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A Template for Mapping Emotion Expression within Hashtag Publics

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Abstract

Current literature on networked publics lacks research that examines how emotions are mobilised around specific actors, and quantitative analysis of affective phenomena is limited to vanity metrics. We address this issue by developing a network analytic routine, which guides the attribution of emotions contained in hashtagged tweets to their sources and targets. The proposed template enables identification of networked inconsequentiality (i.e., inability to trigger dialogue), reply targets (i.e., individuals targeted in replies), and voice agents (i.e., senders of replicated utterances). We demonstrate this approach with two datasets based on the hashtags #Newzealand (n= 131,523) and #SriLanka (n= 145,868) covering two major incidents of terrorism related to opposing extremist ideologies. In addition to the methodological contribution, the study demonstrates that user-driven emergence of networked leadership takes place based on conventional structures of power in which individuals with high power and social status are likely to emerge as targets as well as sources of emotions.

Keywords: *Affect, Emotions, Twitter, Network Analysis, Uptake*

Introduction

Recent years have witnessed a surge of academic interest in digital manifestations of affective phenomena, such as affect (e.g., Blevins, Lee, McCabe, & Edgerton, 2019; Döveling, Harju, & Sommer, 2018; Johns & Cheong, 2019) and emotions (Margolin & Liao, 2018; Neag & Supa, 2020; Wang & Wei, 2020). Concepts such as affective publics that acknowledge the role mediated feelings play in online activism (Papacharissi, 2016) have inspired analysis of digital publics (e.g., Adi, Gerodimos, & Lilleker, 2018; Adlung, Lünenborg, & Raetzsch, 2021; Basmechi & Ignatow, 2021; Dawson, 2020; Hautea, Parks, Takahashi, & Zeng, 2021; Siapera, Boudourides, Lenis, & Suiter, 2018; Ural, 2021). This emphasis on affect and emotionality is necessary to understand networked publics, since platforms enable social formations such as ad hoc publics organised around specific hashtags (Bruns & Burgess, 2011) based on shared feelings and emotions. As Papacharissi (2016) notes, we may envision discourse organized by hashtags “as structures of feeling, comprising an organically developed pattern of impulses, restraints, and tonality” (p.321). Examining such structures can provide insight into the role emotionality plays in mobilising users within affective digital social formations.

While there is an emphasis on affective phenomena as a basis to examine networked structures of feeling (Papacharissi, 2016), there is a lack of attention among researchers who study hashtag publics to examining how specific emotions that indicate different states of affect are mobilised. There are several limitations of current literature on affective and emotional dimensions of digital publics. First, scholars have defined affect in several ways, from a subjective feeling to presubjective intensity (Laszczkowski & Reeves, 2015), reflecting a lack of agreement on how digitally mediated affect can be observed. Second, an emphasis on narratives has resulted in concepts such as affect being umbrella terms rather than specific tools for analysis. Third, social media researchers do not adequately deal with studies in psychology and affective neuroscience that identify affect as a bodily reaction that is intertwined with emotion (e.g., Barrett, 2009, 2011; Posnera, Russell, & Peterson, 2005; Russell, 1980). Despite the availability of automated emotion detection techniques, quantitative analysis of collective activity within affective publics is largely limited to vanity metrics— i.e., measures such as counts of page views and likes that are used to assess how well one is doing online (Rogers, 2018).

Analysis of specific emotions can complement current work on hashtag publics (e.g., Papacharissi, 2016) as it can show how affect, transformed into specific emotions, is verbalised via social media posts. Accordingly, the objective of this study is to propose a template for structural analysis of networked emotions with an emphasis on how platform affordances enable the emergence of networked publics via individual acts, such as posting, reposting and replying to content. We aim to achieve three related goals in order to develop a template for mapping networked emotions. First, we classify social media utterances, specifying three distinct primary orientations (i.e., expression, targeted replies, and replication). Differences between such primary orientations are crucial to establish directionality of emotions and develop an approach for mapping flows of emotion. Second, we suggest a network analytic routine, based on a measure of weighted degree in directed networks, to attribute emotions contained in different types of utterances to their sources and targets. This approach allows contextualising the role individual users play in the construction of hashtag publics and identifies sources and targets of emotions. We use the above mentioned primary orientations and the analytic routine to describe three actor types that characterise affective influence in ad hoc hashtag issue publics. Identification of modes of affective influence can help examine nuanced aspects of digital publics by explicating how affective networked gatekeeping (Meraz & Papacharissi, 2013) takes place via distinct processes of digital engagement, such as celebrity engagement (Bennett, 2014; Click, Lee, &

Holladay, 2013) and populist political leadership (Kaur, Verma, & Otoo, 2021; Masch & Gabriel, 2020).

The third goal was to use Twitter ‘hashtag publics’ related to incidents of terrorism as the empirical context to demonstrate the above approach. Research that examines digital engagement related to terrorism represents a variety of topics. Further work on digital engagement related to terrorism is necessary as accessibility of social media intensifies the mediatization of tragedy. Accordingly, we examine mobilization of affect via uptake activity within Twitter hashtags #Newzealand and #SriLanka, two ad hoc publics that emerged in response to the March 2019 attacks in Christchurch, New Zealand and the April 2019 Easter Day bombings in Sri Lanka, respectively. These two attacks represent acts of terrorism related to opposing extremist ideologies.

Mapping Affective Phenomena within Hashtag Publics: Methodological Challenges

Different conceptualizations of affective phenomena, such as emotion, affect and feeling, have implications for how emotion is understood and applied to examine media phenomena (Alinejad & Ponzanesi, 2020). A discussion of such implications is necessary for the development of different analytical approaches. The notion of affect has evolved through several scholarly traditions across different fields that represent distinct theoretical and epistemological positions (Wetherell, 2013). Many studies that examine affect within the context of digital media depend on the theoretical foundation developed by Baruch Spinoza, Gilles Deleuze and Félix Guattari. Papacharissi (2014) notes that this school of thought, which defined affect as the ability to affect and be affected, paved the way for understanding affect as intensities dependent on, but independent of individual emotions. The Deleuzian school of thought makes a clear distinction between affect and emotion in which the former is considered as an ‘intensity’ that does not require interpretation, while the latter involves secondary cognitive processes (Alinejad & Ponzanesi, 2020). While the critical theoretical approach has its merits, especially in terms of theorizing digital assemblages, our emphasis lies in a conceptual basis that enables empirical analysis of emotionality. The position that affect exceeds subjective experience has troubled researchers, especially in terms of methodological application of the concept (Robinson & Kutner, 2019). Our position is that affect, when used in isolation as a nonsignifying, nondiscursive intensity, offers limited potential for empirically examining digital publics.

Scholars who use affect as a theoretical lens to examine hashtag publics face the above challenge. Affective publics— “public formations that are textually rendered into being through emotive expressions that spread virally through networked crowds” (Papacharissi, 2016, p.320) — deserves attention within this context as it has inspired a wide range of studies (e.g., Adi et al., 2018; Adlung et al., 2021; Basmechi & Ignatow, 2021; Hautea et al., 2021). Papacharissi (2016) conceptualizes affective publics as networked publics mobilized, identified, connected and disconnected through expressions of sentiment, which materialize uniquely, facilitate connective action, and leave distinct digital footprints. She describes affect as a form of subjectively experienced pre-emotive intensity with which individuals experience emotions. This conceptualisation recognises the interrelatedness between affect and emotions. However, it does not identify expressed emotions as evidence of affect. This may limit the ability to analyse specific evidence of affect due to above-mentioned difficulties in measuring individually experienced intensities underlying digital publics.

