“Evacuate everyone south of that line” Analyzing structural communication patterns during natural disasters

Ema Kušen¹ · Mark Strembeck^{1,2,3}

Received: 27 March 2020 / Accepted: 20 October 2020 / Published online: 11 November 2020
© The Author(s) 2020

Abstract

In this paper, we analyze more than 16 million tweets that have been sent from 6.1 million Twitter accounts and are related to nine natural disasters. As part of our analysis, we identify eight basic emotions conveyed in these tweets. We found that during natural disasters, social media messages at first predominantly express fear, while sadness and positive emotions increase in the immediate aftermath of the event. In this context, positive emotions contribute to the social phenomenon of emotional bonding and are often related to compassion, gratitude, as well as donations for disaster relief. In our analysis, we found that the users’ emotional expressions directly contribute to the emergence of the underlying communication network. In particular, we identified statistically significant structural patterns that we call emotion-exchange motifs and show that: (1) the motifs 021U and 021D are common for the communication of all eight emotions considered in this study, (2) motifs which include bidirectional edges (i.e. online conversations) are generally not characteristic for the communication of surprise, sadness, and disgust, (3) the structural analysis of a set of emotions (rather than a single emotion) leads to the formation of more complex motifs representing more complex social interactions, and (4) the messaging patterns emerging from the communication of joy and sadness show the highest structural similarity, even reaching a perfect similarity score at some point during the data-extraction period.

Keywords Emotion analysis · Network motif · Emotion-exchange motif · Natural disaster · Twitter · User behavior

✉ Ema Kušen
ekusen@wu.ac.at

¹ Vienna University of Economics and Business (WU), Vienna, Austria

² Secure Business Austria (SBA), Vienna, Austria

³ Complexity Science Hub (CSH), Vienna, Austria

Introduction

Over the past few years, a number of severe natural disasters happened around the globe. From hurricanes and earthquakes to tsunamis and landslides, these disasters caused communication blackouts, catastrophic damages to critical infrastructures, lack of resources, and humanitarian crises. During disaster events, the information that people have access to considerably shapes their behavior and attitudes towards the event [1]. Online social networks (OSNs) provide a vital communication medium where the ones affected by a disaster can share information, seek help, and bond emotionally. Recent studies have suggested that OSNs are a good source of data to study general sentiment during natural disasters [2]. Moreover, [58] showed that disaster events create a need for human conversation, turning OSNs into conversational and collaborative platforms for disaster communication.

Since a natural disaster causes a sense of urgency [11] as well as the feelings of danger, fear, panic, and shock [6, 54], and may cause depression in those affected [47], the OSN discourse in such events is characterized by a high intensity of negative emotions such as fear and sadness. In fact, [47] showed that victims of a natural disaster may suffer from a depression even weeks after the disaster happened and, as a result, seek for collective bonding to share their emotions with those who went through a similar experience. Such an expression of negative emotions commonly serves as a coping mechanism and, as pointed in [45], can improve a person's mental well-being.

However, in addition to such negative emotions, positive emotions (e.g., joy and relief) are also frequently communicated during disaster events. According to numerous studies [14, 17, 20, 29, 31], positive emotions may even prevail over the negative ones because they help to increase the feelings of hope, gratitude, and empathy.

In this paper, we examine the emotions communicated by Twitter users during nine natural disasters that occurred in 2017 and 2018. In particular, the events we analyzed for this paper are hurricane Harvey, an earthquake in Mexico, hurricane Maria, an earthquake in Costa Rica, an earthquake in Iran and Iraq, a mudslide in California, windstorm Friederike in western Europe, the wildfire in Nairobi, as well as hurricane Irma.

A recent study found that user (communication) behavior plays a significant role in the dynamics of network structures [70]. In this paper, we explore the influence of expressed emotions, as one important aspect of observable user behavior on OSNs, on the structure of the underlying communication network. In our study, we focus on the communication patterns that emerge as Twitter users directly exchange emotional messages during the nine disaster events. We call such patterns emotion-exchange motifs and show that characteristic motifs emerge as Twitter users communicate emotions. Furthermore, we found that the communication structures representing collective coping (conveying joy and sadness) are structurally more similar than the structures emerging from any two negative emotions (e.g., fear and anger).

A network motif is defined as a subgraph that occurs significantly more often in a real-world network as compared to the subgraph patterns that can be found in

a corresponding null model [40]. The concept of network motifs was initially proposed in 2002 by Milo et al. [40], who described motifs as basic building blocks of complex networks. Ever since, the concept has been applied to various types of networks, such as biological networks [71] and co-authorship networks or animal social networks [64]. However, the application of network motifs in studying patterns that emerge as people communicate emotions over OSNs has generally been understudied.

This paper is a part of our ongoing research effort for investigating the influence of emotions on the emergence of local communication patterns during crisis events (see [35] for an analysis of terror and shooting attacks, and [37] for an analysis of riot events). The novel concept of emotion-exchange motifs plays a central role in this research endeavor. In particular, emotion-exchange motifs are statistically significant and frequently recurring patterns that are formed when the individuals affected by a crisis event exchange emotional messages. To the best of our knowledge, this line of work is the first to combine human emotions and network motifs to reveal the basic building blocks of emotional social media conversations.

The remainder of this paper is organized as follows. In “[Related work](#)” we provide an overview of related work, followed by a brief description of the natural disaster events that have been analyzed for this paper (see “[Events of study](#)”). We describe our research method in “[Methods](#)” and provide the results in “[Results](#)”. A discussion on the results is given in “[Discussion](#)”. We conclude the paper and provide directions for future work in “[Conclusion](#)”.

Related work

Use of Twitter during natural disasters

In recent years, a number of studies analyzed the communication behavior in numerous natural disasters. For example, the 2009 Marseille fire [8], the 2011 and 2013 floods in Brisbane [24], hurricane Irene [39], the 2015 Chennani flood [43], typhoon Haiyan in the Philippines [60], the 2011 Tohoku earthquake and tsunami in Japan [42], hurricane Sandy [51, 68], the South East Queensland flood [27], and hurricane Harvey [70], to name just a few.

So far, the role of social media during natural disasters has predominantly been explored in terms of situational awareness. For example, [8, 44, 51, 67] found that people tend to broadcast and re-share (retweet) informative messages that contain references to locations affected by a hazardous event. By doing so, the ones affected by a natural disaster may collectively advance their understanding of the situation and prepare for evacuation [30]. News reports even indicate that more people consulted social media channels rather than the 911 emergency number to seek help during hurricane Harvey¹.

¹ Use of OSNs during hurricane Harvey: <https://patch.com/texas/north-austin/ut-austin-researcher-s-examine-role-played-social-media-during-hurricane-harvey> (accessed: 25 February 2020).

Moreover, people do not only spread informational tweets but also express their sympathy and well-wishes to the victims [60], praise individuals (such as members of the local fire brigade) or organizations for their help and support [38], use Twitter to coordinate disaster relief efforts [60], and share their personal experiences during a disaster event [60]. Thus, online social media can be regarded as a platform for emotional support-seeking and, to a certain degree, a therapeutic channel for those affected by a disaster event. In this context, [15, 45, 46] found that people are coping with the traumatic experience via social media messages and publicly mourn those who did not survive. Moreover, [47] found that mental trauma resulting from a natural disaster is experienced collectively rather than individually (such as a death of an individual's family member) which encourages people to bond and share their emotions with those who have also been affected.

Since natural disasters can be classified as highly traumatic events [48] and involve a sense of urgency and danger, people predominantly experience negative emotions [53]. For example, [57] found that OSN posts sent during a natural disaster predominantly convey negative emotions such as anger, fear, and sadness. Moreover, [49] found that the expression of negative emotions changes over time. By conducting a series of user studies, [49] showed that negative emotions are more intense when they are immediately experienced compared to the emotional intensities reported when retelling stories about the event. In this respect, online social media are a convenient source of data for emotion analysis as researches may analyze the emotional expressions in near-real time.

Application of network motifs in the study of OSN communication patterns

Recently, network motifs have also been applied to examine the formation of human communication patterns. One such study [72] found that star motifs are representative for a network derived from Facebook wall postings. Furthermore, [21] analyzed the structural differences of communication networks derived from Twitter and Facebook and found that Twitter communication is characteristic for a short lasting in-star motif (i.e., a single user is frequently mentioned by many users), while Facebook exhibited longer message-sending behavior between the same set of users. In addition, our previous work studies the emergence of emotion-exchange motifs in social media communication involving human users as well as social bots [35–37].

Events of study

All events in our study can be classified as natural disasters and though these disasters differ in their particularities, they exhibit common characteristics such as causing injuries, threat to life, infrastructure damage, and distress [66].

Hurricane Harvey (August 2017) became a tropical storm on August 17, 2017, crossing the Windward Islands, Barbados, and Saint Vincent. It gradually weakened when it reached the Caribbean Sea and became a tropical storm on August 19. However, the storm rapidly intensified on August 24 and eventually became a Category

4 hurricane. San Jose Island (Texas) was reached at its highest intensity leaving 68 dead. Afterwards, Harvey progressed to Louisiana on August 29 as a Category 3 hurricane. It dissipated on September 3 after causing an estimated damage of \$125 billion.

