Automated Narratives
On the Influence of Bots in Narratives during the 2020 Vienna Terror Attack

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Abstract: A narrative is a set of topic-wise interconnected messages that have been sent/posted via a social media platform. In recent years, social media play an important role in human information seeking behavior during and shortly after crisis events. Moreover, automated accounts (so called social bots) have been identified to play an instrumental role in manipulating the public discourse on social media. In this paper, we investigate the impact of bot accounts on the Twitter discourse surrounding the terror attack that took place in Vienna, Austria, on November 2$^{\text{nd}}$ 2020. The corresponding data-set consists of 399,247 tweets. In our analysis, we derive a structural topic model and map it to the five "narratives of crisis" as proposed by Seeger and Sellnow. Among other things, we were able to identify bot activity in neutral as well as in negative narratives, including breaking news updates, finger pointing, and expressions of shock and grief. Positive narratives, such as stories of heroes, were predominantly driven by human users. In addition, we found that the bots contributing to narratives surrounding the Vienna terror attack did not have the ability of picking up local story lines and contributed to more global narratives instead. Moreover, we identified similar temporal patterns in narratives with high bot involvement.

1 INTRODUCTION

Crisis events, such as terror attacks, induce a state of collective uncertainty and increase the need for information to make sense of the situation (Weick, 1988). In recent years, many people consult social media to look for breaking news, opinions, or eyewitness reports of such crisis events (Stewart and Gail Wilson, 2016; Zahra et al., 2018). In this context, the strategic spreading of narratives via automated accounts (social bots) may hit users in an emotionally vulnerable state. A recent example is the involvement of bots in strategic misinformation campaigns during the ongoing COVID-19 "infodemic" (Zarocostas, 2020; Ferrara, 2020). However, the question of the degree of bots' contribution to specific types of narratives has not been thoroughly invested yet.

In this paper we investigate the role of social bots on the dissemination of specific narratives over Twitter that are related to the 2020 Vienna terror attack. In particular we examined (1) the role of bots during and (two weeks) after the attack and (2) temporal patterns of bots' activities. The remainder of this paper is organized as follows. In Section 2, we provide an overview of related work. This is 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

Social media and crisis events. The role of social media platforms in providing and diffusing information during and after a crisis event has been studied from various perspectives. For example, the role of the #JeSuisCharlie hashtag after the attack on the French satire magazine "Charlie Hebdo" in 2015 has been investigated in the context of individual coping strategies (Kiwan, 2016; Giglietto and Lee, 2017). Stieglitz et al. analyzed the public Twitter discourse during and after three different crisis events and especially investigate the sense-making efforts of social media users (Stieglitz et al., 2018). Another study applied the terror management theory (Greenberg et al., 1986) to conceptualise collective sense-making after the 2016 Berlin terror attack and applied structural topic modeling to identify prevalent narratives and their development over time (Fischer-Preßler et al., 2019). They found that within the first days after a crisis event users primarily share emotional content and information updates and, later on, more opinion related tweets, see also (Kušen and Strembeck, 2021a; Kušen and Strembeck, 2021b).

Bots and narratives. Some studies investigated the role that bots play in the formation of narratives on social media platforms. One of such studies revealed that social bots and human accounts tend to share thematically different hashtags, thereby indicating that bots try to influence the corresponding social media discourse (Allem et al., 2017). Another study analyzed bot behavior related to the COVID-19 debate on Twitter and discovered large discrepancies in topics promoted by humans (mainly public health concerns) and bots (political conspiracies), suggesting that bots try to influence the public discourse during crisis events (Ferrara, 2020). Al-Rawi et al. analyzed bot behavior in the ongoing discourse about climate change and global warming (Al-Rawi et al., 2021). They report that bot-generated messages mainly contribute to narratives supporting climate change sceptics. Shao et al. studied the quality of content propagated by bots (Shao et al., 2018). Their findings suggest that Twitter bots act as super spreaders of low-credibility content and contribute to its mass exposure. In this light, a study on a mass shooting event found that humans tend to retweet bot-injected content at a higher rate than vice versa, thus concluding that bots play a significant role in the framing of narratives (Schuchard et al., 2019).

As noted in (Wirth et al., 2019), bot-injected content may also lead to uncertainty and unpredictability. Their key findings indicate a strategical contribution of bots to certain conversations. For example, they report that bots tend to be more active in conservative conversations rather than liberal or random conversations. Moreover, in each conversation bots seem to follow a certain predefined procedure – in political conversations, bots share political posts and to a lesser degree spam, while in trending topics bots are predominantly responsible for spam and topic promotion. Furthermore, (Khaund et al., 2018) studied the behavior of bot accounts during four different natural disasters in 2017. They found that bot accounts hijack hashtags related to the respective events in order to disseminate irrelevant information and alternative narratives. Several studies also investigated bot activity in terms of emotional content (Kušen and Strembeck, 2018), pre-defined topics (Wirth et al., 2019), and particularities of their information sharing behavior (Schuchard et al., 2019).