The above issue also relates to the question of whether affect can be measured on a collective level. Social media researchers discuss affective intensity and networked rhythms on a collective level. For instance, Papacharissi uses the total volume of tweets to show networked rhythms of activity in the hashtag #Egypt and notes that, within the hashtag, affect was present through the intensity that permeated the stream of tweets, and rhythms and pace of storytelling. Siapera et al. (2018) follows a similar approach to examine hashtags related to a refugee crisis in 2016 in which they use the volume of messages as an indicator of rhythms of tweeting. Similarly, Papailias (2016) describes the high level of views generated by a specific video tribute as affective energy. While Papacharissi (2016) highlights rhythms as an indicator of affective intensity, she also points to what can arguably be described as individual traces of verbalised affect, using a sample of tweets, which displayed a variety emotions. We suggest that intensity and rhythms should be considered as separate phenomena as rhythms is a collective property (i.e., temporal changes in the extent of engagement) while intensity is a subjectively felt experience. While vanity metrics (Rogers, 2018), such as the volume of tweets, can help examine rhythms, more sophisticated methods are needed to examine outcomes of subjective intensity.

While quantitative analysis of digital affective publics reflects an emphasis on collective rhythms, related qualitative work pays attention to the emergence of narratives. For instance, Hautea et al. (2021) discuss how Tik-Tok content related to climate change (re)produces affective publics. They demonstrate how the platform is used to produce content that can indicate earnestness and mockery, move between care and indifference, and rely on repetition and variation of existing creative styles. The authors argue that their analysis offers empirical traces of affective publics by documenting the production and reproduction of textures of storytelling. Dawson (2020) discusses the hashtag #MeToo from the perspective of emergent storytelling. He examines narratives within the hashtag and argues that, although Twitter is not designed for a narrative experience, the platform facilitates interactive construction of narratives and the affective encounters that such interaction produces. Both Hautea et al. (2021) and Dawson (2020) focus on how the discourse unfolds within chosen digital publics and the role individual utterances play in the construction of collective narratives. In a similar vein, Ural's (2021) analysis of the Twitter hashtag #AliErbaşYalnızDeğildir, which framed public debate in Turkey, shows how the hashtag served as a performative site for imagining a Muslim self. He identifies themes emerging from content and examines the extent to such themes articulate subject positions, such as truth of Islam and hatred. Ural identifies such subject positions as ‘affective resonances of hashtag discourse’. While these studies provide useful insight, the emphasis on narratives has resulted in a disconnection between theory and empirical work because affect is used as an umbrella term to describe a given hashtag public, rather than as an analytical tool that guides specific analysis.

The emphasis on affect as the main analytical unit seen above poses challenges. Within this context, we observe a lack of structural analysis that explains how subjectively felt affect is verbalised in structures of interaction. To address this issue, we consider specific emotions as discursive outcomes of affective intensity. Therefore, analysis of emotions serves as an approach to demonstrate evidence of affective intensities underlying emotional social media content.

Empirical Analysis: Emotion as an Analytical Unit

We draw on research in the field of social psychology (Barrett & Bliss-Moreau, 2009; Barrett, 2011; Barrett & Russell, 1999; Russell & Barrett, 1999) to suggest that emotion can serve as a viable analytical unit to observe affective behaviour. Core affect— “consciously accessible elemental processes of pleasure and activation” (Russell & Barrett, 1999, p.805) is a precise concept, which Barrett and Bliss-Moreau (2009) identify as a “neurophysiologic barometer of the individual’s relationship to an environment at a given point in time, with self-reported feelings as the barometer readings” (p.5). Russell (2003, p.147) defines core affect as “a neurophysiological state that is consciously accessible as a simple, nonreflective feeling that is an integral blend of hedonic (pleasure–displeasure) and arousal (sleepy–activated) values.” According to Russell (2003), core affect can be experienced as “freefloating (mood) or can be attributed to some cause (and thereby begin an emotional episode)" (p.145). Core affect provides the basis for the analytical approach developed in this study as previous work explains how core affect is intertwined with specific emotions.

Prototypical emotional episodes, which Russell and Barrett (1999) described as what many individuals identify as the clearest cases of emotions, include a complex set of subevents concerned with an object. Russell and Barrett argue that emotional episodes include several elements: core affect; overt behaviour in relation to, attention toward, appraisal of, and attributions to an object; experience of emotion; and neural, chemical and other bodily reactions. Barrett and Russell (1999) note that affective feelings are central to emotional experience and emotional episodes may not exist in the absence of strong affective feelings. The circumplex model (Barrett & Russell, 2009; Posner, Russell, & Peterson, 2005; Russell & Barrett, 1999) shows how affect-related items can be decomposed into basic psychological properties. In this model, affective states arise from valence and arousal and affective experiences, which represent specific emotions, result from a linear combination of such systems (Posner et al., 2005). For instance, fear indicates high activation and unpleasantness while sadness can be characterised by high unpleasantness and slight deactivation. This supports the argument that traces of emotions contained in digital text can be seen as visible evidence of latent states of core affect. Accordingly, emotion is a more viable analytical unit as it is traceable in digital text data. In this model, sadness, disgust, anger and fear show somewhat similar levels of subjectively felt unpleasantness. However, they differ in terms of activation in which anger and fear can be seen as highly active states. The extent to which these emotions are mobilised in digital text data can show the level of activation as well sources and targets of such intensity, enabling mapping flows of emotion and characterising affective influence. The following discussion builds an empirical basis for such analysis.

Step 1: Specifying Primary Orientations of Social Media Use

This section focuses on specifying how different types of individual acts, such as posting, reposting, and replying to content, contribute to complex structures of interaction. This classification guides mapping of emotions contained in each act to their sources and targets. Social media provide affordances such as replicability, scalability, and searchability, as well as high visibility of content (boyd, 2011), which enable the formation of conversational structures. Affordances such as triggered attending and metavoicing (Majchrzak, Faraj, Kane, & Azad, 2013) facilitate interaction among users. In general, platform affordances are actualized via uptake of elements in digital environments. Uptake is the relationship that emerges when an actor's actions take traces of prior or ongoing activity as relevant for an ongoing activity (Suthers, Dwyer, Medina, & Vatrapu, 2010). Uptake is not limited to transactivity and acknowledges situations where interactions can occur without other-directed utterances (Rathnayake & Suthers, 2018). This concept allows understanding how individual actions aggregate to larger entities within and across platforms. Uptake can take many forms on social network sites. For instance, a user may take up platform elements and features (e.g., Facebook 'Create Post' option, Twitter 'What's Happening' option, a twitter @ handle, Facebook profile) to post content for a public or a community. Outcomes of other users' use of such elements, including content perceived as traces of an imagined public or a community for engagement (e.g., Tweets, retweets, Facebook posts) can also be taken up for engagement. Accordingly, social media use includes different types of uptake that expand into structures of interaction (Rathnayake & Suthers, 2018).

A relational logic for mapping networked affect via uptake activity on Twitter can be developed based on three layers of primary orientation (see Table 1 for definitions). Bruns and Moe (2014) identify three layers of communication on Twitter: 1) macro (hashtag), 2) meso (follower networks), and 3) micro (@replies). They argue that, while Twitter affordances allow inherent interconnections between layers, users may also deliberately transition between layers. The primary orientations defined in this section reflect this model. Tweets, retweets and replies in an ad hoc public function within the macro layer as they contain hashtagged text. They also relate to meso and micro layers as the tweeted text is visible to follower networks and that some messages may take the form of '@replies' or mentions. However, the use of original tweets (without mentions), retweets, and replies (or mentions) reflect disctinct orientations

An original tweet takes up platform features and affordances for posting content. If the user marks the tweet with a hashtag, the message becomes a member of a collective (i.e., a public organised around a hashtag 'frame' and the macro layer as suggested by Bruns and Moe). Although original tweets contain potential for future uptake, they do not in themselves constitute explicit structures of interaction among users since by definition they do not tag other users or reference existing contributions. Accordingly, our graph representation of original tweets consists of a vertex, which represents a user, and a self-loop that indicates that the tweet takes up emotions originating in the user. In contrast, replies, mentions and retweets explicitly take up existing twitter handles and content for engagement (i.e., structures within the micro layer). Accordingly, both replies and retweets contribute to 'explicit interactive uptake structures', represented using vertices connected by edges. Replies/mentions and retweets have distinct primary orientations. A reply can be identified as primarily a targeted response as they are other-directed utterances made in reply to a previous utterance. A reply may act as an invitation for further engagement and it motivates triggered attendance (Majchrzak et al., 2013). Other-directed tweets that mention specific users also fall under this category. In contrast, a retweet is a specific act of metavoicing— i.e., engagement by reacting to content created by others, rather than voicing one's opinion (Majchrzak et al.). Retweets are primarily replicative as the main intention behind retweeting is to take up an existing tweet and make it visible to a user's follower network with or without an emphasis. In the following section, we discuss how these orientations provide a basis for understanding directionality of networked emotions.

