From Push Brooms to Prayer Books: Social Media and Social Networks During the London Riots

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Abstract

Social media, such as microblogging, is a powerful medium for sharing information and organizing response in times of crisis or extreme events. We propose methods to integrate topical and social information and behavior derived from social media to improve situational understanding during an extreme event. Using Twitter data from the 2011 London riots, we analyze emergent social networks directly relating to response to crisis. We construct social networks from these tweets based on *talking to* (directed communication), *quoting* (retweeting), and *talking about* (mentioning) behaviors. We examine networks of riot response oriented around cleanup or prayer activities. These networks differ in size, structure, and membership. We identify prominent network actors and assess their similarity. These methods may enable more effective response during disasters or other emergency events.

Keywords: social networks, social media, Twitter, crisis response, crisis informatics

Introduction

The importance of social networks in helping individuals cope with, navigate, and mitigate challenges in their environments, including crises, has been established. While the rise of social media such as microblogs has provided unique capabilities to rapidly and widely share time-critical information both to members of one's social networks and to broader audiences, this phenomenon is poorly understood in the context of events such as civil unrest or natural disasters.

This research explores ways to identify and understand social networks in times of crisis, response, and recovery, which could contribute to improved situational understanding, crisis communications, or provision of support. Social network analysis (SNA) provides a means to understand individuals, groups, and social phenomena, from a framework in which patterns of interaction are represented as networks. The structure of the network, the positions of individuals within it, its dynamics, and any underlying social processes or mechanisms can inform our comprehension of an event and our ability to respond appropriately.

We examine the use of the microblogging service Twitter during one of the most tumultuous periods in the recent history of London. London was rocked by a series of riots in August 2011. A few days after the police shooting of an unarmed man in the ethnically diverse working class London neighborhood of Tottenham, peaceful protests were followed by an outburst of looting and arson. Five people were killed, hundreds injured, thousands arrested, and over one hundred million pounds of damage was done. Rioting spread to other urban areas in England. During these events, Twitter was used extensively in London. We analyze a corpus of tweets collected from this time. London is known as a city with a relatively high rate of Twitter usage, and many government entities have adopted Twitter as well (Panagiotopoulos and Sams 2011) to communicate with residents.

To better understand the city during a time of crisis, social media activity relating to the event must be distinguished from other activity within the larger stream. We leverage the Twitter convention of hashtags to identify relevant communications from this larger pool. Hashtags are words, phrases, acronyms, or abbreviations that can be explicitly incorporated in a tweet to signal association with the topic or meaning of the term. Hashtags are preceded by a "#", such as *#prayforlondon* or *#riotcleanup*. Use of a hashtag makes a tweet easily discoverable by anyone interested in that tag. It is thus possible to easily follow the conversation around a topic, in contrast to following specific Twitter users.

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We develop a method to categorize hashtags appearing in this data. We then select two categories of hashtags to explore whether we can find evidence of meaningful social networks in social media that are activated during extreme events. We characterize these networks in terms of network properties and prominent actors. Finally, we consider how this knowledge might be used to improve awareness, understanding, or response to these circumstances, or to gauge community reaction.

The two categories of hashtags examined in this research both involve how individuals responded to the riots. Both categories are types of responses to the damage, destruction, and pain resulting from the riots. The first category is riot cleanup. Riot cleanup is an active, public, externally visible response to the damage. Debris and rubbish are swept from the streets. Broken objects are repaired or replaced, and order is restored. The second category is prayer in response to the riots. Prayer is a more personal, internal behavior. It may be performed in private, unobservable to others. It may seek to provide a sense of comfort or control through involvement of a higher power in otherwise overwhelming circumstance. Given these differences, networks of riot response oriented around cleanup or prayer activities might be expected to differ in size, structure, and membership.

Social media can provide a window into social networks in times of crisis or disaster. The rapid reaction time of microblogging creates potential to track reactions to such events in near real time, to assess damage and suffering, and to identify individuals and networks of interest, if the relevant communications can be recognized from within the larger stream. This provides opportunities for performance improvements in emergency management, law-enforcement, and for more effective government communication and improved transparency. If such knowledge were available to everyday citizens, they might benefit from a richer understanding of information and resource flow in extreme circumstances. They might be better able to contribute to response and recovery by sharing personal knowledge or observation more effectively. Their ability to gather critical information or resources in a timely fashion could be magnified. To the degree that the social networks that emerge in times of crisis have some common core prior to the emergency, it might even be possible to proactively nurture, or plug into, these networks.

Related Work

Response to social crisis and disaster has been studied for decades from a broad range of perspectives, from social psychology and organization theory to public policy and emergency management (Quarantelli & Dynes, 1977). Beyond response by organizations with formal responsibilities during emergencies, informal, spontaneous response seems a hallmark of human behavior. For example, the phenomena of convergence by large numbers of people on the physical location of a disaster shortly after the event, often motivated by a desire to help, has long been observed (Fritz & Mathewson, 1957) . With the rise of social media, related online phenomena are appearing (Hughes et al., 2008). Self-organization of individuals into informal, emergent groups to fill gaps and respond flexibly to crisis is not new (Stallings & Quarantelli, 1985), but may take new forms in a social media enabled world (Liu et al., 2008) (Starbird & Palen, 2011).

