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Politics, sentiments, and misinformation: An analysis of the Twitter discussion on the 2016 Austrian Presidential Elections

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ABSTRACT

In this paper, we provide a sentiment analysis of the Twitter discussion on the 2016 Austrian presidential elections. In particular, we extracted and analyzed a data-set consisting of 343645 Twitter messages related to the 2016 Austrian presidential elections. Our analysis combines methods from network science and sentiment analysis. Among other things, we found that: a) the winner of the election (Alexander Van der Bellen) predominantly sent tweets resulting in neutral sentiment scores, while his opponent (Norbert Hofer) preferred emotional messages (i.e. tweets resulting in positive or negative sentiment scores), b) negative information about both candidates continued spreading for a longer time compared to neutral and positive information, c) there was a clear polarization in terms of the sentiments spread by Twitter followers of the two presidential candidates, d) the winner of the election received considerably more likes and retweets, while his opponent received more replies, e) the Twitter followers of the winner substantially participated in the spread of misinformation about him.

1. Introduction

In recent years, social media have become an important channel for politicians to address the public, making them more accessible to their prospective voters [1–3]. Although social media are often used to disseminate informative content, such as event announcements on a candidate's public appearances, recent studies have shown that social media are also used for spreading misinformation as a part of political propaganda [4–6]. In this context, the emotional dimension of a social media discussion [7] is of particular importance as an emotional debate over a controversial topic often develops more dynamically and unpredictably than an objective discussion.

Sentiment analysis methods [8] help classify and understand the users' feelings about a topic of interest. However, the sheer complexity of socio-technical systems [9,10] and the big data characteristics of complex networks [11,12] make the analysis of social media events a difficult task [13,14]. In this context, case studies of real-world political campaigns are of particular interest because they help understand human behavior, detect patterns, and identify generic approaches for analyzing user behavior in online social networks (see, e.g., [2,15–19]).

In this paper, we provide a comprehensive sentiment analysis of the Twitter discussion related to the 2016 Austrian presidential elections and show that during political campaigns conveying emotional content is not always advantageous for the respective political candidate. In particular, we extracted and analyzed a data-set consisting of 343,645 Twitter messages. The resulting data-set is multi-dimensional, including temporal data, structural data (such as the corresponding topic/hashtag network), as well information on the user's emotions that are expressed in the content of the messages. In addition to sentiment polarities, our analysis also identifies specific emotions about each candidate that are conveyed in tweets posted by other Twitter users.

The remainder of this paper is structured as follows. First, we give an overview of the election event in Section 2. Next, Section 3 provides an approach synopsis and discusses the guiding research questions for our study. Subsequently, Section 4 presents our sentiment analysis of the Twitter discussion on the 2016 Austrian presidential elections. In Section 5, we further discuss our findings as well as the limitations of our study. Section 6 discusses related work and Section 7 concludes the paper.

2. Event of study

In the 2016 Austrian presidential elections, Austria has witnessed two polarizing opinions among its citizens. A candidate of

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the Freedom Party of Austria, Norbert Hofer, and his opposing candidate, a former member of the Green Party, Alexander Van der Bellen were in a tight run for the presidential seat. The first round of the elections took place on April 24th, 2016, when Norbert Hofer received a majority of the votes (36.40%), followed by Alexander Van der Bellen (20.38%), while four other candidates (Irmgard Griss, Rudolf Hundstorfer, Andreas Khol, and Richard Lugner) dropped out of the elections. The second round, which took place on May 22nd, 2016, was a run-off ballot between Hofer and Van der Bellen. Alexander Van der Bellen won with 50.3% of the votes. However, the results of this election have been invalidated by the Austrian constitutional court in July 2016 due to procedural irregularities in vote counting.[1] After the re-elections were postponed due to faulty glue on the envelopes for postal voting, the repeat of the run-off ballot finally took place on December 4th, 2016, when Van der Bellen was elected president with 53.8% of the votes. The inauguration ceremony took place on January 26th, 2017.

3. Research questions and approach synopsis

In the subsequent sections, we outline the research questions for our study (Section 3.1) and the approach synopsis (Section 3.2).

3.1. Research questions

We defined the following guiding research questions for our analysis:

RQ1: What is the tweeting behavior of the presidential candidates?
In specific, we examined three aspects: temporal characteristics of each candidate's tweeting behavior (RQ1.1), each candidate's engagement style (RQ1.2), as well as each candidate's campaigning style (RQ1.3).

RQ1.1: What are the temporal characteristics of each candidate's tweeting behavior?
Research question RQ1.1 provides a quantitative analysis of the tweeting behavior and examines how many daily tweets have been posted by each candidate during the presidential elections. For example, we identify associations between important events (such as a TV discussion) and the corresponding tweet count.

RQ1.2: What is the engagement style of each candidate?
In research question RQ1.2, we focus on the way each candidate uses Twitter as a tool for communication with their supporters. In particular, we investigated each candidate's interaction with their followers, including the ratio between the candidates' broadcasting behavior and bilateral (one-to-one) communication. In addition to the quantitative analysis of the engagement styles, we also examine the content of the candidates' tweets and report on the emotions they spread during their presidential campaign. Furthermore, we examine the reactions of Twitter users on the candidates' tweets in terms of retweets, replies, and likes.

RQ1.3: Is there evidence of different types of campaigning?
Political campaigns are generally described as "positive" or "negative", depending on how the candidates address their opponents. In our study, we follow the definition from [20], which describes *negative campaigning* as a type of campaigning which may involve misinformation, "dirty tricks", attacks on the opponent's persona (also called *political character assassination*), or stressing the opponent's weaknesses or failures from the past. In contrast, *positive campaigning* disseminates information about a candidate's positive future plans or his/her past success. For example, the use of negative campaigning has been well-documented by reputable media during the 2016 US presidential elections (see, e.g., [6,21]). Even though this campaigning strategy prospectively contributed to the success of the Republican candidate (Donald Trump), there is evidence that negative campaigning is risky and might backfire, leading to undesired effects (e.g., by making a candidate less likeable, see [20]). As part of our study, we examined cases of negative campaigning found in our data-set (including the spread of misinformation and rumors) and the effects on the candidates' followers. We do this by (1) searching for known false accusations in our data-set and (2) analyzing the sentiment polarities a candidate uses to address the opposing candidate (i.e. does the candidate mention his rival in a positive or a negative context).

RQ2: In which context do other Twitter users mention the candidates?
Here we examine the context in which ("ordinary") Twitter users addressed both candidates. In particular, we used network analysis techniques (see, e.g., [22]) to derive and analyze ego-networks of hashtags for each candidate and the open coding procedure to classify the respective hashtags.

3.2. Approach synopsis

Our analysis involved four phases (see Fig. 1). In particular, we examined the tweeting behavior of the two presidential candidates (Alexander Van der Bellen and Norbert Hofer)[2] and analyzed how their tweeting strategy influenced the tweeting behavior of other Twitter users. In this context, we define *tweeting behavior* as sending a new tweet, replying to a tweet, liking another user's tweet, and retweeting an existing message.

Phase 1 - data extraction: In the data extraction phase, we used Twitter's Search API[3] to collect tweets about the 2016 Austrian Presidential Election. In particular, we collected German language and English language tweets for the run-off election that took place on December 4th, 2016. We started the data extraction procedure on November 14th, 2016 (three weeks before the election) and continued the extraction procedure until December 14th 2016 (10 days after the election). Even though the official language in Austria is German, we were also interested in English language tweets to capture the opinion of foreigners living in Austria as well as people interested in the elections who live outside of the country. The data extraction procedure resulted in a data-set consisting of 343766 tweets, 206372 of which are English language tweets and 136,372 are German language tweets. Moreover, from March 1st, 2016 till December 14th, 2016 we also extracted all tweets directly issued by the two presidential candidates, giving us 602 tweets posted by Alexander Van der Bellen (@vanderbellen) and 420 tweets posted by Norbert Hofer (@norbertghofer). The 343,766 tweets included 121 double entries (see below), giving us a total of 343,645 unique tweets.[4]

[1] Note that on July 1st, 2016, Austria's constitutional court ruled that the presidential election must be repeated due to irregularities and formal errors in the counting procedures for postal votes in 14 voting districts. As a result of those errors, there was an abstract chance of voter fraud. Evidence of actual voter fraud has not been found.

[2] In particular, we analyzed messages sent from the @vanderbellen and @norbertghofer Twitter accounts. It is not possible, however, to determine if a certain message was actually sent by one of the candidates or by some member of their respective social media teams.

[3] https://developer.twitter.com/en/docs.

