* on Twitter. This would enable us to precisely measure information diffusion across the community structure of social media. Also, the network is limited to Facebook, so it does not include other online and offline networks created during disaster responses.

It is critical for the public to receive accurate, reliable and timely information from emergency agencies during disasters. Many literatures identified that social media 1) influences social consciousness, 2) leads rapid information delivery, and 3) reach a broader and more targeted population than any conventional methods(Mohammadi et al., 2016). Thus, social media such as Twitter and Facebook is expected as a powerful tool for rapid information diffusion in emergency.

As our findings reveal, SNA could be applied to understand characteristics of online social network and structure in depth including critical central and intermediate vertices in the network. The results can be used to understand heterogeneity in social networks and applied to accelerate information diffusion in emergency. Thus, emergency agencies need to equip a network analysis tool and database to analyze local-, state- and national level social network in emergency. Also, a collaboration with social media such as Facebook and Twitter will be beneficial to improve reliability of data collection, monitor real-time data, and expedite the overall SNA process in emergency.

As discussed in Section 7, organizations with high betweenness centrality play a critical role to connect online communities in a social network. Thus, emergency agencies have an online partnership with public and private sector including NGOs and NPOs to create stronger bonds in their social network.

A future study is needed for understanding characteristics and effectiveness of different social media platform including Twitter, Facebook, Google+, YouTube and Instagram in disaster responses such as their feasibility and reliability as an information diffuser in emergency. Most questions could be answered by a multi-case study approach that would compare the use and effectiveness of social media across a broad range of disasters. Another future study is also needed for isolated vertices where information might not be reached via an existing online network. Therefore, application of search and location-based advertising services for emergency information is a crucial research topic to improve online information diffusion performance.

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