Hurricane Irma (August/September 2017) hit the Caribbean as a category 5 hurricane killing 37 people. Subsequently, the storm hit Cuba (ten dead) and the US (12 dead), affecting a total amount of 1.2 million people and leading to considerable damages in the infrastructure. It was later reported to be the most powerful Atlantic storm in a decade, causing damages of about 67 Billion US dollars.

Mexico earthquake (September 2017) was an earthquake of magnitude 7.1 that stroke Puebla, Morelos, as well as Greater Mexico City on September 19, 2017 causing the collapse of buildings and killing at least 248 people. It eventually triggered an eruption of the Popocatepetl volcano which covered the surrounding cities with ash and debris and caused a collapse of a church during a mass, causing 15 additional deaths.

Hurricane Maria (September/October 2017) evolved into a tropical storm on September 16, 2017. It reached Category 5 strength on September 18, 2017 hitting the island of Dominica and leaving the island with a communication blackout. After weakening to Category 4, it further progressed to Puerto Rico on September 20, leaving 2975 dead and finally dissipating by October 3, 2017.

Costa Rica earthquake (November 2017) occurred on the coast of Costa Rica (southeast of Jaco) on November 12, 2017, with a magnitude of 6.5 causing three deaths.

Iran–Iraq earthquake (November 2017) an earthquake of magnitude 7.3 occurred on the Iran–Iraq border on November 12, 2017 and became one of the deadliest earthquakes in 2017 resulting in more than 400 deaths and over 7000 injured victims. Moreover, it damaged or destroyed considerable parts of the urban infrastructure (esp. running water, electricity) leaving over 70,000 people in need of shelter.

Southern California mudslides (January 2018) occurred in early January 2018 after a heavy rain period. The mudslide demolished homes in Montecito and caused over 20 deaths.

Friederike windstorm (January 2018) hit Central Europe, as well as the British Islands, France, Benelux, Northern Italy, Poland and parts of Eastern Europe in early 2018 causing heavy snowfall and blizzards. The heaviest losses occurred, however, in Germany and the Netherlands between January 17 and 18, 2018, causing at least eight deaths and damages amounting to one billion Euros in Germany alone.

Lang'ata wildfire (January 2018) occurred in the Lang'ata area of Kenya's capital Nairobi on January 28, 2018 killing three people and leaving hundreds of people homeless.

Table 1 summarizes basic information on each of the nine data-sets included in our study.

Methods

Our research method comprises seven steps.

Table 1 Summary for each of the natural disaster event data-sets (data extraction period, number of tweets, and number of screennames) as well as the derived communication network (number of vertices and edges)

	Extraction period	Tweets	Screennames	Vertices	Edges
Harvey hurricane	23.8.–11.9.2017	7,931,488	2,551,965	285,051	497,285
Irma hurricane	4.9.–18.9.2017	5,421,054	1,784,651	186,866	347,180
Mexico earthquake	7.9.–28.9.2017	1,713,618	966,242	45,882	54,796
Maria hurricane	21.9.–4.10.2017	1,258,515	542,479	60,353	97,916
Costa Rica earthquake	12.11.–2.12.2017	15,492	12,134	601	512
Iran–Iraq earthquake	12.11.–2.12.2017	272,670	145,101	7639	9451
Southern California mudslides	7.1.–27.1.2018	168,303	74,160	8609	12,719
Friederike windstorm	17.1.–28.1.2018	51,694	26,551	3486	3239
Lang’ata wildfire	28.1.–1.2.2018	11,113	6091	695	915

1. Data extraction and pre-processing: We used Twitter’s Search API to extract publicly available tweets sent during the nine natural disaster events. During pre-processing, we removed duplicate entries and tweets that are uninformative with respect to emotion detection (such as tweets that contain URLs only). After the pre-processing step, our data-set comprised 16,843,947 tweets sent from 6,109,374 different Twitter accounts (see Table 1). Privacy of sensitive user data, such as personal identifiers, is an important aspect that needs to be considered while extracting, storing, and analyzing OSN data [4, 12]. Prior to data analysis, we anonymized all personal identifiers (screennames/user IDs as well as @mentions that appear in the text of a tweet) by replacing them with a distinct hash value. All analysis tasks have been performed on the anonymized data-set.

2. Emotion detection: We applied our emotion detection procedure [32] which annotates the eight basic emotions with respect to Plutchik’s wheel of emotions (anger, fear, sadness, disgust, joy, trust, anticipation, and surprise [50]). Our procedure relies on the NRC emotion-word lexicon [41] and the AFINN lexicon for the intensity of an affect [23], as well as a set of heuristics that people naturally use to detect emotions in written texts [59] (e.g. amplifiers, maximizers, downtoners, negation). When comparing the accuracy of our approach to the widely used sentiment analysis tool SentiStrength [61] (see, e.g., [22, 52, 55]), we achieved a better classification of negative emotions (0.85 vs. 0.73) but a comparatively worse accuracy for positive emotions (0.54 vs 0.61). However, also note that such a comparison is biased to a certain degree, because the detection and classification of positive emotions is a more difficult task than classifying negative emotions (see, e.g., [61]) and SentiStrength only identifies the emotional valence (positive or negative) of a text, while our approach explicitly identifies the eight basic emotions found in Plutchik’s wheel of emotions.

3. Construction of the communication network: In general, Twitter users can directly send tweets to another user via @screenname. Following such traces, we reconstructed a directed communication network for each disaster event where every edge is annotated with respect to the dominant emotion that appeared in the

Fig. 1 Emotion-annotated layers and derived layers used in our analysis (green = positive emotion layers, red = negative emotion layers, yellow = surprise)

corresponding tweet. Table 1 summarizes the number of vertices and edges in each of the nine communication networks.

4. Construction of a multiplex network: Next, we constructed a multiplex network for each day of data extraction, and each multiplex consists of eight layers (each layer corresponds to one of the eight basic emotions: anger, fear, sadness, disgust, joy, trust, anticipation, surprise). In addition, we aggregated the edges found on the negative emotion layers (anger, fear, disgust, and sadness) into an aggregated negative layer, and the edges found on the positive emotion layers (joy, anticipation, and trust) into an aggregated positive layer. We also derived a valence interlayer which captures the vertices found on each valence-specific layer (positive and negative) and their adjacent vertices that are active on the two aggregated valence layers. Finally, we aggregated all individual positive- and negative-emotion layers and layer surprise to derive an overall aggregated network. Figure 1 sketches the eight emotion-annotated layers and the four derived layers.

5. Null model construction: To detect emotion-exchange motifs, we generated synthetic random networks (null models) by applying the stub-matching algorithm over each of the eight emotion layers and each of the four derived layers of our multiplex network (see Fig. 1). In total, we generated 1000 null models for each layer by following the approaches described in [9, 56]. Thus, over all days of the data-extraction periods for all nine events, we generated in total 1,704,000 null models that underwent the motif-detection procedure.

6. Motif detection: To detect emotion-exchange motifs (see [35–37]), we first applied the ESU subgraph enumeration algorithm [69] to enumerate all possible subgraphs of size $k = 3$ and subsequently the VF2 isomorphism testing algorithm [5] to check for the isomorphism between any two subgraphs. If two subgraphs were found to be isomorphic, they were placed in their respective isomorphism category (see Algorithm 1). Note that while the exact enumeration counts all existing subgraphs of a fixed size k , this accuracy comes at a high computational cost.

The emotion extraction as well as the motif detection procedures have been performed in parallel on four different machines: a machine with Intel Xeon CPU E3-1240 v5 @ 3.5 GHz (4 cores/8 parallel threads) and 32GB RAM, a machine with

2x Intel Xeon E5-2630 v3 @ 2.4 GHz (16 cores/32 parallel threads) and 288GB RAM, a machine with 2x Intel Xeon E5-2630 v4 @ 2.2 GHz (20 cores/40 parallel threads) and 256 GB RAM, as well as a machine with 2x AMD Epyc 7451 @ 2.3 GHz (48 cores/96 parallel threads) and 512 GB RAM. On these four machines, the emotion extraction and motif detection procedures for all nine data-sets took in total about 245 days and produced over 4.7 terabyte of data to analyze.

