Building blocks of communication networks in times of crises: 
Emotion-exchange motifs

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ABSTRACT

In this paper, we discuss how emotional messages sent during crisis events shape the communication patterns on Twitter. To this end, we analyzed a data-set consisting of 23.3 million tweets that have been sent during eighteen different crisis events in ten different countries. In particular, we use the novel concept of emotion-exchange motifs to uncover the elementary building blocks of complex emotion-exchange networks. Our results show that not all negative emotions are exchanged in the same way, nor do they result in the same communication structures. For example, we found that there is a specific set of emotions which are sent in response to messages including sadness and disgust (e.g., sadness attracts joy/love, while disgust attracts anger). The exchange of fear, on the other hand, is highly representative for its reciprocity and is highly associated with an information seeking behavior. We also found that the expression of positivity is characteristic for the emergence of a cyclic triad communication pattern. In contrast, the exchange of negative emotions is characteristic for a triadic communication structure that not only shows a broadcasting behavior but also reciprocity. Compared to single-emotion exchanges within a triadic pattern, the exchange of a mixture of emotions leads to more complex communication structures.

1. Introduction

Emotional content shared via online social networks (OSNs) has the potential to influence public response and, subsequently, human actions. Recent studies have shown that messages sent via OSNs trigger emotions in their recipients (Zeng & Zhu, 2019) which influence the readers to further disseminate a message (Stieglitz & Dang, 2013; Wang, Zhang, Lin, Zhao, & Hu, 2016), engage in a public discussion, or publicly promote the message by endorsing it with “likes”. Wang et al. (2016) and Starbird, Maddock, Achterman and Mason (2014) showed that messages conveying intense negative emotions (such as panic or anger) may lead to negative aftereffects for individuals or groups of people. One such example was observed during the 2013 Boston marathon bombing when a man was falsely identified as the bomber on Twitter (Starbird, Maddock, Orand, Achterman, & Mason, 2014).

In general, the term crisis is used in a wide variety of different events, including human-made crises (e.g., terrorism, riots, shootings), natural disasters, organizational crises, technological crises (e.g., software failure, industrial accidents), or humanitarian crises (Farazmand, 2016; Lerbiinger, 1997; Seeger, Sellnow, & Ulmer, 1998), all of which can be described as sudden and threat-posing (Shaluf, Ahmadv, & Said, 2003), as well as traumatic. Norris, Galea, Friedman and Watson (2006) indicated that crisis events are most often experienced collectively. In this context, the information available on OSNs influences people’s attitude and behavior (Bakker, van Bommel, Kerstholt, & Giebels, 2018), and, according to Sutton and Shklovski (2008), triggers the human need for information dissemination and conversation.

Darling (1994) indicated that crisis events cause intense feelings of fear, panic, danger, and shock. Thus, the expression of emotions during crisis events can be seen as a therapeutic mechanism and can foster a person’s well-being (Neubaum, Rosner, von der Putten, & Kramer, 2014). Moreover, while sharing of negative emotions (such as sadness and fear) serves as a coping and bonding mechanism, expression of positive emotions (such as love and relief) helps reduce anxiety and increase an overall feeling of hope, compassion, and gratitude (Guo, 2017; Folkman & Moskowitz, 2000; Fredrickson, Tugade, Waugh, & Larkin, 2003; Kim & Niederdeppe, 2013; Kusen, Strembeck, Cascavilla, & Conti, 2017, Kusen, Strembeck, & Conti, 2019).

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Given the wide range of emotions expressed during crisis events that were reported in the literature, we thoroughly examined emotions communicated by Twitter users during three types of crisis events: natural disasters, shootings and terror attacks, as well as riots. The main contribution of this paper is the systematic identification of communication patterns that emerge as Twitter users exchange messages that convey eight basic emotions (anger, fear, sadness, disgust, joy, trust, anticipation, surprise). In particular, the analysis presented in this paper extends prior studies (Kusen & Streembeck, 2019, Kusen & Streembeck, 2020) by examining the temporal evolution of emotion-exchange motifs and by identifying commonalities as well as differences of emotional communication patterns that emerge in different types of crisis events.

For our analysis, emotional message-exchanges among Twitter users are modeled as weighted and directed networks, with vertices representing users and labeled edges representing emotion-conveying messages. We can then use the labeled edges to infer the semantics of the corresponding communication relations. For example, depending on the message direction and the type of emotions that is being conveyed, one can identify users who engage in a heated dispute or emotionally support each other.

By following the communication traces, we identify emotion-exchange motifs (Kusen & Streembeck, 2019, Kusen & Streembeck, 2020) and reveal the roles emotion-exchange motifs play in a network. Emotion-exchange motifs are an extension of network motifs, a concept introduced by Milo et al. (2002) to study the underlying patterns of complex networks. In general, a network motif is a recurring subgraph that appears in a network with a higher frequency than in a similar synthetic network (also called a null model) (Milo et al., 2002).

The remainder of this paper is organized as follows. In Section 2 we provide an overview of related work, followed by a description of our research method in Section 3. Section 4 reports on our findings. A discussion on the results is given in Section 5. We conclude the paper and provide directions for future work in Section 6.

2. Related work

2.1. Communication during crisis events

Over the past years, multiple studies have focused on the role of OSNs in situational awareness during various crisis events. For example, studies have been conducted on hurricane Sandy (Pourrebramih, Sultan, Edwards, Gochanour, & Mohanty, 2019), the South East Queensland flood (Kankanamge, Yigiclanar, Goonetilleke, & Kamruzzaman, 2020), the 2016 Berlin terrorist attack (Fischer-Pirell, Schwemmer, & Fischbach, 2019), and the H1N1 outbreak (Chew & Eysenbach, 2010).

Takahashi, Tandoc, and Carmichael (2015) reported that people predominantly tweet information from secondhand sources, followed by messages of support and prayer, as well as messages for the coordination of relief efforts. Sharing of informative messages, individual interpretation of information, joint finding of missing pieces of information, as well as group discussions during crisis events are generally regarded as means of filling cognitive gaps and a collective sense-making process (Maitlis & Christianson, 2014; Weick, 1988).

As pointed out by Fischer-Pirell et al. (2019) and Chew and Eysenbach (2010), the topics discussed and broadcasted during crisis events differ over time. For example, during the 2016 Berlin terrorist attack, messages of sympathy, prayer, togetherness, and sense-making were predominantly shared during the first days of the event, while the following days involved messages that express nationalism and less tolerance against certain ethnic groups (Fischer-Pirell et al., 2019). During the H1N1 outbreak, Chew and Eysenbach (2010) found that humor, concern, and questions about the virus were the most common content of a tweet, while tweets conveying personal experiences became more dominant as the event progressed. When studying OSN usage during the 2011 terrorist attack in Utøya, Norway, Nilsen, Hafstad, Staksrud, and Dyb (2018) found that information exchange, social support, mourning, symbolic actions (e.g., setting a Norwegian flag as a profile picture), and discussion about the attack were most common among the ones affected. Li, Vishwanath, and Rao (2014) found that the focus of public concerns shifts over time. By analysing the concerns about the 2011 earthquake and the nuclear disaster in Fukushima, Japan, the authors identified a concern about the dead and the missing as well as the devastation caused by the tsunami and the earthquake at the beginning of the crisis event. This was later surpassed by an intense concern about the radiation emitting from the damaged nuclear plant which eventually resulted in public fear and a danger of a public meltdown.

As the aforementioned studies illustrate, sense-making is a highly emotional process and affected individuals share intense emotions via OSN messages. Such messages do not only influence the sender but also the emotional state of the collective (Cornelissen, Maniere, & Vaara, 2014). Two examples that illustrate the adoption of an emotional state by a collective of people are given in (Guo, 2017) and (Kwan, 2016). Guo (2017) showed that many people echoed the emotional tone of previously posted comments during the 2013 Boston marathon bombing, while Kwan (2016) reported on the collective use of the hashtag #JeSuisCharlie (“I am Charlie”) to signal the support and the notion of togetherness in the immediate aftermath of the 2015 shooting at the offices of Charlie Hebdo (a French satirical magazine).

Even though the topics that emerge on OSNs depend on the particularities of a crisis event (see, e.g. (Sayed, AbdelRahman, Bahgat, & Fahmy, 2016)), similarities can be drawn from various crisis events with respect to the responses of those affected. One such similarity refers to the emotions and sentiments expressed during a crisis event and in its immediate aftermath.

