On the Dynamics of *Narratives of Crisis* during Terror Attacks

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***Abstract*—We present an analysis of the narratives that emerged on Twitter during four different terror attacks. To this end, we analyze a data-set consisting of more than five million Twitter messages. We use the structural topic model (STM) approach to automatically detect six *narratives of crisis*. Our findings indicate that i) Twitter users are highly engaged in the dissemination of operational and memorial narratives, ii) emotions and narratives directed towards authority accounts dominate the discourse regarding the entire event, iii) the presence of positive authority nodes (i.e. authority nodes who are predominantly perceived as being positive) directly impacts the type of a discourse and fuels hopeful memorial narratives to a larger extent than accusations and blaming.**

***Index Terms*—Crisis, Narrative, STM, Terror, Topic model, Twitter, Social network**

I. Introduction

Crises and disasters are complex events of high risk and uncertainty [1], [2]. They are rare in nature and difficult to contextualise, while at the same time they trigger an urgent and event-specific information seeking behavior [3]. In this context, Fisher [4] introduced the so-called *narrative paradigm* arguing that humans, as naturally born storytellers, base their decisions and actions on a sequence of stories that match their set of beliefs and values, i.e., a narrative. After the widespread introduction of social media, the public discourse partially shifted to the online world. Different social media platforms provide an environment for users to participate in shaping the public opinion regarding events of interest. In this context, social media can serve as a source of information, such as eye-witness reports to gain understanding of a situation [5], [6] and they can also trigger emotional pain and trauma (see, e.g., [7], [8]). Therefore, analyzing the content and the communication dynamics on social media platforms is crucial to gain insight into human online behavior and threats that might be related to low-probability, high-impact events, such as terror attacks. Different studies have analyzed human responses to crisis events in social media in terms of arising emotional communication patterns [9], [10], sense-making [11], or alternative narratives [12].

In this respect, a structural analysis of social media communication can reveal information that leads to a deeper understanding of the dynamics behind a narrative. In [13], Himelboim et al. propose six categories of network structures found on Twitter based on centralization, density, and isolation fraction metrics. They deduce characteristics and future user behavior from the category assigned to a network, providing insights in spreading and influence dynamics of prevalent topics. Moreover, in [14] Gupta et al. used textual message content, links, and meta-data similarity to cluster users who are contributing to certain topics during crisis events. In our study, we aim to combine topical analysis (to understand what the public discourse regarding a terror event is about) and structural analysis (to provide further insights into who contributes to the respective social media discussions).

The remainder of this paper is organized as follows. Section II gives an overview of related work. Section III describes our research procedure. We report on our findings in Section IV and discuss them in Section V. Section VI concludes the paper.

II. Related work

Narrative framing in social media. Eriksson [15] analyzed tweets after the 2011 Norway attacks and found that the discourse on Twitter was diverging from that in traditional mass media. While traditional media have been suggesting an Islamic background to the attack, social media users framed a competing narrative, blaming the media for its inaccuracy. Pourebrahm et al. [16] conducted an extensive analysis of Twitter communication before, during, and after Hurricane Sandy. Their findings suggest that Twitter acted as a popular source of information concerning damages and warnings for the affected inhabitants and government authorities. Another study used Greenberg's terror management theory (TMT) [17] to analyze collective sense-making on Twitter after the Berlin terror attack [18]. They found that operational updates and emotional content were prevalent during the first two days after the attack, opinion related tweets dominated public discourse afterwards. Hardy and Miller [19] used Twitter data to identify post-crisis narratives after the shooting at a nightclub in Orlando, Florida.

Hidden agendas in social media. In the past, Twitter has frequently been used to fuel narratives and ideas in order to push hidden agendas. For example, this could be observed during the 2016 presidential election campaigns in the US or for narratives regarding global migration movements [20], [21]. Moreover, Mair et al. [22] analyzed narratives during the 2013 Westgate mall attack in Kenya. Their findings suggest that the terrorist group was able to dominate their own social media narrative by applying a dedicated communication strategy. However, to the best of our knowledge, there is a lack of studies which provide an analysis of the dynamics of narratives on social media covering topical and structural aspects across multiple terror events. Our work aims to contribute to this field and offer insights into public discourse connected to terror attacks.

