Structural similarities of emotion-exchange networks
Evidence from 18 crisis events

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Abstract: Online social networks (OSNs) play a significant role during crisis events by offering a convenient channel for information seeking, social bonding, and opinion sharing. In this context, people express their fear, panic, shock, as well as gratitude, well-wishing, and empathy as a crisis event evolves over time. Though emotional responses during crisis events have been studied both in offline and online settings, it is yet unclear which communication structures are representative for the exchange of specific types of emotions. In this paper, we report on new findings which indicate that *not* all negative emotions are exchanged in the same way. In particular, we used *emotion-exchange motifs* to compare the structure of emotion-annotated communication networks that resulted from 18 crisis events via. Our findings clearly indicate that 1) exchanges of sadness on the one hand, and joy/love on the other show more structural similarity than any other pair of emotions, 2) emotion-exchange networks can be clustered into two families, each of which includes different types of emotions, 3) membership in the two families of emotion-exchange networks fluctuates over time. A related data-set is available for download from IEEE DataPort, DOI: 10.21227/yajb-6y77.

1 INTRODUCTION

Emotions motivate human behavior (Holyst, 2016) and influence physiological and mental health (Abdul-Mageed and Ungar, 2017). For example, they trigger a flight reaction when people face danger or provoke tears and sobbing when experiencing loss and helplessness. In this light, emotions play a crucial role in crisis events, which are described as sudden, threatening, and traumatic events which cause intense feelings of danger, shock, panic, and fear (Flynn, 1997). Thereby, emotions considerably shape the collective experience of an event (von Scheve and Ismer, 2013).

Since online social networks (OSNs) are predominantly networks of people, *human emotions* can significantly influence user behavior and information diffusion in OSNs. In this context, (Scheve, 2014) indicated that the study of emotions and their roles in OSNs may reveal dynamic processes and structures that emerge due to interactions between OSN users. For example, previous studies demonstrated that emotions conveyed in OSN messages may boost or decrease the diffusion rate of a message within a social network (Kim et al., 2013; Tsugawa and Ohsaki, 2015). Other findings, such as (Berger, 2011), indicate that emotions of the same affective valence[1] (e.g., anger and sadness) are not exchanged in the same way and inspire different reactions in offline settings.

Although the existing body of literature provides valuable insights into the emotions expressed during various types of events, their influence on the process of emotional contagion and message diffusion, as well as the emergence of collective emotions, there is a lack of studies which systematically examine the underlying communication structures that arise from emotional messaging. In this context, emotions exchanged between pairs of users (so called dyads) has been well studied. Yet, as noted by (Scheve, 2014), emotions exchanged within a dyadic structure may further propagate to other connected individuals. Multiple authors further noted that strongly experienced emotions, such as anger or fear are shared

[1] Affective valence is a term which distinguishes between pleasant (positive) or unpleasant (negative) emotions. For example, negative emotions include anger, sadness, fear, and disgust, while positive emotions include joy, trust, and anticipation.

with others as a form of one's coping mechanism (Fraustino et al., 2012). This phenomenon is rooted in psychology and is referred to as the *social sharing of emotions* (Rimé et al., 1991). Through such a process, emotions that are propagated from a dyad to a larger group of people form a network structure.

In this paper, we report on a study that investigates how emotions contribute to the underlying topological structure of OSN messaging networks. In particular, we examine how emotions contribute to the emergence of families of emotion-exchange networks. Our findings clearly indicate that seemingly similar emotions, such as the negative emotions of anger and sadness, do not only inspire different reactions in terms of forwarding or endorsing a message, but that the way they are exchanged also results in structurally different communication networks.

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 procedure in Section 3. Our findings are reported in Section 4 and discussed in Section 5. Section 6 concludes the paper and provides directions for future work.

2 Related work

Structural similarity of networks has been studied over a wide range of real-world networks, including social networks, air navigation networks, or food networks. Often, network structures are compared via their global properties (network density, degree distributions, average path length, network diameter, transitivity, clustering coefficients) and local (node-centric) properties (such as various centrality measures; see, e.g., (Sun and Wandelt, 2014),(Shi and Macy, 2016)). Other approaches analyze the nodes' influence in order to compare different networks consisting of the same set of nodes (Koutra et al., 2013), or the spectral clustering of graphs (see, e.g., (Gera et al., 2018)).

In recent years, approaches studying network motifs (Milo et al., 2002) led to many interesting insights that could not have been found by comparing global network properties alone. In this sense, network motifs reveal the underlying functional properties of complex networks (Masoudi-Nejad et al., 2012) that would otherwise remain hidden.

For example, (Milo et al., 2004) correlated the significance profiles (SPs) of network motifs found in seemingly unrelated networks from different disciplines, such as WWW links, word-adjacency networks, genetic networks, and sensory transcription networks. Moreover, (Klaise and Johnson, 2017) compared food networks by correlating the SPs of network motifs and applying a trophic coherence measure which reveals how layered a network is. Moreover, (Topirceanu et al., 2016) compared the underlying structure of friendship graphs derived from three online social networks (Facebook, Twitter, Google+). Our paper follows a similar line of work by exploring emotion-annotated communication networks derived from Twitter conversations.

3 Procedure

Our research procedure includes seven main steps, as depicted in Figure 1.

1. Data extraction. We used Twitter's Search API to extract publicly available tweets that have been sent during eighteen crisis events. In order to extract the relevant tweets, we monitored Twitter and systematically selected a set of hashtags and key-terms associated with each crisis event. The data was collected from the first day of an event and stopped when the event did not produce a considerable number of messages anymore (usually after seven to fourteen days). After collecting the raw data, we removed duplicate entries and messages that were uninformative with respect to emotion detection. Our final data-set included 23,308,071 tweets (see Table 1).