While studying human responses to the 2011 disaster in Fukushima, Doan, Vo, and Collier (2012) detected a high level of anxiety expressed on Twitter in the immediate aftermath of the crisis event. As pointed out by the authors, people especially expressed their concern about the victims and the well-being of their family members followed by worries about the radiation emitting from the damaged nuclear plant. In addition to the high intensity of negative emotions during crisis events, positive emotions play an important role in human coping strategies. Messages that convey positive emotions, such as those that express prayers, hope, or gratitude, emerge as a stress reduction mechanism. For instance, Shan, Zhao, Wei, and Liu (2019) examined the sentiments sent during the Tianjin explosion and typhoon Nepartak in China. They observed an increased emotional reaction as the two events occurred, while positive sentiments (conveyed in messages of prayer and support) were consistently more dominant than the negative ones (panic, fear, shock). Moreover, Guo (2017) showed that people expressed both positive and negative emotions in the aftermath of the 2013 Boston marathon bombing, with the positive ones eventually prevailing over the negative ones.

Prior studies also showed that sentiment expression may depend on spatial characteristics (Chen, Mao, Li, Ma, & Cao, 2020; Kankanamge et al., 2020). In one such study (Chen et al., 2020) showed that victims in the areas affected by hurricane Harvey expressed overall more positive tweets than those further away from the disaster, while Kankanamge et al. (2020) reported on a different observation. Upon studying human responses to the 2010–2011 South East Queensland flood, the authors found that those who live in hilly areas and were not hit by the flood generally expressed a more positive sentiment than those who were directly affected.

2.2. Application of network motifs in studying OSN communication patterns

Network motifs have been applied to study the underlying structure of various types of networks, such as co-authorship networks (Yeger-Lotem et al., 2004), protein-protein interaction networks (Alon, Dao, Hajirasouliha, Hormozdiari, & Sahinalp, 2008), or animal networks.
A being a follower of B). For instance, A replies to and follows B was identified as a characteristic non-controversial topics structurally differs from the controversial ones. In the context of emotional direct messages, we report on the conversations man-made crisis events (riots, terror, shootings) (Kuˇsen et al., 2012) and showed that while some motifs are characteristic for the communication via Facebook wall postings and identified star motifs as the representative form of motifs for Facebook wall communication.

Coletto, Gionis, and Lucchese (2017) identified network motifs to characterize discussions on controversial as well as non-controversial topics by considering two types of network edges: “follows” and “replies to”. They found that the discussion of non-controversial topics structurally differs from the controversial ones. For instance, A replies to and follows B was identified as a characteristic dyadic pattern in a discussion of non-controversial topics while controversial topics showed a high occurrence of A replies to B (without A being a follower of B).

Paranjape, Benson, and Leskovec (2017) studied the flow of messages via temporal-motifs. In their study, so-called blocking motifs represent a type of communication in which a node has to wait for a response before the message exchange can continue. Such motifs were shown to be more representative for the communication via Facebook wall postings than for an email network.

With respect to the study of patterns that emerge during emotional message-exchange on OSNs, related work remains rather limited. In our previous work, we examined the role of emotion-exchange motifs during man-made crisis events (riots, terror, shootings) (Kusen & Strembeck, 2019, Kusen & Strembeck, 2020) and natural disasters (Kusen & Strembeck, 2020) and showed that while some motifs are characteristic for a Twitter-like communication in general (message broadcasting and message receiving), others are characteristic for the communication of positive or negative emotions. For instance, specific chain motifs are formed exclusively when users exchange positive messages of hope, gratitude, and love.

3. Research procedure

3.1. Research questions

This paper aims to address the following research questions.

● RQ1: Which emotions are expressed at various stages of the three types of crisis events (natural disasters, shootings/terror attacks, and riots)?

We explore the presence and the intensities of each of the eight basic emotions defined by Plutchik (2001) and examine their temporal flow during the data-extraction period.

● RQ2: Which emotions are exchanged as Twitter users send direct messages (DM)?

The second question focuses on the emotions that are conveyed in messages directly exchanged between Twitter users (i.e., in contrast to broadcast messages). As indicated by Miyabe, Miura, and Aramaki (2012), Twitter users who primarily exchange direct messages are usually physically present in the area struck by the respective crisis event (in contrast, those in remote areas prefer to tweet). To better understand the context of emotional direct messages, we report on the conversational topics associated with each emotion.

● RQ2.1: Which structures are characteristic for the direct exchange of specific emotions?

We identify emotion-exchange motifs as users exchange emotional messages and show their temporal occurrence, variability with respect to their edge distribution, and their size (message-exchange frequency). We focus on identifying motifs that are representative for the communication of sadness, anger, fear, joy, anticipation, disgust, trust, and surprise, as well as combinations of these emotions. We subsequently refer to the topics associated with each emotion in order to enable a contextualized interpretation of emotion-exchange motifs.

3.2. Research phases

Our research procedure comprises seven phases, as shown in Fig. 1.

3.2.1. Phase 1: data extraction and pre-processing

We used Twitter’s Search API to extract publicly available tweets that have been sent during the crisis events in our study (as described in Appendix A). To extract the relevant tweets, we monitored Twitter and systematically selected a set of hashtags and key-terms associated with each crisis event. The extraction procedure started with the day the event occurred and stopped one to two weeks after the event started (depending on the number of messages about the event on Twitter). After collecting the raw data, we removed duplicate entries and those that were uninformative with respect to emotion detection (such as tweets that only contained a URL). Our final data-set included 23,308,071 tweets (see Table 1) that went into the second phase.

3.2.2. Phase 2: Emotion labelling

After pre-processing the initial data-set, we applied our emotion detection procedure (see Kuˇsen, Cascavilla, Figl, Conti, & Strembeck (2017)) which determines the presence and the intensity of eight basic emotions found in Plutchik’s wheel of emotions (Plutchik, 2001). Our algorithm uses the NRC emotion-word lexicon (Mohammad & Turney, 2013) to identify the presence of a particular emotion and the AFINN lexicon to boost or decrease the intensity of an affect (Hansen, Arvidsson, Nielsen, Colleoni, & Etter, 2011). Apart from these lexica, we also applied a set of heuristics that people naturally use to detect emotions in written texts (Taboada, Brooke, Tofiloski, Voll, & Stede, 2011) including amplifiers, maximizers, downtoners, and negation. Moreover, the algorithm also considers features characteristic for OSN messages (especially emotions and common abbreviations). Our algorithm has been designed to run on multiple CPU cores and thereby parallelizes the emotion detection procedure.

To test the accuracy of our procedure, we deployed two independent human raters who have no personal attachment to any of the crisis events studied in this paper. Their task was to assign 0 – emotion not detected, 1 – emotion detected, or 2 – unsure to a sample of 150 tweets (50 randomly selected unique tweets for each type of crisis event from a subset of our data-set that includes directed messages only (n = 1,396,709 tweets)1). Upon annotating the tweets, the raters reached a substantial inter-rater agreement (Cohen Kappa 0.71) and after resolving discrepancies between the two raters, we computed the F-score measure for each emotion, achieving 0.84 for anger, 0.84 for joy, 0.73 for fear, 0.68 for sadness, 0.67 for anticipation, 0.62 for disgust, 0.61 for trust, and 0.50 for surprise.2

1 We chose this particular subset because our subsequent analysis predominantly relies on the directed messages.
2 The accuracy score for surprise is lower compared to the remaining emotions due to the relatively low number of tweets whose dominant emotion is surprise. Moreover, the score is also influenced by the ambiguity of surprise. It is neither a negative nor a positive emotion per se, and its interpretation highly depends on the context of a tweet. Moreover, surprise does not greatly influence our final results since our emotion-exchange motifs predominantly focus on individual positive and negative emotions, as well as their combination.
3.2.3. Phase 3: construction of the direct messaging network

On Twitter, each user can directly communicate with another user via mentioning him/her (@ symbol followed by the recipient’s screen-name). Based on such @-traces, we reconstructed a directed messaging (DM) network for each event. We allow for the presence of multiple edges (i.e., a user can send multiple messages to another user) and self-loops (i.e., a user can mention him or herself in a tweet). Moreover, we label each edge according to its dominant emotion (anger, fear, sadness, disgust, joy, trust, anticipation, or surprise).

3.2.4. Phase 4: construction of a multiplex network

Next, we derived one multiplex network for each day of the data extraction period. Each daily multiplex network consists of eight layers, and each of these layers represents one of the eight basic emotions. In order to gain more insight concerning the interlayer dependencies, we do not only consider individual emotion layers (see Fig. 2a) but also various derived layers. These derived layers are: 1) a negative layer which includes the edges found on the four negative emotion layers (anger, fear, disgust, and sadness), 2) a positive layer which includes the edges found on the three positive emotion layers (joy, anticipation, and trust) (see Fig. 2b). In addition, we derived a valence interlayer which captures the vertices that are active on both aggregated valence-specific layers (positive layer and negative layer) as well as their adjacent vertices that are active on the two aggregated valence layers (as shown in Fig. 2c).

Finally, we also aggregated all positive- and negative-emotion layers as well as surprise to derive the overall aggregated network (Fig. 2d) for each day.