III. Research procedure

In this paper, we define a narrative as: "*a set of topic-wise interconnected messages that have been sent/posted via a social media platform*" (see also [23], [24]). To allow for a generalization of narratives among all data-sets, we annotate them using the "narratives of crisis" framework proposed by Seeger and Sellnow [1]. This framework includes the following types of narratives:

1) Blame: Accusations, references to actions or routines in the past that would knowingly cause harm or lead to a crisis;
2) Renewal: Connections between a crisis and the future, learning from past events, change in structure/policy resulting from the crisis;
3) Victim: Personification of harm and damage caused by a crisis, expressed feelings of empathy for victims;
4) Hero: Personification of positive, pro-social action in relation to a crisis;
5) Memorial: Unity and togetherness of the affected and unaffected communities, establish a connection to the pre-crisis state, and frame the crisis in a larger context of purpose and ideals.

In our previous work [25], we introduced an additional type of narrative called "operational narrative" to account for the high demand of information on social media during the crisis event.

Our work is guided by the following research questions:

RQ 1: *Which narratives of crisis emerge during and in the immediate aftermath of a terror attack on Twitter?*

To detect the narratives, we use a structural topic model (STM) [26] and label the resulting topics according to the "narratives of crisis" (including the "operational narrative").

RQ 2: *Who is responsible for the dissemination of specific narratives?*

This research question focuses on the user characteristics, including their potential influence in the Twitter network (number of followers). We also distinguish whether a Twitter account is a verified user account or not (see also [27]).

RQ 3: *How are narratives of crisis propagated among Twitter users?*

By deriving *mention-networks of narratives*, we explore the structural characteristics of each narrative. We analyse the impact of influential as well as ordinary nodes on the corresponding narrative dynamics via a user data and network analysis.

Our research procedure includes four stages: (i) data extraction, (ii) data pre-processing, (iii) topic modeling, and (iv) network analysis.

Data extraction. We extracted data related to four different terror attacks using Twitter's Search API. To gain a better understanding of the communication structures arising during and after crisis events we selected attacks driven by various motives, ranging from extremist hate crimes to terror attacks. In particular, we considered the following four events: the 2017 bombing attack at the Ariana Grande Concert in Manchester (UK), a domestic terrorist attack in a supermarket store in El Paso (Texas) in 2019, a church mass shooting in Sutherland Springs (Texas) in 2017, and the shooting at the Youtube Headquaters in 2018. Detailed information about each data-set is provided in Table I.

Data pre-processing. Prior to deploying a topic model, we created a subset of our data-set which excludes duplicate tweets (such as retweets). This subset was used to detect prevalent topics in the corpus consisting of original content only. Thereby, we aimed to mitigate any potential bias that could be introduced because of the effects of retweets. In total, this subset counted 777,979 tweets. The subset then underwent a pre-preprocessing procedure including lower-casing, removal of hashtags, screennames, numbers, punctuation, and stop words (as provided by the System for the Mechanical Analysis and Retrieval of Text (SMART) stopwords list), as well as stemming. Words with less than three characters or appearing infrequently (i.e., less than 3 times in a data-set) were discarded.

Topic modeling. We applied the structural topic model (STM)[1] [26] on our subset. The input data for our analysis includes the text of a tweet and the creation date of the tweet (daily interval) as prevalence co-variate in the STM model. Thereby, we followed the intuition of time sensitive topics, e.g., topics dealing with information about an ongoing event are more likely to appear during, or in the immediate aftermath of the respective event. This step is presented as part of our temporal analysis (see Figure 2).

[1]STM is a combination of a Dirichlet multinomial regression model (DMR) [28], the sparse additive generative model for text [29], and the correlated topic model (CTM) [30].

TABLE I
DATA-SETS ANALYZED IN THIS PAPER.