2. Emotion detection. After data pre-processing, we applied our emotion detection procedure (for details see (Kušen et al., 2017)) which determines the presence and the intensity of the eight basic emotions found in Plutchik's wheel of emotions (anger, fear, disgust, sadness, joy, anticipation, trust, surprise). Our approach uses the NRC emotion-word lexicon (Mohammad and Turney, 2013) to identify the presence of each basic emotion and the AFINN lexicon to boost or decrease the intensity of an affect (Hansen et al., 2011). In addition, we also applied a set of heuristics that people naturally use to detect emotions in written texts including amplifiers, maximizers, downtoners, and negation. Moreover, the algorithm also considers characteristic features that are frequently found in OSN messages (especially emoticons and common abbreviations). For example, the tweet "*@screenname I am so very sorry to hear the sad news about lieutenant Arnaud Beltrame. He has displayed the true courage.*" conveys an explicitly named emotion and was annotated in the following way: sadness = 3, fear = 2, trust = 1, the remaining emotions = 0 (whereby the values refer to the emotion intensity). Another example illustrates emotion annotation for a tweet where an emotion is implied – "*@screennameA @screennameB f***ing idiot! How*

Table 1: Basic information about the data-set used in our study: extraction period, number of tweets, vertices and edges of the corresponding communication network, as well as hashtags and key-terms used for data extraction.

	Extraction Period	Tweets	Vertices	Edges	Hashtags
NATURAL DISASTERS					
Harvey hurricane	23.8.-11.9.2017	7,931,488	281,724	494,046	#Harveyhurricane, #HurricaneHarvey, hurricane harvey, hurricane houston, hurricane texas, #HarveySOS, #HarveyRescue, #Houstonflood
Irma hurricane	4.9.-18.9.2017	5,421,054	189,969	348,089	#IrmaHurricane, #Irma2017, #hurricaneIrma
Mexico earthquake	7.9.-28.9.2017	1,713,618	45,882	54,796	#mexicoEarthquake, #earthquakemexico, earthquake mexico
Maria hurricane	21.9.-4.10.2017	1,258,515	60,353	97,916	#hurricaneMaria, #mariaHurricane, hurricane maria
Costa Rica earthquake	12.11.-2.12.2017	15,492	601	512	earthquake costa rica, #earthquake costarica, earthquake #costarica
Iran-Iraq earthquake	12.11.-2.12.2017	272,670	7,639	9,451	#earthquake iran, earthquake iran, #earthquakeinkurdistan, #earthquakeiran, #earthquakeiraq, #iraniraqearthquake, #kurdistanearthquake, #prayforkurdistan
Southern California mudslide	7.1.-27.1.2018	168,303	8,609	12,719	california flood, #castorm, #Montecito, montecito, #montecitoflood, mudslide california, #mudslide california, #santabarbara
Friederike windstorm	17.1.-28.1.2018	51,694	3,486	3,239	deutchland friederike, deutschland unwetter, extremeweather germany, extremeweather netherlands, #friederike, germany hurricane, #orkanfriederike, windstorm netherlands
Lang'ata wildfire	28.1.-1.2.2018	11,113	695	915	#fireKijijini, #langatafire
SHOOTING AND TERROR ATTACKS					
Tehama County school shooting	14.11.-02.12.2017	123,659	3,884	4,140	california shooter, kevin jason neal, #KevinJasonNeal, northern california shoot, #RanchoTehama, #RanchoTehamaShooting
Trebes (France) shooting	23.03.-08.04.2018	142,255	4,199	4,414	#ArnaudBeltrame, #Beltrame, #Carcassonne, #FrenchHero, #redouanelakdim, #Trebes, Arnaud Beltrame, Redouane Lakdim, Trebes France
YouTube HQ shooting	03.4.-10.4.2018	648,501	34,611	47,262	#NasimNajafiAghdam, #PrayersForYoutube, #SanBrunoShooting, #shootingYoutube#YoutubeHQShooting, #YoutubeHQ Tragedy, #youtubeshooter, #youtubeshooting, #YoutubeStrong
Münster (Germany) van attack	7.04.2018-14.04.2018	62,883	1,824	2,737	#MuensterAttack, #MuensterGermany, #Muensteramokfahrer, #Muensteramokfahrt, #MuensterAnschlag, #prayformuenster
Santa Fe school shooting	18.05.-25.05.2018	967,674	30,093	50,208	#DimitriosPagourtzis, #EnoughIsEnough, #SantaFe, #SantaFeGunControl, #SantaFeGunControlNow, #SantaFeGunViolence, #SantaFeHighschool, #SantaFeShooting, #SantaFeStrong, #TexasShooting
RIOTS					
Hamburg G20 summit	6.7-17.7.2017	653,568	25,429	58,768	#G20HH2017, #G20Hamburg, #G20HAM17, #G20HAM, "#G20 #Hamburg", "Hamburg riot", "Hamburg Unruhe"
Charlottesville riot	10.8-16.8.2017	2,202,682	84,638	152,209	#Charlottesville, #UnitetheRight, "Charlottesville riot"
Catalonia riot	28.9-16.10.2017	1,640,829	27,432	54,266	#Catalonia, #CatalanReferendum, #RepublicofCatalonia, "Catalonia violence", "Catalonia protest", "#1oct Catalonia"
Philadelphia Superbowl riot	4.2-10.2.2018	22,073	1,164	1,022	#PhillyBurning, #Phillyriot, "#superbowl #Philadelphia", "#Philadelphia #riot", and "Philadelphia riot"