Table 1

Step 2: Attributing Emotions Contained in Digital Text to Actors

In this section, we use the above classification to attribute emotions contained in original tweets, replies and retweets to their sources and targets. Identification of sources of emotions helps uncover the extent to which affective influence takes place via each orientation.

Sources of Emotions

In primarily expressive utterances (i.e, original tweets) and targeted replies, senders can be identified as sources of emotions. Therefore, the sum of emotions contained in original tweets, replies and mentions shows the extent of emotions originated from who posted them). However, senders of replicative utterances (i.e, retweets) cannot be considered as original sources of emotions as they primarily replicate content originally posted by others. It is more logical to consider the person whose message is retweeted as the source of emotion. Therefore, the total of emotions contained in retweets show the extent to which the original sources (i.e, whose tweets get taken up for retweeting) act as sources of emotions. However, since the graph representation of targeted replies and replicative utterances is the same (see Table 10), separate networks should be constructed for these orientations.

Targets of Emotions

Emotions in replies and mentions can be assigned to targets (i.e., those who are replied to or mentioned) to identify the extent to which users have been targets of emotional uptake. In contrast, assigning emotions in retweets to senders of retweets shows the extent to which users replicate emotional content. This distinction is crucial when identifying sources and targets of emotions in Twitter reply and retweet structures. In retweet structures, specific targets of (retweeted) emotions cannot be identified as the audiences are imagined by the sender. In other words, traceable retweet structures are limited to ties between sources of emotion and 'replicators' (i.e., users to replicate content posted by such sources). Figure 1 summarises this argument and Table 2 shows network metrics that can be used based on this argument to identify the extent to which users become sources and targets of emotions.

Figure 1

Metrics

Weighted vertex degree can be used to attribute emotions to sources and targets in uptake relationships described above. Weighted degree is defined to be the sum of edge weights (i.e., emotion scores for each reply/mention or retweet) for each vertex. In directed networks, weighted indegree calculates the sum of emotions contained in incoming edges. Accordingly, weighted indegree can be used to measure (c) strength of emotions originating from a user whose message is retweeted and (b) the extent to which a user becomes a target of emotional uptake via replies and mentions. Weighted outdegree can be used to assess the extent to which (c) users replicate emotional content in retweet networks, and can also show (b) the strength of emotions originating from users as they reply to messages or mention others (see Figure 1).

Weighted degree measures actors' total emotional engagement in the network summed across all of their interactions. This will naturally favor actors who have high degree, which is appropriate if one is interested in characterizing the emotionality of a network as a whole and identifying those who have the greatest impact on this emotionality. However, weighted degree is not identical to degree: examples to be given shortly illustrate how different actors emerge as prominent in the same network (holding degree distribution constant) under different emotions. If one were instead interested in the emotionality of single actors' typical individual interactions with others (controlling for how many others they interact with), one could use the mean weight, i.e., weighted indegree or outdegree divided by the respective degree. However, such a measure could mark as prominent individuals with only one or a few very emotionally intense interactions who are not significant from the standpoint of emotionality in the the overall network.

Table 2

Data, Emotion Detection and Network Construction

To illustrate the approach, we use two datasets based on the hashtags #Newzealand (n= 131,523; 29,993 original tweets, 2,294 replies and mentions, and 99,236 retweets) and #SriLanka (n= 145,868; 40,273 original tweets, 6,388 replies and mentions, and 99,207 retweets) gathered using the standard Twitter API for analysis. The Christchurch attack took place on March 15, targeting two mosques. The first dataset, which covered the six hours immediately after the attack, represented the hashtag #Newzealand that was used to express sentiments relating to the attack. The second dataset that included #SriLanka was gathered on April 21 covering Sri Lanka's Easter attacks. These bombings included multiple suicide attacks targeting several churches and luxury hotels. Data collection started immediately after the first attack tookplace, and the full dataset covered eight hours. Accordingly, our samples cover the most intense period of Twitter activity that emerged immediately after the incidents.

Emotions contained in tweets were calculated using the NRC Emotion Lexicon (EmoLEx) (Mohammad & Turney, 2013). EmoLex contains a repository of word-sense associations that marks the presence of a given emotion in a word. The lexicon includes more than 14,000 words, which help quantify the extent to which a given emotion is present in a corpus. Emolex is a widely used lexicon and it has been applied to examine Twitter content (Yu & Wang, 2015). Total sentiment scores for each tweet were calculated using the get_nrc_sentiment function in the R SyuZhet package. Words express multiple emotions and overlaps are expected. For example, when called on "IS, as claimed, brutal terrorist attack on #Christians in #SriLanka : World must unite to annihilate these insane, brutal Shaitans for peace", get_nrc_sentiment returns: anger 5; anticipation 1; disgust 1; fear 5; joy 1; sadness 1; surprise 1; trust 1; negative 5; positive 1. While the lexicon-based emotion detection shows the extent to which words that indicate specific emotions are present in each document (i.e., tweet), it does not examine the semantic context within which such words are used (e.g., sarcasm). Therefore, our analysis is limited to the use of emotion words, rather than how such words are used. However, it should be noted that the analysis approach proposed by this paper does not depend on the emotion detection method used. More sophisticated emotion detection methods can be used with the same network analytic template.

A multi-layered graph analysis was used to examine structures of uptake that emerge via replies, mentions and retweets. This approach considers each reply or retweet as having multiple layers of emotions in varying degrees. As recommended earlier in this paper, separate networks were created to examine how different emotions were embedded in reply and retweet structures. Network vertices represented users, and edges were based on acts of replies, mentions, and retweeting. Self-loops were created for original tweets. Edges that had zero emotion scores were removed. Figure 2 summarises the network construction process.

The Louvain method (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008) was used to observe the community structure.

Figure 2

Step 3: Mapping Flows of Emotion

Networked influence takes place within complex structures of interaction, and as Meraz and Papacharissi (2013) note, the power of elites to frame a given issue depends on networked actions of the nonelite. The above classification and the network analytic routine helps observe such bottom-up construction. In this section, we demonstrate the use of the proposed approach and describe how three actor types that characterise different types of affective influence (inconsequentiality, dialogic targets, and voice agents) emerge via individual acts of uptake.

Networked Inconsequentiality

Primarily expressive utterances (i.e., tweets with low indegree) can reveal users who display 'networked inconsequentiality'— i.e., failure to trigger actual uptake at the point of observation. Such unrealised potential for uptake shows a lack of influence. Nodes with self-loops were identified in the full networks that included original (non-tagged) tweets, replies/mentions and retweets. Profiles that emerged as top sources of emotion in original tweets representing both hashtags included regional news outlets. For instance, @DunyaNews (Pakistani media organization, weighted outdegree: Anger: 24, Fear: 31), @MusafirNamah (Indian travel and tourism news outlet, Fear: 36), and @ewnreporter, (Eye Witness News team, South Africa, Fear: 24) were among top sources of emotions in original tweets in #NewZealand. Similarly, local Sri Lankan news outlets and journalists, such as @SriLankaTweet (weighted outdegree: Anger: 62, Fear: 99, Sadness: 60), @newsradiolk

(Anger: 35, Fear: 61, Sadness: 33, Disgust: 13), and @ Kavinthans (Anger: 55, Fear: 82, Sadness: 31) appeared among top sources of emotions in #SriLanka. Individuals with a low Twitter following were also included among top sources of emotions in expressive utterances. This shows that although institutional profiles with local character as well as individuals with relatively small follower groups can use the platform for expression, they fail to mobilise discussion.