Algorithm 1: Motif detection.

```

1  Input: input_network;
2  Output: list_of_motifs ;
3  Initialize: i = 0;
4  # ENUMERATE AND CLASSIFY SUBGRAPHS
5  def procedure: esu_vf2(list_layers)
6  foreach l in list_layers do
7      subgraphs = esu(l)
8      foreach s in subgraphs do
9          subgraphs' = subgraphs \ s
10         foreach s' in subgraphs' do
11             if vf2(s, s') then
12                 assign_common_isomorphism_class
13                 subgraphs' = subgraphs' \ s'
14                 subgraphs = subgraphs \ s'
15             end
16         end
17     end
18 end
19 end procedure
20 # GENERATE LAYERS AND INTER-LAYERS
21 detect layers in input_network
22 layer_negative.add_edges_from(layer_anger, layer_sadness, layer_disgust, layer_fear)
23 layer_positive.add_edges_from(layer_joy, layer_anticipation, layer_trust)
24 foreach i in range(length(V(input_network))) do
25     if vi ∈ V(layer_negative) & vi ∈ V(layer_positive) then
26         inter_layer.add_edges_from(layer_negative.edge_containing(vi), layer_positive.edge_containing(vi))
27     end
28 end
29 list_layers = [layer_anger, layer_joy, ... , layer_surprise, layer_negative, layer_positive, interlayer, input_network]
30 esu_vf2(list_layers)
31 # GENERATE NULL MODELS
32 while i < 1000 do
33     foreach l ∈ list_layers do
34         null[l] = matching(l.in_degree(), l.outdegree())
35     end
36     esu_vf2(null)
37     i = i+1
38 end

```

Results

Emotions expressed during natural disasters

The integrated crisis mapping (ICM) model [25] is a theoretical framework which examines emotions that are likely to be experienced by the public as part of their coping strategy during different types of crisis events. According to the ICM, people experience a range of emotions when facing a crisis event. The corresponding list

Fig. 2 Average emotional intensity of tweets sent during the nine natural disasters and Kendall's rank coefficient of the emotional intensities conveyed in tweets sent during Harvey hurricane (HH), Mexico earthquake (ME), Maria hurricane (MH), and Costa Rica earthquake (CE), Iran–Iraq earthquake (IIE), Southern California mudslide (SCM), Friederike windstorm (FW), Lang'ata wildfire (LW), and Irma hurricane (IH)

of emotions has been compiled from reputable mainstream US newspapers covering 259 news stories [26]. The model identifies four dominant emotions that occur during crisis events, namely anger, fear, anxiety, and sadness. So-called primary emotions are experienced instantly, while so-called secondary emotions occur in the aftermath of an event. The exact definition of what qualifies as a primary or a secondary emotion depends on the type of a crisis event. Thus, for example, riots and (violent) protests are characteristic for a primary emotion of anger and a secondary emotion of anxiety. Acts of terrorism or psychopathic acts (such as school shootings), on the other hand, instantaneously cause fear followed by sadness. Moreover, according to the ICM the emotions of fear and sadness are predominantly expressed during natural disasters². In our analysis, the average emotional intensities (ei) of fear ($ei_{\text{fear}} = 13.92$) and sadness ($ei_{\text{sadness}} = 10.80$) dominate over the other six emotions (see Fig. 2). This finding can be generalized over all nine natural disasters in our study, where we found similarities with respect to the emotion intensities in each of the events. Figure 2 shows a positive value for Kendall's rank coefficient for each pair of events³.

The temporal analysis of emotional messages is shown in Fig. 3. In particular, we found that negative emotions of fear and anger are predominant at the beginning of a natural disaster event. In contrast, the emotion of sadness gradually

² Note that the ICM suggests that sadness is a primary emotion and fear a secondary emotion experienced during natural disasters.

³ The pairing of the Lang'ata wildfire and the Friederike windstorm is the only exception. The two events exhibit a slightly negative correlation coefficient of -0.07 .

Fig. 3 Average daily number of tweets and average daily emotional intensity in tweets sent during natural disaster events

increases its intensity as the consequences of a natural disaster are revealed over time and peaks towards the end of the data-extraction period (prevailing over anger and afterwards also over fear) (see Fig. 3). Positive emotions such as joy,

Table 2 User reactions and tweet length of messages conveying positive (joy, anticipation, trust) and negative (fear, anger, sadness, disgust) emotions

Emotion	Likes	Retweets	Length
Joy	2.10	12.62	23.24
Anticipation	2.39	23.16	24.39
Trust	1.83	10.10	21.78
Mean	2.1	12.62	23.24
Fear	0.89	0.67	24.56
Anger	1	0.60	25.20
Sadness	0.86	0.57	23.71
Disgust	1	0.6	25.2
Mean	0.89	0.67	24.56

trust, and anticipation, although not expressed as intensely as the negative ones, are also present throughout natural disaster events and on certain days even peak over the dominant negative emotions (e.g., trust peaks over sadness and anger from days 5 to 10).

During natural disasters, emotional tweets attract more attention than neutral ones in terms of likes ($\text{mean}(\text{likes}_{\text{emotional}}) = 1.98 \pm 221.69$, while $\text{mean}(\text{likes}_{\text{neut}}) = 1.79 \pm 248.13$). We also found that Pearson's coefficient is (weakly) positive with respect to the level of emotionality and the number of likes (5.79×10^{-5}). In contrast, neutral tweets result in comparably more repeated message spreading (retweeting) than the emotional messages ($\text{RT}_{\text{neutral}} = 11066.25 \pm 32002.86$ vs. $\text{RT}_{\text{emotional}} = 6248.476 \pm 16,418.51$). In this context, neutral messages are usually of informative nature where people share information related to the disaster event. In fact, [3] showed that people tend to retweet timely content and breaking news.

When distinguishing between positive (joy, trust, anticipation) and negative (anger, fear, sadness, disgust) emotions in our data-sets, user reactions in terms of liking a tweet and passing it forward (retweeting) differ considerably. As summarized in Table 2, tweets conveying a high intensity of positive emotions on average receive considerably more likes and retweets, while tweets conveying a high intensity of negative emotions are slightly longer (i.e., on average, they include more words).

Our data-set includes a total of 729,698 messages that have directly been exchanged between a pair of users via @-mentions. In general, the emotions communicated via direct messaging (see Fig. 4) are comparable to the ones communicated via broadcast messages (Kendall's coefficient is a strong positive 0.85). Thus, since there are measurable similarities in the expression of specific emotions among the nine data-sets, we examine whether the direct messaging behavior is also comparable when users express emotions. To this end, we refer to the structural patterns (motifs) that emerge daily as groups of three users directly exchange messages (i.e., we analyze subgraphs of size 3, see also Table 3).

Fig. 4 Average emotional intensity and average daily emotionality in tweets sent directly via @-mentions during the natural disaster events

Emotion-exchange motifs

While directly exchanging emotional messages, Twitter users form statistically significant subgraphs that we call emotion-exchange motifs (see [35–37]). In total, we found 90,142,095 subgraphs which we categorized into 1824

Table 3 Frequency, variability, graph properties (min, max, and mean number of edges $\pm$ standard deviation), and event-wise occurrence of MAN-labeled motifs

Label	Shape	Freq. (%)	Variability	Properties	Occurrence
021U		398126 (79.42%)	330 (8.3×10^{-4})	2, 21, 7.41 ± 3.62	8
021D		60984 (12.17%)	270 (0.004)	3, 21, 7.08 ± 3.55	9
021C		22171 (4.42%)	218 (0.009)	3, 23, 7.14 ± 3.84	8
030T		10681 (2.13%)	322 (0.03)	3, 24, 7.37 ± 3.99	9
111D		4425 (0.9%)	99 (0.02)	3, 23, 7.34 ± 3.66	7
111U		3463 (0.7%)	75 (0.02)	3, 21, 7.65 ± 4.25	8
120U		731 (0.14%)	25 (0.03)	3, 20, 7.88 ± 4.81	8
120D		557 (0.11%)	43 (0.08)	3, 17, 7.23 ± 3.29	7
201		55 (0.01%)	13 (0.24)	3, 14, 7.08 ± 4.01	2
120C		31 (0.006%)	8 (0.26)	4, 15, 7.38 ± 3.93	2
030C		19 (0.004%)	5 (0.26)	3, 13, 7.8 ± 4.15	2
210		6 (0.001%)	2 (0.33)	5, 6, 5.5 ± 0.71	2
300		-	-	-	0

isomorphism classes (i.e. isomorphic graphs are grouped together). Out of these 1824 isomorphism classes, 1410 are statistically significant for the input networks (emotion-exchange motifs) across all nine data-sets. For the sake of simplicity,

we classified the 1410 motifs according to the MAN-labeling scheme (mutual edges (M), asymmetric edges (A), non-edges (N) followed by a letter U = up, D = down, C = cyclic, or T = transitive, which distinguishes among different types of triads [7]) as shown in Table 3 (i.e., we currently disregard edge weights in a motif).

As shown in Table 3, 12 of the 13 MAN subgraphs are statistically significant for the message-exchange during the nine natural disaster events. The most common motif is 021U (see Table 3) with a relatively low variability (with respect to its edge distribution). Two motifs occur in all nine data-sets (021D, 030T), while the motifs 201, 120C, 030C, 210 are representative for only two data-sets each. Thus, we do not consider 201, 120C, 030C, 210 common motifs with respect to their overall occurrence. One motif (ID = 300) did not occur in any of the studied events.

Motif 120U has the highest average number of edges ($\text{mean}(\text{edge_count}) = 7.88 \pm 4.81$) while the maximum number of edges is found in motif 030T ($\text{max}(\text{edge_count}) = 24$). Though the theoretical minimum number of edges is 3 (i.e., one edge between each pair of vertices in a 3-subgraph), two motifs come with a minimum number of 4 and 5 edges (motifs 120C and 210, respectively).

The motif distribution on the eight layers (representing Plutchik's eight basic emotions) as well as the four derived layers of our multiplex network is shown in Table 4. On all layers, motif 021U is the most commonly occurring motif followed by 021D. For the other motifs, the distribution varies for each layer. Motif 021C is the third most frequent on the layers representing anger, fear, sadness, anticipation, and the derived layers negative, positive, interlayer, and aggregated while the layers disgust, joy, trust, and surprise show a relatively high presence of the motif 030T. Moreover, motif 210 only appears as Twitter users exchange mixed-emotion messages (i.e., positive as well as negative messages). Finally, motifs 210, 120C, and 201 appear only on the derived layers and are, thus, not representative for the communication of a single emotion (see Table 4).