3.2.5. Phase 5: null model construction

A general procedure to detect motifs is to identify characteristic subgraphs in the real-world network and compare them to the subgraphs found in synthetically generated networks that resemble the real-world network, so-called null models. For our motif detection procedure, we generated null models for each of the daily real-world multiplex networks by using the stub-matching algorithm. This algorithm uses the concept of stubs defined as “sown-off arrow heads” (or dangling edges), which are rewired so that the synthetically generated network preserves the degree sequence of the corresponding real-world network (Newman, Strogatz, & Watts, 2001). In total, we generated 1000 null models for each of the 8 multiplex layers and the 4 derived layers for each day of each crisis event, resulting in 2,964,000 null models in total.

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3 Note that for this procedure we removed the retweets from our data-set.
4 A self-loop is a mechanism commonly used by Twitter users to extend the content of their tweet and by-pass the character restriction.
5 Note that “surprise” can be associated to positive as well as negative emotions and is therefore treated separately.
3.2.6. Phase 6: Motif detection

In order to detect emotion-exchange motifs, we performed an exact enumeration of all possible subgraphs of a pre-defined size $k$ (in our case $k=3$) in the network by using the ESU subgraph enumeration algorithm (Wernicke, 2006). Next, we performed an isomorphism test for the different subgraphs by applying the VF2 algorithm (Cordella, Foggia, Sansone, & Vento, 2004). Since isomorphism testing for each pair of subgraphs is regarded a general bottleneck when performing an exact motif detection (in contrast to approaches that estimate or count the number of motifs), we categorized the subgraphs according to their degree sequence to test the set of possible candidates for isomorphisms (again, the procedure was designed to use multiple CPU cores in parallel to speed up the process). Algorithm 1 provides a detailed specification of our motif detection procedure.