3 RESEARCH PROCEDURE

On November 2$^{\text{nd}}$, 2020 a 20-year-old gunman fired shots at civilians in the center of Vienna, Austria. Before the perpetrator was shot dead by the police he killed four victims and injured more than 20 others. The Twitter messages related to the event mainly transported shock, grief, and empathy, as well as hate and disgust towards the attacker. In addition to pure text messages, a number of event-related videos have also been disseminated via Twitter. For example, one video showed three men carrying a wounded police officer to an ambulance, risking their lives as the attacker has not been detained at this point. After the video of the incident went viral, the hashtag #helden (German for heroes), was trending on Twitter in Austria. For our analysis, we collected event-related tweets from November 2$^{\text{nd}}$ until November 16$^{\text{th}}$, 2020. Our study is guided by the following research questions:

RQ1: *What is the role of bots in event-related narratives during and after the terror attack?*

For the purposes of this case study, we use the concept of the "rhetorical arena" proposed by Frandsen and Johansen (Frandsen and Johansen, 2007; Frandsen and Johansen, 2010). The "rhetorical arena" considers crisis communication as a multi-vocal public space. As opposed to traditional sender-receiver broadcast communication (e.g. government-to-public or organisation-to-public), the rhetorical arena allows any actor to influence crisis communication and thereby create multiple crisis-response narratives. In (Coombs and Holladay, 2014), the authors argue that the rhetorical arena consists of numerous sub-arenas. For this paper, we will interpret these sub-arenas as different narratives in social media. The rhetorical arena concept assumes that every actor has the ability to frame a narrative before, during, and after a crisis event (Gascó et al., 2017). To this end, we examine the topics injected and disseminated by bot accounts and compare them with those fuelled by human accounts. For our analysis, we use the five "narratives of crisis" as proposed by (Seeger and Sellnow, 2016). In particular, Seeger and Sellnow suggest the following typology of crisis narratives:

1. Blame: Accusations, references to actions or rou-

tines 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 community, establish a connection to the pre-crisis state, and frame the crisis in a larger context of purpose and ideals.

As those "narratives of crisis" mainly refer to a post-crisis state, we added a sixth category called "operational update" to account for messages referring to an operational update on developments during the crisis. For the first research question, we analyzed prevalent topics in our data-set, assigned them to a crisis narrative, and determined the extent of bot engagement in the respective narrative.

RQ2: *Which temporal patterns can be observed in the event-related narrative activity of bots?*

Our second research question examines the temporal prevalence of narratives. In this context, we focus on narratives with a high bot contribution and search for patterns behind their activity.

Our research procedure includes five phases.

Data extraction. We extracted tweets related to the 2020 Vienna terror attack using Twitter's Search API and a predefined list of hashtags related to the event.[1] In total, we extracted 399,247 English language tweets. The messages in the data-set have been sent by 114,520 unique screennames, 27,800 of which with a high botscore (see Table 1).

Data pre-processing. First, we removed duplicate tweets (i.e. tweets that include multiple hashtags and have therefore been extracted multiple times). Following (Sasaki et al., 2014; Wang et al., 2017; Nerghes and Lee, 2019), we kept the retweets in our data-set in order to gain a better understanding of topic prevalence. Although retweets do not represent original content, they allow users to express consent and opinion and thus contribute to a topic's prevalence in the corpus.

Text processing was conducted in R with the structural topic model (stm) package. For our analysis, we also applied the following pre-processing steps: converting to lowercase, removing stopwords, removing punctuation, and removing words with less than three characters (see also (Roberts et al., 2019)).

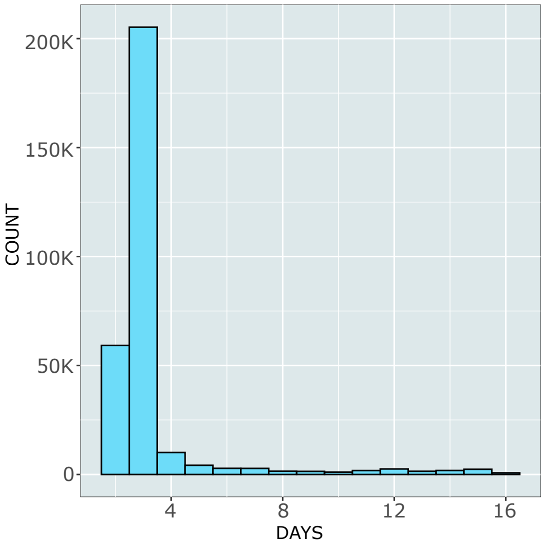


Figure 1: Tweet distribution for the data extraction period.

Bot detection. For bot detection, we used Botometer's Python API[2]. As discussed in (Daniel and Millimaggi, 2020), bots may have many different characteristics, some of which do not necessarily result in a high bot score. For example, some accounts may only be partially automated and are thus partially operated by one or more human users. Nevertheless, for the purposes of this paper we introduced a binary classification rule to ensure a meaningful interpretation of our results. Following the suggestion of (Varol et al., 2017), we set our threshold for bot accounts at a Botometer score of ≥ 0.6[3].