Figures 5, 6, 7, 8, 9 and 10 show the temporal occurrence of MAN-labeled motifs with respect to the 12 emotion-annotated layers of our multiplex network. The temporal evolution of specific motifs on the different emotion layers indicates characteristic differences among the motifs. Motifs 021D, 021C, 030T, 111U, 030C, 120U, 120D, 120C, and 210 peak within the first half of the data-extraction period (the latest on day 11) on all layers. In contrast, motif 021U does not show a general pattern. On the one hand, it peaks in the second half of the data extraction on layer anger; on the other, it peaks within the first week on the layers trust, fear, as well as the derived layers negative, positive, and interlayer. Motif 111D generally peaks within the first half of the extraction period with the exception for the joy layer where it peaks at the end of the data extraction period (see Fig. 7).

Furthermore, we found that certain motifs appear within a specific time-frame only. For example, motifs 201 and 120C (shown blue and black, respectively, in Figs. 11 and 12), only occur on the derived layers and within the first 14 days of the data-extraction period. Similar for motif 030C, which only appears within the first 11 days of the data-extraction period and only on the derived layers that involve positive emotions (i.e., positive, interlayer, and aggregated) as well as the anticipation layer.

Table 4 Frequency of motifs on single emotion layers and the derived layers

Single-emotion layers							
Label	Anger	Fear	Sadness	Disgust	Surprise	Joy	Trust
021U	0.65	0.75	0.98	0.99	0.73	0.59	0.47
021D	0.23	0.17	0.02	0.01	0.26	0.34	0.37
021C	0.07	0.05	0.004	0.00008	0.002	0.03	0.07
030T	0.05	0.02	0.0009	0.0001	0.004	0.04	0.09
111D	0.003	0.006	0	0	0.0002	0.001	0.001
111U	0.004	0.002	0.00004	0.00008	0	0.003	0.01
120U	0.0005	0.0008	0	0	0	0	0.0003
120D	0.0006	0.0004	0	0	0	0	0.0001
030C	0	0	0	0	0	0	0.0001
Derived layers							
Label	Negative		Positive		Interlayer	Aggregated	
021U	0.67		0.57		0.48	0.74	
021D	0.20		0.21		0.32	0.12	
021C	0.08		0.12		0.11	0.06	
030T	0.03		0.05		0.04	0.03	
111D	0.01		0.03		0.02	0.02	
111U	0.01		0.01		0.02	0.02	
120U	0.002		0.003		0.004	0.004	
120D	0.0008		0.002		0.002	0.003	
201	0.00008		0.00007		0.0004	0.0004	
120C	0.00002		0.0004		0.0002	0.0002	
030C	0		0.0001		0.0001	0.00005	
210	0		0		0.00006	0.00004	

With respect to motif durability, we found that motifs 120C and 210 occur on an average of three days only, while motif 030C only occurs on an average of 2.8 days. This is in contrast to motifs 021U and 021D that are present throughout 21 days of data-extraction (see Figs. 5, 6, 7, 8, 9, 10).

The motif size (i.e., the number of edges in a motif, resp. the weight of the edges) gives information about how many messages are exchanged among the Twitter users, as well as the direction of the message flow. In general, we distinguish unidirectional and bidirectional edges. Table 5 shows the average number of unidirectional and bidirectional edges for each layer of the multiplex network. The results indicate that, with the exception of anger, the derived layers generally show a comparatively lower number of unidirectional edges compared to the single-emotion layers. The anger layer has on average the smallest number of unidirectional edges, while the highest number of unidirectional edges is found in the motifs on the sadness layer followed by the fear layer. In contrast, the number of bidirectional edges are esp. high on the derived layers (the aggregated layer, interlayer, negative layer, and positive layer). The lowest number of bidirectional edges is found on the sadness layer followed by the remaining negative single-emotion layers disgust, fear, and anger. Moreover, positive single-emotion layers exhibit on average a higher frequency of bidirectional communication.

The motifs 021U, 021D, and 030T are the largest in size (i.e. with respect to their edge count) on all layers of our multiplex network (see Figs. 11, 12). However, though 021U is the largest motif on most of the layers, the edge count of 021D dominates over 021U on layers sadness, joy, and disgust. All layers show a decrease in the edge count towards the end of the data-extraction period.

To mitigate the 140-character, resp. 280-character, restriction⁴, Twitter users use self-mentioning to “link together” messages, i.e., messages that span over multiple tweets. In our emotion-exchange motifs, such behavior is represented via self-loops (i.e., tweets where a Twitter user mentions herself via @username).

Motifs that contain self-loops appear in eight of the nine events studied in this paper (no motifs with self-loops were found in the Costa Rica earthquake data-set). In total, 12.69% of all motifs identified in this study contain self-loops. These motifs occur on every layer of the multiplex network. Table 6 summarizes the shape of motifs containing self-loops on each layer of our multiplex network as well as their relative occurrence on each layer.

In general, motifs containing self-loops predominantly appear as Twitter users send messages conveying mixed emotions (the aggregated layer contains 39.39% of all motifs containing self-loops, followed by the interlayer with 27.36%). Considering single-emotion layers only, self-loops are most frequently found on the layers representing fear (5.42%) and anticipation (4.56%).

In general, we found that it takes some time after the respective event occurred until the number of motifs including self-loops, i.e. self-mentioning, peaks (see Fig. 13). For the mixed emotions, the peak is found on day four, for the negative emotions on day five, while the positive emotions layers show the highest peak on day nine.

⁴ Originally, a tweet was a short message with a maximum length of 140 characters. In late 2017, this limit has been lifted to a maximum of 280 characters per tweet.

Fig. 5 Frequency of the motifs on layers anger and disgust averaged over all natural disaster events

Fig. 6 Frequency of the motifs on layers fear and sadness averaged over all natural disaster events

Structural similarities of emotion-annotated networks

Lastly, we report on the daily structural similarities of emotion-annotated networks by considering the distribution (frequency) of the different isomorphism classes for emotion-exchange motifs (i.e., we take into account a motif's variability expressed as the edge distribution including self-loops, and the number of occurrences of each motif). To this end, we use the arithmetic fidelity measure φ (see [63]) which is defined as $\varphi_A = \frac{\sum_i r_i^1}{n}$ where n is the number of unique isomorphic classes and r is a ratio defined as $r_i^1 = \frac{\min(m_i, m_i^1)}{\max(m_i, m_i^1)}$, with m_i being the frequency a motif belonging to an isomorphic class i occurring in a network $M1$ and m_i^1 being the frequency a motif

Fig. 7 Frequency of the motifs on layers joy and trust averaged over all natural disaster events

Fig. 8 Frequency of the motifs on layers anticipation and surprise averaged over all natural disaster events

belonging to the same isomorphic class i occurring in a network $M2$. Over time, the motifs found in each pair of layers formed from the 12 emotion layers⁵ show at least a weak structural similarity. Figures 14, 15 and 16 show the respective mean similarity score averaged over the data-extraction period (solid line) and the range (minimum and maximum score) of the respective similarity score reached at some point during the data-extraction period (blue-shaded area).

On average, the inter-group similarity score for pairs of positive emotion layers exhibits the highest value ($\varphi_{\text{POS-POS}} = 0.12$), followed by pairs of one

⁵ In total, we count 66 pairs (e.g., (anger, fear), (anger, disgust), etc.).

Fig. 9 Frequency of the motifs on layers positive and negative averaged over all natural disaster events

Fig. 10 Frequency of the motifs on layers interlayer and aggregated averaged over all natural disaster events

negative and one positive layer ($\varphi_{\text{NEG-POS}} = 0.08$), and pairs of two negative layers ($\varphi_{\text{NEG-NEG}} = 0.06$). The lowest similarity score is found when comparing motifs on the layers aggregated, surprise, and interlayer ($\varphi_{\text{ASI}} = 0.05$). When considering pairs of single-emotion layers only (i.e., excluding the derived layers), the highest similarity score averaged over the data-extraction period is found between sadness and joy $\varphi_{\text{SADNESS-JOY}} = 0.15$, while the lowest one occurs between fear and disgust $\varphi_{\text{FEAR-DISGUST}} = 0.02$ as well as fear and sadness $\varphi_{\text{FEAR-SADNESS}} = 0.02$.

Table 5 Number of unidirectional and bidirectional edges for each layer of the multiplex network, averaged over each event

Layer	Unidirectional	Bidirectional
Anger	65.03 (12)	2.28 (9)
Fear	412.98 (2)	2.11 (10)
Sadness	506.42 (1)	1.53 (12)
Disgust	316.26 (4)	2.00 (11)
Joy	300.39 (5)	2.48 (8)
Trust	268.64 (6)	2.59 (6)
Anticipation	344.77 (3)	2.67 (5)
Surprise	248.18 (7)	2.52 (7)
Positive	227.16 (8)	3.38 (4)
Negative	221.25 (9)	4.25 (3)
Interlayer	207.52 (10)	4.36 (2)
Aggregated	199.41 (11)	5.74 (1)

The number in brackets shows the relative ranking of each value

Fig. 11 Daily motif size on layers negative, sadness, fear, anger, and disgust over all natural disaster events

Fig. 12 Daily motif size on layers positive, aggregated, trust, anticipation, joy, and interlayer over all natural disaster events

In 74% of the emotion layer pairs, the maximum φ score is reached after 14 days of data extraction. Interestingly, the highest maximum similarity score is found between the layers joy and sadness where $\varphi = 1$ exhibits the perfect similarity with respect to their motif distribution (see Fig. 15).