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 i in list_layers do
7     subgraphs = end();
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            end
15        end
16    end
17 end
18 # GENERATE LAYERS AND INTER-LAYERS
19 detect layers in input_network
20 layer_negative.add_edges_from([layer_anger, layer_sadness, layer_disgust, layer_fear])
21 layer_positive.add_edges_from([layer_joy, layer_anticipation, layer_trust])
22 foreach i in range(length(input_network)) do
23    if i in [V(layer_negative) & V(layer_positive)] then
24        inter_layer.add_edges_from([layer_negative.edge_containing(v), layer_positive.edge_containing(v)])
25    end
26 end
27 list_layers = [layer_anger, layer_joy, .., layer_sadness, layer_disgust, layer_fear, layer_positive, layer_interlayer, input_network]
28 esu_vf2(list_layers)
29 # GENERATE NULL MODELS
30 while i < 1000 do
31    foreach l in list_layers do
32        null(l) = matching(l.in_degree(), l.out_degree())
33    end
34    esu_vf2(null)
35    i = i + 1
36 end
```

Finally, we mapped each simplified emotion-exchange motif found in the input (real-world) networks to one of the thirteen possible 3-node

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6 Here, a “simplified emotion-exchange motif” is one that disregards self-loops and multi-edges.
directed subgraph classes.

The emotion extraction and motif detection procedures have been performed on four different machines: a machine with Intel Xeon CPU E3-1240 v5 @ 3.5 GHz (4 cores) and 32 GB RAM, a machine with 2x Intel Xeon E5-2630 v3 @ 2.4 GHz (16 cores) and 288 GB RAM, a machine with 2x Intel Xeon E5-2630 v4 @ 2.2 GHz (20 cores) and 256 GB RAM, as well as a machine with 2x AMD Epyc 7541 @ 2.3 GHz (48 cores) and 512 GB RAM. On these machines the emotion extraction and motif identification procedures for all 18 events took in total about 435 days and produced 8 terabyte of data to analyze.

3.2.7. Phase 7: Motif analysis

For each of the events in our study, we identified the topics that are associated with each basic emotion in order to better understand what people talk about as they exchange emotional messages and what type of a communication the emotion-exchange motifs represent (see Appendix B).

Since our data-set counts over 1.3 million direct message exchanges, we deployed a machine-assisted topic modeling approach for this task rather than human coders. In particular, we used the R package for structural topic models (Roberts, Stewart, & Tingley, 2019). In structural topic modeling, each topic is regarded as a mixture of words, and each word belongs to a topic with a certain probability. By definition, each document (i.e., tweet) is therefore a mixture of topics. Since tweets have a limited number of characters (up to 280 since November 2017) and due to our focused data-extraction, we expected that predominantly one main topic will arise for each document (tweet). We first cleaned the data-set from common stopwords and punctuation. Next, we applied the structural topic model over the data-set and tested for a pre-defined k number of topics, where k was set to 10, 20, 30, and 40 if the number of messages exchanged per basic emotion layer exceeded 100 messages, and 5, 10, and 15 if the number of messages was up to 100. We then evaluated the resulting models by applying statistical analysis and qualitative validation.

For the statistical analysis, we applied the semantic coherence and exclusivity measures. The semantic coherence score is higher if more probable words in a topic frequently occur together, while exclusivity is higher if words are exclusive to the topic (Roberts et al., 2019). As recommended in (Roberts et al., 2019), we also manually inspected a random sample of tweets and their automatically assigned topics as well as words that are associated to a sample of topics. Upon finding a model that fit our purposes, we mapped the topics to the categories adapted from an empirically derived set of human reactions to terror attacks (see Terror Management Theory (TMT) in (Yum & Schenck-Hamlion, 2005)) and (Greenberg, Pyszczynski, & Solomon, 1986); (Nilsen et al., 2018), (Woods, 2011)), natural disasters (see (Liu, Lai, & Xu, 2018; Takahashi et al., 2015)), and riots (see (Jasper, 1998)). In total, we mapped the 228 resulting topics\(^7\) into eight main first-level categories and 28 subcategories (see Appendix B).

For the qualitative validation of the topic models, we asked two human raters to independently assign a given list of possible topics to a randomly selected sample of 57 tweets (we selected 25% of the tweets assigned to the overall number of topics by the stm package). The raters reached a strong inter-rater reliability (Cohen kappa = 0.88). The raters later discussed and resolved the remaining discrepancies. Upon reaching a consensus over the tweet-topic assignment, we checked for the agreement between the rater-assigned labels and the labeling provided by the topic modeling algorithm and also reached a strong reliability (Cohen Kappa = 0.81).

4. Results

4.1. Emotions expressed during crisis events

During the three types of crisis events, the emotions of fear, anger, and sadness have been dominantly expressed on Twitter. This empirical finding is in line with the theoretical framework called the Integrated Crisis Mapping (ICM) model proposed by Jin (2009). The ICM identifies emotions that are publicly experienced during various types of crisis events and that serve as the coping strategy of the ones affected. According to the ICM, fear and sadness are dominant emotions during natural disasters, sadness and fear during shootings and terror attacks, as well as anger and fear during riots. We can largely confirm these findings. In our data-set, we found that the average emotional intensities (ei) of fear (ei = 0.24) and sadness (ei = 0.14) dominate over the remaining emotions during natural disasters, anger (ei = 0.18) and fear (ei = 0.22) during riots, and fear (ei = 0.29) and anger (ei = 0.19) during shootings and terror attacks (see also Fig. 3).

Emotions expressed during individual events show a moderate to strong correlation (Kendall’s τ) with respect to their intensities. This indicates that the emotional communication is consistent and similar among individual events of the same type of crisis (as shown in Fig. 4).

As shown in Fig. 5-a, emotions fluctuate over time. During all three types of crisis events, fear is dominant in the first couple of days and slowly decreases its intensity towards the end of the data-extraction period. Eventually, other negative emotions such as sadness (natural disasters) and anger (riots), or positive emotions such as trust (riots, shooting, and terror attacks) become stronger than fear. Upon aggregating positive emotions (joy, trust, anticipation) and negative emotions (sadness, fear, anger, disgust), we observe that the intensity of positive emotions closely follows the overall intensity of negative emotions throughout the data-extraction period. For short time-frames in the data-extraction period, positive emotions dominate over the negative ones. While comparing the discrete points representing the daily intensities of aggregated positive and aggregated negative emotions, we found that positive emotions are only occasionally more intense than the negative ones (for shootings and terror attacks 4 days, riots 3 days, natural disasters no such day was found) and this usually happens towards the end of the data-extraction period when the initial shock and anger have been subdued. However, although the positive emotions peak over the negative ones only occasionally throughout the crisis events, they closely follow the negative emotions (distance between the negative and positive emotions dp(naturalDisasters) = 0.002, dp(shootings) = 0.004, dp(riots) = 0.003).

4.1.1. Analysis of directed messages

By following the @-traces in our data-set, we re-constructed a direct messaging (DM) network for each of the 18 crisis events. In total, our data-set counts over 1.3 million directed messages (see Table 1).

As shown in Fig. 3, emotions expressed in direct messages are comparable to the ones expressed in the data-set excluding the DM messages and exhibit a strong Kendall’s rank coefficient τ throughout the data-extraction period (during the first two days τ(natural disasters) = 0.928, τ(riots) = 0.927, τ(shooting and terror attacks) = 0.930, while for the remaining data-extraction period τ(natural disasters) = 0.857, τ(riots) = 0.928, and τ(shooting and terror attacks) = 0.857). Fear is again the dominant emotion in the first couple of days of the data-extraction period and is later passed by anger (riots, terror, and shooting attacks), trust (riots, terror, and shooting attacks), and sadness (natural disasters) (see Fig. 5-b).

Compared to broadcast messages, we found that positive emotions and disgust are expressed more intensely during direct messaging (DM), while broadcast messages (BM) exhibit a higher intensity of anger, fear, and sadness (see Fig. 3).

Although the overall ranking of emotional intensities is comparable, the emotions exhibit differences in their temporal fluctuation. Fig. 5-b

\(^7\) In total, we counted 228 topics identified for each of the eight single emotions in each of the 18 crisis events.
shows the emotional intensities in the DM network. When correlating
the discrete time-series points that represent the daily intensities of DM
and those that represent the daily broadcast messages, Spearman’s $\rho$
coefficient is strongly positive in all three types of crisis events (see
Table 2).

During the eighteen crisis events, Twitter users directly exchanged
messages that convey a range of topics. Our topic models indicate that
users predominantly exchange messages of altruistic and pro-social
behavior ($p(TP) = 28.98 \pm 28.41$), criticise the officials ($p(TP) = 27.51 \pm 19.53$),
and express gratitude ($p(TP) = 10.29 \pm 15.02$), and express gratitude ($p(TP) = 7.97 \pm 10.79$) (see Table 5). When
mapped to specific emotions (see Figs. 9 and 10), the exchange of anger
is associated with the expression of disapproval (e.g., towards the ac-
tections of the government or the local police ($p(TP) = 27.24$) and general
negative opinion sharing ($p(TP) = 43.56$). Similarly, disgust is expressed
in messages of disapproval ($p(TP) = 43.74$) and general opinion sharing
($p(TP) = 24.65$), but is also widely associated with hate speech ($p(TP) = 22.59$). In contrast, fear is generally conveyed in messages related to
news updates ($p(TP) = 27.66$). Sadness is expressed in messages of
sympathy ($p(TP) = 19.39$) and disapproval ($p(TP) = 44.12$).

Positive messages, such as those conveying joy, trust, and
anticipation are highly associated with words of kindness ($p(TP)_{joy} = 28.37$, $p(TP)_{trust} = 19.85$, $p(TP)_{anticipation} = 5.62$), prayers and well-
wishing ($p(TP)_{joy} = 38.70$, $p(TP)_{trust} = 30.14$, $p(TP)_{anticipation} = 44.57$). However, unlike joy, anticipation is also expressed in messages of disapproval ($p(TP) = 25.39$). Trust, in addition to prayers and well-
wishing, is also highly involved in the messages of gratitude ($p(TP) = 8.81$) and hero-praising ($p(TP) = 23.38$).

4.2. Emotion-exchange motifs

While exchanging emotional directed messages, Twitter users form
numerous communication patterns, 729,368 of which were identified as
statistically significant and representative for the communication during
crisis events (called emotion-exchange motifs). In total, we identified
1480 unique shapes (isomorphism classes) of emotion-exchange motifs
that convey multiple edges and self-loops. Upon simplifying the sub-
graphs (i.e., reducing the multi-edges to a single edge and removing all
self-loops), the 1480 subgraph shapes are represented via exactly twelve
k-3 subgraphs. Table 3 shows a summary of the simplified emotion-exchange motifs, each labeled with respect to the MAN

\footnote{p(TP) stands for the proportion of the topic model.}