Exploratory data analysis. The Vienna terror attack happened on November 2$^{\text{nd}}$ 2020 around 8 pm. 20% of all tweets in the data-set were posted on the same day and nearly 69% during the subsequent day, whereas tweeting activity rapidly declined after that (see Figure 1). Following the estimates of Varol et al., 9% to 15% of all active Twitter accounts are assumed

[1] We extracted tweets including the following hashtags: "vienna terror", "terrorist attack #Vienna", "#ViennaAttack"", "#Viennashooting", "#prayforvienna", "#wienATTACK", "angriff vienna"", "#terrorwien", "#PrayforWien", "#viennaattacks", "#ViennaTerrorAttack", "#austriaAttack", "sorgen Wien", "#Viennaterror", "#ViennaTerroristAttack", "#viennapolice", "#austriashooting", "terror wien", "wien Hintergrund", "vienna background", "#Schwedenplatz", "wien #staysafe", "vienna #staysafe", "#StayStrongAustria", "#zibspezial", "#Nehammer", "#0211w", "@ORFBreakingNews", "#Synagoge", "#Schießerei", "#terroranschlag wien", "#terroranschlag vienna", "#schleichdiduoaschloch".

[2] Botometer: https://botometer.iuni.iu.edu/ (see also (Davis et al., 2016))

[3] Botometer delivers scores between 0 and 1.

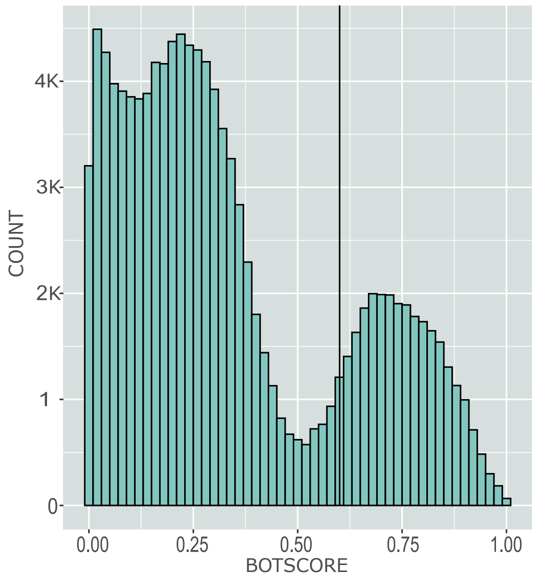


Figure 2: Distribution of bot scores with threshold at 0.6.

to be bot accounts (Varol et al., 2017; Davis et al., 2016). In our data-set, 24.28% of the respective Twitter accounts have been identified as bots according to the threshold described above. The histogram in Figure 2 depicts the distribution of bot scores indicating peaks around a score of 0.25 (most likely human) and 0.75 (most likely bot). In our data-set, 82.29% of the messages are retweets. Interestingly, bots distribute a higher share of retweets (87.41% as compared to 80.21% for humans). An overview of basic information about the data-set is provided in Table 1.

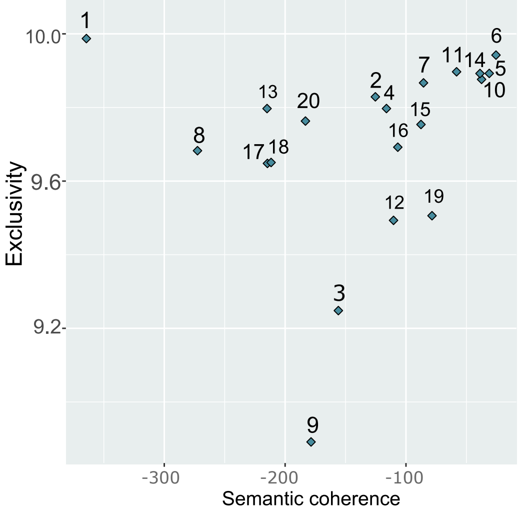


Figure 3: Semantic coherence and exclusivity of each topic with k = *20*.

Topic model. We derived a structural topic model to find prevalent topics in our data-set. For implementation purposes, we used R and the stm package (Roberts et al., 2019). In particular, we treat each tweet as a separate document and assign one or more topics to each tweet. To identify a meaningful number of topics k for our data-set, we first ran several topic models with a flexible number of topics (between 5 and 40 topics) and then decided on the most suitable number k, based on semantic coherence, exclusivity, residuals, and held-out likelihood, see also (Roberts et al., 2019). Our final model consisted of $k = 20$ topics (see Figure 3).

In contrast to other topic models, e.g. LDA (Blei et al., 2003), structural topic models allow to incorporate covariates. For our model, we introduced a dummy variable ("bot class") to distinguish between "bot" and "human" accounts. This variable was then used as a covariate besides the creation date of a tweet.