Table 6 Presence of self-loops on each layer of the multiplex network

Layer	Motifs	Occurrence
Anger		3.75%
Fear		5.42%
Sadness		0.33%
Disgust		0.31%
Joy		0.93%
Trust		2.27%
Anticipation		4.56%
Surprise		0.33%
Positive		10.58%
Negative		12.75%
Interlayer		27.36%
Aggregated		31.39%

The color of the motif indicates the highest frequency at which a self-loop was found on a specific node in each motif

Fig. 13 Average daily number of motifs that contain self-loops aggregated over negative layers (anger, fear, sadness, disgust, negative), positive layers (joy, trust, anticipation, positive), and mixed-emotion layers (aggregated, interlayer)

Discussion

During natural disasters, Twitter users predominantly express their emotional distress via the emotions of fear and sadness. Beginning with the initial expression of intense fear and anger, the emotion of sadness along with positive emotions slowly peak as the Twitter discourse evolves over time.

Messages that express sadness and positive emotions (trust, joy) convey compassion, hope, and love for those affected by the disaster as well as gratitude for those who helped the ones affected by the disaster. Below, we provide examples of messages conveying fear and anger:

- I think the constant warnings on my phone that are loud as hell freak me out more than what is gonna happen #HurricaneIrma #Irma #wegotthis
- San Juan PR Mayor says she is “mad as hell over hurricane Maria response..... help us we are dying!”
- I hate this crazy wind. It howls like condemned werewolf from the deepest abyss of hell #Friederike”

To a certain degree, OSNs serve as a therapeutic channel for the ones affected by the disaster [15, 45, 46]. In this context, messages conveying sadness, unlike fear and anger, predominantly express compassion:

Fig. 14 Similarity scores for the motifs found on pairs of emotion layers (here: pairs of negative emotion layers, pairs of positive emotion layers, as well as pairs including aggregated, surprise, and/or interlayer)

Fig. 15 Similarity scores for the motifs found on pairs of emotion layers (here: pairs of one positive and one negative emotion layer respectively)

- My heart hurts looking at the damage & those already affected by these horrible storms. Please stay safe. #HurricaneIrma

Fig. 16 Similarity scores for the motifs found on pairs of emotion layers (here: pairs of one positive/negative layer as well as aggregated, surprise, or interlayer)

- @BBCBreaking Our heart go out to the victims & the victims of the hurricane Maria in Puerto Rico. For those dying
- Our thoughts are with the government and people for the loss of life and damage following the devastating earthquake #Iraq #Iran

Messages that convey love for the ones affected by the natural disaster, messages of hope and admiration/thankfulness for those involved in the rescue efforts are found as well. Below we provide examples of messages conveying joy (love), trust, and anticipation.

- Cuba has a very special place in my heart; all my love to the island and her wonderful people #HurricaneIrma #Irma
- If there was 1 good thing about #HurricaneIrma it allowed me to be here with people I've grown to love! #WageHope
- Please continue to pray for our wonderful city of Montecito! We are believing for love, peace and restoration of many lives
- I've love being part of the Montecito community. I send love to all the families and the amazing rescue workers
- Holy God we pray for all victims of natural disaster's of Hurricane Harvey, quickly send them help, comfort them
- Rescue Dogs In Mexico City's Earthquake Should Be Honored By An Award Equal To The Nobel Peace Prize. God Bless All
- Good note & good prep by @Westin in #StMaarten. Staff have been amazingly professional. Now let's pray! #Irma2017

Pasupathi [49] found that negative emotions exhibit a higher intensity when they are immediately experienced as opposed to emotions that occur when just remembering the event. In our study, we analyzed tweets that have been published in real-time during and shortly after a natural disaster. For all nine events, we found a considerable decrease in the emotional intensities of fear and anger towards the end of the data-extraction period (see Fig. 3). Positive emotions, on the other hand, show a comparatively lighter decrease and remain in a confined range throughout the data-extraction period (between 0.3 and 0.8).

The emotion of sadness always peaks in its intensity during the second half of the data-extraction period and reaches a relatively high intensity towards the end of the extraction (thus, not following the trend of other negative emotions such as anger and fear). As discussed above, during natural disasters positive emotions and sadness express compassion, love, gratitude, and hope, and thus play a role in the collective coping with the emotional distress and contribute to the emotional well-being. Fredrickson [16] referred to this phenomenon as the undoing hypothesis (a use of positive emotions to undo the effects of negative emotions).

We also found that positive messages attract more reactions in terms of likes and message distribution (retweeting) than the negative ones. Retweeting is especially seen as a convenient mechanism to extend the audience of a particular message by increasing its visibility in the Twitter sphere. Upon studying the reasons why people repeat messages, [3] found that the retweeting mechanism is used to publicly mark oneself as a listener, to approve one's message, agree with someone, or to support and encourage social action. Examples of highly retweeted messages from our data-set read:

- RT @screenname⁶: Sanctions on Iran make it difficult to donate, but here's a GoFundMe set-up to help the victims of the devastating earthquake (conveys anticipation)
- RT @screenname: I'm sending peace and love and prayer to the hundreds of people who perished in the Earthquake ♥(conveys joy (love))
- RT @screenname: As we pray for those affected by #HurricaneHarvey, let us also honor all of the brave heroes and first responders. (conveys joy (love))

Positive messages that call for social action coupled with Twitter's re-tweeting mechanisms turn out to be quite effective in reaching a large number of users. For example, in our data-set, the most frequently retweeted message "RT @screenname: With the current devastation in Houston, we are pledging \$0.15 for every RT this gets! Please forward this along to help!" conveys anticipation and was retweeted in total 1,154,211 times.

User behavior in terms of emotional expression directly contributes to the emergence of the underlying communication network [70]. For the nine disaster events, we found that 12 out of 13 possible directed 3-subgraphs are statistically significant building blocks of the emotion-annotated networks. Among those, motifs 021U and 021D were the most frequent and the largest in size with respect to their number of edges.

⁶ Note that we anonymized the screennames.

Due to the nature of Twitter to predominantly serve as a channel for broadcasting short messages, the high frequency of the broadcaster motif 021D does not come as a surprise. Moreover, the message-receiver motif 021U is also typical for Twitter. Message-receiving behavior (via @-screenname) emerges during information seeking (e.g., the police was repeatedly asked for official information during the 2017 G20 Hamburg riots [33]), as a reaction to another user's tweet/public statement, or by publicly mentioning a public person (such as a politician). These findings comply with our former studies on emotion-exchange motifs that emerge on Twitter during bombing and shooting attacks [35] as well as during riot events [37].

The motifs 021C (a message cycle motif) and 030T (a transitive motif) are the next most frequently occurring motifs. Similar to 021U and 021D, the motifs 021C and 030T appear on all layers of our multiplex network. The example below shows the formation of a motif 030T ($A \rightarrow B \rightarrow C \rightarrow A$) which expresses a one-way (negative) reaction to an episode of an event being discussed.

- Person A: No way will the president give 1 million to Hurricane Irma relief, 'The Art of the Deal' @B
- Person C: @A can [anonymous] be sued for loss of life by those ignorant enough to listen and stay in the path of #Irma?
- Person B: @C Honestly, people are having fun joking about the #LAHeatwave. No one's seriously complaining, no one!!

Though Twitter is mainly seen as a platform for message broadcasting, we identified four common motifs that contain bidirectional edges. These motifs are 111D, 111U, 120U, and 120D. A bidirectional edge in a motif signals a two-sided communication (message exchange) between a pair of users. Such a form of a communication represents a discussion about an event, an exchange of opinions, or calls for social action. We found that motifs of the shapes 111D and 111U are not characteristic for the communication of surprise, sadness, and disgust (they either appear very rarely on one of these three layers or not at all). Their low significance profile or even absence on these layers suggests that it is more common to respond to these particular emotions with other types of emotions. This finding, however, does not entirely come as a surprise. Communication of sympathy, compassion, and comfort typically involves messages of love, hope, and support as a response to someone else's sadness [19]. In our data-sets, we also found that positive emotions (average number of messages $\mu_{\text{trust}} = 1.4$, $\mu_{\text{joy}} = 0.91$, $\mu_{\text{anticipation}} = 1.4$) are typical responses to a sad message. However, because crisis events are related to intense feelings of fear, we could also confirm that sadness is frequently responded by fear ($\mu_{\text{fear}} = 1.37$). According to [18], the individuals affected by a natural disaster often search for someone to blame (e.g., for a lack of preparation or the poor construction of buildings) to regain their sense of control of the highly threatening and uncertain situation. As a consequence, we also found a high number of angry responses to sad messages ($\mu_{\text{anger}} = 1.38$) as well as messages conveying disgust ($\mu_{\text{anger}} = 1.16$). The exchange of anticipation,

trust, as well as mixed emotions (on the derived layers of our multiplex network) is often related to the motifs 111D and 111U. Below we provide an example from our data-set for a discussion involving anger (motif 111U $A \leftrightarrow B \rightarrow C$).

- Person B: @A @C This earthquake hit a major American ally called Kurdistan. Kurdistan more then it did to Iran.
- Person A: @B No. The earthquake affected Iran more.
- Person B: @C What? You know there fighting Kurdistan right? SO why would god hit earthquake at the most peaceful region in the area??