During a crisis or emergency event, the local population fills invaluable roles, from detecting early indications of an event, to providing updates as the event unfolds, to supporting recovery efforts (Starbird, Palen, Hughes, & Vieweg, 2010) (Vieweg et al. 2010). The empowering capacity of Information and Communication Technologies (ICTs) such as microblogs may expand this phenomena (Palen, et al. 2009) (Jaeger et al. 2007). Changes in online language behavior, such as blogging behavior, during crisis have already been observed (Cohn, Mehl, & Pennebaker, 2004). The new field of crisis informatics provides insights and observations on ICT use during disasters (Shklovski, Palen, & Sutton, 2008).

Social networks are important for providing social support (Gottlieb, 1985), acquiring resources and critical information (Granovetter, 1973), and for buffering the effects of psychological trauma (Flannery, 1990) or stress, to include events such as dislocation following a natural disaster (Bland et al., 1997). Less is known about social networks in online community, though networks of empathic communication in an online discussion board have been studied (Pfeil & Zaphiris, 2009). However, research interest in this area is high despite challenges (Savage & Burrows, 2007) (Watts, 2007).

More broadly, Twitter and hashtag use in Twitter has been studied in terms of trending topics (Kwak, Lee, Park, & Moon, 2010), political polarization (Conover et al., 2011), contagion and diffusion (Romero, Meeder, & Kleinberg, 2011), and other topics.

Methods

Data Collection

Twitter data used in the research was collected from Twitter after the riots started on August 6, 2011 using Twitter's Application Program Interface (API) for search. This API permits location-based queries and will return a sample of recent tweets from a particular location specified by a coordinate pair and a radius. We use the center coordinates of the Greater London administrative area of 51.502 latitude and -0.127 longitude, with a radius of 20 miles. To improve on the sample returned from the API, we also used the Search API to query against the users whose tweets were returned for the London query. We continued this process through September 30, 2011, covering the riots and several weeks of recovery. The data includes over 14 million tweets from hundreds of thousands of users. The Twitter API returns location metadata with tweets: either a *geotag* containing a latitude and longitude from users that have enabled the geotagging feature on their mobile Twitter client, or the location string from the user's profile. The user profile location string may be a place name entered by the user or a coordinate pair populated by a mobile client. We match the location metadata against a gazetteer[1], looking for place name that matches or, if coordinate data, the closest populated location in the gazetteer. If we are able to match the location we use the administrative level information from the gazetteer to assign the tweet to a particular administrative district within the Greater London area. For example, a user who gives their location in their profile as Tottenham would be assigned to administrative district F3 (Haringey) and a tweet with the coordinate location or geo tag of 51.63 latitude and -0.14 longitude would be assigned to district E3 (Enfield). This step allows us to aggregate tweets by their relative location within London when there are coordinates or a place name is given that is below the level of the city. It also allows us to eliminate data that may not be from London because the place name is not resolvable because of the use of alternate spellings or nicknames (*LANDAN!*, *crackney*) or because a non-place-name was given (*nonyah*, *WithBiebs*). This process does not address errors attributable to the Twitter API. For example, a user giving their location as *London* may be in London, England or in another London, such as London, Ontario. We have no measure of the level of this error in the data. However, since we only focus on tweets that contain content directly related to the riots and the aftermath, we argue that this error source will not significantly impact our results. Our analysis is limited to tweets that we were able to geolocate to the level of the Greater London administrative area or below.

Hashtags in Twitter

Nearly 400,000 unique hashtags appear in the overall corpus. During the week of rioting, the most common hashtag was *#londonriots*. This tag was used over 25,000 times that week. Many other hashtags relating to the London riots emerged spontaneously in the early days of the event. The *#prayforlondon* hashtag was a Twitter trending topic. Hashtags pertaining to everyday activities, such as entertainment or shopping, coexist in the data with hashtags referencing the riots. Riot-related hashtags described locations of rioting and destruction, expressed concern, or recommended responses to rioting and rioters. Hashtags relating to two aspects of response to the riots, riot cleanup activity and prayer in response to the rioting are examined in more detail.

Each of the most frequently used hashtags in the first week of the disaster was reviewed to identify a seed set of hashtags for riot cleanup. The review began with the hashtags that comprised the top half of the hashtag distribution (that is, the hashtags that accounted for 50% of total hashtag usage instances in the data). This set contained about 150 hashtags. The meaning of each these hashtags was determined through inspection of the term itself, use of online hashtag dictionaries, and through scanning the content of tweets containing the hashtag. This identified a seed set of hashtags clearly related to riot cleanup. This was used to search the remainder of the tag corpus, and a final set of 65 relevant hashtags was identified. These include *#riotcleanup, #riotwombles, #londoncleanup*, and *#cleantottenham*, and a variety of spelling and morphologic variations, such as *#cleanuplondon*. Tweets containing riot cleanup hashtags allow us to identify individuals in London who played a role in riot cleanup communications through Twitter**.**

[1] http://www.geonames.org

A second seed set of prayer hashtags was constructed in the same fashion. This set contained nearly the same number of hashtags (63), though fewer tweets. The role of prayer as a potential positive mechanism for coping with and responding to crisis has been repeatedly documented (Meisenhelder, 2002). It was among the most common responses to the terrorist attacks on September 11th in the United States in a national survey of stress responses to the attacks (Schuster et al., 2001). Ninety percent of respondents reported turning to prayer, religion, or spirituality to help cope with the crisis.

Talking to, Quoting, and Talking about within Twitter

Twitter functionality and conventions allow a user to express more nuanced communicative behaviors than the broadcast of a short message. Users can specify an intended recipient toward whom the message is directed.

> *@joemcelderry91 my hometown is burning right now! #prayforlondon Please get people to RT this*

Users can echo another user's tweet by retweeting it, and credit that author.