As shown in Table 3, eight out of twelve identified motifs are common communication patterns. The remaining four (201, 120C, 030C, 210) are event-specific. The motifs 210, 030C, and 120C emerge only during natural disasters, while 201 appears during all three types of crises. Due to the message-broadcasting purpose of Twitter, the message-receiver motif 021U ($f = 35074.00; 729.37 \text{ per 1000 motifs}$) and the broadcasting motif 021D ($f = 4674.38; 115.36 \text{ per 1000 motifs}$) are the most frequent ones in all crisis events considered in the corresponding case studies. These two motifs also count a relatively high number of edges (ec) ($ec_{021U} = 5.53 \pm 2.52; ec_{021D} = 4.97 \pm 1.53$).

The application of emotion-exchange motifs as well as their temporal emergence revealed that the communication of seemingly similar emotions exhibit substantial differences with respect to their underlying structures.

4.2.1. Exchange of anger

The exchange of anger is high in its volume in the immediate aftermath of a crisis event, while the volume drops in the remaining period (see Fig. 6). In general, anger-exchange motifs involve a rather limited...
set of motifs with reciprocal edges (111D, 111U, 120D, 120U) whose significance in an anger-exchange is relatively low. Thus, the number of reciprocal edges per motif is only moderate (n(reanger) = 1.03). As shown in Table 4, we found that angry messages highly attract angry responses, leading to heated discussions. We also found that anger-exchange motifs contain self-loops, albeit to a small extent (n(slanger) = 0.71). The exchange of anger is also characteristic for the high presence of active message-sending nodes (apart from 021D where only one node is a message-sender, the remaining motifs contain multiple active nodes – two active nodes in 021U, 021C, 030T, 111U, and 120U; three active nodes in 111D and 120D).

| ID  | Shape | Frequency  | Prevalence  | Variability | Edge count | Occurrence |
|-----|-------|------------|-------------|-------------|------------|------------|
| 021U|       | 596258     | 729.37      | 54.35 ± 73.97 | 5.53 ± 2.52 | 17         |
|     |       | (35074.00 ± 58538.54) | | | | |
| 021D|       | 84139      | 115.36      | 40.94 ± 56.56 | 4.97 ± 1.53 | 18         |
|     |       | (4674.38 ± 7756.13) | | | | |
| 021C|       | 25640      | 35.15       | 26.12 ± 50.12 | 3.76 ± 0.84 | 17         |
|     |       | (1508.23 ± 3303.97) | | | | |
| 030T|       | 13240      | 18.15       | 37.94 ± 74.29 | 4.09 ± 1.07 | 17         |
|     |       | (778.82 ± 1518.81) | | | | |
| 111D|       | 4621       | 6.33        | 12.83 ± 27.53 | 3.88 ± 0.86 | 12         |
|     |       | (385.08 ± 872.08) | | | | |
| 111U|       | 3785       | 5.18        | 9.07 ± 18.29  | 3.54 ± 0.56 | 14         |
|     |       | (270.35 ± 556.35) | | | | |
| 120U|       | 997        | 1.37        | 4.46 ± 5.97   | 4.42 ± 0.39 | 14         |
|     |       | (76.69 ± 124.78) | | | | |
| 120D|       | 572        | 0.78        | 7.00 ± 13.45  | 4.51 ± 0.62 | 9          |
|     |       | (63.55 ± 134.78) | | | | |
| 201 |       | 60         | 0.08        | 4.25 ± 5.19   | 4.45 ± 0.58 | 4          |
|     |       | (15.00 ± 16.02) | | | | |
| 120C|       | 31         | 0.04        | 5.50 ± 3.53   | 4.68 ± 0.26 | 2          |
|     |       | (15.50 ± 16.26) | | | | |
| 030C|       | 19         | 0.03        | 3.00 ± 0.83   | 3.64 ± 0.9  | 2          |
|     |       | (9.50 ± 2.12) | | | | |
| 210 |       | 6          | 0.008       | 1.50 ± 0.71   | 5.12 ± 0.18 | 2          |
|     |       | (3.00 ± 1.41) | | | | |
| 300 |       | 0          | –           | –            | –           | 0          |
4.2.2. Exchange of fear

Compared to the anger-exchange motifs, fear-exchange motifs are relatively small in volume ($n(e_{\text{fear}}) = 61.10$ vs. $n(e_{\text{anger}} = 208.78$)), contain a high number of reciprocal edges ($n(re_{\text{fear}}) = 1.83$), and are characteristic for the high presence of self-loops ($n(sl_{\text{fear}}) = 1.66$). The set of motifs involved in the exchange of fear is identical to the ones when exchanging anger but with clear distinctions in their significance profiles (SPs) (importance of a motif in a network) and in the temporal emergence of motifs that contain reciprocal edges. As shown in Fig. 7, motif 111D ($A \leftrightarrow B \leftarrow C$) is highly representative for the exchange of fear.

4.2.3. Exchange of sadness and disgust

The exchange of sadness and disgust largely differ from the exchange of anger and fear. While the motifs 120D and 120U were characteristic for the exchange of anger and fear, these two motifs are not representative for the exchange of sadness or disgust. Moreover, while anger and fear were characteristic for a greater fluctuation and a wider range of motifs (as shown in Fig. 8), sadness and disgust exhibit a strict dominance of the message-receiver motif 021U throughout the entire data-extraction period for the exchange of disgust and sadness. The volume of motifs remains low for the subsequent days of the extraction period in both networks. Disgust- and sadness-exchange networks show a high importance of motif 021D, followed by 021C (disgust), 021U (disgust, sadness), 030T (disgust), while the remaining motifs (esp. bidirectional motifs 111D, 111U) are still representative, albeit less important (see Fig. 7).

4.2.4. Exchange of joy, trust, and anticipation

Compared to negative emotions, positive emotion-exchange networks exhibit an even larger distinction in their intra-valence class. Neither of the three positive emotion-exchange networks show comparable properties with respect to the underlying motifs. While joy-
exchange motifs are relatively moderate in their volume ($n_{\text{joy}} = 109.56$), trust-exchange motifs are large ($n_{\text{trust}} = 476.19$), and anticipation also forms a small volume of motifs ($n_{\text{anticipation}} = 51.40$). Anticipation-exchange motifs convey a high presence of reciprocal edges ($n_{\text{reciprocal}} = 1.31$), while joy- and trust-exchange motifs a small number of reciprocal edges ($n_{\text{reciprocal}} = 0.17$; $n_{\text{reciprocal}} = 0.66$). However, although reciprocal edges occur in a limited set of motifs compared to motifs including asymmetric edges, the motifs including reciprocal edges are of a relatively high importance (i.e., according to their SPs, anticipation-exchange motifs exhibit a high importance of 120U and 111D while 111U is the most significant motif for the exchange of trust, see Fig. 7).

With respect to the evolution of the subgraph volume over time, joy- and anticipation-exchange motifs exhibit a similar temporal flow with a peak towards the end of the data-extraction period and a relatively low volume in the remaining data-extraction period (see Fig. 6). Trust, on the other hand, is characteristic for an initially larger volume of motifs which already drops considerably in the beginning of a crisis event. Unlike the joy-exchange network, trust- and anticipation-exchange networks contain an identical set of motifs that widely differ in their SPs. With respect to the motif significance, the reciprocal-edge motif 111U is highly representative for the communication of trust, while joy- and anticipation-exchange are characteristic for the message broadcaster motif 021D and message receiver motif 021U, though anticipation-exchange is in addition characteristic via reciprocal-edged motifs 120U, 111D, and 111U (see Fig. 7).

Moreover, motif 030C is found in anticipation- and trust-exchange networks. This motif carries a particular and exclusive role in emotion-exchange networks as it appears only in the networks associated with the exchange of positive emotions or a mixture of emotions where positive emotions are always involved (anticipation-, trust-, positive-, interlayer-, aggregated-emotion exchange network, see Fig. 7).

### 4.2.5. Exchange of surprise

The surprise-exchange network conveys a relatively moderate volume of the underlying motifs ($n_{\text{surprise}} = 72.50$), with a moderate presence of reciprocal edges ($n_{\text{reciprocal}} = 0.43$) and self-loops ($n_{\text{loop}} = 0.43$). Highly representative motifs for the exchange of surprise involve 021D, 021U, and 021C, none of which convey reciprocal edges.

### Table 4

Mean number of emotional responses to emotional messages (index i designates an initial message which conveys a particular emotion and r an emotional response. Abbreviation nd stands for natural disasters, rs for riots, and sta for shootings and terror attacks.)

| Anger, i | Fear, i | Sadness, i | Disgust, i | Joy, r | Antici, r | Trust, r | Surprise, r |
|----------|---------|------------|------------|--------|-----------|----------|-------------|
| $n_{\text{Anger}} = 12.01$ | $n_{\text{Fear}} = 3.5$ | $n_{\text{Sadness}} = 0.03$ | $n_{\text{Disgust}} = 1.29$ | $n_{\text{Joy}} = 2.25$ | $n_{\text{Antici}} = 2.21$ | $n_{\text{Trust}} = 1.47$ | $n_{\text{Surprise}} = 0.34$ |
| $n_{\text{nd}} = 19.93$ | $n_{\text{nd}} = 4.49$ | $n_{\text{nd}} = 1.16$ | $n_{\text{rs}} = 4.82$ | $n_{\text{rs}} = 2.47$ | $n_{\text{rs}} = 15.17$ | $n_{\text{rs}} = 4.55$ | $n_{\text{rs}} = 2.13$ |
| $n_{\text{rs}} = 15.88$ | $n_{\text{rs}} = 4.94$ | $n_{\text{rs}} = 1.59$ | $n_{\text{rs}} = 0.66$ | $n_{\text{rs}} = 0.44$ | $n_{\text{rs}} = 8.71$ | $n_{\text{rs}} = 2.9$ | $n_{\text{rs}} = 1.14$ |
| $\mu_{\text{Anger}} = 15.94$ | $\mu_{\text{Fear}} = 6.67$ | $\mu_{\text{Sadness}} = 0.15$ | $\mu_{\text{Disgust}} = 0.12$ | $\mu_{\text{Joy}} = 0.84$ | $\mu_{\text{Antici}} = 0.57$ | $\mu_{\text{Trust}} = 0.98$ | $\mu_{\text{Surprise}} = 0.33$ |
Finally, we also discuss the derived layers of our multiplex network. The exchange of a mixture of emotions leads to the formation of a wider range of motif shapes, some of which do not emerge at all when only a single emotion is exchanged (see Fig. 8). These motifs are 201, 210, and 120C. All three are characteristic for the presence of reciprocal edges, involve no passive nodes (with respect to the message-sending behavior), and exhibit a local hierarchy. Compared to the single-emotion-exchange motifs, motifs found on the derived layers are comparatively moderate to small in volume ($n_{positive} = 54.30$, $n_{negative} = 48.40$, $n_{interlayer} = 28.90$, $n_{aggregated} = 29.00$), contain substantially more reciprocal edges ($n_{positive} = 1.44$, $n_{negative} = 2.19$, $n_{interlayer} = 1.25$, $n_{aggregated} = 5.66$), more self-loops ($n_{positive} = 1.07$, $n_{negative} = 1.71$, $n_{interlayer} = 0.80$, $n_{aggregated} = 4.67$), and form a larger variety of isomorphic subgraphs ($\text{var}_{positive} = 8.42$, $\text{var}_{negative} = 12.9$, $\text{var}_{interlayer} = 18.40$, $\text{var}_{aggregated} = 17.2$). As shown in Fig. 6, positive-emotion exchange motifs gradually but consistently become smaller in volume as a crisis event progresses. The same trend does not hold for the remaining derived layers, though. Negative- and aggregated-emotion-exchange networks show multiple peaks in the motif volume over time, while the interlayer shows an inclining tendency in peaks throughout the extraction period.

Fig. 7. Significance profiles (SPs) of the different motifs averaged daily over each crisis event (in the plot depicting the mean significance profiles on single-emotion layers, negative emotions are shown via dashed lines and the remaining emotions via solid lines for a better distinction between the emotions belonging to positive and negative affective valence).

5. Discussion

Social media messages sent during the eighteen crisis events largely show the human tendency to share intense emotions of fear as a crisis event strikes and subsequently intensely express other negative emotions (such as anger and sadness) but also a considerable volume of positive emotions (joy, trust, anticipation) as an individual event evolves.

Such an emotional expression as a reaction to a crisis event corroborates the findings of Flynn (1997), who found that the ones affected by a crisis express distinct emotions in different phases which are universal across various crisis events. We observe a very strong correlation (Kendall’s $\tau$) between each pair of aggregated crisis events (between...