An example for motif 111D ($A \leftrightarrow B \leftarrow C$) shows a public gratification of the ones involved in the disaster relief efforts.

- Person A: S/o to the amazing @B who braved #HurricaneHarvey
- Person B: @A Hey JJ thanks for giving us a shoutout. We'd love to work with you on our #HurricaneHarvey relief.
- Person C: Our friends at @B are doing amazing work to help those affected by #hurricaneharvey URL

Motifs 120U and 120D are even more rare as compared to 111U and 111D, and are not found on the layers representing sadness, disgust, surprise, and joy. In fact, the relative frequency of these two motifs (120U and 120D) shows that they are predominantly characteristic for the communication of messages that convey positive emotions (the most frequent occurrence on layers anticipation, positive, interlayer, and aggregated). The example below (motif 120U: $A \rightarrow B \leftarrow C \leftrightarrow A$) illustrates a message conveying a generally positive sentiment (a call for social action and the sharing of information on the disaster relief efforts, where persons A and C mutually mention each other as well as person B).

- Person A: Help for the victims of hurricane Harvey. @C: Here's how to help after deadly hurricane: URL
- Person C: Hey, @A Facebook followers: If you want to see the latest #HurricaneHarvey news in your feed, make sure to subscribe URL
- Person C: Do you have photos from #HurricaneHarvey? Share them with @A
- Person A: Eat for a cause! MT @B: Donate to hurricane survivors, eat good food too this weekend in Cy-Fair URL.
- Person C: Local @B students are doing their part to help Hurricane Harvey victims URL

In addition, four uncommon emotion-exchange motifs (120C, 201, 030C, and 210) are particularly interesting as they emerge exclusively on the derived layers (with an exception of the motif 030C) and are therefore not representative for the communication of single emotions. Motif 210 ($A \rightarrow B \leftrightarrow C \leftrightarrow A$) emerges on the mixed emotion layers (aggregated and interlayer), motif 030C ($A \rightarrow B \rightarrow C \rightarrow A$) appears only on the derived layers that involve positive emotions (positive, interlayer, aggregated) as well as two positive single-emotion layers anticipation and trust, while motifs

120C ($A \rightarrow B \rightarrow C \leftrightarrow A$) and 201 ($A \leftrightarrow B \leftrightarrow C$) appear only on the derived layers (incl. positive and negative derived layers).

Furthermore, these four motifs (120C, 201, 030C, and 210) do not emerge before the third day of the data-extraction period, they do not appear consistently (i.e., they have a tendency to re-appear rather than consistently appear on a daily basis), and have a relatively short life-span. Unlike the three most frequent motifs (021U, 021D, 021C), the four uncommon motifs (120C, 201, 030C, and 210) indicate a more complex social interaction—201 represents a discussion between two pairs of users; 030C, a closed message cycle; and 210 as well as 120C, a message cycle with a discussion. Our analysis showed that such social interactions (though present on Twitter) are in general not characteristic communication patterns for Twitter. These results comply with our previous findings on emotion-exchange motifs occurring during riot events [37] as well as bombing and shooting attacks [35].

Emotion-exchange motifs are a useful feature to compare the underlying structure of emotion-annotated communication networks. We found that motifs representing the communication of a single negative emotion are structurally more dissimilar than those conveying a single positive emotion. Interestingly, when negative emotion-exchange motifs are compared to positive emotion-exchange motifs, they exhibit a greater similarity within the inter-valence group than in their own intra-valence group. The two emotions contributing most to high inter-valence similarity scores are joy (positive valence) and sadness (negative valence). In fact, emotion-exchange motifs on these two layers show a higher similarity score than the motifs found in any pair of negative emotion layers (such as fear and disgust, which exhibit the lowest similarity score). Semantically, messages conveying joy express love, gratitude, and hope, while sadness is associated with an expression of well-being wishes and grief over the victims of the natural disasters. In both cases, these messages are also associated with compassion. Thus, our analysis showed that the exchange of semantically related messages form comparable emotion-exchange motifs.

Limitations

This study comes with certain limitations. For one, though we systematically monitored Twitter and picked carefully chosen hashtags and search terms for our data collection, Twitter's Search API comes with a restriction regarding the availability of tweets one can fetch (i.e., not all tweets are indexed and made available via Twitter's public API). Thus, we cannot exclude the possibility that we missed relevant tweets due to this API restriction.

Furthermore, bots play a significant role on Twitter. According to [65], as much as 15% of all Twitter accounts can be attributed to automated bot accounts. Such accounts, apart from serving as mere chat bots, may also be designed to disseminate a large volume of spam, influence one's opinion, and can mimic a human-like behavior making them difficult to distinguish from human users (see, e.g., [10, 13, 34]). Though in this study we did not distinguish between human and bot accounts, the involvement of bot accounts might impact the formation of communication patterns (see [37]). In our future work, we plan to further examine the role of bots on

the formation of structural network patterns and in specific on the emergence of emotion-exchange motifs.

Due to the complexity of human emotions, limited information about the context in which an emotion was experienced, and the tendency of people to differently interpret the same emotion, identifying emotions is a challenging task (see also [28]). In order to detect emotions in our data-sets, we relied on our emotion detection algorithm and existing emotion-word lexicons. In our prior work, we tested for the appropriateness of publicly available emotion-word dictionaries (see [32]) and chose the one with the best performance to mitigate errors and incompleteness in our studies. Furthermore, we enhanced the emotion detection procedure via a set of heuristics (e.g., amplifiers, maximizers, downtoners, negation, emojis) that considerably increased the accuracy of the approach. However, since even human raters (e.g., from different cultural backgrounds) sometimes disagree on the emotional valence of written texts, we cannot rule out the possibility that some of the tweets have been mislabeled. This especially happens for ironic or sarcastic messages.

Finally, our motif detection procedure relies on the exact enumeration of all 3 subgraphs in a particular network. This procedure is computationally very demanding (see also “[Methods](#)”). As previously noted in [62], networks derived from real-world OSNs are complex and lead to computational challenges.

Conclusion

In this paper, we analyzed over 16 million tweets sent from 6.1 million different Twitter accounts that have been sent during nine natural disasters. In particular, we analyzed the structural communication patterns (emotion-exchange motifs) that emerge as Twitter users directly exchange emotional messages. Our findings show that emotional messages receive considerably more attention in terms of likes compared to neutral ones. For each of the nine events, we found that the affected individuals predominantly experience fear and sadness as a natural disaster strikes. Moreover, in the immediate aftermath of a disaster event, Twitter users especially convey disgust and anger, as well as a range of positive emotions that serve as an antidote against the disruptive effects of the experienced negative emotions. These findings about the general emotional tone during natural disasters comply with other related scientific contributions.

Our approach to studying emotional responses during crisis events especially uses the novel concept of emotion-exchange motifs—small network structures that are statistically representative for the communication of specific emotions. To the best of our knowledge, this interdisciplinary approach is the first to combine network motifs with the study of human emotions. In particular, we found that individuals affected by a natural disaster tend to frequently broadcast unidirectional messages conveying fear, sadness, and disgust, while positive emotions, such as joy, trust, and anticipation inspire online conversations. Moreover, online conversations involving positive emotions show a relatively high number of bidirectional messages of the same (positive) emotional tone. On the other hand, for messages conveying sadness and disgust the low presence of emotion-exchange motifs containing bidirectional

edges (111U) revealed that sadness and disgust (unlike fear and anger) are typically responded to by other types of emotions. For example, sadness is frequently found in messages of compassion and is responded to by joy/love, while disgust is connected to a high response rate of angry messages.

In addition, the emotion-exchange motifs found in our data-set reveal that the communication of positive emotions forms a unique and distinct set of motifs (cyclic subgraph 030C) that do not appear as Twitter users exchange negative emotions. In contrast, a mixture of different emotions in a conversation leads to more complex structures (120C, 201, 210) where all three users participating in an emotion-exchange motif take an active role with respect to their message-sending behavior and exhibit a clear local hierarchy with respect to the choice of a conversational partner.

Finally, we used emotion-exchange motifs to examine the structural similarities of different emotion-annotated networks. In this context, we showed that the intra-valence networks (e.g., sadness and fear) exhibit a lower similarity score than inter-valence networks (e.g., joy and sadness). In fact, emotion-exchange motifs representing the communication of sadness and joy showed the highest similarity score, even reaching a perfect (maximum) similarity score at some point during the data-extraction period. We attribute this finding to the semantics of the messages conveyed as people communicate the two emotions. Supported by findings from the related work and empirical evidence found in our data-sets, the emotions of joy and sadness are commonly used to express the feelings of compassion, gratitude, and hope.

Based on our improved understanding of the statistically significant and recurring communication patterns that emerge during natural disasters, our future research will further investigate whether the identified emotion-exchange motifs are universal across different types of crisis events (such as riots, terror, and shooting attacks) and examine whether during negative events certain emotion-exchange motifs are characteristic for the communication of specific emotions. Furthermore, to gain a more in-depth understanding of the communication structures that emerge as people exchange emotions, we plan to further investigate the concept of temporal emotion-exchange motifs.

Author contributions Both authors contributed to the study conception and design. Data extraction was carried out by both authors, data pre-processing by MS, and data analysis by EK. Both authors read and approved the final manuscript.