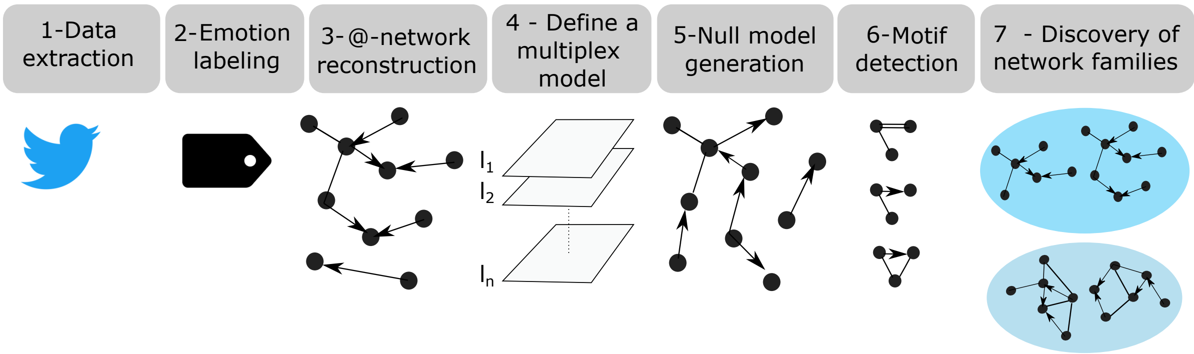


Figure 1: Research procedure.

many shootings will it take for you to wake up and change the law about gun control? #guncontrol" which was annotated in the following way: anger = 2, disgust = 3, fear = 2, all remaining emotions = 0. Our algorithm was designed to run on multiple CPU cores and thereby parallelizes the emotion detection procedure.

Testing the accuracy. To test for the accuracy of our procedure, we deployed two independent human raters. To mitigate potential bias in emotion detection, we chose the raters who were personally not involved in 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 tweets from each type of a crisis event) selected randomly from a subset of our data-set that includes only directed messages (n=1,396,709 tweets), as the directed messages are used to derive the communication network in the subsequent step. 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-measure score for each emotion and achieved 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. The score for surprise is influenced by the relatively low number of tweets in which "surprise" is the dominant emotion as well as the ambiguity of surprise which is neither a positive nor a negative emotion and its interpretation highly depends on the context of a tweet.

3. Construction of the messaging network. On Twitter, each user can send a direct message to another user via @screenname. 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 to bypass the character restriction imposed by Twitter). Moreover, we label each edge according to the dominant emotion conveyed in the corresponding message.

Table 2: Mean value of global network properties: number of connected components (CC), node degree, network diameter, eccentricity (ECC), and radius.

Layer	CC	Degree	Diameter	ECC	Radius
Anger	225.01	1.70	1.89	3.42	0.44
Fear	222.01	1.58	1.70	2.94	0.45
Sadness	49.4	1.39	1.24	2.04	0.77
Disgust	39.6	1.44	1.20	2.21	0.83
Anticipation	219.01	1.51	1.73	2.82	0.57
Joy	95.8	1.42	1.30	2.06	0.72
Trust	119.99	1.57	1.56	2.76	0.64
Surprise	44.9	1.43	1.21	1.98	0.82

The resulting emotion-annotated networks already show first differences with respect to their global network properties. For example, the networks representing anger-, fear-, and anticipation-exchange have a comparatively large number of connected components, compared to disgust- and surprise-exchange networks (see Table 2). We also found that the average messaging rate per user (expressed as an average node degree) assumes it's highest value in the anger-exchange network ($degree_{anger}$ = 1.70) and it's lowest value in the joy- ($degree_{joy}$ = 1.42) and sadness-exchange ($degree_{sadness}$ = 1.39) networks.

4. Construction of a multiplex network. Next, we derived one multiplex network for each day of the data extraction period, separately for each event. Each daily multiplex network consists of eight layers, and each of these layers represents one of the eight basic emotions. Moreover, in order to gain more insight concerning the interlayer dependencies, we do not only consider individual emotion layers (see Figure 2a) but also various aggregated layers. These aggregated 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 Figure 2b)[2]. 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 those of their adjacent vertices which are also active on the two aggregated valence layers (as shown in Figure 2c). Finally, we also aggregated all positive- and negative-emotion layers as well as surprise to derive the *overall aggregated* network (Figure 2d) for each day.

5. Null model construction. A general procedure for detecting network motifs is to determine the presence of specific subgraphs in the respective real-world network and compare them to the subgraphs found in a synthetically generated network that resembles the real-world network (a so-called null model). 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 et al., 2001). In total, we generated 1000 synthetic networks 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.

6. Motif detection. In order to detect *emotion-exchange motifs* (Kušen and Strembeck, 2020; Kušen and Strembeck, 2019), we first enumerated all possible subgraphs of a pre-defined size k (in our case $k = 3$)[3] 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 et al., 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 approximate the number of motifs), we categorized the subgraphs according to their degree sequence to only test the set of possible candidates (see Algorithm 1). Finally, we mapped each simplified emotion-exchange motif[4] found in the input (real-world) networks to one of the thirteen possible 3-node directed subgraph classes and labeled them according to MAN-labeling scheme (Davis and Leinhardt, 1972).

