On the Public Perception of Police Forces in Riot Events
The Role of Emotions in Three Major Social Networks During the 2017 G20 Riots

Ema Kušen[1] and Mark Strembeck[1,2,3]
[1] *Vienna University of Economics and Business, Vienna, Austria*
[2] *Secure Business Austria (SBA), Vienna, Austria*
[3] *Complexity Science Hub (CSH), Vienna, Austria*

Keywords: Emotion Analysis, Riots, Social Network, User Behavior.

Abstract: In this paper, we present a study on the impact of emotions on information diffusion during a riot event. In particular, we analyze a data-set consisting of more than 750 thousand social media messages related to the 2017 G20 summit that have been extracted from Facebook, Twitter, and YouTube. Because of the controversies surrounding police operations during violent protests, our analysis especially focuses on emotions conveyed in messages related to the local police. We found that a) negative emotions of high arousal (anger and fear) dominate in messages mentioning the police on all three social networks, b) emotional content was forwarded (retweeted) more often, regardless of the corresponding emotion valence, and c) in contrast to previous studies we found that emotions have a considerably larger impact on the retweeting behavior than the number of hashtags a message contains.

1 INTRODUCTION

"Everything because of the G20 2017 summit in Hamburg this weekend... everything burns and everything's broken", posted a Facebook user concerning the riots that occurred during the G20 summit which took place in Hamburg, Germany, in July 2017. The G20 summit has been established as a regular conference meeting of world leaders that provides a forum for discussing global issues, such as migration and climate change. In the past, the G20 summit was often accompanied by non-violent demonstrations as well as violent protests which also involved clashes with the local police. The 2017 G20 summit in Hamburg witnessed some of the longest and most violent protests in G20 history that were accompanied by vivid social media discussions.

Crowd psychology suggests that in events of social unrest, people who would normally not break the law suddenly escape the norms of socially accepted behavior. According to the *deindividuation theory* (O'Connell and Cuthbertson, 2009) people are more likely to join a larger crowd in such events because they become anonymous as they blend into a mob. However, the question remains what triggers people to join such violent crowds. According to the deindividuation theory, one of the dominant determining factors are *emotions*. For example, (Berkowitz, 1972; Pardy, 2011) noted that high emotion arousal (e.g. emotions of anger and hate) considerably contributes to the formation of public unrest. In addition, (Gross, 2011) found that riots are characteristic for a spontaneous spread of emotions between the members of a social group. However, identifying emotions as well as their impact on user behavior in online social networks (OSNs) is a challenging task (Kušen et al., 2017).

During such emotionally intense events when matters progress rapidly and unexpectedly, people often turn to the local police to seek official information and make sense of the potentially threatening situation (Huang et al., 2017). Given the controversies surrounding the actions of the Hamburg police (see Section 3), we study whether the controversy was transferred to the OSN discourse about the event. In particular, we focus on emotions expressed by people who contributed to the OSNs discussions about the event. To this end, we study 1) if emotions expressed about the local police are consistent across the three OSNs, 2) how these emotions compare to the emotions expressed in other messages related to the event (i.e. messages that do not mention the local police), and 3) temporal patterns of emotion expression on the three OSN platforms.

Kušen, E. and Strembeck, M.
On the Public Perception of Police Forces in Riot Events.
DOI: 10.5220/0006763301200127
In *Proceedings of the 3rd International Conference on Complexity, Future Information Systems and Risk (COMPLEXIS 2018)*, pages 120-127
ISBN: 978-989-758-297-4

For the purposes of this paper, we systematically extracted more than 750 thousand publicly available messages concerning the 2017 G20 summit from three of today's most popular OSN platforms – Facebook, Twitter, and YouTube. We relied on these three OSNs to capture the public expression of emotions that can be generalized beyond a single OSN platform.

The remainder of this paper is organized as follows. In Section 2, we summarize related work, followed by an overview of the 2017 G20 riots (Section 3). In Section 4, we outline our research and data analysis and present the results in Section 5. A further discussion of the results is provided in Section 6 before Section 7 concludes the paper.

2 RELATED WORK

Since a substantial amount of scientific literature on social unrest and riots exists, we limit our related work to studies focusing on OSN interactions of citizens and authorities during riots.