[4] In order to extract relevant tweets from the Twitter message stream, we thoroughly examined the hashtags used by each campaign and then applied the following list of hashtags for filtering: *#vdb, #vdb16, #VanDerBellen, #MehrDennJe, #Nor-*

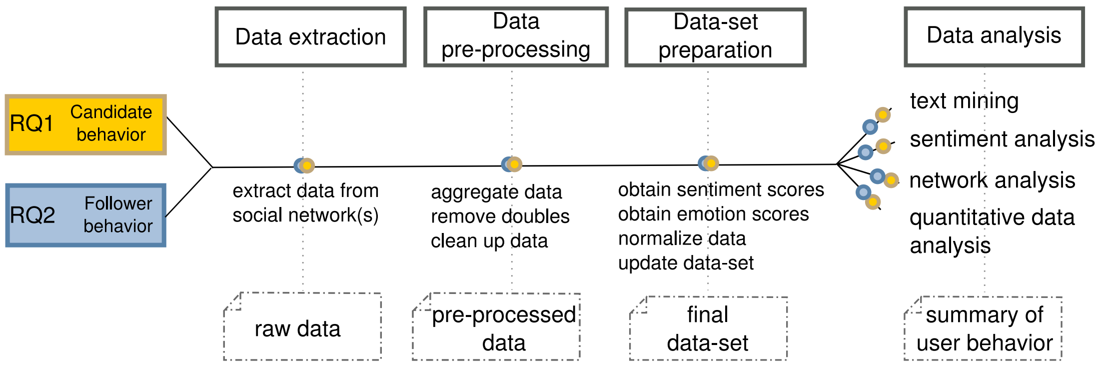

Fig. 1. Approach overview: Sentiment analysis of the 2016 Austrian presidential elections

Phase 2 - data pre-processing: In the data pre-processing phase, we dealt with aggregating and encoding the raw data gathered in Phase 1. Among other things, we applied a data cleaning procedure to identify and remove 121 double entries from our data-set. Moreover, since people freely express themselves on Twitter, the language is not formal and contains spelling errors, abbreviations, alternative spelling, and slang words, which, if not addressed properly, might cause errors in a subsequent data analysis. Thus, in order to normalize the extracted data we manually searched for and adjusted typing errors or alternative spellings of common terms (see, e.g., [23]).[5]

Phase 3 - data-set preparation: In this phase, we ran the data-set through SentiStrength [24], which is based on a lexicon of sentiment words, a list of idioms, and a list of emoticons. In particular, SentiStrength deals with spelling correction, booster words, negation, and repeated punctuation to finally assign two scores for each individual tweet – one positive sentiment score from the interval [1,5] and one negative score from the interval [−1,−5]. These two scores are used to capture the presence of mixed emotions [25]. For example, a sentence such as "I enjoyed *[3]* this debate, but I hate *[−4]* it when candidates lie.", is assigned a positive score of +3 (for the term "enjoyed") and a negative score of −4 (for the term "hate") by SentiStrength.

In addition, we also applied the NRC emotion-word lexicon [26] over the tweets and stored emotions identified in the tweets. These scores were then added to our data-set (see also Section 4).

Phase 4 - data analysis: In the analysis phase, we conducted our data analysis over the final version of the data-set (see Fig. 1). In particular, we used text mining techniques, sentiment analysis, network analysis, and quantitative data analysis (see Section 4).

Software tools: For data extraction, pre-processing, and data analysis, we used R[6], as well as the following R packages: *igraph*[7], *stringr*[8], and *tm*[9]. Furthermore, we used the SentiStrength[10] tool and the NRC dictionary[11] for extracting sentiment polarities and emotion vectors.

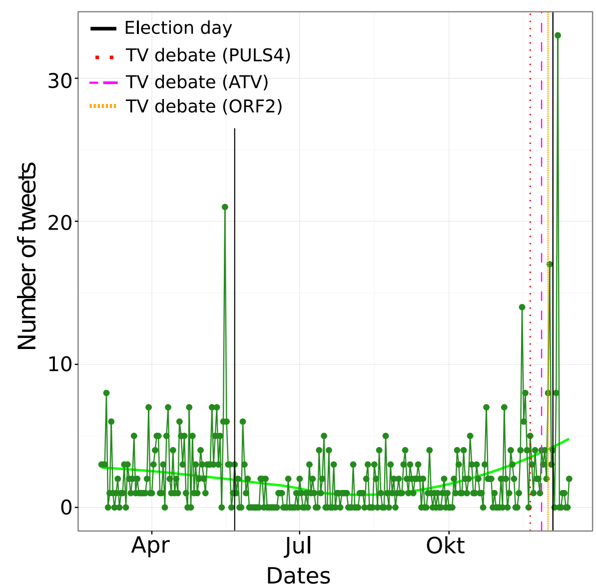

Fig. 2. Van der Bellen's tweeting timeline.

4. Data analysis

In the subsequent sections, we report on the results on the tweeting behavior of the presidential candidates (Section 4.1) and other Twitter users (Section 4.2).

4.1. Tweeting behavior of the presidential candidates (RQ1)

4.1.1. Temporal properties of the candidates' tweeting behavior

Figs. 2 and 3 show the tweet count per day for each candidate, with dashed lines indicating important real-world events that happened during the campaign. In particular, the two black lines mark the election days (May 22nd and December 4th 2016), the orange, magenta, and red lines each mark the dates of different TV discussions between the candidates respectively.[12] The plots in Figs. 2 and 3 show the tendency of the candidates to increase their tweeting activity shortly before an important event. Such behavior has also been observed in other elections in Europe (see, e.g.,

bertHofer, #NorbertHofer2016, #Hofer, #bpw16, #AustrianElection, as well as combined occurrences of *#Austria and #election*. For each of the 343,645 tweets, we extracted the following information: the text body of the tweet, the corresponding Twitter username, the time and date when the tweet has been published, the corresponding retweet count, and the corresponding "like" count.

5 We paid a special attention to terms that were important in our data analysis. In German, mutated vowels (so called Umlauts) such as ö, ä, ü can alternatively be written as oe, ae, ue. For example, we encountered two variants of the German word for Austria – Österreich and Oesterreich. Moreover, we dealt with misspellings. For example, Alexander Van der Bellen's name was misspelled as *Van der Belen* or *Von der Bellen*.

6 https://www.r-project.org/.

7 http://igraph.org/.

8 https://cran.r-project.org/web/packages/stringr/.

9 https://cran.r-project.org/web/packages/tm/.

10 http://sentistrength.wlv.ac.uk/.

11 http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm.

12 The red line marks the discussion broadcast on PULS4 (November 20th), the magenta line marks the discussion broadcast on ATV (November 27th), and the orange line marks the date of a TV debate broadcast on ORF2 (December 1st).

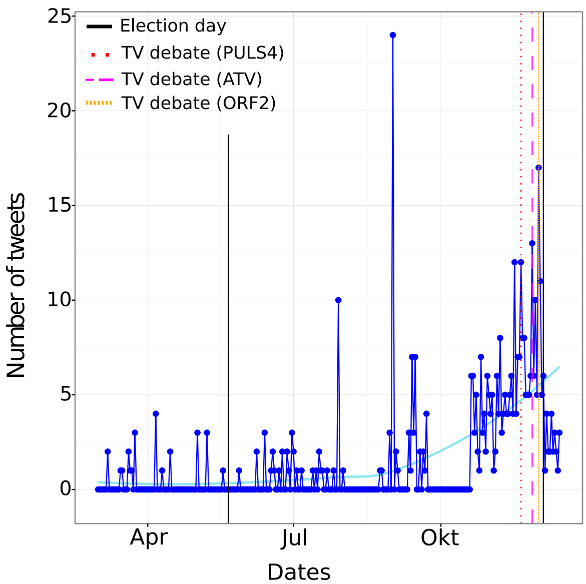

Fig. 3. Hofer's tweeting timeline.

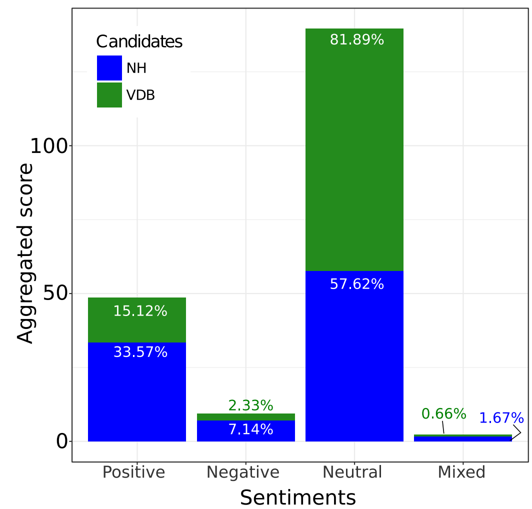

Fig. 4. Sentiments in Van der Bellen's and Hofer's tweets.

[27]). In our data-set, this trend is particularly evident in Van der Bellen's tweeting timeline. In contrast, Norbert Hofer's tweeting activity was comparatively low during the first round of elections but increased considerably since October 2016. Moreover, Fig. 3 shows a peak on September 1st. Since no important political event (such as an election day or a TV discussion) took place around that date which would explain such an increase in the tweet count, we manually examined the content of the corresponding tweets. In this particular case, the candidate responded to negative tweets that were directed at him.