> *RT @artistsmakers: Getting the clean up together - Meet outside Tackle Shop, Roman Road, hackney 9am in the morning to help local shops clean up. #riotcleanup*

Finally, a user can easily comment on another user by referencing that username.

> *MP of the day: @HackneyAbbott. With her constituents, on the streets with those affected. Only MP in right place at right time #londonriots*

These behaviors can be considered analogous to *talking to* another, *quoting* another, or *talking about* another user. A sender of a tweet can easily choose any of these three behaviors when tweeting. Connecting to another in each of these ways is sociologically and semantically distinct. The patterns and networks that emerge may provide insight into roles played by individuals in these networks of crisis communication, how they are perceived by other network members, and even the robustness of the network as a whole (Borgatti, Mehra, Brass, & Labianca, 2009).

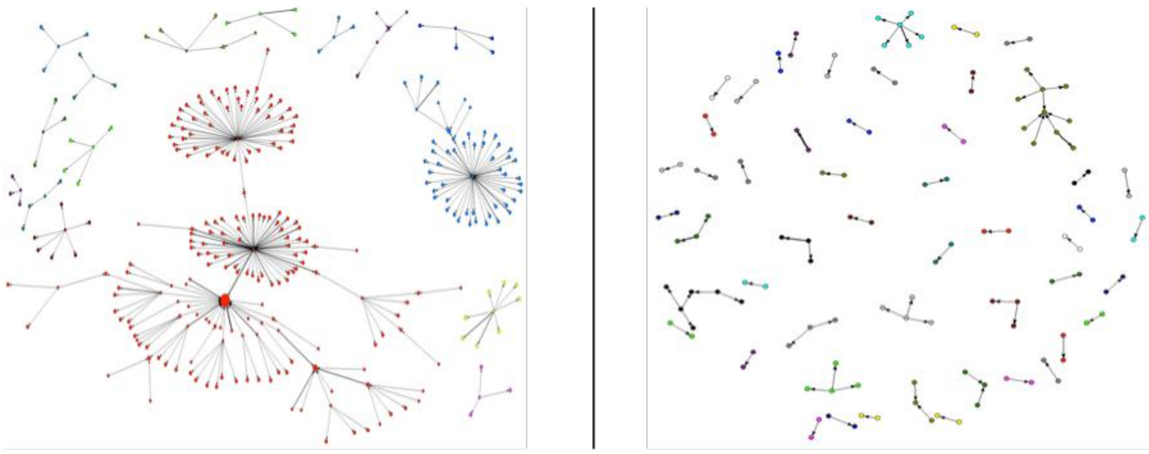
Findings

All tweets containing riot cleanup hashtags were used to construct a set of social networks reflecting riot cleanup communications for the three types of behaviors described above, *talking to*, *quoting*, and *talking about*. These tweets generated network data encompassing roughly 4000 actors and 5000 ties. The same process was used to create prayer networks. Prayer communication was less common, generating less than a third as much network data, and fewer than 1400 actors. All of the networks contained multiple unconnected components. Each network will first be introduced and visualized. Later, the networks will be described and compared in more detail. Prominent actors in the networks will be discussed.

Talking to Networks

The first riot cleanup network captures only tweets that directly addressed ("talked to") another Twitter user. It contained 437 ties ranging in strength from 1 to 6, where tie strength is a count of the number of tweets from one member of the pair to the other. It has a large main component, and a number of smaller components. Dyads (components with 2 members) are not shown for visual clarity. For prayer communication, the "talk to" network is substantially smaller. It is quite fragmented, consisting of a number of small components of size 2 to 5, and one slightly larger component. Directly communicating with others is observed to be the least popular or frequently chosen behavior. Figure 1 shows the riot *cleanup* network on the left, and the *prayer* network on the right. Visualizations are created in Netdraw (Borgatti, 2002).

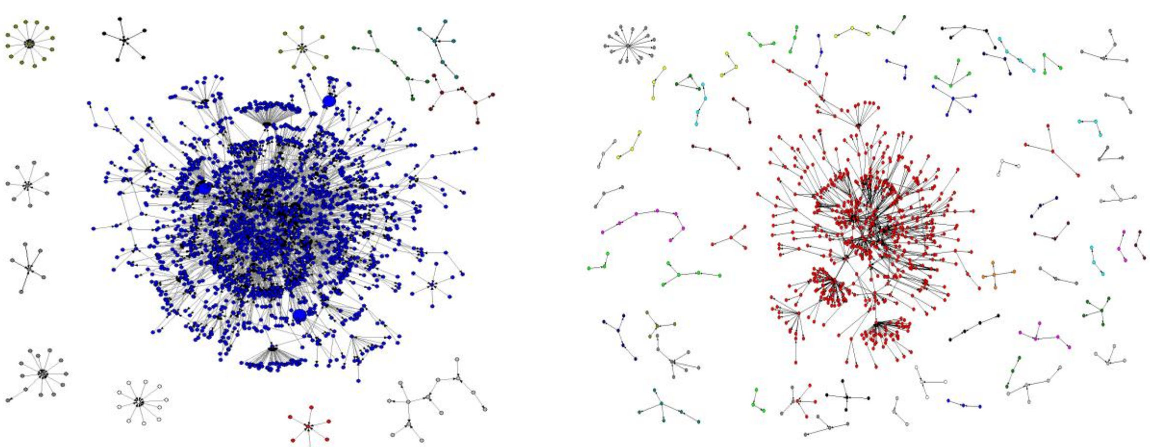
Figure 1. Riot Cleanup and Prayer Networks: Talking To



Quoting Networks

The network of quoted (retweeted) messages was much larger, containing 3035 ties for riot cleanup. Quoting others was also the predominant behavior for prayer communication, though this network is roughly one-third the size of the *cleanup* network. Both networks have a majority of the actors appearing in the main component. In the visualization, small components are not shown for visual clarity. Figure 2 shows the riot *cleanup* network on the left, and the *prayer* network on the right.