Data-set	Extraction period	Tweets	Unique tweets	Users	Search terms
Manchester	2017/05/21 - 2017/09/29	1,754,394	193,833	724,349	#manchesterarena, #manchesterbomb, #manchesterstrong, terror manchester
Youtube HQ	2018/04/03 - 2018/04/10	646,736	71,845	312,208	Nasim Najafi Aghdam, #youtubeshooting, #youtubeshooter, #YouTubeHQ shooting, #YouTubeHQ tragedy, #PrayersForYouTube, #YouTubeStrong, shooting YouTube, San Bruno Shooting
Sutherland Springs	2017/11/05 - 2017/12/02	1,043,226	194,030	491,940	texas church shooting, #texasChurchMassacre, texas shooting, #sutherlandsprings, #DevinKelley, #SutherlandSpringsShooting, #SutherlandSpringsTX, #SutherlandSpringsTexas, #TexasShooter, #PrayForTexas,#TexasStrong
El Paso	2019/08/03 - 2019/08/18	2,300,018	318,271	939,952	#ElPaso, #ElPasoStrong, Patrick Crusius, #elpasoshooter, #ElPasoShooting, #ElPasoTerroristAttack, #PrayersForElPaso, #PrayForElPaso, #walmartshooting

STM requires a pre-defined number of topics (k) to search for. For the purposes of this paper, we searched for the optimal k by applying three steps. (i) We derived a vector of possible k values from a sample of tweets and used it as an input for STM models; (ii) We interpreted the evaluation metrics held-out likelihood, semantic coherence, and residuals for every value of k. The most promising values were selected and used as input for STM; (iii) We applied a two-fold evaluation which comprised a comparison of semantic coherence and exclusivity values for each topic of each model accompanied by a human interpretation of the corresponding topics (i.e., assignment of the "narratives of crisis" labels to the topic). The respective human interpretation task involved two annotators who assigned narrative labels to the STM topics[2]. The final assignment of narrative labels per topic was based on a consensus vote after discussing any discrepancies between the annotators. Overall, we reached a moderately high annotators' agreement score (Cohen κ = 0.73).

To analyze the underlying dynamics of narratives, we merged the STM output (at this stage already labeled with respect to the narratives of crisis) with the original data-set (which also includes retweets). Ultimately, this led to 5,744,374 tweets associated with a narrative label.

Table II shows a tweet example labelled for each narrative.

Network analysis. We derived a mention-network by using the author id of a tweet as a source node and the users being addressed in the text of a tweet as target nodes[3]. Our mention-network includes the following information: source node ID, target node ID, timestamp, narrative labels assigned to the edges. Table IV provides general information about each network.

IV. RESULTS

A. Prevalent narratives of crisis

All six narratives according to the "narratives of crises" (see Section III) were identified in our data-sets. Our analysis points to a dominance of operational narratives (see Figure 1), with an exception of the El Paso data-set. The hero narrative was found in one data-set only, describing the bravery of an Army veteran, who offered shelter to disoriented children in the wake of the El Paso attack.

TABLE II
NARRATIVES EXAMPLES

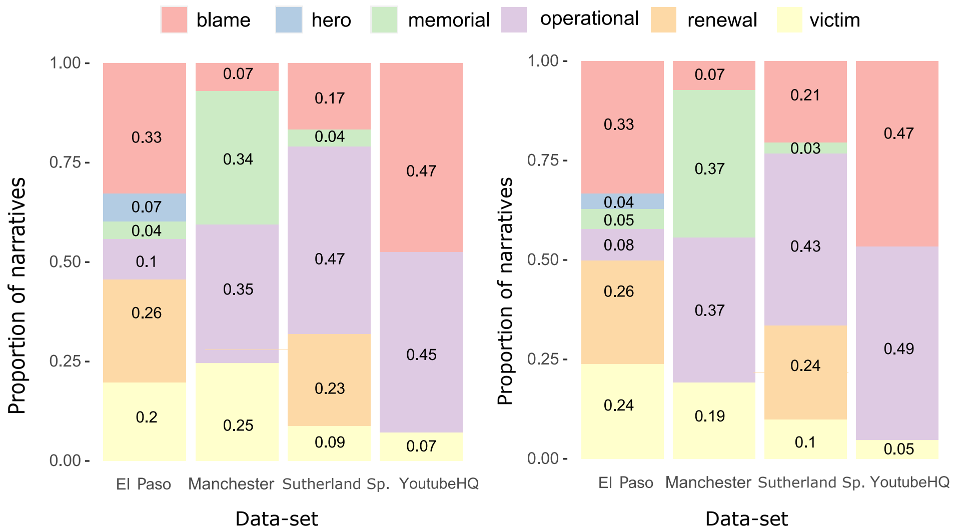
Narrative	Example quote
Blame	"This isn't a mental health issue. The events of this weekend are a gun issue and a white supremacist issue."
Renewal	"The House passed gun safety legislation HR 8 and HR 1112 You wont allow a vote in the Senate on either bill."
Victim	"Thoughts and prayers goes out to all the victims and their families affected by this tragedy sending love and prayers."
Hero	"Glen Oakley, a genuine American hero!!! I'm so grateful for humans like him! Remember HIS name and call the murderer by his true name #terrorist #ElPasoShooting #DomesticTerrorism"
Memorial	"A big Texas Thank You to our community for coming together and showing your love and support to the victims and the [...]"