Previous studies have shown that authorities (such as the local police, elected politicians, and government agencies) are regularly mentioned on OSNs when users seek official information (Huang et al., 2017). In general, authorities predominantly disseminate informational messages and rarely engage in a one-to-one conversation with the citizens (Crump, 2011; Heverin and Zach, 2010; Waters and Williams, 2011). However, this conversational pattern might spontaneously change during crisis events, such as riots.

For example, (Panagiotopoulos et al., 2014) investigated Twitter activity of the local government during a 2011 riot in England. Their findings show that the local government utilized citizen sourcing to gain near real-time information about the riot and supported the local community by disproving rumors and sending direct replies to residents asking for information. In addition to studying the role of the local government, (Procter et al., 2013) examined the role of the local police during the same event. They found that, in contrast to the local government, the police neither used OSNs as a source of information nor as an engagement tool in this particular riot event.

In contrast to the above-mentioned studies, authorities may also fuel riots by disseminating ideological messages over OSNs. One such case is analyzed in (Karkin et al., 2015) which indicates that political parties may actively contribute to the polarization and conflict among citizens.

3 EVENT OF STUDY

In 1999, the G20 summit was first organized as an international forum for governments to discuss financial and economic questions, including climate change, trade, and migration. Today, the G20 group includes 19 different countries plus the European Union. The G20 members contribute 80% of global GDP, with two thirds of the whole world's population living in the member countries.

The 2017 G20 summit took place on Friday July 7th and Saturday July 8th in Hamburg, Germany.

The summit was met with a number of demonstrations and protests prior to the actual event. Already on Sunday July 2nd, minor clashes occurred between the local police and protesters, followed by the so-called "Welcome to Hell" march on the following Thursday (July 6th) which counted about 8,000 protesters[1]. The march escalated into a violent protest after the local police requested that hooded protesters remove their masks. Rising tensions between the protesters and the local police resulted in a series of violent confrontations in Hamburg's harbor area, leading to 14 injured demonstrators with one being in a critical condition, as well as 76 injured police officers.

On the first day of the G20 summit (July 7th), the riots continued with further acts of violence including automobile arson, shop looting, as well as throwing objects and so-called molotov cocktails at the police. According to the corresponding news reports, 160 police officers ended up being injured. Following the protests, mutual accusations arose where the protesters as well as the police have been blamed for their violent behavior. German chancellor, Angela Merkel, condemned the rioters saying: "I have every understanding for peaceful demonstrations, but violent demonstrations put human lives in danger"[2]. On the other hand, the police has been accused of fueling the violence with allegedly oppressive tactics and risking lives of the demonstrators after aiming water cannons at people standing on bridges and rooftops.

4 DATA COLLECTION

Selection of Data Sources. The G20 summit was subject to lively discussions on popular social media channels, with messages ranging from personal

[1] Note that the background information in this section relies on information published by reputable news sources (esp. CNN, Spiegel Online, and The Guardian).

[2] https://www.theguardian.com/world/2017/jul/07/g20-protests-hamburg-altona-messehalle

recalls of the recent happenings and experiences, amateur videos and pictures taken by eye-witnesses, citizens asking for information, to messages praising or opposing the local authorities. In order to capture and trace emotions communicated over OSNs, we considered three types of platforms: 1) a microblog (Twitter), 2) a social networking site (Facebook), and 3) a community video site (YouTube). Each of the OSN platforms we selected can be seen as characteristic for its unique set of content-related features and usage norms.

In terms of message content, Twitter users are limited to 140 characters of text, whereby event- or topic-related tweets are often accompanied by a corresponding hashtag # (e.g., #HamburgG20). Facebook, on the other hand, provides more freedom for its users in terms of content length. Usually, Facebook comments are lengthier than tweets and may also include embedded multimedia content and pictorial icons (emoticons). In contrast, YouTube is primarily a video-sharing platform on which users may upload their videos, such as vlogs, recordings of their experiences, tutorial videos, etc. Thus, users visit these platforms with different intentions and generate platform-specific content.

Each of the three platforms provides a unique set of actions for their users, such as for disseminating one particular instance of a message (e.g., retweeting), favoring a message (e.g., liking), sending a directed message to another user (e.g, @username on Twitter, +username on YouTube), or replying to a message. These user actions are observable via public API functions offered by each of the platforms. Thus, by observing public user actions, OSNs enable researchers to gather rich sets of platform-specific data which can then be used to analyze OSN user behavior.