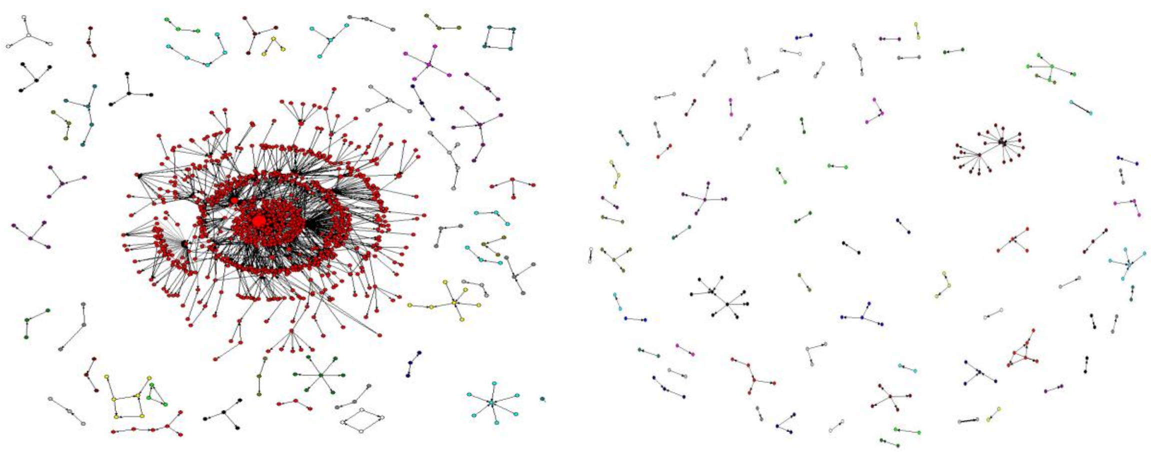
Figure 2. Riot Cleanup and Prayer Networks: Quoting



Talking about Networks

This network captures those who mentioned another user in their tweet. For riot cleanup, it was intermediate in size, containing 1526 ties, but had the largest range in tie strength (1-50). For the prayer network, a different pattern emerges. This network is substantially smaller than its companion network, indicating that mentioning others in the context of a prayer hashtag is less common. Figure 3 shows the riot *cleanup* network on the left, and the *prayer* network on the right.

Figure 3. Riot Cleanup and Prayer Networks: Talking About



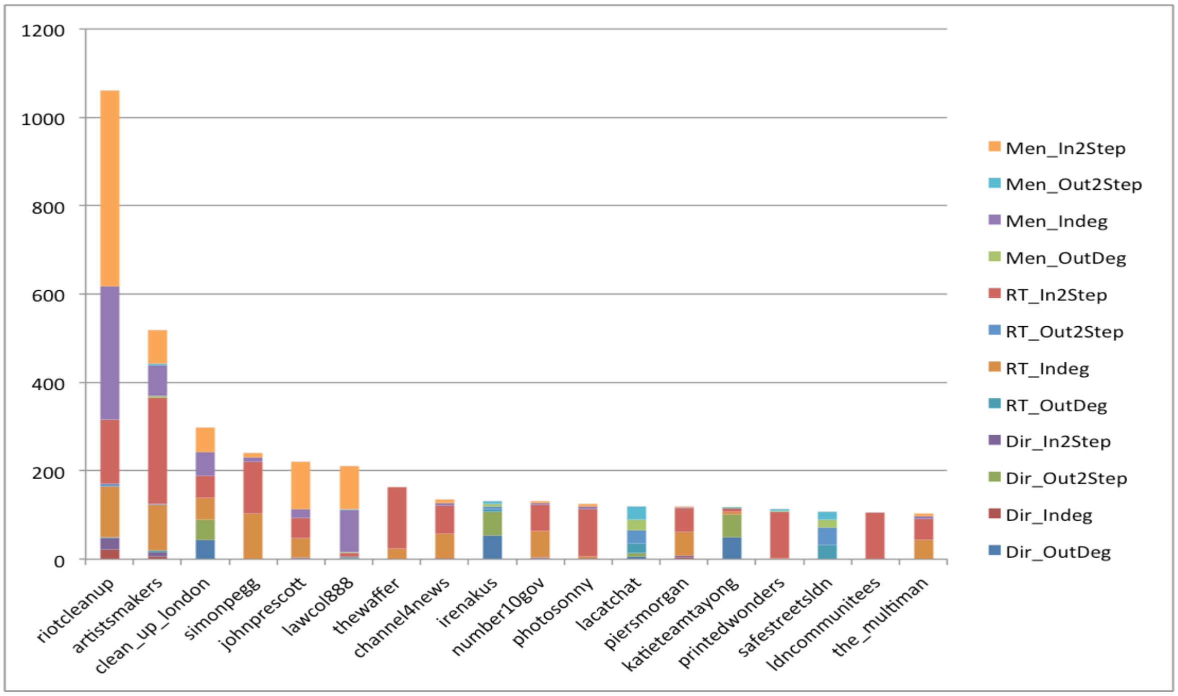
Prominent actors in Riot Cleanup and Prayer networks

For each of these three networks, social network metrics that assess an actor's centrality or prominence within the network were computed (in-degree, out-degree, in-2step reach, and out-2step reach) using UCINET 6 (Borgatti, Everett, & Freeman, 2002) . *Degree centrality* assesses how prominent, or "central" an actor is, based on how many ties the actor has to others (Freeman, 1979). Indegree captures how many ties come in to an actor from other network members, while outdegree measures how many ties originate with the actor. *K-step reach* counts the number of nodes that a given actor can reach in k or fewer steps. K=2 finds both neighbors, and "neighbors of neighbors" who can be reached by the actor (Out2Step) or who can reach the actor in 2 hops (In2Step). These twelve metrics were summed to produce an aggregate representation of actor prominence across all three networks.