Algorithm 1: Motif detection.

```
Input: input_network;
Output: list_of_motifs ;
Initialize: i = 0;
# ENUMERATE AND CLASSIFY SUBGRAPHS
def procedure: esu_vf2(list_layers)
foreach l in list_layers do
    subgraphs = esu(l)
    foreach s in subgraphs do
        subgraphs' = subgraphs \ s
        foreach s' in subgraphs' do
            if vf2(s, s') then
                assign_common_isomorphism_class
                subgraphs' = subgraphs' \ s'
                subgraphs = subgraphs \ s'
            end
        end
    end
end
end procedure
# GENERATE LAYERS AND INTER-LAYERS
detect layers in input_network
layer_negative.add_edges_from(layer_anger, layer_sadness,
    layer_disgust, layer_fear)
layer_positive.add_edges_from(layer_joy, layer_anticipation,
    layer_trust)
foreach i in range(length(V(input_network))) do
    if v_i ∈ V(layer_negative) & v_i ∈ V(layer_positive) then
        inter_layer.add_edges_from(layer_negative.edge_containing(v_i),
            layer_positive.edge_containing(v_i))
    end
end
list_layers = [layer_anger, layer_joy, ... , layer_surprise,
    layer_negative, layer_positive, interlayer, input_network]
esu_vf2(list_layers)
# GENERATE NULL MODELS
while i < 1000 do
    foreach l ∈ list_layers do
        null[l] = matching(l.in_degree(), l.outdegree())
    end
    esu_vf2(null)
    i = i+1
end
```

7. Discovery of network families. We followed the approach suggested by (Milo et al., 2004) which uses network motifs and their significance profiles to compare networks of different sizes. To account for the temporal aspect of emotion-exchange motifs, we defined three time-frames for each crisis event: a) the first two days of a crisis event (referred to as *time-frame 1*), b) the subsequent days 3-6 (referred to as *time-frame 2*), and c) the remaining days of a cri-

[2]Note that “surprise” can be associated to positive as well as negative emotions and is therefore treated separately.

[3]We pre-defined the size $k = 3$ to capture the smallest possible group of nodes, as dyads would be trivial for this type of an analysis. In future work, it would be interesting to set k to other values (> 3). However, given the computational costs of the current procedure (with $k = 3$), detecting motifs of larger sizes is infeasible and would require significant performance improvements of the motif detection procedure.

[4]Here, a “simplified emotion-exchange motif” disregards self-loops and multi-edges.

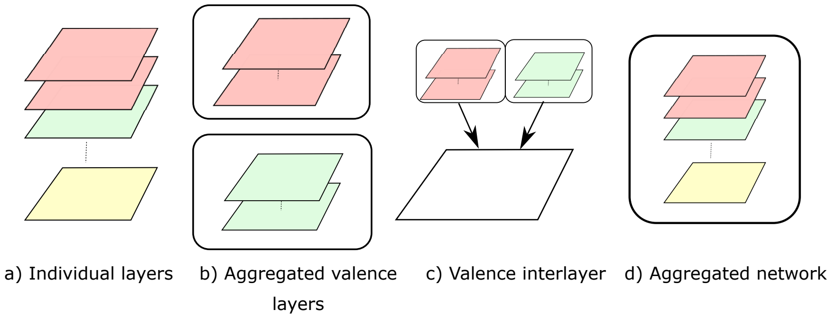


Figure 2: Individual emotion-annotated layers and the corresponding derived layers used in our analyses (green = positive emotion layers, red = negative emotion layers, yellow = surprise).

sis event (referred to as *time-frame 3*). For each pair of emotion-exchange networks, we computed Spearman's ρ coefficient while considering the temporal aspect. The results are presented for a *p-value*< 0.05. In order to identify families of emotion-exchange networks, we used the complete linkage method for hierarchical clustering.

4 Results

Emotional intensities during crisis events. Our data analysis indicates that three negative emotions are universally dominant during the crisis events studied in this paper. The average emotional intensities (*ei*) of fear (ei_{fear} =0.24) and sadness ($ei_{sadness}$ =0.14) dominate over the remaining emotions during natural disasters, fear (ei_{fear} =0.22) and anger (ei_{anger} =0.18) during riots, while fear (ei_{fear} =0.29) and anger (ei_{anger} =0.19) dominate during terror and shooting attacks. Our empirical findings complement those of (Flynn, 1997), who found that people universally express emotions according to particular phases across different types of crisis events, with shock and fear being initially expressed with a high intensity. Such initial emotions are subsequently followed by a wide range of other emotions, depending on the particularities of a crisis event and one's personal coping strategy. For example, we observe an increase in the intensity of positive emotions during natural disasters when people express well-wishing and prayers, as well as during terror and shooting attacks when people express gratitude to the helpers and "heroes" (e.g., the local police), anger which is highly associated with blaming mechanisms (Freyd, 2002) during riots, terror and shooting attacks, and sadness which is communicated in messages of compassion and condolences.

User reactions to emotional content. Our analysis of user reactions to emotional content revealed

Table 3: User reactions to emotional content. The *retweet* and *likes* values are presented as mean values over each crisis event and the extraction date, while the messaging rate stands for the average number of daily messages sent by a unique user during each crisis event.

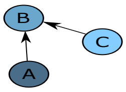
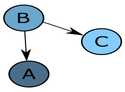
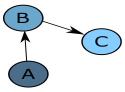
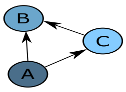
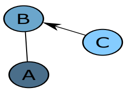
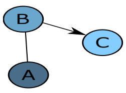
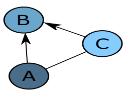
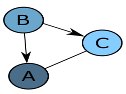
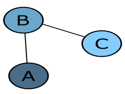
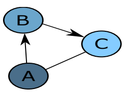
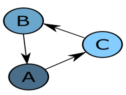
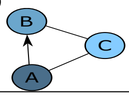
Emotion	Retweet	Likes	Mssg. rate
Anger	114.91 ± 213.86	5.58 ± 17.76	1.07 ± 0.19
Fear	403.84 ± 1078.04	1.68 ± 2.79	1.07 ± 0.18
Sadness	178.29 ± 346.81	1.26 ± 1.17	1.06 ± 0.16
Disgust	20.99 ± 38.3	0.95 ± 0.73	1.03 ± 0.11
Anticipation	176.19 ± 300.85	6.9 ± 21.48	1.01 ± 0.04
Joy	123.39 ± 273.27	3.34 ± 4.67	1.02 ± 0.07
Trust	266.32 ± 475.94	5.36 ± 8.18	1.04 ± 0.11
Surprise	65.36 ± 103.08	1.5 ± 1.37	1.02 ± 0.06