Targeted Replies and Replicative Utterances

Replies and retweets form traceable structures of interaction among users. Analysis of such structures can show how content is chosen by followers for engagement and the user-driven ‘construction’ of top actors. We identify two modes of influence within these structures. In reply/mention structures, users whose profiles and/or expressions are taken up by others can be identified as reply targets. Within retweet structures, sources of content retweeted by others can be seen as agents of voice. These two types of affective influence are different from each other as users direct their voice at targets in replies while they take up voice from agents in retweets. Table 3 shows the sizes of reply and retweet networks for each emotion. These networks had strong structures characterised by clearly defined partitions (modularity values estimated by the Louvain method ranged between 0.972 and 0.853).

Table 3

Reply Targets

Reply targets can be characterised as actors who emerge via targeted replies. Reply targets emerge when users respond to previous utterances or profiles (‘@handles’), inviting ‘triggered attendance’ (see Majchrzak et al., 2013). This allows users to respond to individuals with different levels of power and social capital although such figures may not engage in an active dialogue with followers. However, the ability to target such figures itself is a soft form of influence afforded by platforms. Table 4 shows top actors based on indegree values for the full reply/mention network (prior to the construction of networks based on emotions) as well as the and weighted indegree values for separate networks. Figure 3 shows the largest partitions in reply/mention networks in each hashtag. Node size indicates weighted indegree (i.e., the extent to which a user becomes a target of a given emotion). As the visualizations show, political leaders, such as Jacinda Ardern (weighted indegree: Anger: 105; Fear: 130; Sadness: 88; Disgust: 72), Donald Trump (Anger: 49; Fear: 49; Sadness: 36), Imran Khan (Anger: 59; Fear: 56; Sadness: 40; Disgust: 28), and accounts representing media organizations including CNN (Anger: 26; Fear: 38; Sadness: 17) and BBC World (Anger: 40; Fear: 47; Disgust: 25) emerged as top reply targets in each network layer in #Newzealand.

Similarly, the largest partitions in #SriLanka formed around political figures, such as Donald Trump (weighted indegree: Anger: 42; Fear: 53; Sadness: 40; Disgust: 32) and Barack Obama (Anger: 34; Fear: 66; Sadness: 40; Disgust: 24), religious leaders (e.g., @Imamofpeace; Anger: 21; Fear: 48; Sadness: 26; Disgust: 16) and media organizations (e.g., @washingtonpost; Anger: 27; Fear: 24; Sadness: 19; Disgust: 19, and @nytimes; Anger: 20; Fear: 23; Sadness: 9; Disgust: 7). This indicates that, although general users may reply to each other within the context of issues, targeted replies gather around accounts that represent individuals or organizations that have high political power and/or social status. These top accounts had zero weighted outdegree values, indicating that although they are targets of uptake, they do not engage in active dialogue with others. Within this context, influence can be characterised mainly based on the mere availability of such accounts as targets.

Table 4

Figure 3

Voice Agents

In retweet structures, influence takes place when users become agents of voice as their utterances are selected by others for reposting. Table 5 shows indegree values of top ten accounts in both general and weighted networks. Figure 4 shows the largest two partitions in retweet networks representing each hashtag. Replicative structures in #Newzealand included accounts representing political figures, such as RT_Erdogan (Recep Tayyip Erdoğan, President of Turkey; weighted indegree: Anger: 19,641; Fear: 13,094), MBA_AlThani (Sheikh Mohammed bin Abdulrahman Al-Thani, Deputy Prime Minister and Minister of Foreign Affairs, Qatar; Anger: 795; Sadness: 530), MevlutCavusoglu (Mevlüt Çavuşoğlu, Minister of Foreign Affairs of the Republic of Turkey; Anger: 1278; Fear: 852), and sayedzbukhari (Sayed Bukhari, Pakistani-British entrepreneur, Special Assistant to Prime Minister Imran Khan; Anger: 1470; Fear: 1470; Sadness: 980),. These networks also included religious figures, such as Dr Tahir-ul-Qadri, Founding Leader and Patron-in-Chief of Minhaj-ul-Quran International, Pakistan (weighted indegree: Anger: 1655; Fear: 1110; Sadness: 1110), Dr. Omar Suleiman (Imam and academic; Anger: 9778; Fear: 9778) and diplomats (e.g., KoblerinPAK, Martin Kobler, former German Ambassador to Pakistan; Anger: 710; Sadness: 710; Disgust: 355).

Celebrities and religious figures appeared more frequently among sources of emotion in retweet networks in #SriLanka. Celebrity accounts including sachin_rt (Sachin Tendulkar, former Indian cricketer; weighted indegree: Anger: 3410, Fear: 3410, Sadness: 1705), SAfridiOfficial (Shahid Afridi, former Pakistani cricketer; Anger: 2355; Sadness: 1884), Ninja (Richard Tyler Blevins, gamer and YouTuber; Anger: 2535, Fear: 5070, Disgust: 2535), Kaya Jones (Canadian-American singer; Fear: 3028), were among top twenty actors with high indegree. Results also show that accounts representing religious leaders, such as Imamofpeace (weighted indegree: Anger: 2149), Muftimenk (Islamic scholar based in Zimbabwe; Anger: 2149) had high indegree in these networks. Retweet networks also included individuals representing distinct orientations, such as Paul Joseph Watson (British right-wing YouTuber), Pakistani Nobel laureate Malala Yousafzai, and the former US Secretary of State Mike Pompeo.

Table 5

Figure 4

Methodological Implications

Social network sites are complex conversational environments that enable different modes of user engagement. Fine-grained analysis is required to examine how emotions flow among users representing different levels of socio-political power and cultural capital play in such environments. Our primary goal is to develop a network analytic template for mapping flows of emotion within hashtag publics. Empirical analysis of #NewZealand and #SriLanka show that mapping networked emotions provides useful insight that can characterise hashtag publics. The analysis encapsulates the view that affect ranges from “individual expressions of feeling to the production of sensation within human-technology assemblages” (Pedwell, 2017, p.149). Not only is this approach consistent with the argument that the attribution of emotion words to specific actors is a key element in the identification of affect in language (Adlung et al., 2021), it also shows a systematic basis for such attribution.

The three types of actors introduced in this study complement previous work that discusses networked gatekeeping (e.g., Meraz & Papacharissi, 2013) by providing a framework for fine-grained analysis that allows understanding the emergence and positionality of actors and the role emotions contained in their messages play in determining such positionality. Meraz and Papacharissi's work on the hashtag #egypt focuses on prominent users, gestures and conversational practices. Our findings show structural positioning of such users and the nuanced nature of affective influence that they display within hashtag publics. Twitter users follow each other for different reasons and interaction within global ad hoc publics emerge based on such logics. As we demonstrate in the current study, such leading actors locate in separate clusters. This characterises polymorphic publics that display internal diversity in terms of user orientation (Rathnayake, 2020; Rathnayake & Suthers, 2018), such as political followership and fandom. While identification of top actors is commonly applied in social media research (e.g., Ausserhofer & Maireder, 2013; Chen, Tu, & Zheng, 2017), the above approach can differentiate actors under different emotions and allow observing how emotions accumulate as such power structures develop.

While the three actor types discussed above provides a basis for empirical analysis of soft forms of influence, these three modes of construction require further refinement and application. While we define actor types within a relational context, using network analysis as the method, qualitative analysis can allow close reading of the role played by different types of social media users in the construction of networked leadership. Such analysis enables observation of how different power relationships are embedded in ad hoc publics and interpreting mobilisation of networked emotions. Moreover, further work is needed to examine the extent to which shared affective intensities and emotions determine the formation of communities around key figures. While the above results show flows and accumulation of emotions within chosen hashtags, our illustrative results are subject to limitations of lexicon-based emotion detection. However, the analysis template proposed does not depend on the emotion detection method used in the example, and more sophisticated methods of natural language analysis for emotion detection can be applied within this template to enable more accurate mapping of networked emotions.