This aggregate measure was used to select the most central actors in the riot cleanup communications networks from the roughly 4000 actors in the *cleanup* network, and from the nearly 1350 actors in the *prayer* network. Figure 4 summarizes the scores for each of the most prominent actors from the riot cleanup communication networks, and Figure 5 does the same for the *prayer* networks. The most central actors in the riot *cleanup* communications and in the *prayer* communications are distinct.

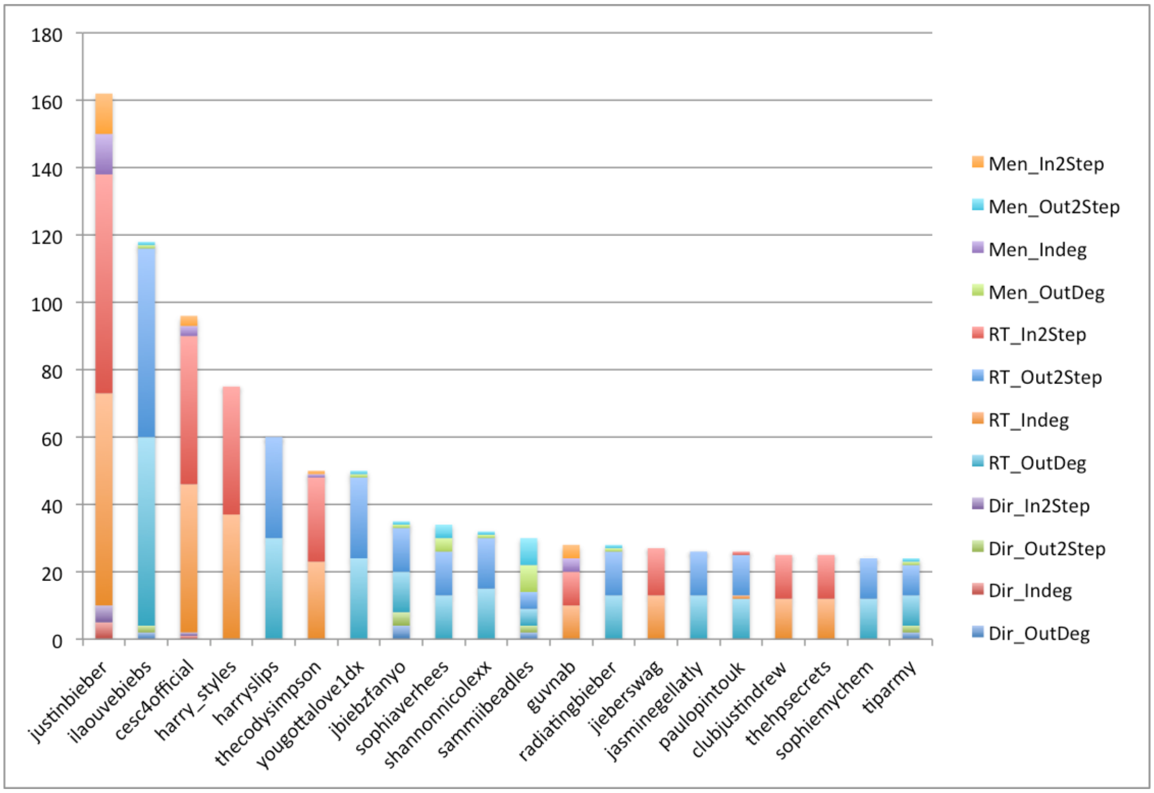
Prominent actors differ in both magnitude and the relative proportion contributed by each social network metric. Actors differentially engage in *talking to, talking about* or *quoting* others, and are subject to the same phenomena, being differently perceived by other network members as worth being talked to, talked about or quoted. These directed (Dir) communications, mentions (Men), and retweets (RT) for degree centrality and 2-step reach are weighted equally. None of these behaviors is theoretically asserted as being more critical for establishing prominence in this case.

Figure 4. Actor prominence in riot cleanup



Patterns indicative of actor roles may thus emerge. For example, an actor with high indegree for retweets and mentions, that is, one who is talked about and quoted frequently, might be a respected member of the riot cleanup community who contributes information and perspectives that are valued by others. An actor with low indegree for these two communicative behaviors, but high outdegree, shares and publicizes other network members and their contributions without being comparably recognized or esteemed by other members of the network. This member's status appears lower. Nevertheless, this network member is still making a contribution to the community.