an increased retweeting behavior for fear-conveying messages ($mean(retweet_{fear}) = 403.84 \pm 1078.04$), followed by messages of trust ($mean(retweet_{trust}) = 266.32 \pm 475.94$), as shown in Table 3. Anticipation-conveying messages received on average the highest number of likes ($mean(likes_{anticipation} = 6.9 \pm 21.48$), while anger resulted in the highest tweeting rate ($mean(mssg.rate_{anger} = 1.07 \pm 0.19$), closely followed by fear ($mean(mssg.rate_{anger} = 1.07 \pm 0.18$). These results indicate that basic emotions inspire remarkably different user behavior, irrespective of their affective valence.

Emotion-exchange motifs. In our data-set, the exchange of emotional messages during crisis events is documented via 729,368 emotion-exchange motifs that come in 1,480 shapes (isomorphism classes). For presentation purposes, we only visualize the simplified motifs in Table 4.

Since Twitter's main purpose is that of a message broadcasting service, the message-receiver motif 021U (f=596258; 729.37 per 1000 motifs) and the broadcasting motif 021D (f=84139; 115.36 per 1000 motifs) appear most frequently in each of the 18 crisis events (see Table 4). These two motifs also count a relatively high number of edges (ec) (ec_{021U}=5.53±2.52; ec_{021D}=4.97±1.53) and exhibit a relatively high variability with respect to the edge dis-

Table 4: Basic information about the MAN-labeled motifs identified in the data-set – motif frequency (absolute and averaged), prevalence rate per 1000, motif variability (absolute and averaged), as well as the mean edge count and its average standard deviation.

Shape	Frequency	X:1000	Variability	Edge count
021U 	596258 (35074.00±58538.54)	729.37	366 (54.35±73.97)	5.53±2.52
021D 	84139 (4674.38±7756.13)	115.36	286 (40.94±56.56)	4.97±1.53
021C 	25640 (1508.23±3303.97)	35.15	219 (26.12±50.12)	3.76±0.84
030T 	13240 (778.82±1518.81)	18.15	338 (37.94±74.29)	4.09±1.07
111D 	4621 (385.08±872.08)	6.33	99 (12.83±27.53)	3.88±0.86
111U 	3785 (270.35±556.35)	5.18	75 (9.07±18.29)	3.54±0.56
120U 	997 (76.69±124.78)	1.37	26 (4.46±5.97)	4.42±0.39
120D 	572 (63.55±134.78)	0.78	43 (7.00±13.45)	4.51±0.62
201 	60 (15.00±16.02)	0.08	13 (4.25±5.19)	4.45±0.58
120C 	31 (15.50±16.26)	0.04	8 (5.50±3.53)	4.68±0.26
030C 	19 (9.50±2.12)	0.03	5 (3.00±2.83)	3.64±0.9
210 	6 (3.00±1.41)	0.008	2 (1.50±0.71)	5.12±0.18

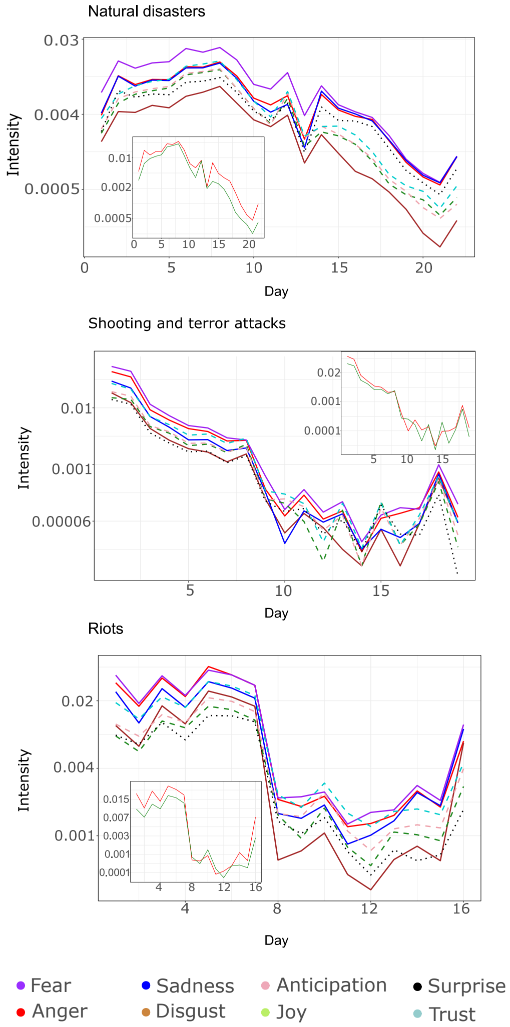


Figure 3: Relative emotion intensities during natural disasters, shooting and terror attacks, as well as riots, normalized for the range [0-1]. Positive emotions are depicted via dashed lines, negative via solid lines, and surprise via a dashed line. The inlay plots show the daily intensity of aggregated positive (trust, joy, anticipation; green line) and aggregated negative (anger, fear, sadness, disgust; red line) emotions.

tribution (var_{021U}=366; var_{021D}=286).