riots and shooting and terror attacks $\tau = 0.92$, between shooting and terror attacks and natural disasters $\tau = 0.85$, and between natural disaster and riots $\tau = 0.93$, all values are computed for significance level of 0.05). According to Flynn (1997), people initially experience shock and fear.

**Twitter User:** “@NAME Call me NERVOUS in Doral!!! After seeing what #HurricaneHarvey has done to #Texas everyone is running scared!”

**Twitter User:** “I’m scared by events in Catalonia. It’s a violence under peaceful people and this is not elections for liberty from Spain”

Shock and fear are followed by an expression of a wider range of emotions, depending on the emotional state of those affected, their individual coping strategy, and the particularities of an event. The second phase thus exhibits a range of positive emotions such as relief, joy, and appreciation, but also sadness, disapproval, and rage towards the ones who are (supposedly) to blame. According to Flynn (1997) and Freyd (2002), blaming is a psychological mechanism of sense-making and is often expressed in messages conveying anger. Our data-sets show that anger is expressed relatively more intensely during shootings, terror attacks, and riots compared to the natural disasters (see Fig. 3). Freyd (2002) pointed to a reason why people experience intense anger during crisis events. In highly threatening events that cause fear, people tend to focus on anger to regain their sense of control and feel safer. Thus, naturally experienced emotions such as sadness and fear may be masked or hidden through anger. Typically, anger is associated with a subsequent prejudice, hostility, or calling out an “enemy” to blame. As pointed out by Coombs (2007), man-made crisis events are more subject to blame than natural disasters. Below we provide examples from our data-set that convey anger and, to some extent, blame.

**Twitter User:** @NAME You have blood in your hands. Shame on you. Shame on you. Shame on you. Shame on you. #youtubeshooting

**Twitter User:** @NAME GET OFF YOUR FAT ASS!!! Puerto Ricans are still waiting for aid a week after Maria’s devastation #hurricanemaaria

**Twitter User:** @NAME I’m not saying you’re an idiotic, #fcc, #hatriot, #reichwing, #fakechristian, bitch...oh wait, YES I am!

**Twitter User:** “I’m not one to call a guy I don’t know a piece of shit, but @NAME seems like a piece of shit. #houstonflood #HurricaneHarvey”

Directly-exchanged messages differ in their intensities from broadcast messages. Depending on a type of a crisis event, we found that positive emotions (joy, trust) are more intense in direct messages than in broadcast messages during natural disasters, and negative emotions are more intense in direct messages during riots, shooting, and terror attacks. In general, anger was expressed more intensely during riots, shooting, and terror attacks compared to natural disasters. A possible explanation lies, on the one hand, in the presence of human culprits (Flynn, 1997), and on the other, in the victims’ reminder of their mortality (Greenberg et al., 1986; McGregor et al., 1998). With respect to the presence of culprits, both riots and shootings/terror attacks are directly caused by an individual or a group of people who are usually either identified soon after the event took place (e.g., a shooter) or publicly held responsible for their aggressive actions (e.g., rioters). The initial presence of intense anger and disgust in these events is thus to be expected.

However, blaming is not the only factor which influences the high intensity of anger in shootings and terror attacks. According to the Terror Management Theory (Greenberg et al., 1986), people universally engage in social actions as part of their coping mechanism when faced with life-threatening moments. Numerous studies have shown that people tend to become more aggressive towards persons who challenge their worldview and show more defensive reactions in situations when they are reminded of their mortality (see, e.g., McGregor et al., 1998).

The expression of anger structurally differs from fear. While both are dominant during crisis events and form the same set of motifs, the heated exchange of anger occurred only at certain points during the crisis events, while fear was persistently exchanged throughout all the phases of the crisis events studied. A possible explanation is the availability of information and news updates during crisis events that might have sparked angry reactions and the exchange of angry messages in the light of a crisis event (see also Back, Küfner, and Egrloff (2010)). Fear, on the other hand, is ubiquitously present throughout a crisis event and is highly associated with an information seeking behavior (see Wollebaek, Karlsen, Steen-Johnsen, and Enjalras (2019) and the resulting topic models in Fig. 9). A high intensity of fear as a reaction to uncertainty that has been caused by a crisis event was also confirmed in other related studies (see, e.g., Li et al. (2014)). Two motifs are characteristic for the exchange of fear – a relatively long-lasting 120U which stretches over the extraction period and 120D in the first half of the extraction period, both of which exhibit a clear local hierarchy with respect to the selection of a conversational partner (with 120U exhibiting one and 120D two “popular” selected nodes) and reciprocal edges.

Thus, although anger characteristically sparked more heated one-way message sending behavior targeted at a specific user than fear ($n_{anger} = 208.78$ vs. $n_{fear} = 61.10$), fear is characteristic for longer-lasting complex structures, such as the motif 120U. Below we provide an example for 120U which involves reciprocal fear-exchange between two users who each actively involve a third user into the conversation.

**User A:** “@UserB The people are devastated, have not slept and are afraid of rain it was a lot deeper than what the media could show about #HurricaneMaria”

**User B:** “@UserA @userC Only to recover from #HurricaneMaria to only be smacked by #HurricaneMaria along with #PuertoRico, they had to go on boats.”

**User A:** “@userC What do you expect these people to do when they have absolutely nothing?? They have nothing left. Oh and shout out to the #Airports that charged between 5k and 10k per ticket, for people trying to get out. #HurricaneMaria #HurricaneIrma”

Sadness, being the third most intense emotion during riots, shootings, and terror attacks, and the second during natural disasters is predominantly expressed in messages of compassion and empathy. According to Batson et al. (1991), such emotions are targeted predominantly at others and can be seen as a form of altruism.

**Twitter User:** “@NAME We send our deepest condolences to the victims of #Earthquake at the Iran-Iraq border. Our thoughts & prayers are with you all”

**Twitter User:** “@NAME Painful loss. May the soul of Lt Col Arnaud Belframe rest in peace. Condolences to his loved ones.”

**Twitter User:** “Was havin’ a great day bc I started my new job & now I’m crying on my bed bc of the sick people carrying out acts of hate in #Charlottesville”

The exchange of sadness is characteristic for a relatively low presence of reciprocal edges but a high frequency of the sadness-exchange
motifs. Thus, it is typically expressed towards another person (e.g., notice the high relevance and frequency of the broadcaster motif 021D) and is not responded by the same emotional tone (i.e., messages that also convey sadness). Sadness rather attracts messages that convey other emotions (such as joy/love).

User A: (sadness) “On Mother’s Day, she gave her host mom a shawl from her home country of Pakistan. Days later, this exchange student was killed in the #SantaFeShooting. Yesterday, her body was returned to her family: ‘I’m glad that I could help.’”

User B: (love) “@USER A May God bless your family. You will always live in the heart of Texans.”

A similar pattern emerges while exchanging disgust, which is responded by messages conveying other emotions, such as anger.

User A: (disgust) “This is disgusting. Poor babies! #petarefamilytoo #IrmaHurricane”

User B: (anger) “@USER A I have a message for all you horrible people who abandoned these animals -- f*** you. Never get a pet unless you treat them like family.”

As revealed by our emotion-exchange motifs, the exchange of disgust is characteristic for the presence of unidirectional edges (motifs of a high significance profile for disgust are 021U, 021D, 021C, 030T). Moreover, disgust appears to spark a relatively frequent message sending behavior by a clearly emotionally aroused user, as illustrated below.

User A: “@USER B this disgusting inhumane administration is checking IDs of people evacuating from the hurricane”; “@USER C [name] administration checking IDs of people trying to evacuate! Inhumane, disgusting!”; “@USER D @USER E This disgusting inhumane administration is checking IDs for people evacuating!!”.

Moreover, messages conveying positive emotions (e.g., messages of prayer, gratitude, compassion, and hope) prevail over the negative ones on certain days during the data extraction period. This is particularly evident during shootings, terror attacks, and riots. Such a relatively high presence of positive emotions can be attributed to the undoing hypothesis (Fredrickson, Mancuso, Branigan, & Tugade, 2000) which describes positive emotions as an antidote against the disruptive effects of negative emotions. Complementarily to the undoing hypothesis, relief theory (Meerloo, 1966) postulates that laughter (mapped to joy) serves as a form of stress release. We observe that the relatively high presence of positive emotions is evident throughout the data-extraction period but their peak over the negative emotions is evident towards the end of the data-extraction period after the initial shock has subdued, signaling a higher expression of hope, gratitude, love and prayer by those affected.

Twitter User: “@NAME: Prayers to everyone involved in the shooting I hope everyone is okay at @YouTube”

Twitter User: “@NAME: Some can be heroes just for one day. And will be remembered and thanked forever for that. #ArnaudBeltrame”

Twitter User: “@NAME Endless gratitude to the brave men and women that kept our city safe during #Irma.”

Exchange of positive emotions is particularly characteristic for the presence of the motif 030C (a closed cyclic motif where all nodes are equivalent and show no preference in a selection of a conversational partner).

User A: (joy) “We have an Awesome God that gives us what we need when we need it the most. @USER B @USER C #HurricaneHarvey”

The emotion-exchange motifs also revealed that the inclusion of positive emotions in a message-exchange is highly characteristic for the presence of reciprocal edges. Reciprocity, according to Wubben, Cremer, and van Dijk (2009), promotes cooperation. The reciprocal exchange of messages that include positive emotions (i.e., cooperative and supportive behavior) is seen as an especially important mechanism during crisis events since it inspires the spirit of togetherness (Tikka, 2019) in contrast to negative emotions (such as anger) which lead to escalation or a defection of both conversational partners (Wubben et al., 2009). In contrast, motif 120D (which exhibits a clear local hierarchical structure and depicts a message broadcaster and a pair of nodes mentioned by the broadcaster who exchange mutual messages) has a higher importance in the networks that convey negative emotions (interlayer-, aggregated-, and negative-emotion exchange networks).

Considering the affective arousal as another dimension to describe human emotions (see Russell, 1980), we found that the expression of high arousal emotions (anger, fear, anticipation, and surprise) highly varies in a motif volume over time. The exchange of the four high arousal emotions shows numerous peaks throughout the data-extraction period. In contrast, low arousal emotions (sadness, love/joy, and trust) show a distintively different pattern. The volume of motifs peaks once at the beginning of a crisis event to maximally two times during a crisis event, while the remaining period shows a rather stable amount of messages being sent among the users.