Data Extraction. We extracted tweets by using Twitter's Search API[3] and a list of predefined hashtags (#G20HH2017, #G20Hamburg, #StPauli, #Schanzenviertel, #Sxhanzenviertel, #schulterblatt, #G20HAM17, #G20HAM, #hamburgraeumtauf, #NoG20, #FightG20, #G20 + #Hamburg, #wellcometohell), as well as two combinations of key terms (*Hamburg + riot* and *Hamburg + Unruhe (German for "unrest")*) to also capture those tweets that are relevant to the event but do not contain any of the chosen hashtags. In total, we extracted 762404 tweets for the time period from July-06-2017 to July-17-2017.

For extracting Facebook posts, we first identified a number of relevant public pages on Facebook and then extracted comments to the posts related to the Hamburg riots. The list of public Facebook pages we used in our study include local (German) news media, such as Deutsche Welle, BILD, Spiegel Online, ZDFHeute, and Radio Hamburg, as well as foreign (non German) news media such as Yahoo news, or BBC news. Moreover, we included the public Facebook page of the Hamburg police department in our extraction. For our analysis, we extracted comments to posts that received at least 100 comments. Moreover, we also extracted comments from 3 public videos posted on Facebook by eye-witnesses. In particular, we used Facebook's Graph API[4] to extract 98546 Facebook comments on the 2017 G20 summit.

The smallest of our data-sets counts 31976 YouTube comments related to a set of 24 selected YouTube videos about the event. We collected these comments by using YouTube's Data API[5]. For our analysis, we restricted the comment extraction to videos counting at least 100 comments. The pool of videos consists of 17 private videos filmed by bystanders and 7 news reports by commercial media sources (e.g. CNN, spiegeltv, HD1).

Data Pre-processing. For each of the three data-sets, we applied the following procedure: We first identified and removed duplicates from our data-set. For example, duplicates in a Twitter data-set can emerge when multiple hashtags appear in the same tweet. After removing the duplicates, we used the *langdetect* Python package[6] to split each data-set into two subsets (German language and English language). Next, we identified the emotions conveyed via the messages in each subset by using the corresponding NRC word-emotion lexicons[7], as well as a set of heuristics that resemble the natural way humans assess emotions in written texts (Kušen et al., 2017). In order to identify the intensity of emotions in the tweets, Facebook posts, and YouTube comments, we used the AFINN lexicon[8].

After applying the pre-processing procedure outlined above, our data-set counted in total 653568 tweets, 29904 YouTube comments, and 72350 Facebook comments, resulting in a data-set consisting of 755822 unique OSN messages about the event.

Research Scope. Our analysis includes three aspects: 1) messages mentioning the local police (RQ1), 2) messages sent to the local police (RQ2), and 3) a temporal analysis of positive and negative emotions on three OSN platforms.

[3] https://dev.twitter.com/overview/api

[4] https://developers.facebook.com/docs/graph-api

[5] https://developers.google.com/youtube/v3/

[6] https://pypi.python.org/pypi/langdetect

[7] NRC lexicon: http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

[8] http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=6010

In order to address our research questions (see below), we re-constructed a subnetwork of mentions (where the central node of interest is the Hamburg police) and a Twitter communication network (subsequently referred to as "@-network").

RQ 1: Do messages mentioning ("talking about") the local police exhibit significantly different emotions compared to other messages concerning the G20 event?

RQ1.1: If yes, is the observed pattern comparable on all three OSN platforms?

RQ 2: Are messages sent to ("talking to") the local police emotionally-charged? How do these messages compare to the messages mentioning the police and the remaining messages?

RQ 3: Do OSN users mention the police at times of higher emotional intensity?

5 RESULTS

5.1 Messages Mentioning the Police

In order to examine which emotions OSN users express in messages mentioning the local police and how they react to messages that mention the police, we split our data-set into two parts: 1) messages that mention the terms "police" as well as its German equivalent "Polizei", and 2) messages concerning the G20 event that do not mention the police.