The "creation date" covariate was estimated via a spline function. We added custom stopwords[4] and excluded words that appeared in less than five tweets or appeared in more than 80% of all tweets. Figure 5 shows the topics resulting from our model.

While different methods for an assisted validation of topics exist, see, e.g., (Grimmer and Stewart, 2013; Ramirez et al., 2012; Chan and Sältzer, 2020), we opted for a human interpretation of the respective topics. To this end, we used two raters to assign narratives to each topic based on the top 10 words (see Figure 5) and example quotes for each topic. The inter-rater agreement (Cohen's kappa) was between 72.22% and 84.38% for all six groups of narratives. Disagreement cases were discussed after the first round of rating. Table 2 shows an overview of the results of the procedure. Afterwards, further analysis of the output was conducted by running a linear regression using the *estimateEffect* function of the stm package with the "botclass" and "creation date" variables (see also (Roberts et al., 2019)).

4 RESULTS

Among the 20 overall topics that we used in our analysis, four belong to the "operational updates" category. These topics include breaking news content (Topic 14 and Topic 15) describing the situation, appeals to refrain from posting footage of the scene, spreading rumours (Topic 5 and Topic 7) and requests for staying at home or seek shelter (Topic 5). Operational updates belonged to the most prevalent topics

[4]The custom stopwords included: vienna, terror, terrorattack, austria, attack

Account type	Count	Tweets	Retweets
Bots	27,800 (24.28%)	115,784 (29.00%)	101,209 (30.80%)
Humans	86,720 (75.72%)	283,463 (71.00%)	227,369 (69.20%)
Total	114,520	399,247	328,578

Table 1: Basic information about the data-set.

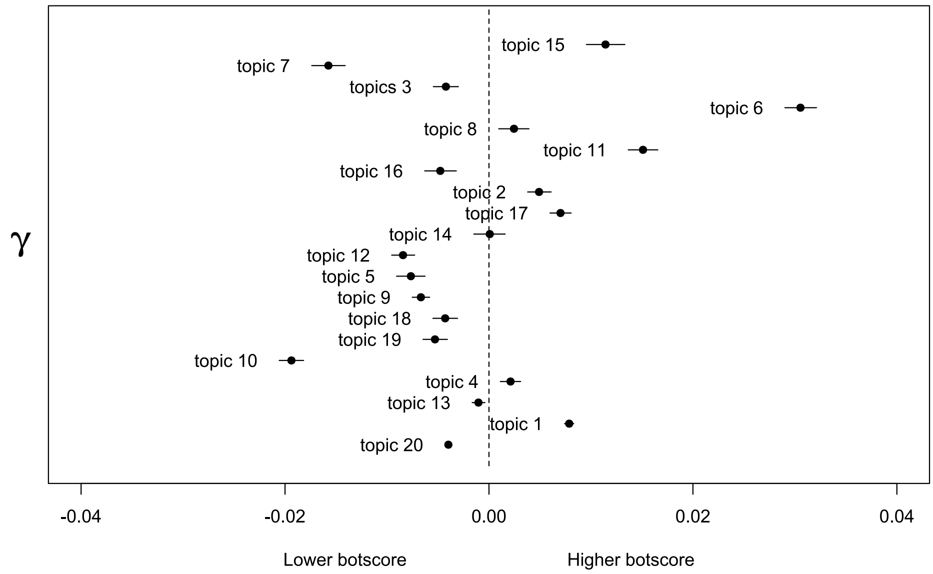


Figure 4: Effect of bot score on topic proportion with γ indicating the probability of a topic over all tweets.

in our data-set.

Aside from operational updates, "blame narratives" dominated the discourse (see Table 2) with five topics in this category (Topics 4, 8, 11, 12, 17). These topics covered accusations against government officials from different countries, referrals to other terror attacks, a lack of lessons-learned from previous terror attacks, and different types of criticism towards Muslim values. Surprisingly, one blame and one victim narrative included the term "India" inside of their top ten terms (see Topic 6 and Topic 11). These occurrences were traced back to a high activity of bots as indicated in Figure 4.

Moreover, "victim narratives" were characterised by the expression of emotions (see Topic 6 and 13) as well as empathy towards the victims of the attack. They were tightly connected to "memorial narratives", with the distinction of putting empathy for victims and their family before an appeal for unity.

Only two topics have been assigned to the "hero narrative" category. The first one refers to three men who carried a police officer to an ambulance despite the continued threat of the perpetrator (Topic 19). Whereas, the second hero narrative (Topic 10) included praise for the commitment of the police forces involved and several Viennese cultural institutions (e.g. Wiener Konzerthaus) which continued with their (musical) performances to distract the audience and keep them inside the premises.

The "memorial narratives" category (Topics 1, 2, 16, 20) especially includes expressions of unity and togetherness. Sometimes these expressions reflected retweeted statements of foreign government officials (e.g. "*During a phone call with the Austrian Chancellor I conveyed to him our deepest condolences following the terror attacks in Vienna. We stand united with Austria in its fight against extremism and we look forward to expanding our joint cooperation on this front*", Topic 2).