Families of emotion-exchange networks. Over the course of time, two sets of networks emerged that form two families of emotion-exchange networks. While the number of families remains constant over time, the membership of networks in one of the two families is fluctuating over time. We name the families according to the initials of the core members which include the networks whose membership to a particular family is constant over all three time-frames. The resulting families of emotion-exchange networks are shown in Figure 5.

The first family, is called the JSSIA (joy-sadness-surprise-interlayer-aggregated) family, and includes sadness- and joy-exchange networks (time-frame 1: $\rho_{joy-sadness} = 0.63$; time-frame 2: $\rho_{joy-sadness} = 0.67$ (albeit not significant); time-frame 3: $\rho_{joy-sadness} = 0.68$), as well as surprise (time-frame 1: $\rho_{joy-surprise} = 0.74$, $\rho_{sadness-surprise} = 0.73$; time-frame 2: $\rho_{joy-surprise} = 0.74$, $\rho_{sadness-surprise} = 0.67$; time-frame 3: $\rho_{joy-surprise} = 0.45$, $\rho_{sadness-surprise} = 0.41$). Interlayer- and aggregated-emotion exchange networks share the membership with joy-, sadness-, and surprise- in all time-frames, however with a larger distance from the other three networks.

The second family, is called the PAF (positive-anticipation-fear) family. The three consistent members of the PAF family show a greater dissimilarity among each other as compared to the closely correlated core (joy-sadness-surprise) of the JSSIA family. In the PAF family, two core networks of the same affective valence (positive- and anticipation-exchange networks) show the highest structural similarity (time-frame 1: $\rho_{positive-anticipation} = 0.74$; time-frame 2: $\rho_{positive-anticipation} = 0.43$; time-frame 3: $\rho_{positive-anticipation} = 0.49$).

The two dominant emotions during crisis events (anger and fear) show a high fluctuation with respect to their family membership. While at the beginning of a crisis event, the exchange of fear is highly associated with the exchange of positive emotions (see Figure 5), the networks representing the exchange of fearful messages become structurally more similar to the exchange of other negative emotions (time-frame 2: $\rho_{negative-fear} = 0.5$), and anger (time-frame 3: $\rho_{negative-fear} = 0.62$, $\rho_{anger-fear} = 0.64$) over time. Anger initially highly resembles the aggregated network (time-frame 1 $\rho_{anger-aggregated} = 0.53$) and eventually becomes more similar to the exchange of fear (see time-frame 3 in Figure 5).

5 Discussion

Our results clearly indicate differences between the communication networks representing the eight basic emotions. We found that the eight emotions not only inspire different user reactions/behavior during crisis events, but that they are also different from a structural point of view. Such an effect on the underlying structure of Twitter's direct messaging network can be attributed to the functional role of emotions. For example, as reported in previous studies, fear is highly associated with an information seeking and sharing behavior (Wollebaek et al., 2019) which explains the high retweet rate of messages conveying