The NRC lexicon provides scores for 8 basic emotions according to Plutchik's wheel of emotions (Plutchik, 2001) (anger, disgust, fear, sadness, trust, joy, anticipation, and surprise). In our analysis, we classify anger, disgust, fear, and sadness as negative emotions while trust and joy are classified as positive emotions. In order to classify surprise and anticipation, we relied on Spearman's rank coefficient with a confidence level of 0.95. Since anticipation showed a strong relation with joy on Twitter (ρ_t) and Facebook (ρ_f) (ρ_t=0.45, ρ_f=0.43) compared to negative emotions, such as fear (ρ_t= 0.24) and anger (ρ_f=0.27), we classify it as a positive emotion for the Twitter and Facebook data-sets. In contrast, anticipation correlated comparatively high with both negative and positive emotions on YouTube (ρ_y) (ρ_y=0.32 for joy and ρ_y=0.24 for disgust). Thus, for the YouTube data-set anticipation was treated as a separate category (neither positive nor negative).

Moreover, we did not find a distinctive difference in correlations of the surprise emotion with positive (joy, trust) or negative (fear, anger, sadness, disgust) emotions. In our Twitter data-set, Spearman's ρ between surprise and fear was 0.52 and between surprise and trust 0.49. We observed similar coefficient values in our Facebook data-set (ρ_f=0.54 for trust and ρ_f=0.46 for fear) and YouTube data-set (ρ_y=0.57 for fear and ρ_y=0.6 for trust). Thus, surprise was also treated as a separate category (neither positive nor negative).

Tables 1 and 2 show that messages mentioning the local police make up a comparatively small portion of the Facebook (1.61%), YouTube (3.94%), and Twitter data-sets (15.34%). However, our data indicates that, though smaller in proportion, these messages are "liked" more than the remaining messages (on Facebook and on Twitter before adjusting for the effects of retweets, see below), and contain more @username mentions on Twitter.

Moreover, messages mentioning the local police are more emotionally charged as compared to the remaining messages. To test for the significance of such an observation, we turn to Welch's two sample t-test.

Our results show that anger (t_f=13.826, t_y=9.53, t_t=56.63 for $p < 0.05$), fear (t_f=20.58, t_y=12.51, t_t=73.20 for $p < 0.05$), and trust (t_f=21.24, t_y=12.35, t_t=42.25 for $p < 0.05$) are significant for the confidence level of 0.95 on Facebook (t_f), YouTube (t_y), as well as Twitter (t_t). Moreover, the results further reveal that sadness (t_f=11.64, t_y=8.1 for $p < 0.05$), disgust (t_f=9.25, t_y=7.32 for $p < 0.05$), anticipation (t_f=10.28, t_y=7.49 for $p < 0.05$), surprise (t_f= 7.74, t_y=6.72 $p < 0.05$), and joy (t_f=9.47, t_y=6.92 for $p < 0.05$) were significant on Facebook and YouTube.

These findings indicate that negative emotions of high arousal (anger and fear) dominate in messages mentioning the police on all three OSNs as compared to positive emotions and negative emotions of low arousal (sadness).

Retweets and Retweeting Behavior

Next, we examined whether retweets in our Twitter data-set influence the results. We therefore removed the retweets and considered unique tweets only. After removing the retweets (see Table 2), our data-set exhibited a smaller fraction of unique tweets mentioning the police (*police* or *Polizei* 12.72%) and a larger fraction of tweets that have directly been sent to the police (*@polizeihamburg* 3.37%). The results of Welch's test revealed that negative emotions – anger (t_t=6.82 for $p < 0.05$), fear ($t_t = 18.5$ for $p < 0.05$), and sadness (t_t=3.42 for $p < 0.05$) – one positive emotion, trust (t_t=12.5 for $p < 0.05$), as well as surprise (t_t=5.56 for $p < 0.05$) were amplified by the effects of the retweets.

Next, we examined whether emotions contributed to the diffusion of particular messages (retweeting). In our data-set the standard deviation (*sd*=233.79)

Table 1: Summary of the Facebook and YouTube data-sets – average number (μ) and standard deviation (sd) of emotions conveyed in the comments.