Topics pointing to future measures that should follow the terror attack were assigned to the "renewal narratives" category. For example, those narratives include tweets about an announcement of the amendment of the Austrian "Islamgesetz" which was established in 1912 and was amended in 2015 for the last time (Topics 9 and 18). In particular, resentment to-

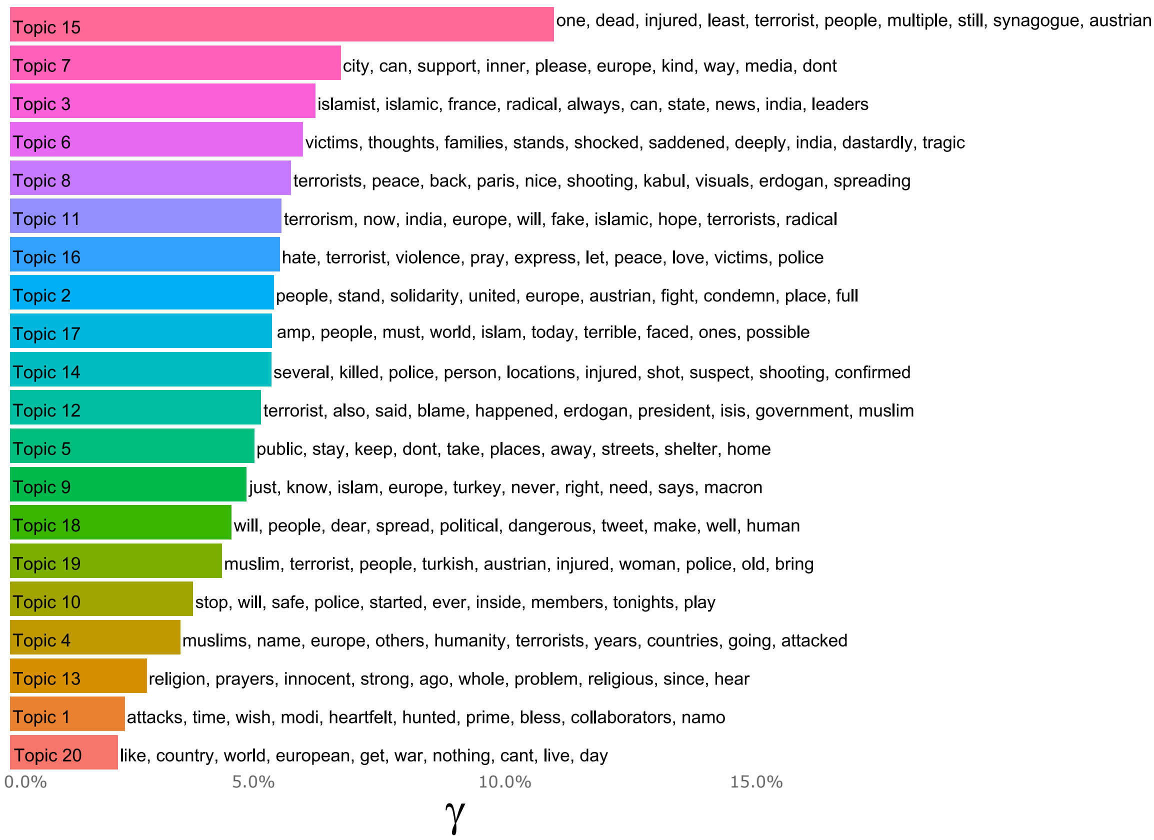


Figure 5: Topic proportion and top 10 words per topic with γ indicating the probability of a topic over all tweets.

wards the amendment and mentioning of critical factors to prevent terror attacks in the future (Topic 3) dominated this narrative.

Overall, most topics were assigned to the blame (5 topics), operational updates (4 topics) and memorial (4 topics) narrative categories. Our case study led to the following observations.

Bots favour global narratives. Figure 4 shows how topic preference changes with respect to account classification. Twitter accounts that have been classified as bots show a disproportionately strong contribution to Topics 6, 11, and 15. The elevated bot activity in Topic 15 might be explained by its “breaking news” content which has already been linked to elevated bot activity by other studies, see, e.g., (Al-Rawi and Shukla, 2020). Topic 6 and 11 (blame and victim narrative) include statements of finger-pointing and empathy with a strong relation to India (see Table 2). In contrast, topics with a strong local connection (e.g. local heroes, comments about the Austrian “Islamgesetz”) are preferred by humans rather than bots. The prevalence of two globally connected topics (6 and 11) gives rise to the hypothesis that bot accounts operate on a more international level whereas humans show a preference for local narratives.