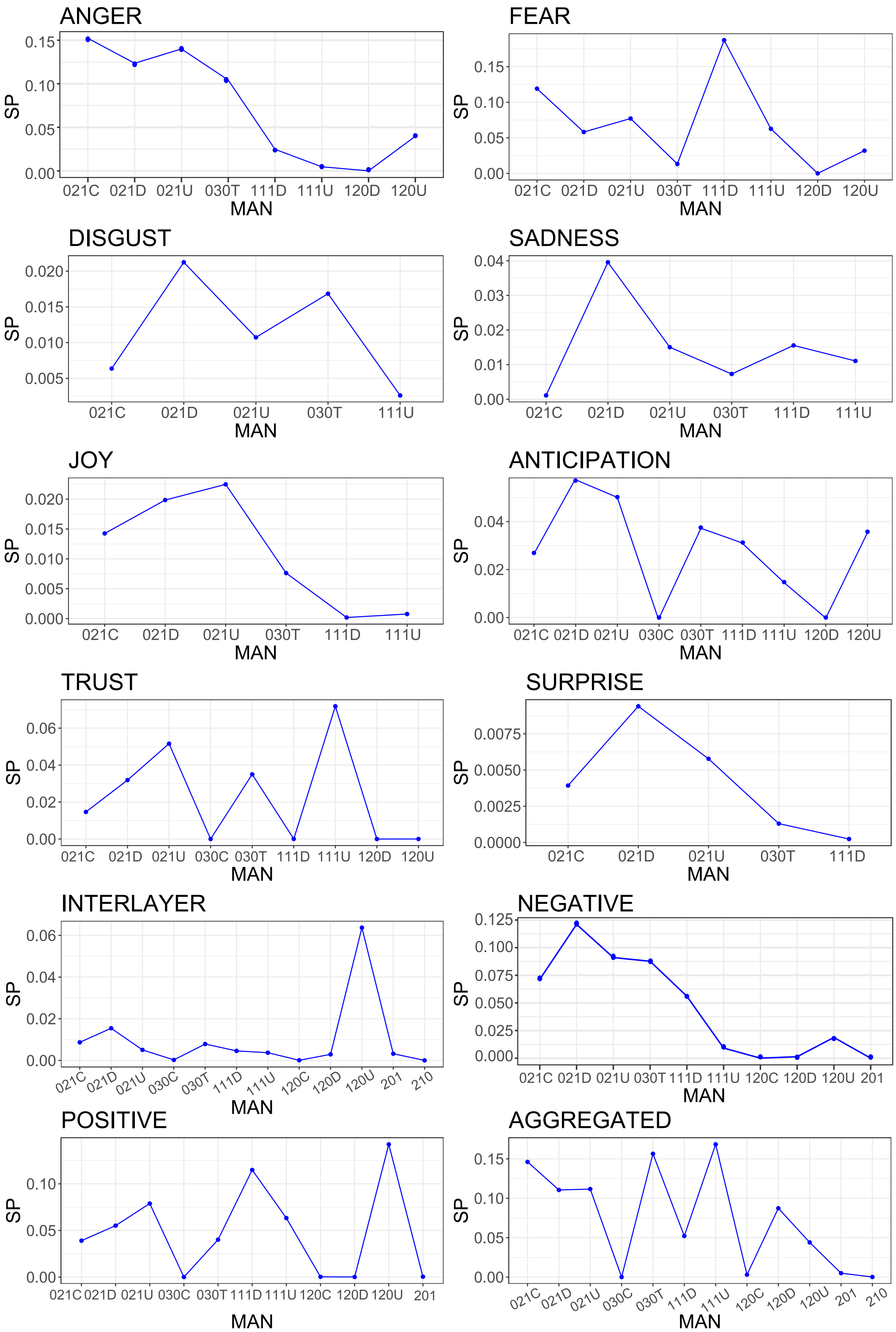


Figure 4: Significance profiles of the simplified motifs averaged over each day of each each crisis event.

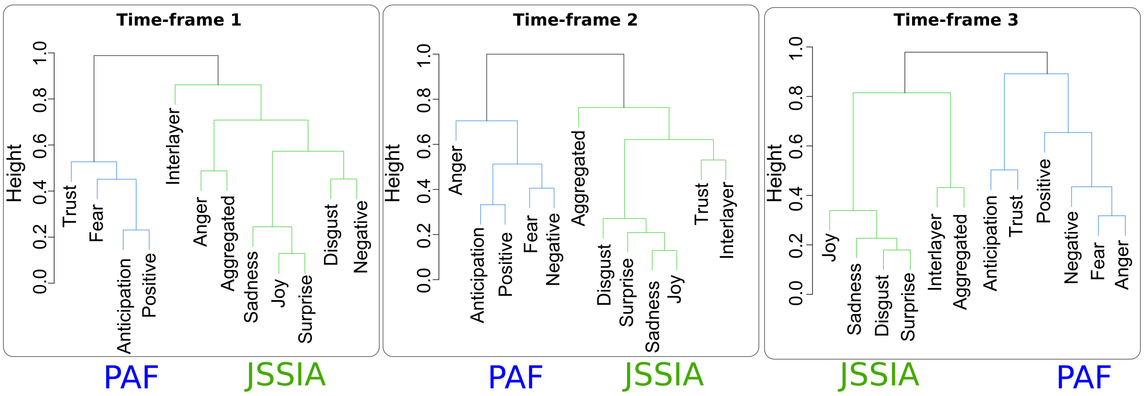


Figure 5: Hierarchical clustering of emotion-exchange networks.

fear. This behavior is reflected in the underlying fear-exchange motifs. Fear was characteristic for a high significance of the message receiver motif (111D) that involves a mutual edge (i.e., it involves a discussion between a pair of users). Another example is the expression of anger which structurally differs from fear and does not persistently share the same family with fear. Intense feelings of anger experienced during crisis events are highly associated with blaming mechanisms. According to (Freyd, 2002), people regularly search for culprits who are to blame for a terror attack, riots, or for the lack of help in the aftermath of natural disasters. In this context, we found that anger is representative for a heated message-sending behavior and is characteristic for message chains (021C) and message receiver (021U) motif shapes.

Interestingly, message-exchanges representing joy and sadness, which belong to two distinct affective valence categories, show the highest structural similarity compared to all other pairs of networks. A possible explanation for such a similarity lies in the expression of sympathy and condolences that both emotions are associated with. According to (Batson et al., 1991), messages of sympathy and condolences can be seen as a form of altruism. We found that such altruistic messages are associated with the expression of gratitude to individuals perceived as ”heroes” (e.g., those who sacrificed themselves to save the lives of others) or those who got injured, lost their homes, or whose family members were victims of a crisis event. This is reflected in the underlying motifs 021D (a broadcaster motif) and 021U (a message receiver motif) rather than the discussion motifs (those that convey mutual edges). Since the exchange of sadness and joy is represented by the same set of motifs, we also observed a more tightly correlated core of the JSSIA family as compared to the PAF family.

6 Conclusion

In this paper, we studied the intensity of basic emotions that were communicated during eighteen different crisis events, including terror and shooting attacks, riots, as well as various types of natural disasters. Prior studies highlighted the general expression of fear and shock as a crisis event happens, as well as the emergence of a range of other emotions in the aftermath of a crisis event. Based on a data-set counting over 23 million messages, our study empirically shows that these findings also apply to message-exchanges happening in online social networks.

Moreover, we found that considerable differences exist how emotions belonging to the same affective valence influence OSN communication behavior. This is reflected in the user reactions to emotional content. For example, while fear was highly associated with increased retweeting behavior, anger showed the highest messaging rate, and messages conveying anticipation received most likes.

However, the main contribution of this paper is an analysis of statistically significant network structures that are representative for the exchange of the eight basic emotions. To this end, we used the novel concept of *emotion-exchange motifs* (Kušen and Strembeck, 2020; Kušen and Strembeck, 2019) and found that the exchange of sadness and joy are structurally more similar than the exchange of any other pair of emotions. Moreover, after clustering the emotion-exchange networks, two families of networks emerged whose membership highly fluctuates over time. According to their core members we named the two families JSSIA (joy-sadness-surprise-interlayer-aggregated) and PAF (positive-anticipation-fear), whereby JSSIA has a more tightly correlated core compared to PAF.

In our future work, we plan to further examine the emergence of temporal emotion-exchange motifs to provide an even more fine-grained analysis of the underlying properties of human communication networks.