Figure 1-a) shows the proportion of narratives in the entire corpus and Figure 1-b) in the subset of original tweets.

Our temporal analysis covers the first seven days since the event occurred. Figure 2 shows the dissemination of original tweets and retweets for each narrative on a logarithmic scale, averaged for each event to account for the different data-set sizes. The plot reveals clear differences in the narratives' diffusion dynamics. As expected, original messages related to operational narratives, such as breaking news, dominate the first day of the terror attacks and are also highly disseminated in the Twitter network via retweeting. Over the subsequent days of a terror attack, operational narratives steadily decline and are surpassed by two narratives, namely blame and memorial. While the blame, operational, renewal, and victim narratives already emerge on the first day of the event, memorial and hero narratives exhibit a time-lag and emerge in the early aftermath of the event (third and second day, respectively). We also observed that the relative latecomer

[2]Note that STM suggests a list of enumerated topics (Topic 1, Topic 2, ..., Topic n) which should then be interpreted by human analysts.

[3]Each Twitter user can be directly addressed (or mentioned) by using the @ symbol followed by the recipients screen name.



a) Proportion of narratives (entire corpus) b) Proportion of narratives (original tweets)

Fig. 1. Proportion of narratives per data-set.

(memorial narrative), remains one of the dominant narratives throughout the extraction period and, over time, surpasses all other narratives except the operational narrative.

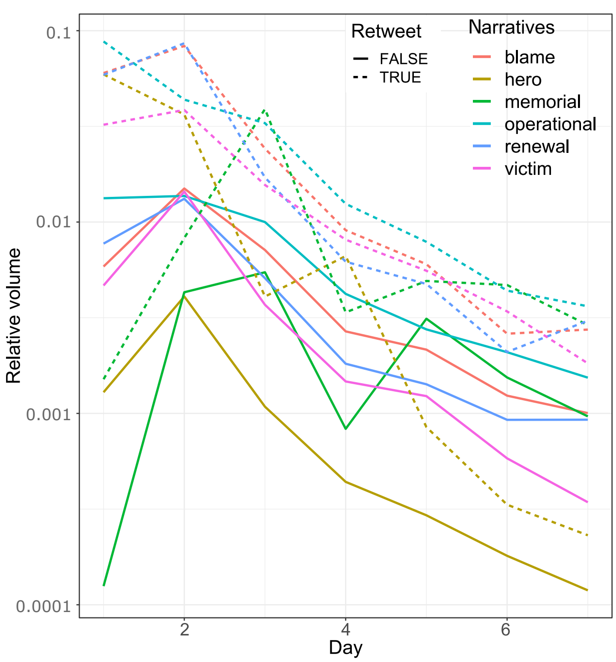


Fig. 2. Percentage of daily tweets assigned to each narrative among all data-sets during the first seven days of the corresponding event.