Bots contribute to neutral or negative narratives. Bots tend to be more active in operational updates, blame, and victim narratives – which are often associated to a negative or neutral sentiment, see also (Kušen and Strembeck, 2019). Even though victim narratives might exhibit an expression of hope and togetherness, their main focus lies on grief, shock, and fear. In contrast, positive narratives, such as hero narratives, are propagated predominantly by human accounts. This finding is in line with previous case studies on the behavior of bots during crisis events, see, e.g., (Stella et al., 2018; Shi et al., 2020; Kušen and Strembeck, 2020).

Bot activity follows a temporal pattern. Figure 6 shows the temporal development of each narrative and Figure 6f provides an overview of topics with a high bot involvement. The temporal analysis shows that the three narratives with the highest bot involvement exhibit a similar temporal pattern. Moreover, we found that narratives with a low bot involvement show peaks that can be linked to certain events after the attack. For example, the renewal narrative from Topic 18 (connected to the “Islamgesetz”) started picking up popularity shortly after November 9th (see Figure 6e). This development coincides with the date of a press conference where the Austrian Minister of the Interior announced changes in the corresponding law.

5 DISCUSSION

The findings of our study suggest that bots especially contributed to neutral and negative narratives rather than to positive ones. In particular, our analysis indicates elevated bot participation in “victim”, “blame” and “operational update” narratives. This finding is in line with other studies of bot behavior, such as (Stella et al., 2018; Shi et al., 2020; Kušen and Strembeck, 2020). Moreover, we found that bots preferably spread topics with an international focus and fail to pick up local narratives, as for example the praise for “local heroes”. Interestingly, narratives with high bot involvement show a tight connection to India (see Topics 6 and 11 in Table 2).

By means of a temporal analysis, we also found that narratives showing a high bot contribution also exhibit a similar temporal pattern (see Figure 6f). This pattern can be distinguished from other narrative patterns, see Figures 6 (a) to (e).

Our study is subject to several limitations. Firstly, our data-set has been extracted from Twitter only. Therefore, all findings only apply to social media discussions conducted via Twitter. Moreover, we collected tweets based on popular hashtags that appeared in connection with the Vienna terror attack and cannot guarantee the full coverage of all conversations about the event on Twitter. Therefore, our findings should be reviewed and contrasted with results from other social media platforms, e.g. (Wang et al., 2020; Bolsover and Howard, 2019).

One conclusion suggested by our analysis is that bots contribute more to global than local narratives about the event (e.g. topics including the term “India”), which could result from the fact that the data-set we analyzed for this case study included English language tweets only (while the official language in Austria is German). Nevertheless, we believe that our findings can still contribute to a better understanding of social bot behaviour. In particular, the ignorance that bots appear to show towards local narratives is an interesting prospect for further investigations.

We used the structural topic model approach to analyse our text corpus. Since such topic models are derived via unsupervised learning algorithms, it is difficult to provide a robust measure for the quality of the corresponding results. Nevertheless, for our study we used human raters to check the results for plausibility (see Section 3).

As discussed in (Rauchfleisch and Kaiser, 2020), bot detection in general and Botometer in particular might produce inaccurate results when used in any other language than English. Also, the implementation of arbitrary thresholds can lead to either false positive (humans are classified as bots) or false negatives (bots are classified as humans). To reduce the risk of incorrect bot scores for our accounts, we included English tweets only. However, a change of our threshold for bot classification would certainly affect our results. Therefore, we chose the threshold of ≥ 0.6 based on previous studies on large Twitter data-sets (see Section 3) and an exploratory analysis of the distribution of bot scores in our data-set (see Figure 2).

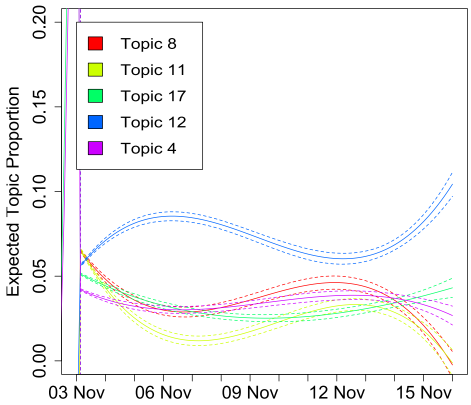
Based on our findings, we suggest further research to investigate the role of locally emerging narratives (e.g. the “hero narrative”) during and after crisis events to deduce policy measures for preventing bots from influencing the public discourse.

6 CONCLUSION

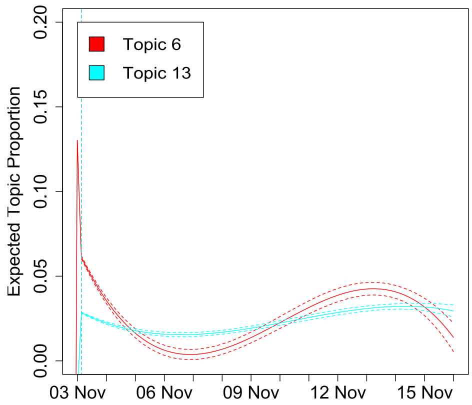
We analysed a data-set consisting of 399,247 English language tweets related to the Vienna terror attack in November 2020. We used the structural topic model approach to identify 20 topics that have been discussed along with the terror attack. In order to detect narratives during and after the attack, we applied the “narratives of crisis” as proposed by Seeger and Sellnow (Seeger and Sellnow, 2016). The framework suggests that five types of different narratives (blame, victim, memorial, renewal and heroes) mainly occur in the immediate aftermath of a crisis. Moreover, due to Twitter’s role as a breaking news outlet (Petrovic et al., 2021), we introduced the “operational update” narrative as an additional category.