Characterising Hashtag Publics

While we reveal reply targets and voice agents within #NewZealand and #SriLanka, we emphasize a more general characterisation of ad hoc and affective publics based on the above results. Specifically, the above analysis helps determine whether ad hoc affective publics constitute citizen-oriented, non-hierarchical, grass-roots social formations or merely reproduce offline social and political structures. Posts that accumulate within affective publics mainly consist of content subjectively retold and repeated, displaying a variety of emotions (Papacharissi, 2016). The above analysis reveals the logics based upon which such repetition and retelling take place. Dominance of political figures, religious leaders, and celebrities show that user-driven emergence of top actors takes place based on power in which individuals with high power and social status are likely to emerge as targets as well as sources of emotions. Actors who have high indegree in general non-weighted networks frequently appear among top actors in emotion weighted networks (Table 4 and 5). Their dominance in weighted networks results from the fact that popular actors have larger networks, more visible, and are likely to become reply targets and voice agents. However, their positionality among leading actors changes across different emotion networks. An inspection of the top 100 profiles in weighted networks revealed that differences in rankings among networks representing distinct emotions gets even more noticeable when examining a large number of top actors. As Tables 4 and 5 show, several new profiles appear among top ten actors in emotion-weighted networks. A considerable number of new actors appear in different ranking positions in the top 100 profiles in weighted emotion networks.

Table 6 provides examples of replies directed at and retweets taken up from top actors that had relatively high emotion scores. As the examples show, emotions expressed in some replies in Table 5 were directed at political leaders such as Jacinda Arden and Donald Trump as well as media organizations, rather than those who committed acts of terrorism. Replies received by the top actors included messages that showed sympathy with emotions that some top accounts expressed. However, these replies did not have high emotion scores. While replies showed political motives, especially in terms of critiquing how acts of terrorism committed by different groups are portrayed, retweets were mainly limited to expression of sympathy and condemnation of terrorism. This shows that Twitter affordances allow contentious exchanges as well as replicative utterances to emerge within the same issue public.

Table 6

The prominence of actors with high power and cultural status show that hashtag publics do not reflect an internal logic — i.e, a logic or a purpose unique to such publics themselves. Instead, they form based on pre-existing interests and follower relationships (e.g., political and religious leadership, and fandom), which are reflected not only in degree distribution but also the expressed emotions. Interconnections among the three layers of communication (Bruns & Moe, 2014) allow ad hoc formation of momentary publics based on pre-existing structures. Accordingly, the above results do not show evidence of a distint type of leadership that is primarily driven by emotions. Nevertheless, our results are consistent with Papacharissi's (2016) observation that that affective publics are driven by affective statements of opinion, fact, or a blend of both. However, the prominence of conventional actors or opinion leaders in the above networks contradict with Papacharissi's claim that affective publics typically disrupt dominant political narratives. As argued above, affective publics dominated by conventional actors and opinion leaders, such as #NewZealand and #SriLanka are unlikely to produce alternative or disruptive narratives. Therefore, the true disruptive potential of affective public lies in more intense issues, such as the hashtag #egypt, a hashtag that forms the basis of Papacharissi's study.

The above results are consistent with the argument that digital politics constitutes phatic communion characterized by gestures intended to enable communion, rather than motivating action or political dialogue (Miller, 2015). Uptake or profiles (i.e., '@handle') and media expressions (i.e., tweets) and the lack of reciprocity shows that hashtag publics provide feelings of engagement, rather than active dialogue against terrorism. Moreover, dominance of figures with high political power and cultural capital in above results support Miller's argument that such communion is likely to reproduce the status quo. Accordingly, while the current study confirms Papacharissi's (2016) claim that ad hoc affective publics are structures of feeling, it also suggests that such feelings reinforce top-down power structures. Globally connected ad hoc publics that we examine do not show potential in contributing to significant dialogue among citizens that can help address the issue of terrorism. Yet, as self-organizing networks (see Bennett and Segerberg, 2012) they play a crucial role by enabling expressions, gestures, and acts of sharing that motivate global-level engagement with minimal effort, especially among those users who are less likely to participate in any organizationally enabled or brokered networks. This claim is also consistent with the argument that affective publics can be characterised by connective rather than collective action (Papacharissi, 2016).

Although a generalizable power structure reflects tie formation, the two hashtags are considerably different from each other in terms of top reply targets and voice agents. While political leaders representing countries with a Muslim majority (i.e., Pakistan, Turkey) and religious leaders dominate #NewZealand, a more diverse set of leaders, including athletes, political leaders from Western countries, as well as religious figures, emerge in #SriLanka. This indicates the possible impact of religious faith in triggering affective responses related to violence against Muslim communities within the context of the Christchurch attack. The diversity of leaders who emerged within #SriLanka shows that violence against Catholic places of worship mobilised different populations. This may show signs of religio-political tensions and a global divide in digital affective engagement related to violence against different faith groups. However, as this characterization is based on the preliminary structural analysis discussed above, an in-depth analysis of the content of tweets can strengthen our claims.

The above analysis helps explain the socio-technical infrastructure that allows the emergence of ad hoc publics (Bruns and Burgess, 2011). Digital platforms allow actors to maintain presence by creating profiles, articulating a list of connections, and traversing such connections within a bounded system (boyd & Ellison, 2007). This apparatus also contains a layer of social and cultural power based on which users form connections. This includes hierarchical relationships, such as fandom, which, as previous studies highlighted, can lead to mobilization (e.g., Bennett, 2014; Click, Lee, & Holladay, 2013, 2017), emotive political leadership (Kaur et al., 2021; Masch & Gabriel, 2020) and journalistic practices (Hasell, 2021). While the technological architecture affords uptake, such hierarchical social and political structures determine the extent to which some utterances gather momentum. Accordingly, we argue that ad hoc publics, such as responses to tragic events, can be seen as momentary manifestations of pre-existing structures enabled by platform affordances. In general, our analysis shows that global ad hoc publics are driven by a dual logic characterised by bottom-up construction as well as top-down influence. In other words, ad hoc publics are bottom-up social formations as they emerge via individual acts of uptake. However, such acts are triggered by top-down impact of reply targets and voice agents.

Conclusion

Emotionality within hashtag publics emerges via interaction among users. The proposed approach enables fine-grained analysis of affective publics, showing how subjective emotionality is positioned within structures of interaction that contribute to collective expression of emotions related to a given issue. While this is a first step towards detailed analysis of networked emotions, future work can focus on more detailed analysis of emotionality within uptake structures. Metadata, such as timestamp, and location, can be used to examine how sequences of uptake can transform over time and analyse how users in different locations are positioned within such sequences. Moreover, the methodological basis that we develop should not be limited to a technique for analysing Twitter networks. The concept of “uptake” applies to any media, and indeed was first proposed to characterize interactions that are distributed across different media (Suthers et al, 2010). Further work is needed to adapt the classification of primary orientations for different social network sites.

As mentioned previously, the analysis approach suggested in the current study does not depend on the emotion detection method used. More sophisticated emotion detection methods can be used to map flows of emotions using the template we suggest. Applications of the template should also not to limited to mapping, emotions such as anger and fear. General sentiments (i.e., negative and positive sentiment scores) as well as other qualities, such as toxicity, can be mapped using this technique. Moreover, qualitative analysis of sentiments can compliment network analysis of emotions. In general, we encourage mixed methods analysis of distinct primary orientations that characterise different platforms and their use in different social and political contexts.