4.1.2. Engagement style of the presidential candidates

Tweets originating from Van der Bellen's account frequently used the candidate's first name, the name of the country (*Österreich*, en: Austria), as well as a range of positive words, such as "together" (de: *gemeinsam*), "collaboration" (de: *Zusammenarbeit*), "support" (de: *unterstützen*), as well as informative words about his presence in the media (de: *Gast, Interview, Plakatpräsentation*). Tweets originating from Norbert Hofer's account used a more personal approach to address his supporters. The tweets often started with the term "*dear friends*" (de: *liebe Freunde*) and ended with "*yours Norbert*" (de: *Euer Norbert*).

We applied SentiStrength [24] in order to gain more insight into the sentiment polarities both candidates target in their followers. Moreover, we identified 8 basic emotions according to Plutchik's wheel of emotions [28] by applying the NRC lexicon [26] over the candidates' tweets. Our analysis was based on the assumption that a single tweet may contain positive emotions, negative emotions, or a mixture of both.

Fig. 4 summarizes the sentiment polarities we identified in each candidate's tweets.[13] In particular, we considered three sentiment categories that are traditionally used in sentiment categorization – positive, negative, and neutral (see, e.g., [27,29]). In this respect, a tweet is classified as positive if the assigned positive sentiment score dominates over the assigned negative score. The same analogy follows while classifying texts carrying negative sentiments. Neutral texts, with respect to sentiment analysis, are those that neither express positive nor negative sentiments. In our data-set, a tweet such as "*Austria: 83% of people with university degree voted for green candidate Alexander Van der Bellen*", is considered neutral with respect to it's sentiment score. In addition to these three categories, studies from the field of psychology have shown that people can also experience and express two emotions of opposing affective valence (positive and negative) simultaneously [25,30]. Thus, in order to also capture such tweets in our analysis, we considered an additional category "mixed emotions" (e.g., "*There's nothing more entertaining (or depressing?) than reading comments on krone.at for breakfast #bpw16*"). In total, we therefore grouped the tweets into one of the following four categories: positive, negative, neutral, or overlap between positive and negative polarity ("mixed emotions"). This classification was done based on the sentiment scores assigned by the SentiStrength algorithm.

Fig. 4 shows a substantial difference in sentiment polarities as communicated by each candidate. For one, Van der Bellen predominantly posted neutral tweets (81.99%) where he announced TV debates, radio talk shows, and other pre-election events. In addition, a number of positive tweets originated from Van der Bellen's account (15.12%), with their number increasing on election day when the candidate expressed his gratitude and thanks to his supporters. While the number is comparatively low, Van der Bellen's tweets also include some tweets with negative sentiment scores (2.33%). Those negative messages mostly refer to negative events that happened around the world, such as the bombings in Istanbul (Turkey) that took place on December 10th 2016. In comparison, tweets originating from Norbert Hofer's account are more emotionally driven (42.38%, as compared to Van der Bellen's 18.11%). In particular, he shared comparatively more tweets with positive and negative emotions, such as his love for the country, and gratitude to his supporters (positive), as well as tweets with a negative content (such as answers to negative tweets about himself and his opinion on terrorist attacks).

In order to examine whether the same sentiment-related patterns hold when observing the candidates' tweeting behavior surrounding the five important events reported in Section 4.1.1 (three TV discussions and the two election days), we extracted the sentiments conveyed by each candidate during a time window of three days for each of the five events (date of the respective event, as well as one day before and one day after the event). Fig. 5 shows that Van der Bellen predominantly sent messages with a neutral sentiment score and no messages conveying negative sentiments. In contrast, Hofer's messages exhibit a comparatively higher count of emotionally-driven messages. When contrasting the tweeting

[13] Note that we use the following abbreviations in the paper to refer to the two candidates: Van der Bellen (VDB) and Norbert Hofer (NH).

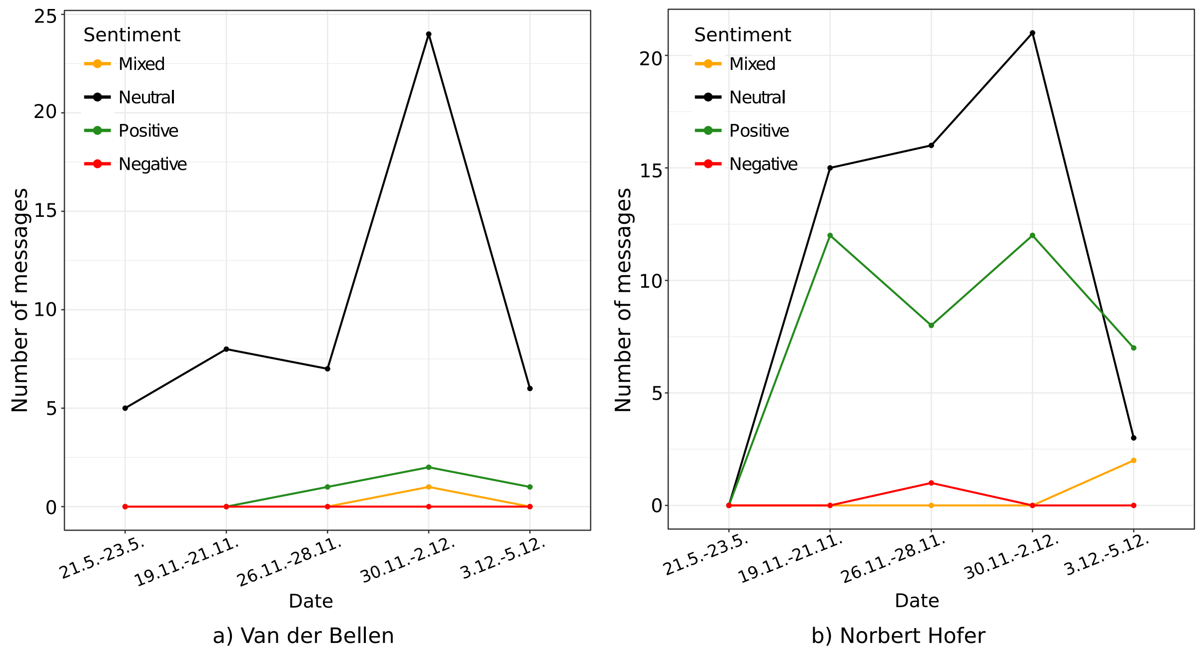

Fig. 5. Sentiments conveyed in tweets posted during major events.

Table 1
Emotions conveyed in the candidates' tweets.

		NH		VDB	
	Emotion	Mean	SD	Mean	SD
Negative	Sadness	0.54	0.6	0.33	0.59
	Anger	0.59	0.59	0.39	0.98
	Fear	0.68	0.52	0.72	1.18
	Disgust	0.51	0.55	0.17	0.51
Positive	Trust	0.45	0.7	0.69	0.99
	Joy	0.26	0.51	0.44	0.69
	Surprise	0.14	0.39	0.26	0.47
	Anticipation	0.3	0.6	0.41	0.63

behavior surrounding the important events with the rest of the data-extraction period, we found a high similarity for each of the two candidates ($cos_{SIM}(VDB)$=0.993; $cos_{SIM}(NH)$=0.985), where cos_{SIM} stands for a cosine similarity between the sentiment scores surrounding the important events and the rest of the extraction period.

To further examine which emotions contribute to the positive and negative sentiment scores, we used the NRC lexicon to identify eight basic emotions according to Plutchik's wheel of emotions. In particular, we found anger, disgust, fear, and sadness for negative SentiStrength sentiment scores as well as joy, trust, surprise, and anticipation for positive SentiStrength scores. In specific, we classified anticipation and surprise as positive emotions because they exhibited a stronger Spearman's rank coefficient ρ (95% confidence interval) with the remaining positive emotions, namely joy and trust (e.g., ρ_{VDB}=0.63 and ρ_{NH}=0.57 between joy and anticipation, ρ_{VDB}=0.68 and ρ_{NH}=0.63 between joy and surprise) in the data-set as compared to the negative emotions, namely disgust, fear, anger, sadness (e.g., ρ_{VDB}=0.19 and ρ_{NH}=0.04 between anger and surprise, ρ_{VDB}=0.07 and ρ_{NH}=0.15 between anger and anticipation).

The results indicate a comparable set of emotions used by both candidates in their Twitter discourse. Fear dominated in both candidates' negative tweets while positive tweets conveyed predominantly trust (see Table 1). However, Van der Bellen's tweets were less emotional compared to his opponent's.