B. User analysis

Table III shows the average number of retweets per original tweet among the narratives as RT ratio (e.g., for the blame narrative: one original tweet on average produces 5.093 retweets), the proportion of users who posted about the event and contributed (via an original message or a retweet) to the narrative, and the average number of messages per user for each narrative (Mean Messages). The retweet ratio of the hero narrative (13.877) exceeds the other narratives more than twofold. This points to a few initial messages which were amplified by many retweets. After tracing back the most prevalent tweets related to the hero narrative, we identified a small number of original posts (including a video) which were responsible for the high amount of retweets.

TABLE III
DESCRIPTIVE STATISTICS

Narrative	RT ratio	Active users	Mean messages
Blame	5.093	0.316	2.028
Renewal	5.292	0.252	1.570
Victim	5.031	0.303	1.596
Memorial	3.595	0.180	1.924
Operational	4.150	0.348	2.218
Hero	13.877	0.065	1.190

The highest share of active users can be observed for the operational narrative (34.8% of all users), followed by the blame (31.6%) and victim (30.3%) narratives.

Among all data-sets, 72.6% of all users contributed to only one narrative, 14.4% of those users contributed to the same narrative multiple times. The one-narrative contributors produced messages related to the operational update (24.5%), victim (21.4%), blame (20.4%), renewal (17.6%), memorial (12.3%) as well as the hero (3.8%) narrative. The memorial narrative received on average 3.011 messages per user, the operational 2.617 and victim 2.33, followed by blame (2.321), renewal (2.196) and the hero narrative (2.135).

In total, 15.9% of all users contributed to two narratives. Among these users, the most prevalent combinations were: (i) operational and blame (19.1% of all users that posted in two narratives), (ii) renewal and blame (12.6%) and (iii) operational and victim (12.5%). The prevalent combinations are shown in Figure 3.

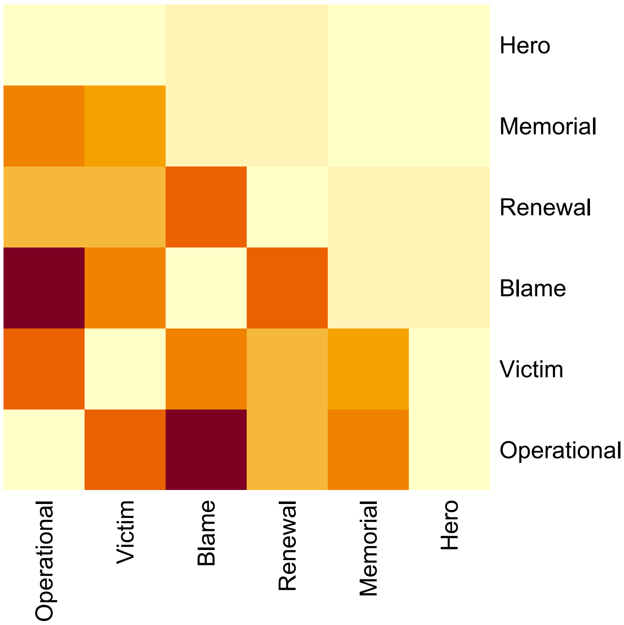


Fig. 3. Heatmap of narrative combinations for users contributing to two narratives.

We observe high rates of combinations with the operational narrative since it is most prevalent among all tweets. Nevertheless, users also exhibit engagement in the combination of the renewal and blame narratives, before the combination of the victim and operational, or the memorial and operational narratives.

While blame narratives often refer to past misdemeanours which supposedly led to the respective terror event, renewal narratives include appeals for (policy) change to prevent future crisis events from happening. Therefore, we conclude a high interest and demand for engagement in the search for possible causes of the event and future prevention strategies from users contributing to the two narratives renewal and blame. A substantially smaller portion of all users engaged in three (6.3%) or more than three narratives (5.1%).

In order to understand which types of users disseminate specific narratives, we analyzed the meta-data attributes for a subset of users whose tweets (original and retweets) account for at least 20% of all tweets related to a specific narrative, per terror attack (e.g., for 20% of all blame tweets in the El Paso data-set). Our list included 60,248 unique users. In total 42.87% of these accounts have been removed or suspended. Thus, we conducted the extraction with 34,417 usernames. The following information was recorded: number of followers and whether the account is verified.