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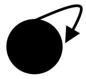
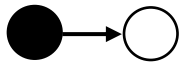
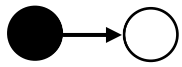
Tables and Figures

Table 1: Primary Orientations of Social Media Utterances

Orientation	Definition	Graph Representation
Expression	Non other-directed utterances that are primarily made to express views and/or sentiments (e.g., original tweets, Facebook posts)	
Targeted Reply	Utterances made in reply to another utterance in order to gain attention of and/or invite the sender of the original message to engage in a dialogue (e.g., Twitter ‘@replies’, Facebook replies)	
Replication	Utterances that take up a message sent by someone and make it visible to one’s follower networks (e.g., retweets, quote tweets, Facebook ‘shares’)	

Note: Black nodes show those who post content (e.g., original tweets, retweets, and replies and mentions); white nodes show users who are replied to and whose content is replicated (i.e., retweeted or shared) by others

Table 2: Identifying Sources and Targets of Emotions

Type of Tweet	**Source of Emotion (Metric)**	**Target of Emotion (Metric)**
Original tweets	Sender of the original tweet (Weighted indegree)	Unspecified (Emotions cannot be assigned to targets)
Replies and mentions	Sender of the reply or mention (Weighted outdegree)	Users replied to or mentioned (Weighted Indegree)
Retweets	User whose message is retweeted (Weighted indegree)	Unspecified (Emotions cannot be assigned to targets)

Table 3: Reply/Mention and Retweet Uptake Graphs

Orientation	**Network**	**Vertices(N)**	**Edges(N)**
#NewZealand			
Dialogic (Replies/ Mentions)	Anger	1473	1079
	Fear	1659	1224
	Sadness	950	1299
	Disgust	834	1156
Replicative (Retweets)	Anger	61,826	69,908
	Fear	64,454	73,219
	Sadness	47,696	51,511
	Disgust	43,242	46,360
#SriLanka			
Dialogic (Replies/ Mentions)	Anger	2,094	1,547
	Fear	5,352	4,717
	Sadness	2,042	1,492
	Disgust	1,540	1,091
Replicative (Retweets)	Anger	45,534	50,524
	Fear	51,284	58,671
	Sadness	43,735	49,011
	Disgust	31,428	33,049

Table 4: Top 10 Accounts based on Indegree (Reply/Mention Networks)

#NewZealand

Account	**Indegree**	**Account**	**Anger-Weighted Indegree**	**Account**	**Fear-Weighted Indegree**
@jacindaardern	109	@jacindaardern	105	@jacindaardern	130
@realDonaldTrump	64	@ImranKhanPTI	59	@ImranKhanPTI	56
@ImranKhanPTI	45	@realDonaldTrump	49	@realDonaldTrump	49
@CNN	31	@BBCWorld	40	@BBCWorld	47
@fraser_anning	29	@fraser_anning	28	@CNN	38
@pewdiepie	29	@CNN	26	@fraser_anning	32
@BBCWorld	28	@nzpolice	25	@nzpolice	30
@Twitter	24	@Twitter	23	@Twitter	28
@cnnbrk	19	@pewdiepie	22	@pewdiepie	26
@nzpolice	18	@spectatorindex	22	@cnnbrk	24
Account	**Sadness-Weighted Indegree**	**Account**	**Disgust-Weighted Indegree**		
@jacindaardern	88	@jacindaardern	72		
@ImranKhanPTI	40	@realDonaldTrump	31		
@realDonaldTrump	36	@ImranKhanPTI	28		
@BBCWorld	27	@BBCWorld	25		
@fraser_anning	24	@fraser_anning	24		
@cnnbrk	18	@cnnbrk	16		
@Twitter	17	@CNN	16		
@CNN	17	@Twitter	14		
@nzpolice	14	@pewdiepie	12		
@pewdiepie	12	@shaunking	11		

#SriLanka

Account	**Indegree**	**Account**	**Anger-Weighted Indegree**	**Account**	**Fear-Weighted Indegree**
@BarackObama	111	@realDonaldTrump	42	@BarackObama	66
@realDonaldTrump	105	@BarackObama	34	@realDonaldTrump	53
@IlhanMN	72	@IlhanMN	28	@Imamofpeace	48
@Imamofpeace	65	@washingtonpost	27	@OlivierGuitta	39
@washingtonpost	44	@Imamofpeace	21	@IlhanMN	36
@HillaryClinton	43	@nytimes	20	@HoneyBadgerRulz	35
@TarekFatah	32	@naralokesh	19	@washingtonpost	24
@kavita_krishnan	32	@KTHopkins	18	@TarekFatah	24
@AzzamAmeen	31	@kavita_krishnan	18	@KashmirIntel	23
@nytimes	31	@MiriamElder	16	@nytimes	23
Account	Sadness-Weighted Indegree	Account	Disgust-Weighted Indegree		
@BarackObama	40	@realDonaldTrump	32		
@realDonaldTrump	39	@IlhanMN	24		
@Imamofpeace	26	@BarackObama	24		
@IlhanMN	24	@washingtonpost	19		
@washingtonpost	19	@MiriamElder	18		
@HillaryClinton	16	@Imamofpeace	16		
@KTHopkins	15	@KTHopkins	12		
@naralokesh	15	@HillaryClinton	12		
@BBCBreaking	15	@naralokesh	12		

Table 5: Top 10 Accounts based on Indegree (Retweet Networks)

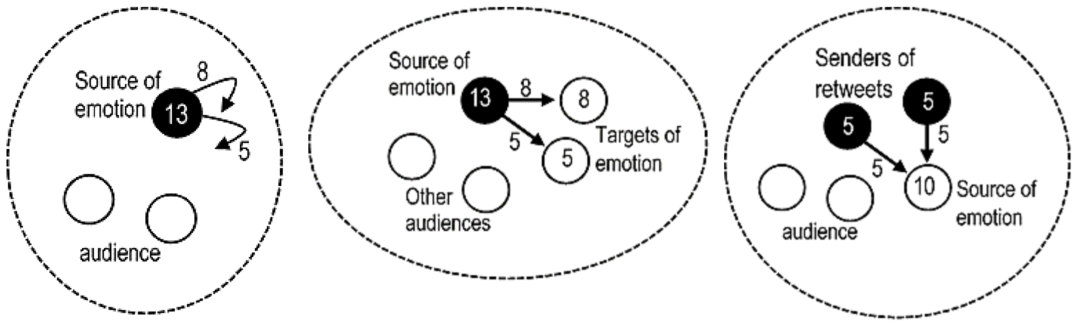
#NewZealand					
Account	**Indegree**	**Account**	**Anger-Weighted Indegree**	**Account**	**Fear-Weighted Indegree**
@omarsuleiman504	9553	@RT_Erdogan	19641	@RT_Erdogan	13094
@RT_Erdogan	6547	@omarsuleiman504	9778	@omarsuleiman504	9778
@M_O_S_A_L_E_H	2362	@absar_ahmed11	3454	@absar_ahmed11	5181
@absar_ahmed11	1727	@M_O_S_A_L_E_H	2362	@M_O_S_A_L_E_H	4724
@ClarkMichle	1606	@SonOfShaheed	1956	@ClarkMichle	3198
@SaimaMohsin	1404	@TahirulQadri	1665	@flls_k	1978
@acmilan	1276	@ClarkMichle	1599	@SonOfShaheed	1956
@flls_k	989	@SayeedaWarsi	1560	@SayeedaWarsi	1560
@SonOfShaheed	978	@sayedzbukhari	1470	@sayedzbukhari	1470
@DarzOSRS	850	@SaimaMohsin	1404	@SaimaMohsin	1404
Account	**Sadness-Weighted Indegree**	**Account**	**Disgust-Weighted Indegree**		
@omarsuleiman504	9778	@omarsuleiman504	9778		
@M_O_S_A_L_E_H	2362	@M_O_S_A_L_E_H	2362		
@ClarkMichle	1599	@ClarkMichle	1599		
@TahirulQadri	1110	@TahirulQadri	1110		
@SayeedaWarsi	1040	@flls_k	989		
@flls_k	989	@sayedzbukhari	980		
@sayedzbukhari	980	@SonOfShaheed	978		
@SonOfShaheed	978	@MevlutCavusoglu	852		
@omarel_	724	@omarel_	724		
@KoblerinPAK	710	@vii_ti	681		
#SriLanka					
Account	**Indegree**	**Account**	**Anger-Weighted Indegree**	**Account**	**Fear-Weighted Indegree**
Imamofpeace	5188	@KTHopkins	7764	@KTHopkins	5176
KTHopkins	4413	@sachin_rt	3410	@Ninja	5070
KayaJones	2982	@Enes_Kanter	3225	@sachin_rt	3410
Ninja	2535	@Ninja	2535	@KayaJones	3028
muftimenk	2074	@SAfridiOfficial	2355	@PrisonPlanet	2826
RepDanCrenshaw	1893	@Imamofpeace	2149	@Enes_Kanter	2580
sachin_rt	1705	@muftimenk	2074	@SAfridiOfficial	2355
SriLankaTweet	1365	@sudarsansand	1893	@Malala	2112
rishbagree	1124	@PrisonPlanet	1884	@SriLankaTweet	1993
daniel86cricket	1089	@RTErdogan	1354	@UKMoments	1394
Account	Sadness-Weighted Indegree	Account	Disgust-Weighted Indegree		
@Ninja	5070	@KTHopkins	2588		
@RepDanCrenshaw	3786	Ninja	2535		
@KTHopkins	2588	@Imamofpeace	2149		
@Enes_Kanter	1935	@Enes_Kanter	1935		
@PrisonPlanet	1884	@sachin_rt	1705		
@SAfridiOfficial	1884	@daniel86cricket	1084		
@sachin_rt	1705	@PrisonPlanet	942		
@SriLankaTweet	1678	@SAfridiOfficial	942		
@UKMoments	1394	@UKMoments	697		
@manakgupta	1307	@sudarsansand	631		