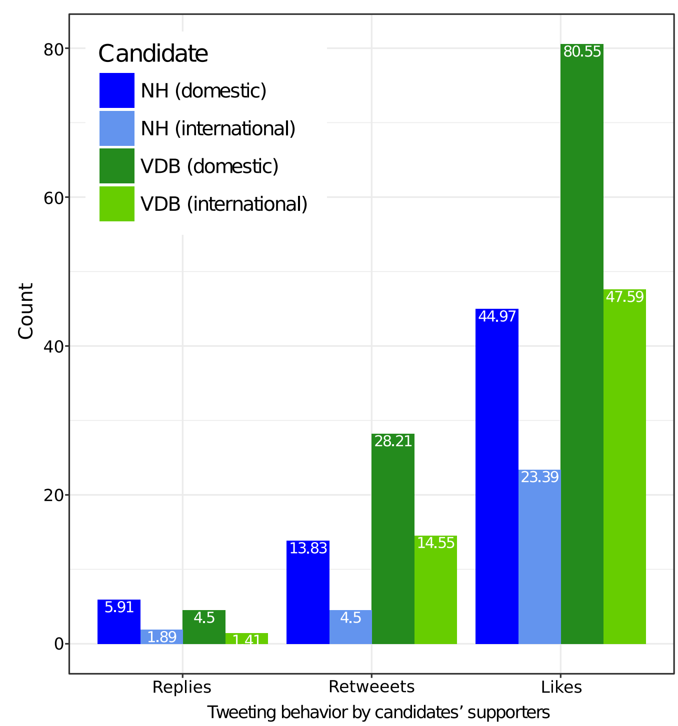

Fig. 6. Summary of the tweeting behavior separated by followers of each candidate.

4.1.3. Reactions of other Twitter users to the candidates' tweets

In order to investigate the reactions of other Twitter users, we examined the mean number of replies, retweets, and likes on two types of tweets posted by each candidate: (1) those targeting a domestic audience (i.e. tweets written in German language), and (2) those targeting an international audience (i.e. tweets written in English language). In total, our data-set comprised 4.29% (18 tweets) English language tweets posted by Norbert Hofer, and 3.65% (22 tweets) English language tweets posted by Van der Bellen. The results are shown in Fig. 6 and indicate that the two candidates

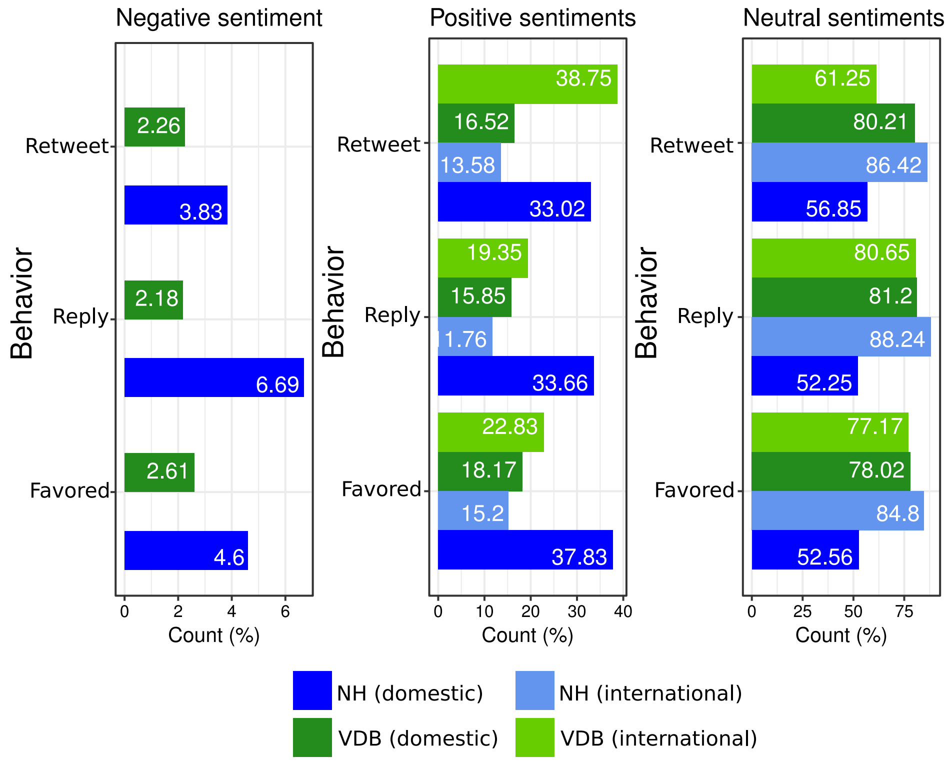

Fig. 7. Tweeting behavior for negative, positive, and neutral sentiment scores targeting domestic and international Twitter users.

received a consistent user reaction, regardless of the language of the tweet. In particular, Norbert Hofer inspired more replies to his German and English language tweets compared to Van der Bellen, while Van der Bellen's tweets received comparatively more likes and retweets.

Since two Twitter users can directly communicate with each other by using the @ character followed by the other user's screen name, we were able to trace such direct communication. In total, 35.05% of the tweets posted by Van der Bellen are messages directed to another user. However, such messages are predominantly directed at domestic Twitter users (169 tweets). English language tweets predominantly occurred towards the end of the data extraction period when the candidate thanked international users for their congratulation messages after winning the presidential elections (in total 16 English language tweets are messages directed at other Twitter users). In contrast, only 15% of the tweets originating from Norbert Hofer's account are direct responses to another user's tweet (also note that no English language tweets of Norbert Hofer have been sent to other Twitter users).

In terms of tweet popularity, we also observed a strong positive correlation between the retweet count and the like count for both presidential candidates. Spearman's coefficient (ρ_s, 95% confidence interval) for retweets of Norbert Hofer's messages and the corresponding likes is a strong positive (0.94 for German tweets and 0.75 for English tweets). The same pattern is observed for the tweets sent from Van der Bellen's account (0.92 for English tweets and 0.95 for German tweets).

While contrasting user behavior with the sentiments conveyed in the corresponding tweets, our results reveal that Hofer's tweets targeting a domestic audience receive comparatively more user reactions (retweets, replies, and likes) when they convey positive or negative sentiments rather than neutral ones (see Fig. 7). In contrast, we found that Van der Bellen's tweets conveying neutral sentiments cause more user reactions when they target a domestic audience. Examples of such tweets include messages of informative nature, such as "*Alexander #VanDerBellen in #DasDuell on #ORF2 #bpw16*". Compared to the domestic audience, international audiences reacted with more likes, retweets, and replies to Van der Bellen's positive messages, such as "*Thank you! Looking forward to a good cooperation. I'm confident we will successfully deal with the challenges lying ahead*" and to neutral messages sent by Norbert Hofer, such as "*I posted a new photo to Facebook*".

Furthermore, our analysis has shown that both candidates received on average more retweets ($rt_{VDB_{IE}}$=82.82, rt_{VDB_R}=22.16; $rt_{NH_{IE}}$=30.35, rt_{NH_R}=8.35), likes ($l_{VDB_{IE}}$=206.67, l_{VDB_R}=66.55; $l_{NH_{IE}}$=83.02, l_{NH_R}=32.34), as well as replies ($r_{VDB_{IE}}$=11.51, r_{VDB_R}=3.67; $r_{NH_{IE}}$=8.43, r_{NH_R}=4.93) during the five important events (three TV discussions and the two election days; indexed *IE* in the reported results) compared to the rest of the data-extraction period (indexed *R* in the reported results).

Since the three most replied tweets from both candidates expressed emotions, we also examined if the behavior of Twitter users (reply count, retweet count, and like count) can be explained by the emotional intensity conveyed in the candidates' tweets. For the retweet count, we consider the following hypothesis.

H1: Emotional tweets positively contribute to the retweet count.

For the reply count, we consider the following hypothesis.

H2: Emotional tweets positively contribute to the reply count.

Finally, for the like count, we consider the hypothesis below.

H3: Emotional tweets positively contribute to the like count.

In our data-set means (μ) of the respective response variables are lower than their variance *Var* (μ_{rt}=21.84, Var_{rt}=2115.24; μ_{reply}=4.94, Var_{reply}=78.13; μ_{like}=64.84, Var_{like}=11912.6). Thus, we used a set of negative binomial regression models to account for the over-dispersion, with the response variables being retweet count (model 1), reply count (model 2), and like count (model 3).

Table 2
Results of the negative binomial regression model with response variables *retweet count, reply count, like count*. Results are presented for the significance levels ***.001 and **.01.