In order to understand narrative dynamics, we divide Twitter users into four categories using follower count and verification status of an account as criteria (as proposed by [27]). In particular, we differentiate among:

1) distant individuals (less than the median amount of followers, i.e. 1,436, not verified),
2) average individuals (between 1,436 and 24,827 followers, not verified),
3) active individuals (at least 24,827 followers, not verified) and
4) official or regular users accounts with verification.

The verification status of an account can only be obtained if the account is deemed "notable" and "active" by Twitter. Examples for eligible account types would be government agencies, news organisations, or different types of influential users ("influencers").[4]

Figure 4 shows the proportion of user-types among all data-sets. Throughout our analysis, we aim to investigate the amplification factor of each user-type. Therefore, Figure 1-b shows the proportion of narratives each user-type posts, weighted by the amount of tweets issued in the corresponding narrative. In contrast, Figure 1-b shows the amount of users assigned to a user-type. By comparing the two diagrams we find that operational narratives exhibit the highest amplification factor by tweets, especially for official user-types (+ 15.34%). The highest non-operational amplification can be observed for distant users and memorial narratives (+9.21%). On average, we find that the operational (+11.3%), memorial (+7.15%) and blame (+0.25%) narratives have been amplified by the number of tweets while we observe a reduction for the victim (-8.89%), hero (-0.06%) and renewal (-0.04%) narratives.

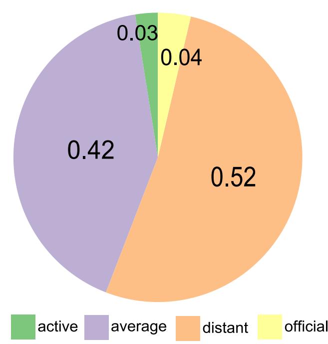


Fig. 4. Proportion of user-types among all data-sets.

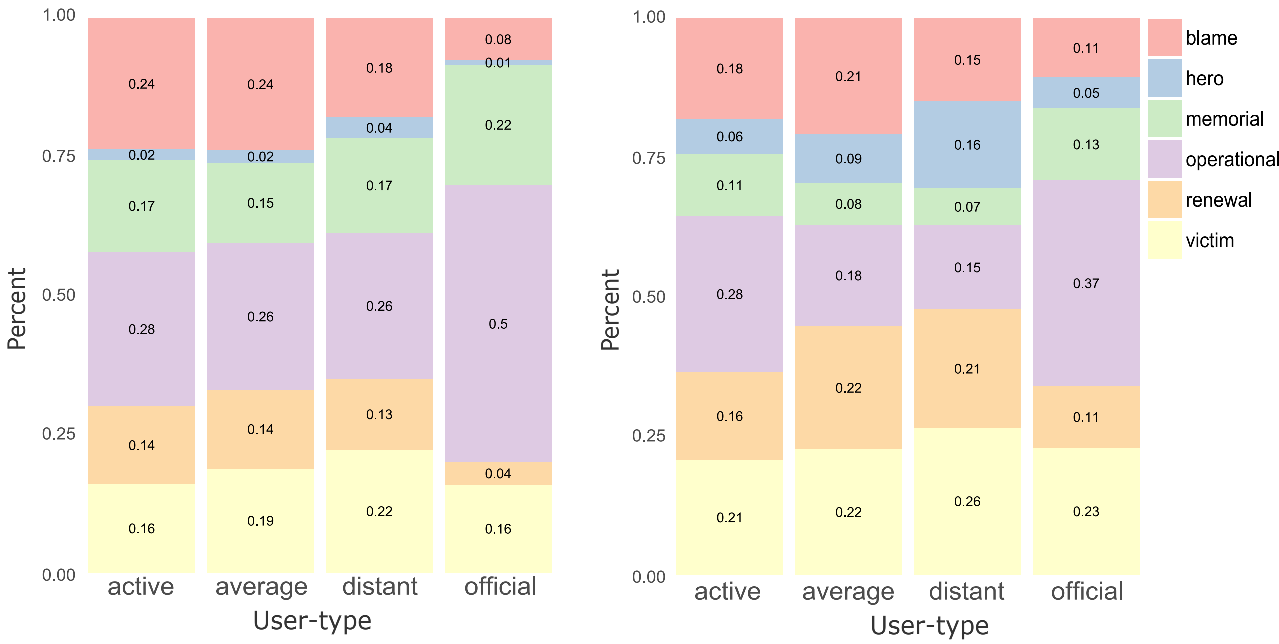
C. Structural characteristics

The structural analysis was carried out on the mention-networks resulting from each event. Table IV includes basic information describing these networks.