Funding Open access funding provided by Vienna University of Economics and Business (WU). Not applicable.

Data availability The network data are freely available for download from our website: https://nm.wu.ac.at/nm/strembeck/data/natural_disasters.zip.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

1. Bakker, M. H., van Bommel, M., Kerstholt, J. H., & Giebels, E. (2018). The influence of accountability for the crisis and type of crisis communication on people's behavior, feelings and relationship with the government. *Public Relations Review*, 44(2), 277–286. <https://doi.org/10.1016/j.pubrev.2018.02.004>.
2. Bhavaraju, S. K. T., Beyney, C., & Nicholson, C. (2019). Quantitative analysis of social media sensitivity to natural disasters. *International Journal of Disaster Risk Reduction*, 39, 101251. <https://doi.org/10.1016/j.ijdrr.2019.101251>.
3. Boyd, D., Golder, S., & Lotan, G. (2010). Tweet, tweet, retweet: conversational aspects of retweeting on twitter. In *2010 43rd Hawaii international conference on system sciences* (pp. 1–10). <https://doi.org/10.1109/HICSS.2010.412>
4. Chang, V. (2018). A proposed social network analysis platform for big data analytics. *Technological Forecasting and Social Change*, 130, 57–68. <https://doi.org/10.1016/j.techfore.2017.11.002>.
5. Cordella, L. P., Foggia, P., Sansone, C., & Vento, M. (2004). A (sub)graph isomorphism algorithm for matching large graphs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26(10), 1367–1372. <https://doi.org/10.1109/TPAMI.2004.75>.
6. Darling, J. R. (1994). Crisis management in international business: keys to effective decision making. *Leadership & Organization Development Journal*, 15(8), 3–8. <https://doi.org/10.1108/0147739410073047>.
7. Davis, J. A., & Leinhardt, S. (1972). *The structure of positive interpersonal relations in small groups*. Boston: Houghton Mifflin.
8. De Longueville, B., Smith, R.S., & Luraschi, G. (2009). “OMG, from Here, I Can See the Flames!”: a use case of mining location based social networks to acquire spatio-temporal data on forest fires. In *Proc. of the 2009 international workshop on location based social networks, LBSN* (pp. 73–80). ACM, New York, NY, USA. <https://doi.org/10.1145/1629890.1629907>
9. Dormann, C., Frund, J., Bluthgen, N., & Gruber, B. (2009). Indices, graphs and null models: analyzing bipartite ecological networks. *The Open Ecology Journal*, 2, 7–24.
10. Everett, R.M., Nurse, J.R.C., & Erola, A. (2016). The anatomy of online deception: what makes automated text convincing? In *Proceedings of the 31st annual ACM symposium on applied computing, SAC* (pp. 1115–1120). ACM, New York, NY, USA. <https://doi.org/10.1145/2851613.2851813>
11. Farazmand, A. (2016). *Global cascades in best and worst practice in crisis and emergency management*. Boca Raton: CRC Press, Taylor and Francis Group.
12. Ferdous, M., Chowdhury, F., Alassafi, M., Alshdadi, A., & Chang, V. (2020). Social anchor: privacy-friendly attribute aggregation from social networks. *IEEE Access*, 8, 61844–61871. <https://doi.org/10.1109/ACCESS.2020.2981553>.
13. Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications ACM*, 59(7), 96–104. <https://doi.org/10.1145/2818717>.
14. Folkman, S., & Moskowitz, J. T. (2000). Stress, positive emotion, and coping. *Current Directions in Psychological Science*, 9(4), 115–118. <https://doi.org/10.1111/1467-8721.00073>.
15. Fraustino, J. D., Brooke, L., & Yan, J. (2012). Social media use during disasters: a review of the knowledge base and gaps. Final Report to Human Factors/Behavioral Sciences Division, Science and Technology Directorate, U.S. Department of Homeland Security, College Park, MD: START
16. Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: the broaden-and-build theory of positive emotions. *The American Psychologist*, 56, 218–226.

17. Fredrickson, B. L., Tugade, M. M., Waugh, C. E., & Larkin, G. R. (2003). What good are positive emotions in crisis? A prospective study of resilience and emotions following the terrorist attacks on the United States on September 11th, 2001. *Journal of Personality and Social Psychology*, 84(2), 365–376. <https://doi.org/10.1037/0022-3514.84.2.365>.
18. Freyd, J. (2002). In the wake of terrorist attack, hatred may mask fear. *Analyses of Social Issues and Public Policy*, 5–8. <https://doi.org/10.1111/j.1530-2415.2002.00020.x>.
19. Goetz, J., Keltner, D., & Simon-Thomas, E. (2010). Compassion: an evolutionary analysis and empirical review. *Psychological Bulletin*, 136(3), 351–374. <https://doi.org/10.1037/a0018807>.
20. Guo, S. J. (2017). The 2013 Boston marathon bombing: publics' emotions, coping, and organizational engagement. *Public Relations Review*, 43(4), 755–767. <https://doi.org/10.1016/j.pubre.2017.07.003>.
21. Gurukar, S., Ranu, S., & Ravindran, B. (2015). Commit: a scalable approach to mining communication motifs from dynamic networks. In *Proceedings of the 2015 ACM SIGMOD international conference on management of data, SIGMOD '15* (pp. 475–489). ACM, New York, NY, USA. <https://doi.org/10.1145/2723372.2737791>
22. Guzman, E., Azócar, D., & Li, Y. (2014). Sentiment analysis of commit comments in GitHub: an empirical study. In *Proceedings of the 11th working conference on mining software repositories, MSR 2014* (pp. 352–355). Association for computing machinery, New York, NY, USA. <https://doi.org/10.1145/2597073.2597118>.
23. Hansen, L. K., Arvidsson, A., Nielsen, F. A., Colleoni, E., & Etter, M. (2011). Good friends, bad news - affect and virality in Twitter. In J. J. Park, L. T. Yang, & C. Lee (Eds.), *Future information technology* (pp. 34–43). Berlin: Springer.
24. Hung, K. C., Kalantari, M., & Rajabifard, A. (2016). Methods for assessing the credibility of volunteered geographic information in flood response: a case study in Brisbane, Australia. *Applied Geography*, 68, 37–47. <https://doi.org/10.1016/j.apgeog.2016.01.005>. <http://www.sciencedirect.com/science/article/pii/S0143622816300054>.
25. Jin, Y. (2009). The effects of public's cognitive appraisal of emotions in crises on crisis coping and strategy assessment. *Public Relations Review*, 35(3), 310–313. <https://doi.org/10.1016/j.pubre.2009.02.003>. (Special Section on China Public Relations).
26. Jin, Y., Pang, A., & Cameron, G. T. (2010). The role of emotions in crisis responses: inaugural test of the integrated crisis mapping (icm) model. *Corporate Communications: An International Journal*, 15(4), 428–452. <https://doi.org/10.1108/13563281011085529>.
27. Kankanamge, N., Yigitcanlar, T., Goonetilleke, A., & Kamruzzaman, M. (2020). Determining disaster severity through social media analysis: testing the methodology with south east Queensland flood tweets. *International Journal of Disaster Risk Reduction*, 42, 101360. <https://doi.org/10.1016/j.ijdrr.2019.101360>.
28. Karyotis, C., Doctor, F., Iqbal, R., James, A., & Chang, V. (2018). A fuzzy computational model of emotion for cloud based sentiment analysis. *Information Sciences*, 433–434, 448–463. <https://doi.org/10.1016/j.ins.2017.02.004>.
29. Kim, H. K., & Niederdepppe, J. (2013). The role of emotional response during an H1N1 influenza pandemic on a college campus. *Journal of Public Relations Research*, 25(1), 30–50. <https://doi.org/10.1080/1062726X.2013.739100>.
30. Kongthon, A., Haruechaiyasak, C., Pailai, J., & Kongyoung, S. (2012). The role of twitter during a natural disaster: case study of 2011 Thai flood. In *Proceedings of PICMET: technology management for emerging technologies* (pp. 2227–2232).
31. Kušen, E., Strembeck, M., & Conti, M. (2019). *Emotional valence shifts and user behavior on Twitter, Facebook, and YouTube* (pp. 63–83). Berlin: Springer International Publishing. https://doi.org/10.1007/978-3-030-02592-2_4.
32. Kušen, E., Cascavilla, G., Figl, K., Conti, M., & Strembeck, M. (2017). Identifying emotions in social media: comparison of word-emotion Lexicons. In *Proc. of the 4th international symposium on social networks analysis, management and security (SNAMS)*. IEEE
33. Kušen, E., & Strembeck, M. (2018). On the public perception of police forces in riot events - the role of emotions in three major social networks during the 2017 G20 Riots. In *Proc. of the 3rd international conference on complexity, future information systems and risk (COMPLEXIS)* (pp. 120–127).
34. Kušen, E., & Strembeck, M. (2018). Why so emotional? An analysis of emotional bot-generated content on Twitter. In *Proc. of the 3rd international conference on complexity, future information systems and risk (COMPLEXIS)*.