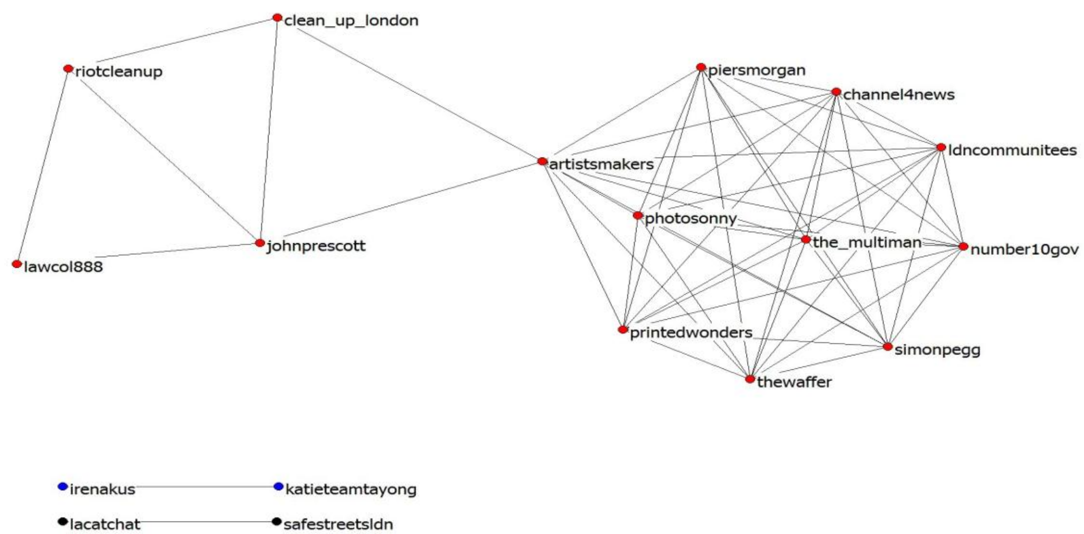
Figure 5. Actor prominence in Prayer



Actor Similarity

The metrics described previously were used to create an actor profile. Correlating these actor profiles create an actor-by-actor similarity matrix. For riot cleanup, this matrix, rendered as a network (ties indicate actor similarity>.55) in Figure 6, shows the majority of prominent actors are connected in a single component with two main clusters. The remaining actors appear in two isolated dyads.

Figure 6. Actor Similarity Network for Riot Cleanup

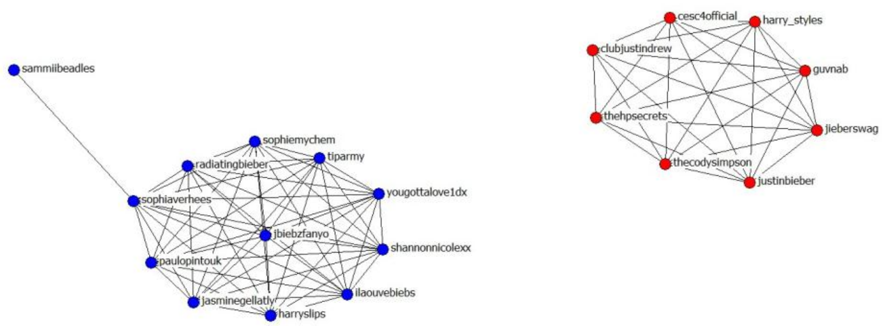


Studies of influential Twitter users have observed the dominance of celebrities and mass media in their ranks (Kwak et al., 2010). For this subset of London riot cleanup communications, we find many prominent actors who are neither. In fact, the structure of the large component of the actor similarity network provides an indication of whether an actor might be classified as celebrity/mass media, or whether that actor appears to play a different role.

Of the five actors in the smaller, leftmost cluster of the large component in Figure 7, four - *artistsmakers*, *clean_up_london*, *lawcol888*, and *riotcleanup* – reflect grassroots citizen efforts to self organize to restore the city. One of these actors, *artistsmakers*, has been credited for coining the hashtag *#riotcleanup*. The rightmost cluster however contains a number of well-known individuals, including a national level political figure, news media, and entertainers. As there are over 900,000 Twitter users in the data, and nearly 4,000 of them appeared in the network of riot cleanup communications, network information demonstrates value in discovering and clustering interesting actors. Thus behaviorally based social network information and information developed from a derived network computed from actor similarity are used to produce a novel method to identify prominent actors. Interestingly, neither local political figures nor the Metropolitan Police figure prominently in network activity, despite being significant players in managing the riots and dealing with their aftermath. Use of Twitter in this context by law enforcement would not be unprecedented (Heverin & Zach, 2011).

Applying the same method to the *prayer* network highlights differences. While a similarity network can be computed from the most prominent actors, and clusters of similar actors can be identified, there is little further commonality with the *cleanup* network. There are no common actors across these networks, despite both networks being composed of individuals who are prominent is aspects of responding to the London riots. The actor composition also differs for the *prayer* network. The rightmost cluster primarily contains celebrities from pop music or sports, and a few fans. The leftmost cluster includes a number of fans of these celebrities, and lesser-known musicians. No political figures or news personalities appear. No religious figures emerge. Individuals who seem to be oriented toward local action or remediation in the context of the London riots, such as the grassroots activists previously observed are not apparent. While most of the prominent actors in riot *cleanup* are based in or clearly associated with the city of London, this is not the case for *prayer*. The London connection instead comes from fans and less famous figures. As this study is focused on Twitter activity from the London area, tweets from celebrities who were not in London at the time are not part of the data set. Their out-degree and out-2step reach scores must be zero. Prominent celebrities in *prayer* thus owe their status to fan response.

Figure 7. Actor Similarity Network for Prayer



Network Characterization

Several descriptive measures for the six networks under examination are summarized in Table 1 and discussed in the remainder of this section. In some cases, *prayer* and *cleanup* for the same communicative behavior (*talking to, talking about,* and *quoting*) are compared. In others, overall patterns at the level of the *cleanup* and *prayer* networks are considered.