REFERENCES

Abdul-Mageed, M. and Ungar, L. (2017). Emonet: Fine-grained emotion detection with gated recurrent neural networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 718–728. Association for Computational Linguistics.

Batson, C. D., Batson, J. G., Slingsby, J. K., Harrell, K. L., Peekna, H. M., and Todd, R. M. (1991). Empathic joy and the empathy-altruism hypothesis. *Journal of personality and social psychology*, 61(3):413–426.

Berger, J. (2011). Arousal increases social transmission of information. *Psychological Science*, 22(7):891—893.

Cordella, L. P., Foggia, P., Sansone, C., and Vento, M. (2004). A (sub)graph isomorphism algorithm for matching large graphs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26(10):1367–1372.

Davis, J. A. and Leinhardt, S. (1972). *The Structure of Positive Interpersonal Relations in Small Groups*. Houghton Mifflin, Boston.

Flynn, B. (1997). Psychological aspects of disasters. *Renal Failure*, 19(5):611–620.

Fraustino, J. D., Brooke, L., and 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.

Freyd, J. J. (2002). In the wake of terrorist attack, hatred may mask fear. *Analysis of Social issues and public policy*, 2(1):5–8.

Gera, R., Alonso, L., and Crawford, B. (2018). Identifying network structure similarity using spectral graph theory. *Applied Network Science*, 3(2).

Hansen, L. K., Arvidsson, A., Nielsen, F. A., Colleoni, E., and Etter, M. (2011). Good friends, bad news - affect and virality in twitter. In Park, J. J., Yang, L. T., and Lee, C., editors, *Future Information Technology*, pages 34–43, Berlin, Heidelberg. Springer Berlin Heidelberg.

Holyst, J. (2016). *Cyberemotions: Collective Emotions in Cyberspace*. Understanding Complex Systems. Springer International Publishing.

Kim, H., Lee, S., Cappella, J., Vera, L., and Emery, S. (2013). Content characteristics driving the diffusion of antismoking messages: Implications for cancer prevention in the emerging public communication environment. *Journal of National cancer institute. Monographs*, 47:182–187.

Klaise, J. and Johnson, S. (2017). The origin of motif families in food webs. *Nature Scientific Reports*.

Koutra, D., JT., V., and C., F. (2013). Deltacon: A principled massive-graph similarity function. In *Proceedings of the 2013 SIAM International Conference on Data Mining*, pages 162–170.

Kušen, E., Cascavilla, G., Figl, K., Conti, M., and Strembeck, M. (2017). Identifying emotions in social media: Comparison of word-emotion lexicons. In *Proceedings of the 4th International Symposium on Social Networks Analysis, Management and Security (SNAMS) (co-located with IEEE FiCloud)*. IEEE.

Kušen, E. and Strembeck, M. (2019). An Analysis of Emotion-Exchange Motifs in Multiplex Networks During Emergency Events. *Applied Network Science*, 4(8):1–33.

Kušen, E. and Strembeck, M. (2020). Evacuate everyone south of that line: Analyzing structural communication patterns during natural disasters. *Journal of Computational Social Science*. DOI: 10.1007/s42001-020-00092-7.

Masoudi-Nejad, A., Schreiber, F., and Kashani, Z. (2012). Building blocks of biological networks: A review on major network motif discovery algorithms. *IET Syst Biol.*, 6(5).

Milo, R., Itzkovitz, S., Kashtan, N., Levitt, R., Shen-Orr, S., Ayzenshtat, I., Sheffer, M., and Alon, U. (2004). Superfamilies of evolved and designed networks. *Science*, 303(5663):1538–1542.

Milo, R., Shen-Orr, S., Itzkovitz, S., Kashtan, N., Chklovskii, D., and Alon, U. (2002). Network motifs: Simple building blocks of complex networks. *Science*, 298(5594):824–827.

Mohammad, S. M. and Turney, P. D. (2013). Crowdsourcing a word-emotion association lexicon. *Computational Intelligence*, 29(3):436–465.

Newman, M. E. J., Strogatz, S. H., and Watts, D. J. (2001). Random graphs with arbitrary degree distributions and their applications. *Phys. Rev. E*, 64(2):026118.

Rimé, B., Mesquita, B., Boca, S., and Philippot, P. (1991). Beyond the emotional event: Six studies on the social sharing of emotion. *Cognition and Emotion*, 5(5-6):435–465.

Scheve, Christian Salmella, M. (2014). *Collective emotions*. Oxford University Press, Oxford, United Kingdom, 1 edition.

Shi, Y. and Macy, M. (2016). Measuring structural similarity in large online networks. *Social Science Research*, 59:97 – 106. Special issue on Big Data in the Social Sciences.

Sun, X. and Wandelt, S. (2014). Network similarity analysis of air navigation route systems. *Transportation Research Part E: Logistics and Transportation Review*, 70:416 – 434.

Topirceanu, A., Duma, A., and Udrescu, M. (2016). Uncovering the fingerprint of online social networks using a network motif based approach. *Computer Communications*, 73:167 – 175.

Tsugawa, S. and Ohsaki, H. (2015). Negative messages spread rapidly and widely on social media. In *Proceedings of the ACM on Conference on Online So-*

cial Networks, COSN, pages 151–160, New York, NY, USA. ACM.

von Scheve, C. and Ismer, S. (2013). Towards a theory of collective emotions. *Emotion Review*, 5(4):406–413.

Wernicke, S. (2006). Efficient detection of network motifs. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 3(4):347–359.

Wollebaek, D., Karlsen, R., Steen-Johnsen, K., and Enjolras, B. (2019). Anger, fear, and echo chambers: The emotional basis for online behavior. *Social Media + Society*, 5(2):2056305119829859.