First, we investigate user accounts who show certain "authority characteristics", which, for the purposes of this paper, we define as nodes with a high in-degree and a low out-degree (as proposed by [31], [32]).

Per data-set, we identified the following authorities: @arianagrande for Manchester, @realdonaldtrump for El Paso and Sutherland Springs, and @youtube for the shooting at the Youtube Headquaters.

[4]Information obtained from https://help.twitter.com/en/managing-your-account/twitter-verified-accounts on August 30th, 2022.



a) Proportion of narratives per user-type by number of messages

b) Proportion of narratives per user-type by number of accounts

Fig. 5. Proportion of user types counted by number of tweets a) and number of users per category b) among all data-sets.

TABLE IV
NETWORK DETAILS

Data-set	Vertices	Edges	Mean Degree	Mean Distance
Manchester	52,736	76,395	2.897	2.424
Youtube HQ	31,571	92,216	2.611	1.401
Sutherland Sp.	55,904	92,216	3.299	3.483
El Paso	70,496	141,939	4.027	2.265

To analyse the influence of authority nodes on narrative dynamics, we applied the rule-based dictionary VADER [33] for sentiment analysis on all tweets in the event-specific mention-networks. Table V presents the average positive, negative, and compound[5] polarity scores for tweets directed at the most influential node of the network vs. the average of all tweets in the network including their standard deviation.

While messages sent to the most influential node in the Manchester and the Youtube HQ networks exhibit more positive sentiment (higher mean positive score, lower mean negative score, positive compound) than the average message in the respective network, the opposite can be observed for the El Paso and the Sutherland Springs data-sets. We analyzed the average positive score for all narratives and found victim and memorial narratives to exhibit the highest scores on average (0.137 and 0.132, respectively). Less positive were tweets assigned the operational (0.058), renewal (0.094) and blame narratives (0.095).

[5]The compound polarity score represents the sum of all rated words, normalized between -1 (most negative) and +1 (most positive).

V. DISCUSSION

Repeated engagement in the memorial narrative is related to the undoing hypothesis. We found that 72.6% of all users contribute to only one narrative. Although operational updates represent the highest share among these users, different members of this group contributed to all different types of narratives.

We found a high prevalence of the memorial narrative in the Manchester data-set. As our sentiment analysis suggests, both the memorial and the victim narratives are associated with positive emotions. Highly repeated engagement in the memorial narrative (3.011 messages per user on average as opposed to the operational narrative with 2.617) suggests support for the undoing hypothesis [34], [35], [36] which states that positive emotions serve as an antidote against the negative mental effects that emerge during negative events such as terror attacks. We analyzed different user groups and found that different memorial narratives can be amplified by each user-type.

Besides official accounts, such as reputable news outlets or government organisations, we found that the memorial narrative were mostly boosted by distant users which have less then the median amount of followers in the data-set. This could point to users with a smaller community engaging more intensely in narratives related to the undoing hypothesis.