	Facebook		**YouTube**	
	Mention police (1.61%)	*Remaining* (98.39%)	*Mention police* (3.94%)	*Remaining* (96.06%)
Likes	μ=3.53, sd=43.85	μ=1.51, sd=24.97	μ=4.41, sd=29.9	μ=6.05, sd=49.72
Posting rate (h)	μ=5.41, sd=17.39	μ=228.15, sd=781.48	μ=13.1, sd=103.78	μ=119.69, sd=1527.96
Comment/user	μ=1.42, sd=1.23	μ=1.57, sd=3.08	μ=1.19, sd=0.62	μ=1.81, sd=2.31
Reply to a comment	μ=9.2, sd=85.14	μ=9.47, sd=634.29	μ=0.67, sd=3.66	μ=0.96, sd=6.4
Emotions				
Anger	μ=1.61, sd=2.84	μ=0.46, sd=1.47	μ=2.09, sd=3.96	μ=0.98, sd=2.41
Disgust	μ=0.87, sd=1.94	μ=0.34, sd=1.13	μ=1.22, sd=2.48	μ=0.68, sd=1.82
Fear	μ=2.31, sd=3.1	μ=0.44, sd=1.43	μ=2.41, sd=4.45	μ=0.78, sd=2.2
Sadness	μ=1.01, sd=2.2	μ=0.26, sd=1.05	μ=1.04, sd=2.38	μ=0.47, sd=1.63
Anticipation	μ=0.78, sd=1.57	μ=0.31, sd=1.01	μ=1.32, sd=2.63	μ=0.73, sd=1.86
Trust	μ=1.59, sd=2.03	μ=0.32, sd=1.12	μ=1.67, sd=2.91	μ=0.61, sd=1.92
Joy	μ=0.66, sd=1.54	μ=0.23, sd=0.93	μ=0.76, sd=1.78	μ=0.39, sd=1.47
Surprise	μ=0.59, sd=1.41	μ=0.27, sd=1	μ=1.04, sd=2.52	μ=0.55, sd=1.59

of the dependent variable (retweet count) is larger than its mean (μ=119.46). Thus, to adjust for over-dispersion, we apply a negative binomial regression model in which we consider negative emotions ($emotions_n$), positive emotions ($emotions_p$), surprise, and hashtag count as independent variables.

$$E(RT) = \beta_0 + \beta_1 emotion_n + \beta_2 emotion_p + \beta_3 Surprise + \beta_4 hashtagCount \quad (1)$$

We first present the results for the subset containing tweets that mention the police.

As shown in Table 3, the coefficients of the emotion *surprise* are positive and significant (significance level 0.001 for the data-set including retweets and 0.05 for the data-set excluding retweets), indicating that surprise positively contributes to the retweet count of the messages mentioning police. An opposite effect can be observed in the data-set containing remaining messages (those that do not address police). In specific, coefficients for the emotion surprise are negative and significant (significance level 0.001 for the subset that includes retweets as well as the one which excludes retweets). However, in contrast to the findings for the tweets mentioning the police, the remaining messages are retweeted more often when they are emotionally-charged (coefficients of both positive and negative emotions are positive and significant at level 0.001).

5.2 Messages Sent to the Police

In order to analyze the emotions conveyed in messages sent to the police, we especially focus on our Twitter data-set as we can easily trace the sender and receiver of a message[9].

After extracting the subset of messages relevant for this analysis, we re-constructed the @-network as a directed network which consists of 25429 nodes and 58768 edges. In this network the official Twitter account of the Hamburg police (@*polizeihamburg*) is the account with the highest in-degree (d_i=4815), the highest eigenvector centrality score, as well as the second highest betweenness centrality score, indicating that this particular account serves as an information hub.

Next, we compare the emotions conveyed in the messages sent to the police with messages that just mention the police and with the remaining messages that are not related to the police. With respect to the values reported in Table 2, our analysis shows that only anticipation was more dominant in the tweets sent to @polizeihamburg compared to those tweets that mention the police (t_t=4.53 for $p < 0.05$). However, when compared with the data-set excluding retweets, the results indicated that anger (t_t=5.96 for $p < 0.05$), disgust (t_t=3.97 for $p < 0.05$), fear (t_t=3.6 for $p < 0.05$), anticipation (t_t=2.75 for $p < 0.05$), trust (t_t=6.81 for $p < 0.05$), and surprise (t_t=6.73 for $p < 0.05$) were significant when paired with the subset containing the remaining tweets which are not police-related. Anticipation (t_t=2.65 for $p < 0.05$) and surprise (t_t=8.26 for $p < 0.05$) were significant when paired with the subset mentioning the police.