Response variable	Est. coeff. *Retweet count*	Std. Error	Est. coeff. *Reply count*	Std. Error	Est. coeff. *Like count*	Std. Error
Intensity	.06***	0.02	.06**	0.02	.07***	0.01
Hashtags	.327***	0.03	−0.001	0.03	.207***	0.02
@-count	−.532***	0.07	−.712***	0.08	−.428***	0.05
URLs	.378***	0.07	.35***	0.07	.366***	0.05
# Observations	1022					

We chose emotional intensity scores as explanatory variables in all three models and controlled them for the content-related features (hashtag count, direct communication (@-count), and URL count in the respective tweet). In the regression models below, β stands for the regression parameter (an unknown constant that is to be estimated from the data) while ϵ denotes a random error which represents the discrepancy in the approximation.

$$E(RetweetCount) = \beta_0 + \beta_1 EmotionIntensity + \beta_2 HashtagCount + \beta_3 @Count + \beta_4 URL + \epsilon \quad (1)$$

$$E(ReplyCount) = \beta_0 + \beta_1 EmotionIntensity + \beta_2 HashtagCount + \beta_3 @Count + \beta_4 URL + \epsilon \quad (2)$$

$$E(LikeCount) = \beta_0 + \beta_1 EmotionIntensity + \beta_2 HashtagCount + \beta_3 @Count + \beta_4 URL + \epsilon \quad (3)$$

The results of the negative binomial regression models presented in Table 2 indicate that emotional candidates' tweets positively attract user reactions in terms of retweeting, replying to, and liking a respective tweet when controlled for the content-related features. In specific, our data supports hypotheses *H*1, *H*2, and *H*3 (estimated coefficients *b* for the emotional intensity in all three regression models are positive and significant, b_{rt}=0.06 for $p < 0.999$; b_{reply}=0.06 for $p < 0.99$; b_{like}=0.07 for $p < 0.999$). Regarding the content-related features, our data shows that the more hashtags and URLs a tweet includes, the more it is retweeted ($b_{hashtags}$=0.327 for $p < 0.999$; b_{URL}=0.378 for $p < 0.999$) and liked ($b_{hashtags}$=0.207 for $p < 0.999$; b_{URL}=0.366 for $p < 0.999$). However, this does not hold for the reply count (*H*2). The estimated coefficients have shown that URLs are the only content-related feature in our model that positively contribute to the reply count.

4.1.4. Analysis of campaign styles with respect to sentiment polarities

In our analysis, we also found some evidence of negative campaigning in the Austrian media (e.g., TV discussions where Van der Bellen was accused of being a former spy). In our data-set, we found a subset of tweets posted by each candidate that mention the opposing candidate or his (former) party (FPÖ for Norbert Hofer and Green party for Van der Bellen). In total, 1.82% (11) of the tweets originating from Van der Bellen's account mention Norbert Hofer, seven of which are neutral (esp. announcements for TV or radio discussions with Norbert Hofer), while the rest share a negative sentiment about the opposing candidate. In comparison, tweets originating from Norbert Hofer's account mentioned his opponent slightly more often. In particular, 3.57% (15) of these tweets mention Van der Bellen, five of which are neutral, while the rest directly express some opinion that results in a negative SentiStrength sentiment score about the Green party or one of Van der Bellen's messages. Figs. 8 and 9 show the emotions found in tweets that each candidate used to address his opponent. Interestingly, the mentioning of the respective opponent predominantly occurred outside of the time-frames around the important events (only two messages posted by each candidate referred to the opponent). In both cases, the candidates announced TV duels by mentioning each others' names (e.g., "*Today Alexander Van der Bellen and I [Hofer] will discuss live on ATV The Duel.*").

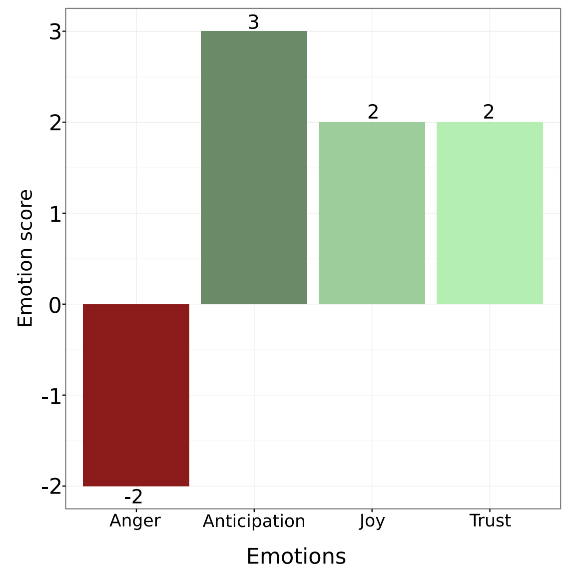

Fig. 8. Emotions in Van der Bellen's tweets that mention Hofer.

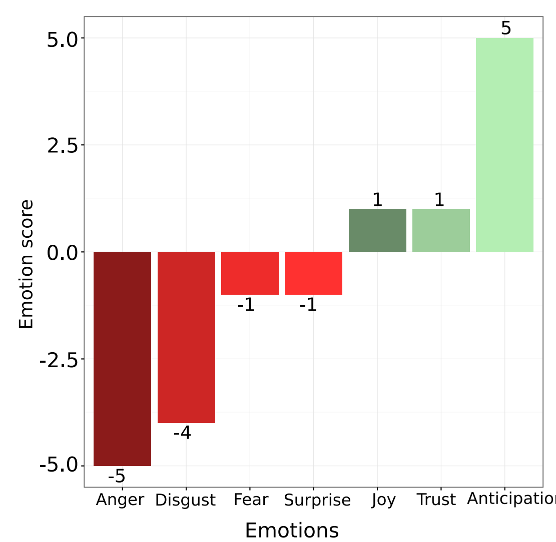

Fig. 9. Emotions in Hofer's tweets that mention Van der Bellen.

Figs. 10 and 11 show the impact of tweets about the opposing candidate in comparison to tweets on other topics. In particular, the plots show the arithmetic mean of the retweet count, reply count, and like count for messages mentioning the opposing candidate in contrast to the respective numbers for tweets on other

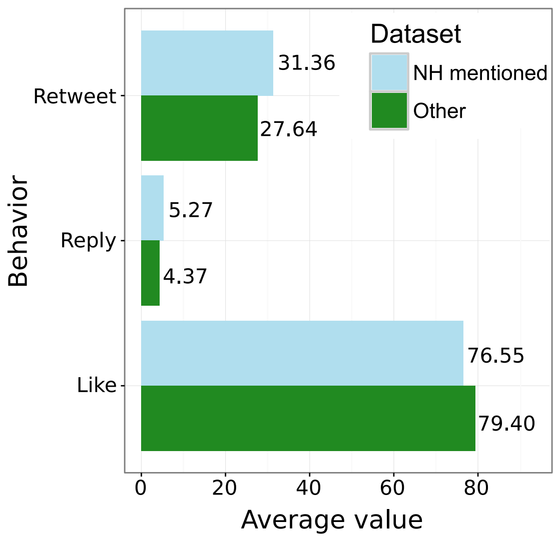

Fig. 10. Comparison of the tweets in which Norbert Hofer was mentioned and other tweets posted by Van der Bellen.

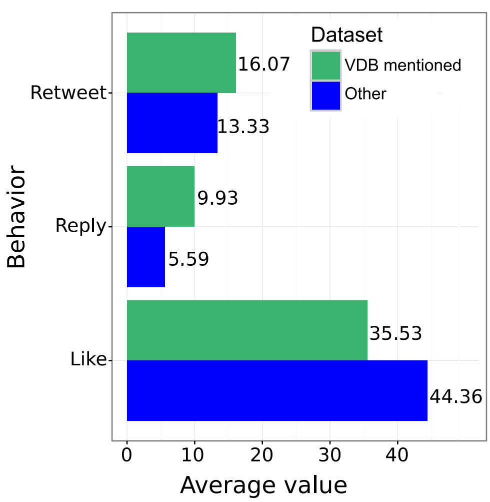

Fig. 11. Comparison of the tweets in which Van der Bellen was mentioned and other tweets posted by Norbert Hofer.

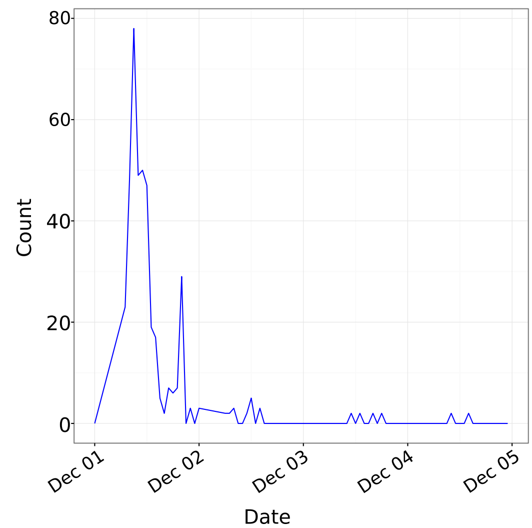

Fig. 12. Retweet count for the video statement *"Up to now, I always voted for the FPÖ. Why I vote now for #VanderBellen."*

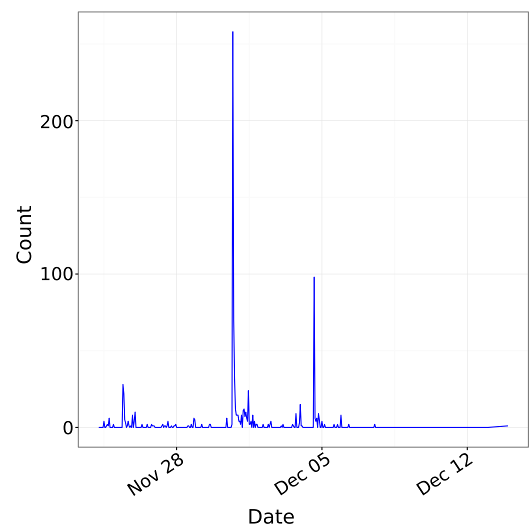

Fig. 13. Retweet count for the video statement *"Gertrude, an 89 year old holocaust survivor warns against FPÖ."*

topics. In general, tweets in which Van der Bellen mentioned Hofer received slightly more retweets and replies than his tweets on other topics. In the same way, Norbert Hofer's tweets that mention Van der Bellen received more replies and retweets than his tweets on other topics, however, considerably fewer likes, compared to other tweets.