In order to map our topics to the six narrative categories, we deployed two human raters who assigned a narrative to each topic. This procedure resulted in the identification of five (25%) blame narratives, four (20%) operational, four (20%) memorial, three (15 %) renewal, two (10%) victim, and two (10%) hero narratives. The most significant contributions made by bot accounts were found in the “operational updates”, “blame”, and “victim” narratives, with two of them having a clear international focus. In addition, our temporal analysis indicated that bots seem to follow the same temporal pattern even when contributing to the different narratives. Since a single case study provides a limited view only, we aim to conduct further analyses on data-sets related to other crisis events in the future.

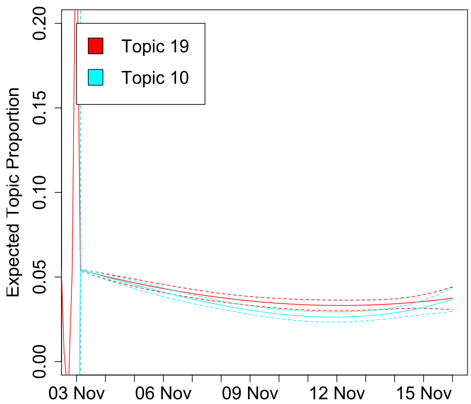
Figure 6: Topic proportion of narratives over extraction period (02-16 Nov 2020) with the covariate day smoothed by a spline function, with 95 percent confidence intervals.



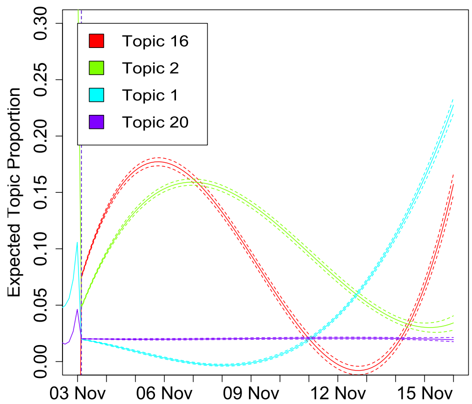
(a) Topic proportion of "blame narratives".



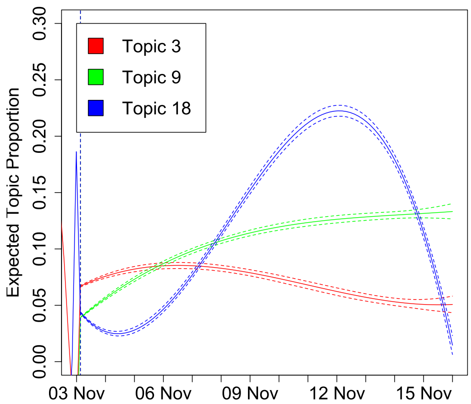
(b) Topic proportion of "victim narratives".



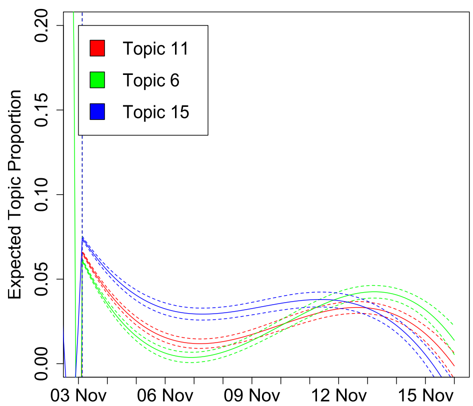
(c) Topic proportion of "hero narratives".



(d) Topic proportion of "memorial narratives".



(e) Topic proportion of "renewal narratives".



(f) Topic proportion of highly bot fuelled narratives.