These results reveal that messages sent to the police have a higher presence of anticipation when compared to the other two subsets. However, tweets directed to the police also exhibited a higher count of negative emotions (such as anger and fear) compared

[9] On Twitter, messages sent to a specific account contain the receiver's @username. A word of caution is in order though: retweets of an original tweet begin with the following string: "RT @username". For our analysis, we removed such occurrences from the "talk to police" subset because such retweets are not considered tweets that have actually been sent to the police.

Table 2: Twitter data-set summary – average number (μ) and standard deviation (sd) of emotions conveyed in the tweets.

Complete data-set (100%)	*Talk to police* (2.3%)	*Mention police* (15.34%)	*Remaining tweets* (82.36%)
Emotions			
Retweets	μ=119.46, sd=233.79	μ=197.76, sd=319.49	μ=646.68, sd=1736.27
One-to-one (@)	μ=1.99, sd=0.82	μ=1.05, sd=0.98	μ=0.98, sd=0.67
Likes	μ=2.72, sd=40.58	μ=1.55, sd=27.64	μ=2.44, sd=92.12
Tweeting rate (h)	μ=52.23, sd=114.94	μ=348.09, sd=586.18	μ=1869.02, sd=3177.08
Tweet/user	μ=1.77, sd=2.5	μ=2.5, sd=6.96	μ=3.28, sd=10.87
Emotions			
Anger	μ=0.29, sd=0.92	μ=0.72, sd=1.46	μ=0.44, sd=1.13
Disgust	μ=0.16, sd=0.59	μ=0.18, sd=0.82	μ=0.18, sd=0.69
Fear	μ=0.27, sd=0.93	μ=0.91, sd=1.73	μ=0.42, sd=1.14
Sadness	μ=0.12, sd=0.5	μ=0.22 sd=0.83	μ=0.22, sd=0.74
Anticipation	μ=0.23, sd=0.65	μ=0.2, sd=0.63	μ=0.26, sd=0.74
Trust	μ=0.22, sd=0.83	μ=0.48, sd=0.98	μ=0.33, sd=0.95
Joy	μ=0.07, sd=0.4	μ=0.1, sd=0.54	μ=0.2, sd=0.77
Surprise	μ=0.19, sd=0.8	μ=0.23, sd=0.9	μ=0.26, sd=0.84
Without retweets (21.42%)	*Talk to police (3.37%)*	*Mention police (12.72%)*	*Remaining tweets (83.91%)*
Emotions			
Retweets	μ=3.6, sd=25.93	μ=7.08, sd=40.31	μ=5.25, sd=56.29
One-to-one (@)	μ=1.5, sd=0.9	μ=0.54, sd=2.01	μ=0.36, sd=0.84
Likes	μ=8.65. sd=72.03	μ=8.71, sd=65.11	μ=11.19, sd=196.95
Tweeting rate	μ=16.42, sd=34.55	μ=61.81, sd=104.88	μ=407.86, sd=655.52
Tweet/user	μ=1.74, sd=2.77	μ=2.21, sd=7.86	μ=2.88, sd=7.82
Emotions			
Anger	μ=0.48, sd=1.24	μ=0.64, sd=1.49	μ=0.37, sd=1.12
Disgust	μ=0.20, sd=0.69	μ=0.17, sd=0.74	μ=0.16, sd=0.72
Fear	μ=0.4, sd=1.19	μ=0.67, sd=1.57	μ=0.33, sd=1.1
Sadness	μ=0.11, sd=0.55	μ=0.2, sd=0.79	μ=0.16, sd=0.72
Anticipation	μ=0.26, sd=0.72	μ=0.22, sd=0.70	μ=0.23, sd=0.73
Trust	μ=0.38, sd=1.12	μ=0.38, sd=0.97	μ=0.27, sd=0.9
Joy	μ=0.09, sd=0.5	μ=0.09, sd=0.55	μ=0.12, sd=0.63
Surprise	μ=0.33, sd=1.1	μ=0.19, sd=0.84	μ=0.23, sd=0.85

Table 3: Results of the negative binomial regression model with a dependent variable *retweet count*. Results are presented for the significance levels *** 0.001, ** 0.01, * 0.05. Numbers in brackets show results for the data-set which excludes retweets.