As pointed out by Back et al. (2010) who studied emotions related to the 9/11 attack, the expression of an emotion may increase as more information becomes available over time. Though in their study, anger (as contrasted to sadness) showed an increase associated with the availability of information, our study points to the increased number of messages associated with a wider range of high arousal emotions. As indicated by (Russell, 2003), high arousal emotions generally spark action, while (Berger, 2011) subsequently demonstrated that high arousal emotions are associated with a higher transmission of messages. The emotion-exchange motifs identified in this paper comply with both the theoretical (Russell, 2003) and the empirical (Berger, 2011) aspects.

Moreover, the emotion-exchange motifs also show that the introduction of a mixture of emotions to a conversation leads to a more dynamic and active message-sending behavior compared to the exchange of a single emotion (more complex motifs 201, 210, and 120C are exclusively found on the derived layers and they involve reciprocal edges and no passive nodes). This finding was expected. As pointed out by (Larsen, McGraw, & Cacioppo, 2001), humans are able to experience multiple emotions at the same time, and crisis events in specific trigger a range of emotions and cause the ones affected to experience various mental states, such as fear, anxiety, confusion, hopelessness, denial, and empathy (Fredrickson et al., 2003; of Health, Human Services, & Prevention, 2019). Motif 201 (characteristic for the presence of two reciprocal edges) is representative for the exchange of a variety of positive and negative emotions (e.g., in compassion-related messages where sadness is responded by joy/love; or a call for political action where anger is responded by anticipation).
5.1. Limitations

The findings of this study have to be regarded with respect to some limitations. The first is the data extraction procedure. Since Twitter’s Search API does not guarantee the extraction of all possible tweets, we cannot exclude the possibility that we missed some of the relevant tweets. Another drawback lies in the nature of Twitter data. Since Twitter does not require its users to disclose their geo-location, we have not been able to analyze location-based emotional expressions. This issue might be addressed by following a different data extraction procedure which allows for the extraction of tweets sent within a certain area/geo-location.

Moreover, our emotion-detection procedure relies on existing word-emotion lexica whose completeness and accuracy is vastly determined by the procedure used by the initial authors of the lexica. To mitigate potential bias in the emotion detection in our studies, we first compared the available word-emotion lexica and selected the most fitting one after deploying human raters (see Kuśen et al., 2017).

A further limitation refers to the presence of bot accounts. In our previous work on riot events, we showed that emotion-exchange motifs can also serve as indicators of a human-like communication behavior which again help to distinguish humans from bot accounts (see Kuśen & Strembeck, 2020). In particular, in (Kuśen & Strembeck, 2018) we found that when studying traditional network motifs (i.e., motifs that do not consider emotion exchanges), the patterns that are formed when bots interact with human Twitter users seem rather sporadic. However, as reported in Kuśen & Strembeck (2019), the analysis of emotion-exchange motifs resulted in clear distinctions between bots and humans. We found that bots generally spread messages which convey emotions that conform with the base mood of an event and receive a higher volume of messages that convey shifted emotions (e.g., negative emotions that conform with the base mood of an event and receive a larger volume of messages that convey other emotions). In our future work, it would be interesting to extend this paper by examining the emergence of emotion-exchange motifs in human-to-human, human-to-bot, and bot-to-bot communication networks respectively, and to study whether the exchange of emotional messages initiated by bot accounts would lead to a comparable set of emotion-exchange motifs that naturally emerge in a human-human communication network.

Lastly, there are two drawbacks in this study that could be addressed in future research, both of which are related to our motif detection procedure. Since our motif detection involves the exact enumeration of all possible subgraphs found in each network and their subsequent isomorphism classification, this procedure is very resource demanding and comes at a heavy computational cost. Please note that this is a well-known limitation to such a motif detection procedure (see, e.g., (Topór-Iceanu, Duma, & Udrescu, 2016)). However, instead of relying on a mere motif approximation procedure, we were able to provide an exact and accurate set of motifs in our networks. The second drawback refers to the use of significance profile scores to compare emotion-annotated networks. These scores largely depend on the choice of the null model used in the motif detection procedure. Thus, the results might differ upon applying another type of null model in our motif detection procedure.

6. Conclusion

In this paper, we discussed a systematic analysis of a data-set consisting of over 23.3 million messages sent via Twitter. The messages in the data-set resulted from eighteen different crisis events – nine natural disasters, four riots, as well as five shootings and terror attacks. We found that people universally experience initial feelings of fear, followed by anger, sadness, but also positive emotions, depending on the particularities of a crisis event.

While the exchange of direct messages resembles the emotional tone of the broadcast messages, higher intensity of joy and trust is found during natural disasters, and higher intensity of anger, disgust, sadness during shootings, terror attacks, and riots. While exchanging direct messages, people express a number of topics that can be mapped to specific emotions. We showed that anger is highly associated with the messages of disapproval, disgust with disapproval and hate speech, fear with news updates, sadness with condolences and sympathy, while positive emotions are associated with words of kindness, prayers, well-wishing, gratitude, and hero-praising.

The direct exchange of emotional messages can be represented by characteristic small subgraphs called network motifs. In this paper, we used used the novel concept of emotion-exchange motifs to characterize the exchange of specific emotions and their combinations. In total, we identified 729,368 motifs belonging to 1480 isomorphism classes. The application of emotion-exchange motifs revealed distinct differences in emotion-exchange networks, thereby signaling that the exchange of specific emotions leads to different dynamics and characteristic local communication structures. To the best of our knowledge, our work is the first to combine the concept of network motifs with human emotions to study the role of emotions in online social networks.

Our emotion-exchange motifs showed that anger inspires heated messages as well as one-way messaging targeted at a single user. Fear, on the other hand, is characteristic for a relatively stable set of local structures that involve reciprocal edges (conversation) and message broadcasting behavior (e.g., news seeking). Communication of sadness, typically found in messages of compassion, is characteristic for the broadcaster motif and does not inspire a response in the same emotional tone. In fact, we found that sadness attracts either positive responses in messages of compassion or even angry responses as part of one’s coping mechanism.

Communication of disgust is characteristic for agitated reactions to a crisis event and structurally takes the form of rather large motifs with many unidirectional edges. We further found that it is not typical (i.e., statistically significant) to respond to disgust with disgust, but rather with anger. Finally, positive emotions play a special role during crisis events and are attributed to the undoing hypothesis and the relief theory. In particular, we found one cyclic motif which is exclusively formed when those affected by a crisis event exchange positive emotions.

Another significant finding of our paper is that emotions of the same...
valence are not structurally the same, are not exchanged in the same way, nor are they conveyed in messages that express the same opinion about an event.

This study opened up a number of questions that we will address in future work. We plan to extend our approach to study temporal emotion-exchange motifs. A second research direction targets events whose base or expected emotion is not negative (i.e., polarizing and positive events) in order to explore whether the motifs emerging in such events are similar or different to the ones resulting from negative events. Furthermore, so far our analyzes rely on Twitter-based communication. It would be interesting to explore how the emotion-exchange motifs identified in this study compare to motifs that result from other social networking platforms.

A data-set related to the analyzes performed for this paper is freely available for download from IEEE DataPort: LINK (removed for the double-blind reviewing process).

Declaration of competing interest

None to declare.

A. Event descriptions

Below we provide a brief description of the eighteen events considered in this paper.

A.1. Natural disasters

In 2017, Hurricane Harvey hit San Jose Island (Texas) as a category four hurricane causing 68 deaths and progressed to Louisiana as a category three hurricane. It caused an estimated damage of $125 billion.

In 2017, Hurricane Irma hit the Caribbean as a category five hurricane, killing 37 people and subsequently hit Cuba (10 dead) and the US (12 dead); a total of 1.2 million people were affected.

Mexico earthquake: In 2017, an earthquake of magnitude 7.1 stroke Puebla, Morelos, and Greater Mexico City leaving 248 dead. It later triggered an eruption of the Popocatepetl volcano which caused a collapse of a church during a mass, causing fifteen additional deaths.

In 2017 Hurricane Maria hit the island of Dominica as a category five hurricane and caused a communication blackout. It further progressed as a category four hurricane to Puerto Rico, leaving 2975 dead.

Costa Rica earthquake: In 2017, an earthquake struck the coast of Costa Rica with a magnitude of 6.5 causing three deaths.

Iran-Iraq earthquake: In 2017, an earthquake of magnitude 7.3 occurred on the Iran-Iraq border. It was one of the deadliest earthquakes in 2017 leaving more than 400 dead and over 7000 injured.

In 2018, the Southern California mudslides occurred after a heavy rain period, leading to numerous demolished homes in Montecito and over twenty deaths.

In 2018, the Friederike windstorm hit Central Europe, the British Islands, France, Benelux, Northern Italy, Poland and parts of Eastern Europe causing heavy snowfall and blizzards. Germany and the Netherlands suffered the heaviest losses with at least eight deaths and damages of one billion Euros.

In 2018, the Lang’ata wildfire occurred in the Lang’ata area of Nairobi (Kenya), killing three and leaving hundreds of people homeless.

A.1.1. Riots

The 2017 G20 riots in Hamburg: a number of riots occurred during the 2017 G20 summit in Hamburg, Germany. The day before the summit, 8000 protesters participated in a so called “Welcome to Hell” march which evolved into violent confrontations between the protesters and the police. Fourteen demonstrators and 76 police officers were injured. Further acts of civil unrest happened on the first day of the summit, with the protesters setting cars on fire and clashing with the police. In total, 160 police officers were injured.