Narrative dynamics are driven by most influential nodes. Our analysis showed that the prevalent narratives vary among our four data-sets. Blame and renewal narratives represent a share of more than 40% in the El Paso and the Sutherland Springs data-sets. On the other hand, the Manchester and

TABLE V
SENTIMENT ANALYSIS

Data-set	Mean positive	Sd	Mean negative	Sd	Mean compound	Sd
Manchester Infl.	0.195	0.199	0.146	0.172	0.066	0.579
Manchester Network	0.159	0.184	0.159	0.177	-0.068	0.558
El Paso Influential	0.096	0.130	0.154	0.163	-0.141	0.455
El Paso Network	0.103	0.145	0.128	0.157	-0.074	0.442
Sutherland Springs Influential	0.079	0.121	0.160	0.164	-0.186	0.429
Sutherland Springs Network	0.096	0.143	0.144	0.162	-0.119	0.429
Youtube HQ Influential	0.160	0.199	0.081	0.129	0.038	0.396
Youtube HQ Network	0.106	0.159	0.095	0.133	-0.027	0.398

Youtube HQ data-sets do not exhibit renewal narratives at all. An extended structural analysis based on the respective mention-networks suggests a connection between the nature of prevalent narratives and event-specifc authority nodes mainly perceived as positive (e.g., Ariana Grande and the memorial narratives found in the Manchester data-set) as well as event-specific authority nodes mainly perceived as controversial (e.g., Donald Trump and renewal narratives for the Sutherland Springs and El Paso data-sets).

Our findings are supported by the results of a sentiment analysis of the tweets that have been sent to authority nodes. In particular, we found that authority nodes perceived as positive (e.g., Ariana Grande for the Manchester attack) receive more messages carrying positive emotions than authorities perceived as controversial (e.g., Donald Trump).

For the YoutubeHQ data-set, we found the official Youtube account to be the most influential node in the event-specific communication network. This was partially due to the fact that that "@youtube" was used to share event-related videos. These findings indicate that not only the nature of an event defines event-related narratives but also the authorities involved.

Limitations. First, all our data-sets have been obtained from Twitter and the Twitter users who have been participating in the online discussions related to the four terror attacks do not necessarily form an adequate/representative sample of the population as a whole. Furthermore, computational results produced via unsupervised learning algorithms are very difficult to reproduce. Because we used STM as an approach to cluster our tweet corpus into subsets, we opted for human raters to decide on the best model initialisation. Nevertheless, numerous alternative methods exist which might affect the distribution of narratives that can be found in the data-sets (see [37], [38], [39], see also Section III).

VI. CONCLUSION

Our study on four terror attacks and the Twitter narratives that emerged in the aftermath of these events produced a topic model based on more than 5 million tweets. In particular, we applied STM to assign each topic to a narrative using the *narratives of crisis* framework proposed by Seeger and Sellnow [1].

We found that all six types of narratives occur in the immediate aftermath of the four terror attacks. Nevertheless, we especially observed high user involvement (multiple tweets per user) for the operational and the memorial narrative types. However, we also found considerable differences between the four events. For example, the El Paso and Sutherland Springs data-sets include a high share of renewal and blame narratives. In contrast, the Manchester and YouTubeHQ data-sets did not include the renewal narrative at all.

Moreover, we also derived and analyzed mention-networks for each of the four data-sets. Our findings indicate that emotions and narratives directed towards authority nodes (e.g., Ariana Grande for the Manchester data-set) can dominate the narrative discourse of an entire event. For example, the Twitter discourse around the bombing at the Ariana Grande concert in Manchester consisted of more hopeful memorial tweets than accusations for the attack.

In contrast, the mention-networks for the Sutherland Springs and the El Paso data-sets do not include any positively perceived authority node. Both of these data-sets only include small proportions of memorial tweets.

In general, social media messages contributing to the memorial narrative can be explained via the undoing hypothesis [34], [35], [36]. In this context, we found that the amplification of a narrative via multiple tweets per user is strongest for memorial narratives.

Furthermore, we found that memorial narratives can become the most dominant narrative around a terror attack. However, these hopeful tweets are often directed at one or few authority nodes. For traumatic events, this might be evidence for a particular type of coping strategy in social media if a positively perceived authority exists. In contrast, our findings also indicate that controversial authorities might have the power to shift narratives that are related to a positive event into negative emotions (see also [36]).

Directions for future work include an extended analysis involving additional terror attacks to further generalize our findings. More data-sets are also needed to support our findings regarding the influence of authority nodes and their effect on coping strategies. Furthermore, a temporal analysis could bring insights about how narratives emerge and which nodes fuel certain types of narratives.

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