Subset: Mentions	Estimated coefficient	Std. Error
Positive emotions	0.003 (-0.17 ***)	0.014 (0.047)
Negative emotions	-0.019 ** (0.018)	0.006 (0.025)
Surprise	0.029 *** (0.059 *)	0.007 (0.029)
No. of Hashtags	-0.059 *** (0.133 ***)	0.004 (0.016)
# Observations	100249 (17802)	
Subset: Remaining	Estimated coefficient	Std. Error
Positive emotions	0.644 *** (0.130 ***)	0.005 (0.019)
Negative emotions	0.378 *** (0.115 ***)	0.005 (0.014)
Surprise	-0.022 *** (-0.089 ***)	0.005 (0.014)
No. of Hashtags	-0.065 *** (-0.005)	0.002 (-0.870)
# Observations	538277 (117463)	

to the remaining tweets.

5.3 Temporal Analysis of Emotions

Next, we analyzed the temporal evolution of emotions for the data extraction period. Because some days during our extraction period exhibited a higher activity in terms of message posting, we scale the emotional intensity by relying on the following formula in order to mitigate a potential bias in emotion intensities[10]:

$$\frac{pos_i + neg_i}{count(tweet_i)}, \forall i \in Time\_of\_day \qquad (2)$$

Figures 1 a-c) show that negative emotions dominate in our data-set throughout the entire period of data-extraction. The red lines in Figures 1 a-c) show the temporal development of negative sentiment scores while the green lines show the corresponding development of positive sentiment scores in messages sent over the three OSNs. By comparing the frequency of messages mentioning the police with the overall daily emotional intensity, we found that messages mentioning the police on Twitter and YouTube strongly correlate (ρ_t=0.7 and ρ_y=0.93 for

[10]For the temporal analysis, we subdivided each day into four six hour time units. Subsequently, we performed our analysis concerning the evolution of emotions for the time slots "time of day", which includes morning (6:00 AM - 11:59 AM), afternoon (12:00 PM - 5:59 PM), evening (6:00 PM - 11:59 PM), and night (12:00 AM - 5:59 AM).

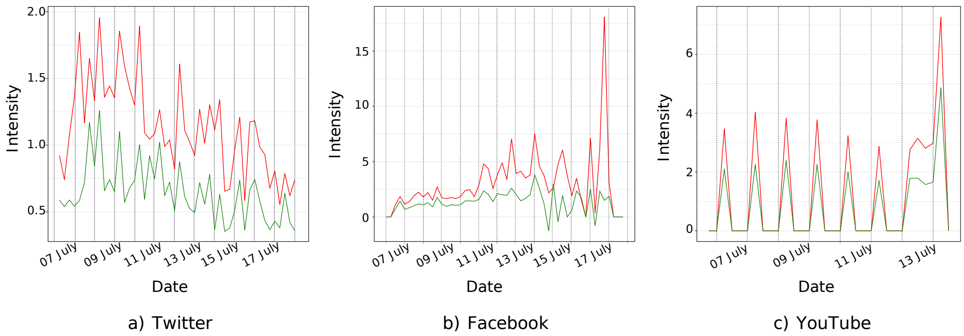

Figure 1: Temporal flow of positive and negative emotions over Twitter, Facebook, and YouTube.

confidence level 0.95) with the corresponding negative emotions in the overall data-set. In contrast, we observed a weak positive correlation for the negative emotions and the daily emotional intensity on Facebook (ρ_f=0.43 for confidence level 0.95).

Thus, temporal patterns indicated that there are OSN platform-related differences in how people refer to the local police. While Twitter and YouTube exhibited a high frequency of police-mentioning during emotionally-intense periods, we did not find the same pattern on Facebook.