The 2017 “Unite the Right Rally” in Charlottesville. The protests in Charlottesville happened in August 2017 as a response to the City Council’s vote to makes changes to two parks named after Confederate generals. In the fights that broke out between protesters and counter-protesters fourteen people were injured. On August 12th a man drove his car into a crowd, killing one person and injuring nineteen others.

The 2017 Catalonia independence referendum riots. The Catalan independence referendum was held on October 1st, 2017 in Catalonia (Spain), resulting in 92.1% of votes in favor of splitting from Spain. During the referendum, the national police tried to prevent people from voting. About 900 people ended up injured in clashes with the police.

The 2018 Superbowl riots in Philadelphia. In Superbowl LII, the Philadelphia Eagles won against the New England Patriots. A series of acts of vandalism and a riot broke out as thousands of Eagles fans celebrated the victory on the streets of Philadelphia. One police officer ended up injured while several rioters had to seek medical help.

A.1.2. Shootings and terror attacks

School shooting in Tehama County, California, USA. In November 2017, a series of shootings occurred in Rancho Tehama Reserve in Tehama County, California, USA. In total five people were killed, 18 injured at a number of separate crime scenes, including an elementary school.

Supermarket siege in Trebes, France. In March 2018, a member of the Islamic State initiated a shooting in Carcassonne, France, killed one person and seriously injured one on his way to the military barracks, where he fired shots at police officers. The attacker then took around fifty hostages at a supermarket in Trebes, three of which were shot dead. One of them was a French gendarme who exchanged himself for a hostage.

Shooting at the YouTube headquarters, San Bruno, California, USA. In April 2018 a shooting occurred at the YouTube headquarters, San Bruno, California, USA. A female shooter injured three people before shooting herself dead.

Van attack in Münster, Germany. In April 2018, an attacker drove a van into a tourist square of the city center of Muenster, Germany. Three people where killed including the suspect, more than 20 people injured. Almost four months after the attack a fourth victim died of his injuries.

School shooting in Santa Fe, Texas, USA. In May 2018, a student of the Santa Fe High School shot eight students and two teachers dead, thirteen other victims were wounded. The shooter eventually surrendered himself to the police.
B. Topics

Fig. 8. Temporal flow of motifs.
Table 5

Topics discussed in messages sent directly among Twitter users, their proportion (in brackets), and associated words (chosen from top 20 most common words). User names were anonymized via @NAME unless the user name is a public person (such as a president) or a news agency (such as CNN).

| TOPIC                                      | SUB-TOPIC                                      | WORDS                                                                 | EXAMPLE                                                                 |
|--------------------------------------------|-----------------------------------------------|----------------------------------------------------------------------|-------------------------------------------------------------------------|
| Information seeking sharing (10.29 ± 15.02)| News update (5.89 ± 9.77)                      | charlottesville, people, foxnews, shooter, chsnws, catalonia, hurricane, victims, cnn, police | @NBCNews Bad month 4 #Disasters. Hurricanes, fires & Mexico’s earthquake killing 60 people.; “Hero. French officer who swapped places with a hostage in terror attack dies @CNN” |
|                                           | Warning against fraud (0.40 ± 1.12)            |                                                                      |                                                                         |
|                                           | Rumoring (0.80 ± 1.64)                         |                                                                      |                                                                         |
|                                           | General information sharing (3.20 ± 4.47)      |                                                                      |                                                                         |
| Altruistic and pro-social behavior (28.98 ± 28.41) | Sympathy (2.42 ± 6.86)                        | good, people, hope, please, wish, safe, everyone, luck, hurricane, happy | “God bless for employees on YouTube HQ for the shooting, I hope employees and people ok on YouTube HQ are ok. So god bless them. via YouTube”; “@NAME can y’all please go to Houston and help out with the flood rescue be good publicity to be good Christians #HurricaneHarvey” |
|                                           | Prayers and well-wishing (15.69 ± 19.02)       |                                                                      |                                                                         |
|                                           | Condolences (2.04 ± 5.47)                      |                                                                      |                                                                         |
|                                           | Call for donations (0.68 ± 1.47)               |                                                                      |                                                                         |
|                                           | Call for disaster relief efforts (0.92 ± 1.93) |                                                                      |                                                                         |
|                                           | Words of kindness (6.73 ± 11.14)               |                                                                      |                                                                         |
|                                           | Gratitude (7.97 ± 10.79)                       | honor, blessing, great, safe, good, wish, please, luck, everyone, people | @NAME Thank you for your church’s faithful support to our ministry & helping #HurricaneHarvey victims. God bless!”; “@EmmanuelMacron Very moving and powerful, honoring a real hero Arnaud Beltrame who selflessly gave his life.” |
|                                           | Gratitude to helpers (2.40 ± 3.81)             |                                                                      |                                                                         |
|                                           | Praise the heroes (3.66 ± 8.09)                |                                                                      |                                                                         |
|                                           | Thankfulness for support (1.24 ± 1.76)         |                                                                      |                                                                         |
|                                           | General gratitude (1.17 ± 1.84)                |                                                                      |                                                                         |
| Counter-bigotry activism (1.65 ± 3.30)     | Call for tolerance (1.32 ± 3.13)               | bitch, feel, racist, victims, violent, abuse, anger, blaming, criminals, evil | @NAME Black violence matter, Black violence matters, Black violence matters”; “@NAME did you apologise for being so blind with hate and blaming the shooting at YouTube on an illegal immigrant…” |
|                                           | Countering propaganda (0.34 ± 0.95)            |                                                                      |                                                                         |
| Nationalistic sentiment (2.60 ± 2.99)      | Hostility towards different cultures, religions, race (1.09 ± 2.31) | illegal, people, angry, bitch, fakenews, gun, hell, antifa, blaming, god | @NAME face recognition please!!! good luck getting a job douchebags #charlottesville; “@munchbust worries Texas will use hurricane to deport illegal immigrants #TTT Let’s hope so!” |
|                                           | Hostility towards different values and views (1.27 ± 2.44) |                                                                      |                                                                         |
|                                           | Hostility towards those who do not contribute to the good of the nation (0.58 ± 1.63) |                                                                      |                                                                         |
| Search for meaning and value (1.17 ± 1.73) | Search for sense (0.25 ± 0.71)                 | luck, many, people, shooting, bad, feel, honor, hope, peace, proud | @NAME Since pastors are saying Hurricane Harvey was “proof” of god’s wrath, what is he so damn angry about?”; “@NAME @YouTube Oh shit, f**king assholes! Why does there have to be so many horrible people?”; “Catalonia: We urge authorities to respect human rights: freedom of peaceful assembly & expression.”; “@NAME good luck? Massive hurricane and you tell @Texas @TexasTribune “good luck”? What is wrong with you? Useless RACIST PIG” |
|                                           | Call for togetherness (0.92 ± 1.74)            |                                                                      |                                                                         |
| Criticism towards officials (27.51 ± 19.53)| Call for political change (0.99 ± 11.14)        | victims, bitch, hope, hell, realdonaldtrump, say, fu**ing, idiot, hate, vote | “@NAME Everyone should be happy and rejoicing hurricane Harvey. It was a wonderful thing”; “@NAME Bitch you betta be thankful y’all got rain cause there’s people drowning in hurricane Harvey. Bitch f**k outs here. Seriously. F**k you. F**king giant idiot Cheeto bitch” |
|                                           | Expression of disapproval (28.06 ± 21.06)      |                                                                      |                                                                         |
| Other (19.81 ± 21.89)                      | Hate speech (3.02 ± 7.92)                      |                                                                      |                                                                         |
|                                           | Expression of worry for one’s safety (0.56 ± 1.58) |                                                                      |                                                                         |
|                                           | General opinion sharing (12.36 ± 15.13)        |                                                                      |                                                                         |
|                                           | Sarcastic comments (1.86 ± 2.26)               |                                                                      |                                                                         |
|                                           | Other (0.46 ± 0.93)                            |                                                                      |                                                                         |
Fig. 9. Topics and their proportions in directly exchanged messages that convey predominantly negative emotions (anger, fear, sadness, disgust).

Fig. 10. Topics and their proportions in directly exchanged messages that convey predominantly positive emotions (joy, trust, anticipation) and surprise.

Credit author statement

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