Spread of negative information: Figs. 12–14 show three examples of negative campaigning that received the most retweets of all messages conveying negative sentiments. In particular, Fig. 12 shows the retweet count for the video statement *"Up to now, I always voted for the FPÖ. Why I vote now for #VanderBellen."*. The tweet was published by Van der Bellen's official Twitter account on December 1st 2016 at 7:37 AM. Subsequently, it has been retweeted and copied over Twitter by 167 distinct followers of Van der Bellen and 2 followers of Norbert Hofer.

A second example is shown in Fig. 13, which is another video statement referred to in a tweet that originated from Van der Bellen's account. This video shows an 89-year old holocaust survivor who warns against voting for FPÖ (respectively Norbert Hofer). The tweet was published by the official Twitter account of Van der Bellen on November 24th 2016 at 10:33 AM. Subsequently, it was also disseminated into the English language Twitter sphere and was retweeted and copied 864 times by 135 distinct followers of Van der Bellen and 2 followers of Norbert Hofer. This particular tweet is also the one that continued to spread for the longest time of all tweets that carried negative information about the opposing candidate. Moreover, it is the third most retweeted message in our data-set, only preceded by two tweets in which Van der Bellen thanks his supporters for their votes and a tweet which invites people to vote.

Fig. 14 shows the retweet count for the video statement *"Hate in the network and why I am against Van der Bellen."* which was published by one of Norbert Hofer's followers on August 7th 2016 on YouTube. Subsequently, it reached Twitter and was retweeted 68 times by 2 followers of Norbert Hofer, and 16 users that do not follow either of the candidates on Twitter. In this example, we witness a higher average retweet count (3.78) by each user, whereby one of Norbert Hofer's followers alone was responsible for 12 out of 68 (17.65%) retweets.

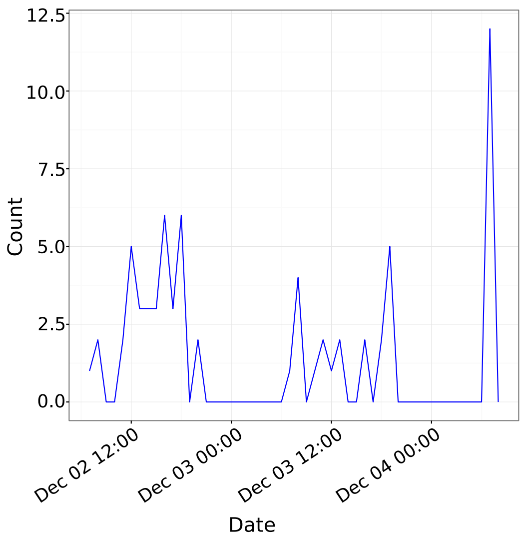

Fig. 14. Retweet count for the video statement *"Hate in the network and why I am against Van der Bellen."*

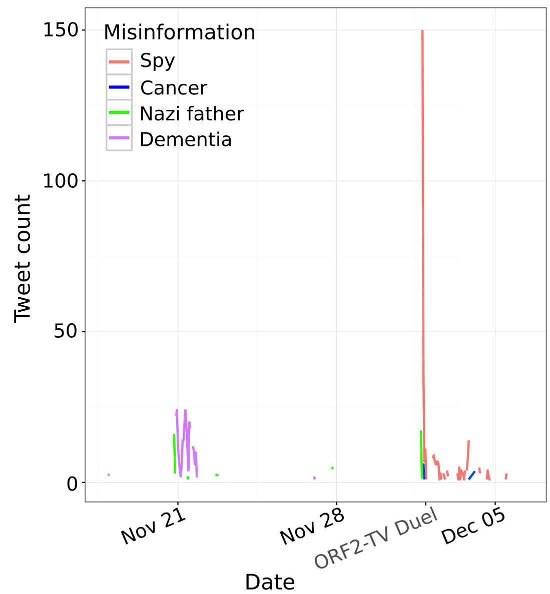

Fig. 15. The time-series plot of 4 instances of misinformation spread over Twitter during the presidential elections.

4.1.5. Spread of misinformation

In addition to the spread of negative information, the 2016 Austrian presidential elections also witnessed a number of messages including misinformation that spread over Twitter, most of which targeted Van der Bellen. In particular, the tweets that carry misinformation refer to false accusations of Van der Bellen being a former communist spy, as well as allegations that he suffers from cancer and dementia. We classified this information as misinformation because it has been rebuked by reputable and credible sources, such as quality newspapers including "Der Standard" and "Die Presse". Note, however, that neither of the aforementioned examples was posted from Norbert Hofer's Twitter account. Nevertheless, it was mentioned during the candidates' TV discussions and later on discussed and spread over Twitter by (predominantly and surprisingly) Van der Bellen's followers. Thus, Van der Bellen's followers substantially participated in the dissemination of misinformation concerning Van der Bellen.

In particular, we identified four cases of misinformation in our data-set. In Fig. 15, the red line represents the misinformation about Van der Bellen being a former spy. In the plot, we can observe that the highest peak of this information stream was reached on December 1st 2016, the date of the ORF2 TV-discussion, when Hofer suggested on TV that Van der Bellen is a former spy. In order to gain further insight into people's reactions and behavior over Twitter once they have been exposed to the misinformation, we manually examined the tweets referring to this false "spy" accusation.[14]

On the one hand, the corresponding tweets exhibited signs of information seeking (e.g., "*Was Alexander #VanderBellen a spy?*" followed by a link to an information source). We found 53 such tweets (including corresponding retweets) that were posted a day after the TV discussion and continued spreading for three days after the discussion. Thus, the misinformation was at first regarded a rumor by some Twitter users that was yet to be confirmed or rebuked. Other users showed signs of annoyance (e.g., *"What next is #VdB going to be?"*) (13 tweets), assumed a threat to Van der Bellen's election success (e.g., *"Spy accusations might cost #VanDerBellen the elections"*) (23 tweets), sarcasm (see, e.g., Fig. 16 and

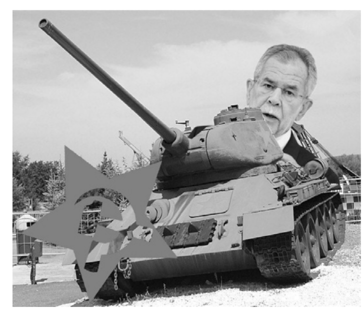

Fig. 16. A sarcastic reaction to the tweet suggesting that Van der Bellen is a former spy that writes: "*I just found a top secret photo of Van der Bellen's spying activities*". This tweet was posted by one of Van der Bellen's followers. It was retweeted by two other of his followers as well as two Twitter users that did not follow either candidate on Twitter.

"*#VanDerBond: A spy who loved me.*" or *"#VanDerBellen aka spy agent, I always wanted to have James Bond as a president!"*) (36 tweets), and tweets that found the accusation amusing (e.g., *"Get your popcorn and turn on @ORF"*) (10 tweets).

Although the defending tweets and information seeking tweets were predominant in our data-set, there was also a smaller number of tweets that fueled the spy accusation by providing alleged evidence (e.g., *"A book of an ex-security manager is a surprisingly good source: VdB actually was a communist spy."*), calling the Van der Bellen "ineligible" (German: *unwhlbar*). In turn, other tweets directly criticized Hofer for bringing up the false accusation in the first place (e.g., *"Mr. #Hofer as a president should speak the truth."* or via a hashtag *#liar* next to *#hofer*). Thus, spreading misinformation as a campaigning strategy has also shown its risks as it partially backfired against the spreader (Hofer).