Table 1:
Selected Network Statistics

	Talk to (directed)		Quote (retweet)		Talk about (mention)	
	Cleanup	Pray	Cleanup	Pray	Cleanup	Pray
Actors	570 (.15)	128 (.10)	3022 (.78)	1155 (.86)	1444 (.37)	205 (.15)
Ties (total)	437 (483)	77 (100)	3035 (3310)	1016 (1188)	1526 (1795)	135 (156)
Maximum tie strength	6	6	7	9	50	5
Main component	190 (.33)	10 (.07)	1963 (.65)	584 (.50)	1028 (.71)	20 (.10)
Maximum indegree	23 (.04)	5 (.04)	115 (.04)	63 (.06)	301 (.21)	12 (.06)
Maximum outdegree	54 (.09)	5 (.04)	33 (.01)	56 (.05)	25 (.02)	8 (.04)

Actors. The number of actors reflects network size. The proportion of actors relative to the total for that communicative behavior is also provided. For example, of all the actors involved in any type of *cleanup* communicative behavior, 37% were involved in *talking about* cleanup, but only 15% *talked to* another actor. In all cases, *cleanup* networks are larger. The ratio is closest for *quoting*, and the gap for *talking about* is largest, with *prayer* only 14% as large.

Ties. Information on both the number of unique ties connecting a pair of actors, and the total count of tweets in the network is provided. Far more ties are observed for *cleanup* than *prayer*. The *quoting* network has the highest number of connections, demonstrating that this behavior is favored.

Maximum tie strength. This reflects multiple tweets from one individual to another. This figure is relatively consistent across five of the six networks. The exception is *talking about* regarding *cleanup*, which is roughly an order of magnitude higher than observed in the other 5 networks, showing sustained commitment to sharing commentary on another network member's actions.

Main Component. The main component consists of the largest set of connected actors and their ties. It is the largest component, though it may not contain the majority of actors. The size of the main component and the proportion of actors are reported. The cleanup network shows greater cohesion overall.

Maximum Indegree and Maximum Outdegree. In a network, an individual can be more active or prolific in sending ties. Alternately, an actor may be more appealing or focal to others, and receive more ties. Maximum indegree and outdegree identify the highest number of others connected to a single individual. While values for these measures tended to cluster around .04-.06 of the maximum number of potential partners for *cleanup* and *prayer*, there are some interesting exceptions and patterns. Indegree ranges from a low of 5 for *talking to* a single individual about *prayer* to a maximum of 301 *talking about* another person in the *cleanup* context (.04 to .21 of maximum partners). Maximum outdegree has a much smaller range from 5 to 56 (.04 to .09 maximum partners). The relative values of maximum indegree and outdegree for each of the 3 *prayer* networks are quite close (1.0-1.5). None of these networks has a disproportionately focal actor or prolific actor. The relative values of maximum indegree and outdegree
for each of the 3 *cleanup* networks show a different pattern. Their respective ratios range from 2.35 to 12.2. Within *cleanup* network for *talking to,* the most prolific actor dominates the ratio. This actor talks to 54 others. It appears that these communications are distributed across actors, rather than being concentrated on a focal, high indegree actor. For *quoting* and *talking about*, the situation is reversed. The dominant actors here are focal actors, receiving ties from 115 and 301 others respectively.

Discussion

Notable differences are observed in the social networks for riot cleanup and prayer communications. Riot *cleanup* is far larger than *prayer* in terms of network size and number of tweets. These networks differ in relative frequency and patterns of *talking to*, *quoting*, and *talking about*. They share no highly prominent members. Prominent cleanup network actors included grassroots activists who organized and promoted neighborhood efforts to clear up debris. Here, the network matched real-life roles. For prayer, a mismatch is observed. Prominent actors did not include members of the clergy or other spiritual figures.

Why is the prayer network both smaller and different? Both types of response at first glance are equally reasonable and normal in the aftermath of disaster. A large majority of Londoners are religious, with Christianity the most common religion (Office for National Statistics, 2007). Engaging in prayer requires less energy and effort than cleanup. Since hashtags from both the categories of *cleanup* and *prayer* were among the most common in the data, and were both trending topics, lack of awareness of
#pray hashtags does not explain the discrepancy. Other factors must contribute.

A large percentage of riot cleanup communications were positive about riot cleanup and those organizing or participating in these activities, or factual and neutral. Few, if any, were critical of cleanup activity.

> *students' unions and students - if you're near somewhere affected, do your bit and get out and help with #riotcleanup #loveyourneighbourhood*

> *Getting the clean up together - Meet outside Tackle Shop, Roman Road, hackney 9am in the morning to help local shops clean up. #riotcleanup*

> *Today was an amazing experience. Incredibly proud to have been a part of the #riotcleanup and show the world that not all of London is feral*

> *My faith in humanity is restored. Thanks to the good & kind people who get together to clean-up their communities #riotcleanup @riotcleanup*

The situation for prayer communications was more complex. In some instances, individuals evoked prayer in the context of describing rioting and rioters, and the emotional response they were experiencing.