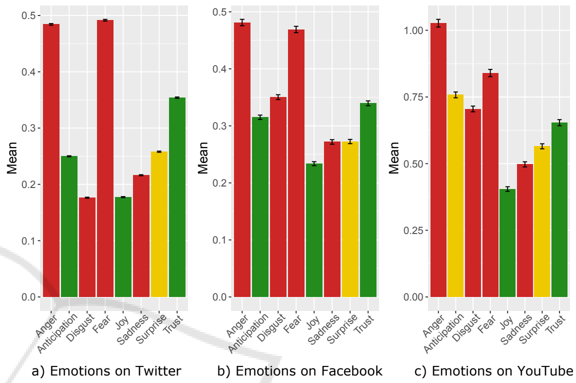

Figure 2: Summary of emotions conveyed in messages on Twitter, Facebook, and YouTube.

6 DISCUSSION

In our analysis, we observed a case where the online mood reflects the offline mood regarding the G20 riot. As noted in (Berkowitz, 1972; Pardy, 2011), emotions of high arousal are present during moments of civil unrest. Our analysis revealed that two emotions of a high arousal (anger and fear) are indeed dominant across all three OSNs (see Figure 2 positive emotions are depicted in green, negative in red, and other emotions in yellow). We found that anger and fear are especially conveyed in two types of messages mentioning the police, thereby revealing additional evidence on how an OSN discourse reflects the mutual accusations between the police and the protesters.

On the one hand, OSN users expressed anger towards the police (e.g., "*Police attacked the press with batons, punched cameras, and broke equipment during the #NoG20*"; "*This was a planned protest WITH a permit. It was peaceful until the police attacked people and blocked the march route.*"). However, anger and fear have also been expressed against the protesters and thus in support of the police (e.g., "*The lack of intelligence is shown by the protesters for destruction of property and hurting of police officers doing THEIR job.*"; "*In this fight I would gladly help the cops and beat up these terrorists in black.*"; "*These police need to start smashing some protester faces*").

While observing the messages sent to the local police (@polizeihamburg), anticipation was the predominant emotion when compared to the messages mentioning the police. These messages convey hope and care (e.g., "*@PolizeiHamburg many thanks for your great job against the protesters! I hope you will all get better soon! #G20HH2017*"; "*@polizeihamburg hopefully all officers will come back safely from their service.*"), but also reflect the citizens' information seeking behavior (e.g., "*#Hamburg police have used pepper-spray against the violent #G20 protesters in #Fischmarkt. Confirm @PolizeiHamburg!"*").

Given the polarity we observed among OSN users with respect to the police and their actions during the riot, we found that emotionally-driven content is spread (retweeted) more often than messages containing hashtags about the event. Thus, we cannot confirm the prior finding of (Suh et al., 2010) that content features, such as hashtags, are generally positively correlated with an increased number of retweets.

7 CONCLUSION

In this paper, we presented a study on the emotions conveyed in more than 750 thousand social media messages related to the 2017 G20 riots in Hamburg, Germany. Because of the controversy surrounding the role the local police played in those riots, a particular focus of our analysis was on messages that are related to the local police.

Our analysis involved three major OSNs (Facebook, Twitter, and YouTube) in order to generalize our findings beyond a single OSN. Our findings show that even though the three platforms are used with different agendas (video publishing, short message dissemination, longer personal recall of the event), they exhibit comparable patterns in emotions communicated about the event. In particular, our work complements related studies by showing that people not only turn to the police during a riot event, but also predominantly express high arousal emotions (anger and fear) in messages that mention the local police. Such online public expression of negative emotions of a high arousal is consistent on all three OSN platforms and reflects the offline mood of the event. This finding confirms "offline studies" from the field of psychology which stated that riots are characteristic for high arousal emotions. Messages that contain negative emotions reflect the polarizing nature of the opinion about the role of the local police during the riot, examples in our data-set range from messages expressing the dissatisfaction with alleged oppressive police actions to the citizens' anger towards the protesters' violent behavior.

With respect to Twitter, we additionally found that emotional messages exhibit a higher impact on the content diffusion rate, as compared to other content features (e.g., hashtags). Compared to messages mentioning the police, those directed to the local police (@polizeihamburg) conveyed significantly more anticipation. This provides empirical evidence that the local police is also regarded as an important actor in OSNs to which people turn while seeking information and reassurance at times of uncertainty and fear.

In our future work, we plan to further study the impact of emotions on information diffusion and user behavior in OSNs.

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