4.2. Context of the tweets mentioning each candidate (RQ2)

In this section, we examine the context in which other Twitter users mention the two presidential candidates. Thus, the subsequent discussion refers to tweets posted by Twitter users other than Van der Bellen and Hofer. We also compare the results that can be obtained from the 136372 German language tweets (subsequently referred to as the "German language data-set") to the

[14] Note that in this paper we provide a detailed discussion of one particular misinformation stream - which is the one related to the spy accusations. We chose to present this case in detail because it was the most abundant stream regarding its scope (i.e. highest number of reactions and the longest time period).

corresponding results of the 206372 English language tweets (subsequently referred to as the “English language data-set”).

First, we were able to confirm that a considerable amount of Twitter content consists of retweets. In particular, only 43.1% of the 136372 tweets in the German language data-set are original tweets, while the remaining 56.9% are retweets. This is even more obvious in the English language data-set, where only 29.89% of the 206,372 tweets are original tweets while 70.11% are retweets. However, this result was expected to a certain degree, since the English Twitter sphere was predominantly used to disseminate important facts about the Austrian elections, with little to no one-to-one discussion (see also [31]). In comparison, the German Twitter sphere witnessed a more extensive discussion about the candidates and the events that happened during the election period.

In order to identify relations between Twitter topics, we derived the corresponding hashtag networks. The hashtag network derived from the German language data-set is an undirected network and consists of 5233 distinct vertices and 23,535 edges, with an average vertex degree of 9.01. In total, the network includes nine connected components. In particular, some hashtags (vertices in the hashtag networks) are isolated and thus never used in a combination with other hashtags.

The vertices (hashtags) with the largest degree (δ) are #bpw16 (δ=3872),[15] #Hofer (δ=1597), #vdb (δ=1464), #vanderbellen (δ=1054), and #Österreich (δ=708). Moreover, it is worth mentioning that in the German language hashtag network, hashtags #MarineLePen (δ=325), #ViktorOrban (δ=293), and #Trump (δ=233) are among the top fifteen vertices with respect to the vertex degree. The German language hashtag network also shows that both candidates were addressed in a positive as well as a negative context (see below).

To examine the context of the discussion related to different hashtags, we also derived an ego-network for each candidate (see Figs. 17 –20). The German language ego-network of Van der Bellen consists of 1463 vertices and 9878 edges (network density $\approx$0.01), while Norbert Hofer's German language ego-network consists of 1596 vertices and 10,846 edges (network density $\approx$0.01).

An ego-network consisting of hashtags may reveal valuable insights about the topics people associate with each candidate. Thus, after a thorough examination of the hashtags directly connected to each candidate, we manually identified five categories of hashtags and assigned the corresponding category to each hashtag in the data-set by following the open coding approach. These categories include:

- *Supporting*: hashtags that directly support a candidate (here we excluded the general hashtag which carries the candidate's name only because it can either appear in a tweet with negative or positive sentiment polarities). Examples include *#vote4vdb, #teamvanderbellen, #Hofer4President, #hofer2016*.
- *General*: hashtags that carry general information about the 2016 Austrian presidential elections (e.g., newspaper titles, TV station names, party names, important dates). Examples include *#bpw16, #presidentialElection, #norberthofer, #VanDerBellen*.
- *Against*: hashtags that directly oppose (speak against) a candidate, e.g., *#notoVDB*, *#VollDerBluff*, and *#womenAgainsthofer, #nohofer*.
- *Important topics*: hashtags that refer to important topics discussed during the presidential election, such as *#Islam, #HillaryClinton, #Trump, #terror, #Brexit, #Burka*.
- *Other*: as well as other (hashtags that neither support, go against, carry general information about the elections, or refer to important topics). Examples include *#Styria, #Monday, #Christmas*.

[15] Note that #bpw16 is an abbreviation of the German term “Bundespräsidentenwahl 2016”, i.e.: “presidential elections 2016”.

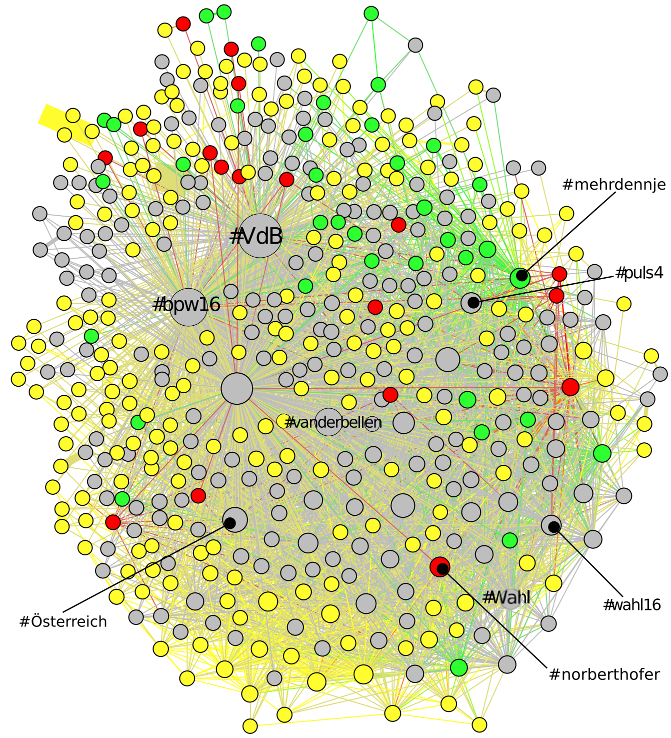

Fig. 17. German ego network of Van der Bellen.

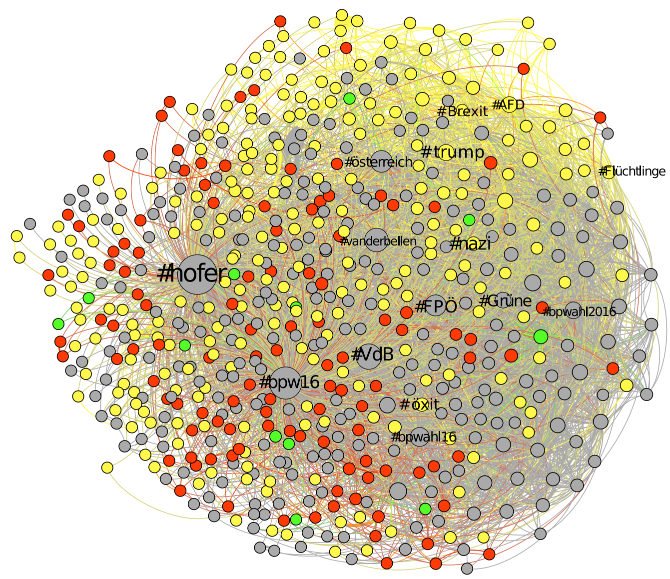

Fig. 18. German ego network of Hofer.

Figs. 17 and 18 show an extract of the German language ego-networks including the vertices which belong to the categories *supporting, general, against*, and *important topics* (i.e. vertices belonging to the “other” category have been excluded from these plots). The corresponding ego-network for Hofer includes 622 vertices and 4826 edges (network density $\approx$0.025). The respective ego-network of Van der Bellen includes 482 vertices and 3938

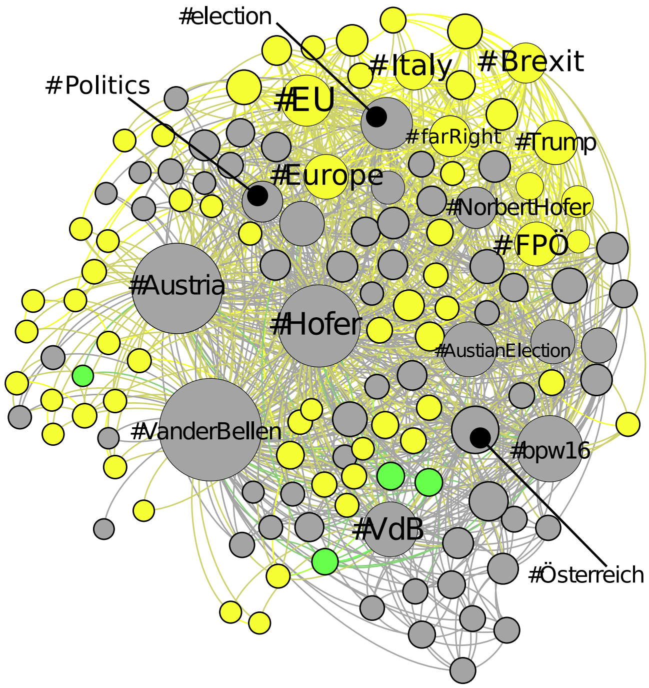

Fig. 19. English ego network of Van der Bellen.