Table 6: Examples of Replies and Retweets Targeted at and Taken Up from Top Accounts

Target	**Reply/Mention**
Jacinda Ardern	"If it was any minority who did the shooting the news would declare it terrorist attack without thinking twice, and now after this fatal terrorist attack at the mosque everyones calling it' shooting' fuck this hypocrisy! #NewZealand #ChristchurchMosqueAttack #Attack #christchurch" (emotion scores: anger = 5, fear = 4 , sadness = 2, disgust = 1)
Imran Khan	"He is the guy (terrorist) who killed many Muslims in Mosque of #NewZealand But world's media is calling him "Shooter" not "Terrorist" because he is not a Muslim! Terrorist label is only for Muslims? #TerroristAttack #Christchurch #MosqueAttack" (emotion scores: anger = 2, fear = 2 , sadness = 1, disgust = 1)
CNN	"Did this cowardly heinous act not branded yet as terrorist attack? #ChristchurchMosqueAttack #NewZealand #standwithnewzeland" (emotion scores: anger = 2, fear = 3 , sadness = 1, disgust = 1)
Donald Trump	"I hope that you make it clear to the #Cult45 that this act of terrorism, however despicable, was most likely carried out by the LTTE in the ongoing Civil War in #SriLanka and not by #Muslim #ISIS. Probably hard for you to understand, but important." (emotion scores: anger = 2, fear = 3 , sadness = 1, disgust = 2)
Barak Obama	"Didn't you gave $1.7 billion in cash to the terrorist regime of Iran in your last year as president? Was that not an attack on humanity? Shame on you!! You are a terrorist sponsor!! #SriLanka #IRGCTerrorists #IranRegimeChange" (emotion scores: anger = 3, fear = 4 , sadness = 4, disgust = 2)
Washington Post	"More rubbish invective from The Washington Post. The absolute state of this over-rated shit rag. Your headlines are as incendiary as anything any terrorist group says. @npr @nprpolitics #SriLanka #SriLankaBombings" (emotion scores: anger = 3, fear = 2 , sadness = 1, disgust = 3)
Originator	**Retweeted Text**
Recep Tayyip Erdoğan	"I strongly condemn the terror attack against the Al Noor Mosque in #NewZealand and Muslim worshippers. May Allah have mercy on the victims and grant a speedy recovery to the wounded." (emotion scores: anger = 3, fear = 2 , sadness = 0, disgust = 0)
Sheikh Mohammed bin Abdulrahman Al-Thani	"We strongly condemn the heinous terrorist attack on two mosques in #NewZealand. We wish Allah's mercy upon those who lost their lives and speedy recovery to the wounded #ChristchurchMosqueAttack" (emotion scores: anger = 3, fear = 2 , sadness = 2, disgust = 1)
Sayed Bukhari	"Prayers of the Pakistani nation go out to victims of the devastating #NewZealand attack.Terrorism is a global issue and we stand with the people of NZ to combat it. #Christchurch" (emotion scores: anger = 4, fear = 4 , sadness = 2, disgust = 2)
Sachin Tendulkar	"Saddened to hear about the terror attacks in various parts of Sri Lanka. Strongly condemn these acts of terror. Hatred and violence will never overpower love, kindness and compassion. #SriLanka" (emotion scores: anger = 3, fear = 4 , sadness = 2, disgust = 1)

Richard Tyler Blevins	“Woke up to another horrifying act of humanity in #SriLanka a bombing killing over 200 people in several churches... on Easter. Praying for every single person, family and religion affected by this tragedy. This madness needs to stop.” (emotion scores: anger = 2, fear = 4 , sadness = 3, disgust = 1)
Kaya Jones	“This was a sophisticated attack. With 8 bombings in total on the Sri Lankan people. #srilanka #eastersunday #prayforsrilanka #christianpersecution” (emotion scores: anger = 1, fear = 1 , sadness = 0, disgust = 0)

Figure 1: Sources and Targets of Emotions



(a) Original tweets (b) Replies and Mentions (c) Retweets

Uptake arrows point to the entity taken up, which is distinct from the source of emotion: a) original tweets: self-loop indicating the act of self-uptake, b) replies and mentions: arrow pointed at the person who is replied to or mentioned, and c) retweets: arrows pointed at users whose tweets are retweeted; values in black nodes show weighted outdegree; values in white nodes show weighted indegree; values for each edge show the amount of quantifiable emotion contained in the message

Figure 2: Network Construction and Analysis Process

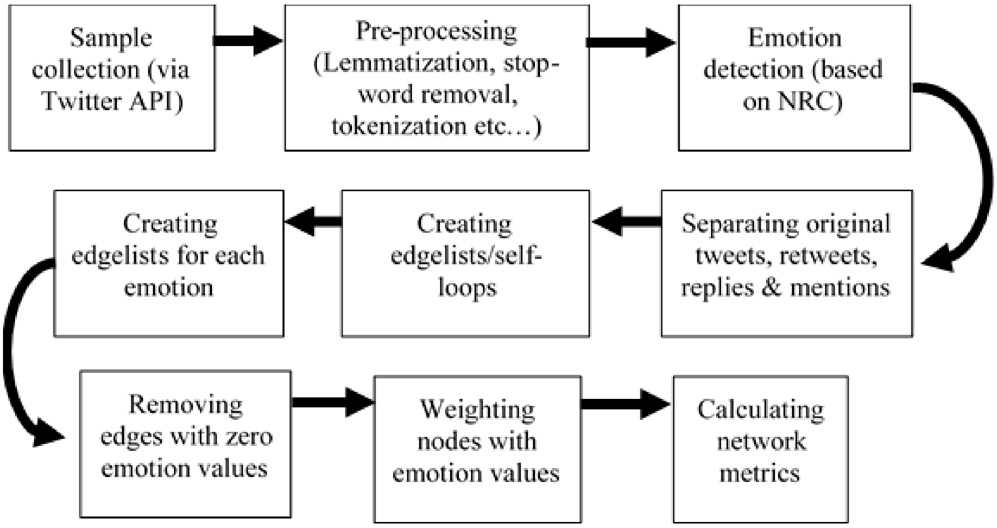
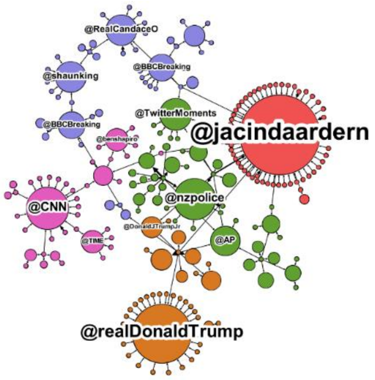
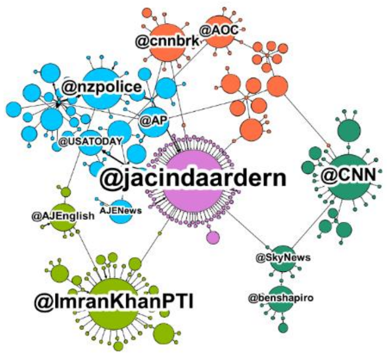