> *scared stiff. Omg the looters are here. My hometown:(#prayforuk*

> *A girl died in a burning house while saving her brother and sister.She sacrificed her life for them.I'm crying. #prayforlondon.*

Some tweets were clearly sympathetic and supportive of prayer as an appropriate response to events:

> *#prayforUK ... my heart with all those affected by the riots - please keep my family in your thoughts*

> *Let's all #prayforlondon and continue to heal the world through love, creativity and positivity. Don't let the dark forces win!!!*

However other tweets expressed a more negative or judgmental attitude towards praying for London as an appropriate response to the crisis. Some found the riots lesser causes for which to invoke a greater power, while others found prayer itself an insufficient response compared to more direct action:

> *Vomit! #PrayForLondon is trending! If you're going to hassle God, maybe #PrayForSomalia, #PrayForTalibanWomen, #PrayForChildSoldiers.*

> *Don't #PrayForLondon we aren't that lame. We have free education and healthcare. We get paid even if we don't have a job.*

> *#controversialmood #londonriots its actually really really boring+ #prayforlondon -blimey how bout actually helpin sort out some root issues*

Some individuals undoubtedly held prior beliefs on these topics, and their tweets may simply reflect pre-existing views. Additionally, actual participation in prayer discussion could be diminished by individual beliefs about the inappropriateness of invoking prayer in the social media context. This would suppress the likelihood of tweeting about prayer as a response to begin with, as well as the likelihood of *talking to*, *quoting*, or *talking about* others in that context. Comparable beliefs discouraging taking part in cleanup may not have been present. They are not expressed in the data to any degree.

Social media is inherently not an individual activity. Social influences and forces are likely to have played a role in additional to purely personal views. Through social media, London Twitter users may have been exposed to negative responses to prayer. Individuals who held no beliefs about the prayer response, or held neutral or mildly positive views, would find themselves in a social media environment inconsistent with their position. Burt has discussed how individuals moderate their information sharing and statement of opinions based upon perception of network members' positions. They may withhold information or bias the information they do share in order to "echo" other's predispositions (Burt, 2001). Both selective exposure to prayer-related views, rooted in the homophily of social network members, and selective disclosure, driven by a wish to appear consistent with group norms, bias the information environment and influence individual's behavior in a larger social context (Kitts, 2003). This could discourage adoption of prayer hashtags, and *talking to*, *quoting*, and *talking about* behaviors.

Some actors may also need to navigate constraints imposed by formal roles, organizational policy or mandate regarding social media. For example, in the U.S., it was initially unclear if tweeting was a violation of existing Congressional rules on mass communication, and members of Congress remain more likely to use Twitter to broadcast than to engage in dialog with the public (Golbeck, Grimes, & Rogers, 2010). This pattern has been observed for government agencies (Waters & Williams, 2011) and metropolitan police departments (Heverin & Zach, 2011). High-ranking members and spokespersons for these organizations may be sensitive to the implications of evoking and encouraging prayer even in the absence of formal restrictions. Picking up a push broom and sweeping up debris from city streets is less controversial. Other individuals in the public eye, such as celebrities from the entertainment world and sports figures, may feel freer to speak on a broad range of topics using social media, and may benefit from publicity (Marwick & boyd, 2010).

Future Directions

While the presence of a meaningful hashtag is a clear signal of relevance, this method may not capture all relevant tweets. Users might neglect to include the appropriate tag. Use of alternate methods, such as topic models, may help improve tweet recall.

The research examines Twitter communications originating in London beginning with the riots and continuing through the initial weeks of recovery. These communications are used to build networks summarizing the riot cleanup and prayer responses to the crisis as observed in social media. However, the inhabitants of London experienced these events moment by moment. Their emotions, behavior, interpretations, and communications may have changed as events unfolded. Temporal exploration of this data could provide additional insight into this process. Timelines for hashtag categories may show differences. For example, prayer might emerge more quickly in social media data, yet have a shorter half-life and diminish rapidly, perhaps dampened by negative evaluations while cleanup may peak more slowly, and plateau at an elevated rate (Glasgow & Fink, n.d.).

We have treated riot cleanup and prayer as two distinct networks, and observed radically different membership at the top. We have suggested factors at the both individual and social level that might explain this phenomenon. Yet co-occurrence of both types of tags in the same tweet does occur, and these networks do share members. We have not explored frequency or patterns of hashtag co- occurrence or network co-membership. Clustering derived from co-occurrence could produce different sets of tags than the semantically based method that was used, and help refine our understanding of these communities.

Actor profiles are based on a limited set of metrics that capture network information based on actor behavior, response of others to actor, and the actor's local neighborhood. These profiles could be extended by including additional social network metrics, by adding information on broadcast tweets, or by incorporating connections between network members.

Conclusion

This work explores the microblogging landscape of London during the worst period of rioting and public disorder in decades, the riots of August 2011. Through categorizing the hashtags from a corpus of tweets from the city, we identify communications relevant to riot communications in general, and subsets of riot communications relating to specific riot responses, such as *cleanup* and *prayer*. Constructing social networks from these tweets based on *talking to*, *quoting*, and *talking about* provides a mechanism for additional insights. Computing social network measures on network actors allows us to identify prominent actors and assess their similarity. We find numerous differences between networks of *cleanup* and *prayer* in terms of size, structure and network membership. Patterns differentiating the networks and actors may indicate social processes and forces at work.

For local residents coping with disaster, up-to-date, locally relevant information is critical, and social media may be preferred over mass media (Shklovski et al., 2008). This research shows a more advanced means to purposefully navigate microblogging space than browsing or searching keywords, and provides hooks to engage and share more effectively.

These findings have implications for authorities or emergency responders in terms of improving their overall situational awareness during extreme events. Analyzing relevant social media communications can aid in understanding networks of community communication and response, and in recognizing individuals who play prominent roles in these networks. It can aid in determining if messages are penetrating to the right people, and achieving the desired effect. The role of social media, and ICT more broadly in improving government transparency, and increasing trust and empowerment among the citizenry has been noted (Bertot, Jaeger, & Grimes, 2010) This is an important matter, as lack of transparency regarding the police investigation into the shooting death of a Tottenham resident motivated the protest that sparked the riots.

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