Topic No.	Narrative	Prob.	Top 10 words	Quote
Topic 15	operational update	10.97%	one, dead, injured, least, terrorist, people, multiple, still, synagogue, austrian	“At least one killed in suspected Vienna terror attack says interior minister READ MORE (URL)”
Topic 7	operational update	6.67%	city, can, support, inner, please, europe, kind, way, media, dont	“If you have footage of any kind of the shooting incident in the inner city of Vienna please upload it on this link DONT share it on social media This way you can support us”
Topic 3	renewal	6.16%	islamist, islamic, france, radical, always, can, state, news, india, leaders	“With an official claim of responsibility by releasing a video of the perpetrator pledging allegiance to top leader AlHashimi alQurashi calling him an Islamic State fighters is reminding us all that neither its external nor internal ops are over”
Topic 6	victim	5.90%	victims, thoughts, families, stands, shocked, saddened, deeply, india, dastardly, tragic	“Deeply shocked and saddened by the dastardly terror attacks in Vienna India stands with Austria during this tragic time My thoughts are with the victims and their families”
Topic 8	blame	5.66%	terrorists, peace, back, paris, nice, shooting, kabul, visuals, erdogan, spreading	“Enough with the opendoor and bleedingheart policies today more than ever we need to declare zero tolerance towards Islamic fanatics lurking in our societies close ports control our borders protect our children defend our identity”
Topic 11	blame	5.47%	terrorism, now, india, europe, will, fake, islamic, hope, terrorists, radical	“Europe ignored radical islamic terrorism in India. They kept teaching us fake secularism funding campaigns for fake human rights of terrorists. Now the same terror is knocking at their door Hope they will now take it seriously GRAPHIC VIDEO”
Topic 16	memorial	5.44%	hate, terrorist, violence, pray, express, let, peace, love, victims, police	“I express my sorrow and dismay for the terrorist attack in and I pray for the victims and their families Enough violence Let us together strengthen peace and fraternity Only love can silence hate”
Topic 2	memorial	5.32%	people, stand, solidarity, united, europe, austrian, fight, condemn, place, full	“During a phone call with the Austrian Chancellor I conveyed to him our deepest condolences following the terror attacks in Vienna We stand united with Austria in its fight against extremism and we look forward to expanding our joint cooperation on this front”
Topic 17	blame	5.28%	amp, people, must, world, islam, today, terrible, faced, ones, possible	“If any holy book under any circumstances propogates killing beheading lynching owning women amp stoning gays to death then that book amp its ignorant followers belong in the dark ages Time to call for rewrites of such problematic passages amp to demand reforms”
Topic 14	operational update	5.27%	several, killed, police, person, locations, injured, shot, suspect, shooting, confirmed	“CONFIRMED at the moment 0800 pm several shots fired beginning at Seitenstettengasse several suspects armed with rifles six different shooting locations one deceaced person several injured 1 officer included 1 suspect shot and killed by police officers”
Topic 12	blame	5.07%	terrorist, also, said, blame, happened, erdogan, president, isis, government, muslim	“I am Muslim and I blame Turkish president Erdogan for what happened in [removed] I also blame every government that empowered and funded Wahhabist terrorist ideology. We await your apology”
Topic 5	operational update	4.93%	public, stay, keep, dont, take, places, away, streets, shelter, home	“Please dont stare any rumours accusations speculations or unconfirmed numbers of victims that does not help at all Stay inside take shelter Keep away from public places.”
Topic 9	renewal	4.76%	just, know, islam, europe, turkey, never, right, need, says, macron	“After the terror attack in Vienna Austria wants to ban political Islam s government wants powers to close mosques strip citizenship and imprison terrorists for life tells you more”
Topic 18	renewal	4.46%	will, people, dear, spread, political, dangerous, tweet, make, well, human	”Austria will make it a criminal to offence to spread political Islam following Islamic extremists terror attack”
Topic 19	hero	4.28%	muslim, terrorist, people, turkish, austrian, injured, woman, police, old, bring	“Turkish youths who rescue an old woman in a terrorist attack in the Austrian capital Vienna and bring an injured police officer to an ambulance Yes these people are Muslim”
Topic 10	hero	3.69%	stop, will, safe, police, started, ever, inside, members, tonights, play	“Police kept us safe inside the after tonights performance While we waited members of phil started to play No [removed] will ever stop the music in [removed] ”
Topic 4	blame	3.43%	muslims, name, europe, others, humanity, terrorists, years, countries, going, attacked	“Terrorists attacked multiple places in Austrian capital Many dead n several others injured 1 terrorist gunned down others on the run Europe is going to pay massively in coming years for supporting amp giving refuge to radicals in the name of humanity”
Topic 13	victim	2.76%	religion, prayers, innocent, strong, ago, whole, problem, religious, since, hear	“Incredibly shocked to know about the ongoing terror attack in Vienna. Having lived in that city its even more heartbreaking to hear whats happening since last night. All my love amp prayers to the ppl of Vienna Hope the perpetrators are brought to justice soon Stay strong”
Topic 1	memorial	2.32%	attacks, time, wish, modi, heartfelt, hunted, prime, bless, collaborators, namo	“Ahm deeply shocked by tterrible attacks in vienna tonight tuks thoughts are wi tfolk of austria we stand united wi you against terror”
Topic 20	memorial	2.17%	like, country, world, european, get, war, nothing, cant, live, day	“If someone Hurt your Religious feelings You Can 1 Protest on Social media 2 File FIR 3 File Court cases 4 Do Peaceful protest March But You Cant 1 Behead people 2 Burn Cities 3 Loot their properties 4 Rape their women 5 Start Genocide”

Table 2: Topic overview including assigned narrative, topic probability, top 10 most frequent words and an example quote of a tweet with a high proportion of the topic.

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