35. Kušen, E., & Strembeck, M. (2019). An analysis of emotion-exchange motifs in multiplex networks during emergency events. *Applied Network Science*. <https://doi.org/10.1007/s41109-019-0115-6>.
36. Kušen, E., & Strembeck, M. (2019). Something draws near, I can feel it: an analysis of human and bot emotion-exchange motifs on Twitter. *Online Social Networks and Media*, 10–11, 1–17. <https://doi.org/10.1016/j.osnem.2019.04.001>.
37. Kušen, E., & Strembeck, M. (2020). You talkin' to me? Exploring human/bot communication patterns during riot events. *Information Processing & Management*, 57(1), 102126. <https://doi.org/10.1016/j.ipm.2019.102126>.
38. Liu, W., Lai, C. H., & Xu, W. W. (2018). Tweeting about emergency: a semantic network analysis of government organizations' social media messaging during hurricane Harvey. *Public Relations Review*. <https://doi.org/10.1016/j.pubrev.2018.10.009>. <http://www.sciencedirect.com/science/article/pii/S0363811117304162>.
39. Mandel, B., Culotta, A., Boulahanis, J., Stark, D., Lewis, B., & Rodrigue, J. (2012). A demographic analysis of online sentiment during hurricane Irene. In *Proceedings of the second workshop on language in social media, LSM* (pp. 27–36). Association for computational linguistics, Stroudsburg, PA, USA.
40. Milo, R., Shen-Orr, S., Itzkovitz, S., Kashtan, N., Chklovskii, D., & Alon, U. (2002). Network motifs: simple building blocks of complex networks. *Science*, 298(5594), 824–827. <https://doi.org/10.1126/science.298.5594.824>.
41. Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word-emotion association Lexicon. *Computational Intelligence*, 29(3), 436–465.
42. Murakami, A., & Nasukawa, T. (2012). Tweeting about the tsunami?: mining twitter for information on the Tohoku earthquake and tsunami. In *Proceedings of the 21st international conference on world wide web, WWW companion* (pp. 709–710). ACM, New York, NY, USA. <https://doi.org/10.1145/2187980.2188187>.
43. Nair, M. R., Ramya, G., & Sivakumar, P. B. (2017). Usage and analysis of twitter during 2015 Chennai flood towards disaster management. *Procedia Computer Science*, 115, 350–358. <https://doi.org/10.1016/j.procs.2017.09.089>. In *7th International conference on advances in computing & communications, ICACC-2017*, 22–24 August 2017, Cochin, India.
44. Neppalli, V. K., Caragea, C., Squicciarini, A., Tapia, A., & Stehle, S. (2017). Sentiment analysis during hurricane sandy in emergency response. *International Journal of Disaster Risk Reduction*, 21, 213–222. <https://doi.org/10.1016/j.ijdrr.2016.12.011>. <http://www.sciencedirect.com/science/article/pii/S2212420916302151>.
45. Neubaum, G., Rosner, L., von der Putten, A. M. R., & Kramer, N. C. (2014). Psychosocial functions of social media usage in a disaster situation: a multi-methodological approach. *Computers in Human Behavior*, 34, 28–38. <https://doi.org/10.1016/j.chb.2014.01.021>.
46. Nilsen, L. G., Hafstad, G. S., Staksrud, E., & Dyb, G. (2018). Five reasons for using social media among young terror survivors: results from the utøya study. *Computers in Human Behavior*, 84, 285–294. <https://doi.org/10.1016/j.chb.2018.03.006>.
47. Nolen-Hoeksema, S., & Morrow, J. (1991). A prospective study of depression and posttraumatic stress symptoms after a natural disaster: the 1989 Loma Prieta earthquake. *Journal of personality and social psychology*, 61, 115–121. <https://doi.org/10.1037/0022-3514.61.1.115>.
48. Norris, F., Galea, S., Friedman, M., & Watson, P. (Eds.). (2006). *Methods for disaster mental health research*. New York: Guilford Publications.
49. Pasupathi, M. (2003). Emotion regulation during social remembering: differences between emotions elicited during an event and emotions elicited when talking about it. *Memory*, 11(2), 151–163. <https://doi.org/10.1080/741938212>. (PMID: 12820828).
50. Plutchik, R. (2001). The nature of emotions. *American Scientist*, 89(4), 344–350.
51. Pourebrahim, N., Sultana, S., Edwards, J., Gochanour, A., & Mohanty, S. (2019). Understanding communication dynamics on twitter during natural disasters: a case study of hurricane sandy. *International Journal of Disaster Risk Reduction*, 37, 101176. <https://doi.org/10.1016/j.ijdrr.2019.101176>.
52. Prastowo, E. Y., Endroyono, & Yuniarno, E. M. (2019). Combining sentiment strength and multilayer perceptron in twitter sentiment classification. In *2019 International seminar on intelligent technology and its applications (ISITIA)* (pp. 381–386).
53. Seligman, M., & Csikszentmihalyi, M. (2000). Positive psychology: an introduction. *American Psychologist*, 55, 5–14. <https://doi.org/10.1037/0003-066X.55.1.5>.

54. Shaluf, I. M., Ahmadun, F., & Said, A. M. (2003). A review of disaster and crisis. *Disaster Prevention and Management: An International Journal*, 12(1), 24–32. <https://doi.org/10.1108/09653560310463829>.
55. Shalunts, G., Backfried, G., & Prinz, P. (2014). Sentiment analysis of german social media data for natural disasters. In *ISCRAM*.
56. Shi, H., & Shi, L. (2014). Identifying emerging motif in growing networks. *PLoS One*, 9(6), 1–12. <https://doi.org/10.1371/journal.pone.0099634>.
57. Spence, P. R., Lachlan, K. A., Lin, X., & del Greco, M. (2015). Variability in twitter content across the stages of a natural disaster: implications for crisis communication. *Communication Quarterly*, 63(2), 171–186. <https://doi.org/10.1080/01463373.2015.1012219>.
58. Sutton, J., & Shklovski, I. (2008). Backchannels on the front lines: emergent uses of social media in the 2007 southern California wildfires. In *Proc. of the 5th international ISCRAM conference, ISCRAM'08*.
59. Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational Linguistics*, 37(2), 267–307.
60. Takahashi, B., Tandoc, E. C., & Carmichael, C. (2015). Communicating on Twitter during a disaster: an analysis of tweets during Typhoon Haiyan in the Philippines. *Computers in Human Behavior*, 50, 392–398. <https://doi.org/10.1016/j.chb.2015.04.020>. <http://www.sciencedirect.com/science/article/pii/S0747563215003076>.
61. Thelwall, M., Buckley, K., Paltoglou, G., D., C., & Kappas, A. (2010). Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, 61, 2544–2558.
62. Topirceanu, A., Duma, A., & Udrescu, M. (2016). Uncovering the fingerprint of online social networks using a network motif based approach. *Computer Communications*, 73, 167–175.
63. Topirceanu, A., & Udrescu, M. (2017). Statistical fidelity: a tool to quantify the similarity between multi-variable entities with application in complex networks. *International Journal of Computer Mathematics*, 94(9), 1787–1805. <https://doi.org/10.1080/00207160.2016.1247437>.
64. Tran, N. T. L., DeLuccia, L., McDonald, A. F., & Huang, C. H. (2015). Cross-disciplinary detection and analysis of network motifs. *Bioinformatics and Biology Insights*, 9, BBI.S23619. <https://doi.org/10.4137/BBI.S23619>.
65. Varol, O., Ferrara, E., Davis, C., Menczer, F., & Flammini, A. (2017). Online human-bot interactions: detection, estimation, and characterization. In *Proc. of the international AAAI conference on web and social media*.
66. Verger, P., Rotily, M., Hunault, C., Brenot, J., Baruffol, E., & Bard, D. (2003). Assessment of exposure to a flood disaster in a mental-health study. *Journal of Exposure Analysis and Environmental Epidemiology*, 13, 436–442.
67. Vieweg, S., Hughes, A.L., Starbird, K., & Palen, L. (2010). Microblogging during two natural hazards events: what Twitter may contribute to situational awareness. In *Proc. of the SIGCHI conference on human factors in computing systems, CHI '10* (pp. 1079–1088).
68. Wang, Z., Lam, N. S., Obradovich, N., & Ye, X. (2019). Are vulnerable communities digitally left behind in social responses to natural disasters? An evidence from hurricane sandy with Twitter data. *Applied Geography*, 108, 1–8. <https://doi.org/10.1016/j.apgeog.2019.05.001>.
69. Wernicke, S. (2006). Efficient detection of network motifs. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 3(4), 347–359.
70. Yang, Y., Zhang, C., Fan, C., Yao, W., Huang, R., & Mostafavi, A. (2019). Exploring the emergence of influential users on social media during natural disasters. *International Journal of Disaster Risk Reduction*, 38, 101204. <https://doi.org/10.1016/j.ijdrr.2019.101204>.
71. Yeger-Lotem, E., Sattath, S., Kashtan, N., Itzkovitz, S., Milo, R., Pinter, R. Y., et al. (2004). Network motifs in integrated cellular networks of transcription–regulation and protein–protein interaction. *Proceedings of the National Academy of Sciences*, 101(16), 5934–5939. <https://doi.org/10.1073/pnas.0306752101>. <http://www.pnas.org/content/101/16/5934>.
72. Zhao, Q., Tian, Y., He, Q., Oliver, N., Jin, R., Lee, & W.C. (2010). Communication motifs: a tool to characterize social communications. In *Proc. of the 19th ACM International Conference on Information and Knowledge Management* (pp. 1645–1648).