Figure 3: Partitions in Reply/Mention Networks

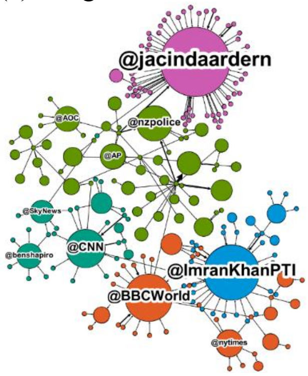
#NewZealand



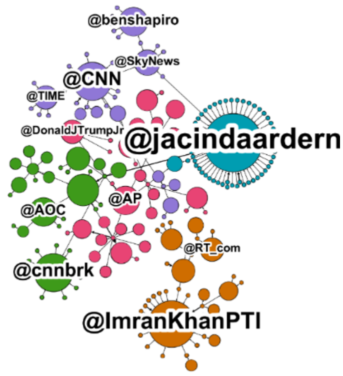
(a) Anger



(b) Fear

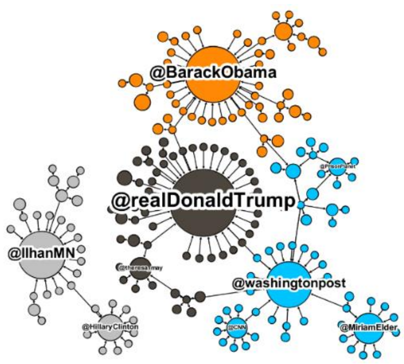


(c) Sadness

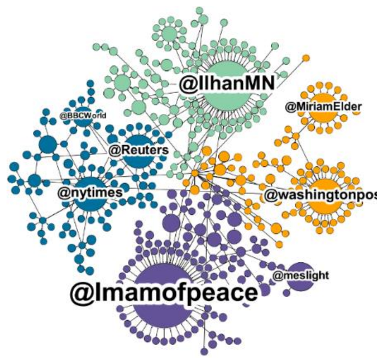


(d) Disgust

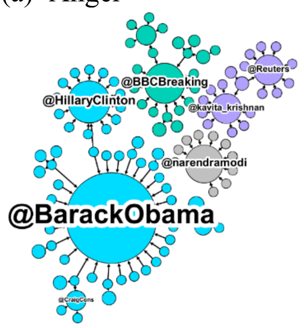
#SriLanka



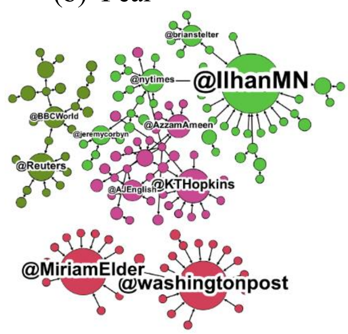
(a) Anger



(b) Fear



(c) Sadness

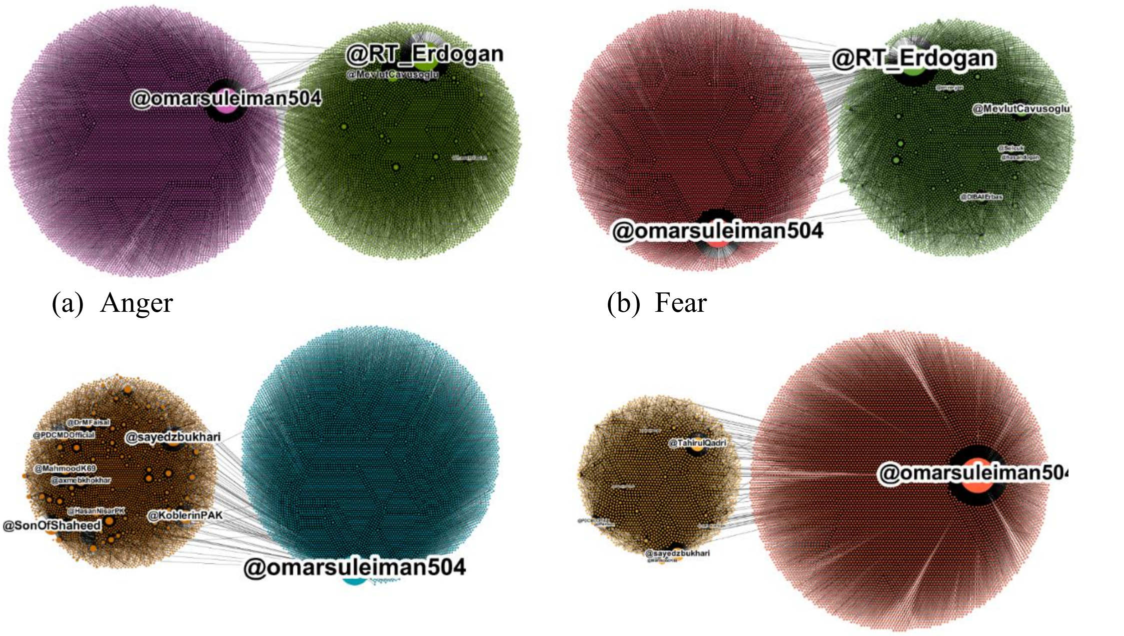


(d) Disgust

Vertex colour shows modularity partition by the Louvain method; vertex size shows weighted indegree for each emotion

Figure 4: Partitions in Retweet Networks

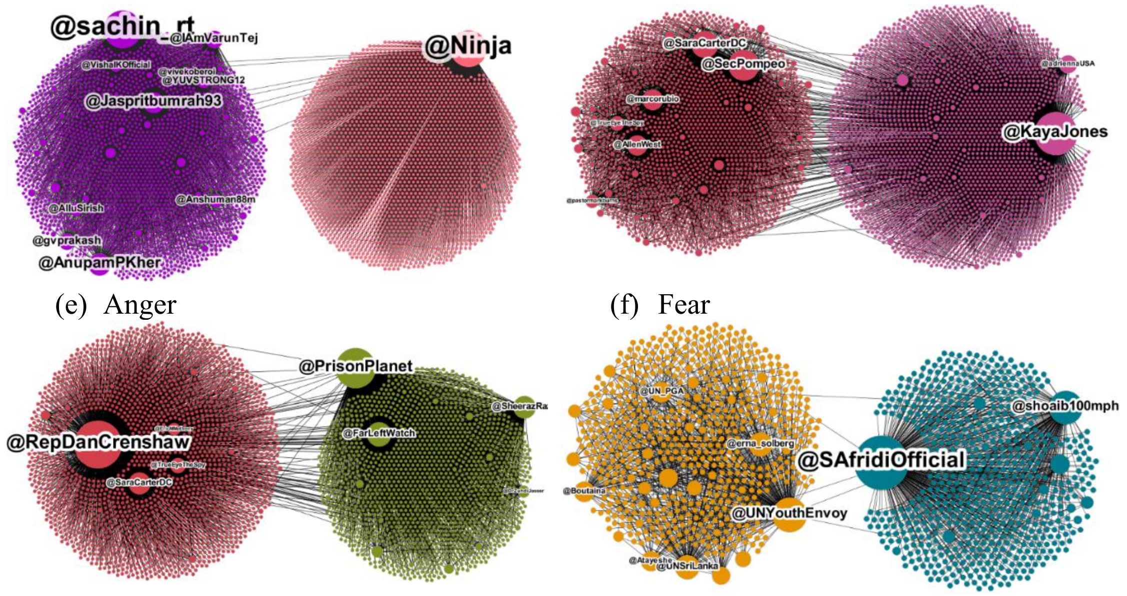
#NewZealand



(a) Anger (b) Fear

(c) Sadness (d) Disgust

#SriLanka



(e) Anger (f) Fear

(g) Sadness (h) Disgust

Notes: Vertex colour shows modularity partition; vertex size shows weighted indegree for each emotion