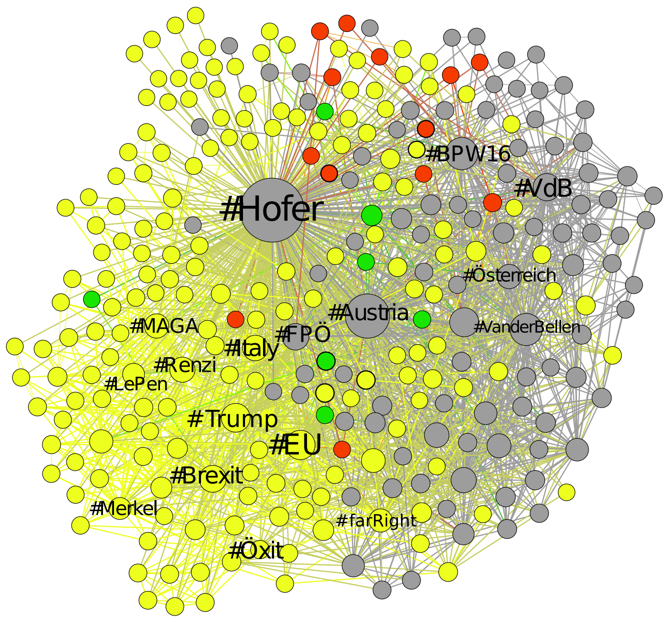

Fig. 20. English ego network of Hofer.

edges (network density ≈0.034).[16] Vertices in the *Supporting* category are plotted in green color, vertices from the *Against* category are plotted in red, vertices on *Important topics* in yellow, and *General information* in gray.

Compared to the German hashtag ego-network, the English language ego-network includes a smaller number of vertices, indicating a lower variety of hashtags (see Figs. 19 and 20). In particular, the corresponding ego-network of Van der Bellen includes 131 vertices and 1057 edges (network density ≈0.124) while Hofer's ego-includes 293 vertices and 1927 edges (network density ≈0.045). The low number of unique hashtags (vertices) results from the fact that the English data-set predominantly consists of retweets (see above).

Figs. 17–20 show that there is a considerable difference in the way Twitter users refer to each candidate in their tweets. Both, the German and English hashtag ego-networks of Norbert Hofer exhibit more vertices (hashtags) that directly refer to the candidate in a negative context (e.g., *#NoToHofer*) as compared to the ego-networks of Alexander Van der Bellen (see also Table 3). On the other hand, hashtags that put a candidate in a positive light are used more often in Van der Bellen's ego-networks, as compared to the ones of Norbert Hofer. In Table 3, we provide a summary of the relative sizes of the hashtag categories, with the maximum value highlighted in bold respectively.

Table 3
Summary of the hashtag categories.

	Supporting (%)	Against (%)	General (%)	Important topics (%)
VDB (de)	**7.68**	3.73	43.15	45.44
VDB (en)	3.06	0	**50.38**	46.56
NH (de)	1.93	**18.49**	41.64	37.94
NH (en)	2.39	4.44	32.42	**60.75**

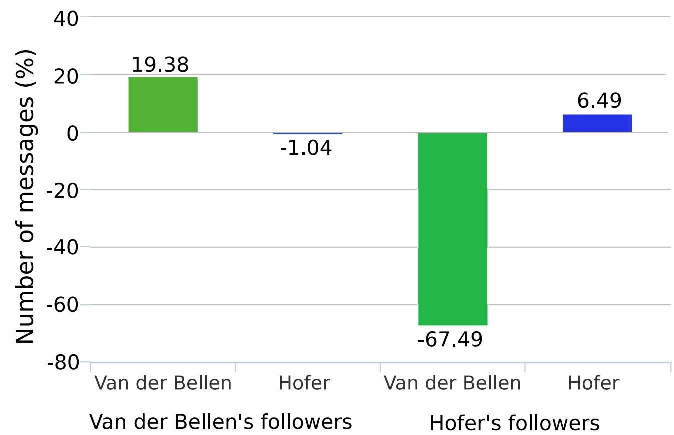

Fig. 21. Supporters' sentiments concerning their candidate and his respective opponent.

4.2.1. *Sentiments of other Twitter users towards the candidates*

We also analyzed the sentiments followers expressed regarding their candidate and his respective opponent. We do this by first separating the data-set into two groups of followers, one for each candidate. For each group we used regular expressions to obtain tweets that mention each candidate individually and extract the sentiment scores as assigned by SentiStrength [24]. If both candidates were mentioned in a tweet, we extracted the corresponding tweets and manually classified them as positive or negative for each candidate. For example, a tweet from our data-set *"God knows Norbert Hofer is a Christian and Van der Bellen is Godless"* is classified under positive for Norbert Hofer and negative for Van der Bellen. We stored this information and extracted the sentiment scores assigned by SentiStrength accordingly. As illustrated in Fig. 21, there is a noticeable difference in the way the followers address the candidates. While Van der Bellen's followers predominantly disseminate positive sentiments regarding Van der Bellen, with a comparatively small number of negative sentiments about Norbert Hofer, the followers of Norbert Hofer tweet mostly negatively about Van der Bellen. Such tweets even substantially exceed the positive tweets about Norbert Hofer.

[16] Note that in the plots the size of a vertex is based on its degree, and the network topology was visualized based on each vertex's community membership. For visualization purposes, we applied the community detection algorithm available in Gephi, as described in [32].

5. Discussion

In our analysis, we found a clear pattern which shows that emotional tweets (negative as well as positive) are retweeted, replied to, and liked more often than the neutral ones. We can thereby confirm the findings from [29] which reported on similar findings for microblogs. An explanation for such a user behavior is that emotionally charged tweets also trigger emotions in other users (see, e.g., [7]). For example, an expression of gratitude (identified in both candidates' data-sets), a message of warning against Norbert Hofer sent by a holocaust survivor, and a message of sadness after losing the elections generally received a high number of user reactions (likes, replies, and retweets; see also Section 4.1.4).

In addition, we found that occasionally tweets with a neutral sentiment score may also be quite influential in terms of the reactions caused in other users. For example, Twitter users highly liked, retweeted, and replied to tweets that carried an invitation for the people to vote. A possible explanation is that such tweets convey an implicit emotion (here: anticipation) which causes a feeling of urgency and importance (e.g., one the respective tweets said *"today every single vote counts"*).

In order to examine which topics Twitter users associate with each candidate, we derived hashtag ego-networks. In particular, we found that hashtags related to important topics are predominant in Norbert Hofer's English language ego-network (60.75%). Such hashtags often carry a controversial note, e.g., "make Austria great again", "Trump", "Oexit", "Brexit", etc. In part, such an ego-network might be attributed to the influence of other media sources (radio shows, online news, etc.), which put Hofer in correlation with the controversial topics.

One might also approach the task of studying associated topics by constructing a network of terms used in the tweets. For example, [16] studied the topics associated with each presidential candidate during the 2012 Korean presidential elections and reconstructed a network of terms that appeared in the same tweet. In our case, we found that Van der Bellen was associated with the topics of respecting human rights and welcoming refugees, to name a few, while his opponent was associated with loving the homeland and protecting the borders. This confirms that the candidates' statements from the TV discussions directly found their way into the social media discussion on Twitter, even though neither of the candidates directly posted a corresponding tweet himself.

With respect to the influence of more traditional media (i.e. non-social-media channels such as newspapers or TV channels), we also examined cases of negative campaigning. In our analysis of negative campaigning, we made use of reputable Austrian media (quality newspapers and TV channels) who published evidence that either confirmed or rejected negative rumors. We used these sources to obtain a list of keywords to find occurrences of misinformation and negative campaigning in our English and German language data-sets. In particular, we performed a time-series analysis, follower analysis, and content analysis, and were able to determine the impact of such tweets on the Twitter discourse. While aligning our findings with existing rumor theories, we found evidence that complies with Rosnow's theory that rumors propagate because of the people's tendency to clarify uncertain events [33].

Another study which complements our findings [20] discussed potential risks to a person spreading misinformation. Our findings confirm that misinformation may lead to negative consequences for the spreader and backfire against him/her. In particular, the accusation of Van der Bellen being a former spy is a good example where Van der Bellen's followers participated in spreading the misinformation over Twitter. In this particular part of our analysis, the importance of using an integrated data analysis approach is evident. As an example of how a combination of analysis methods help to correctly classify user behavior, we refer the reader to the ironic reaction by one of Van der Bellen's followers (cf. Section 4.1). Without the combined analysis approach that we applied to the 343645 unique tweets in our data-set, such a message would have been falsely classified as misinformation or a tweet that goes in disfavor of Van der Bellen. It is, however, important to correctly classify such messages since irony or sarcasm are commonplace in social media messages, and a wrong classification of such messages may lead to false conclusions when interpreting user behavior over social media.

5.1. Limitations

For our study, the main restrictions result from the tools we used for data extraction, pre-processing, preparation, and analysis (see Section 3.2). In particular, we used the Twitter API to extract publicly available tweets. One significant limitation is an API restriction which only allows for the extraction of tweets that are at most seven days old. Thus, if not planned properly, missing data cannot be extracted because the API prohibits access to tweets older than a week. Moreover, Twitter explicitly says that not all tweets are indexed or made available via the free version of Twitter's API.[17] Thus, even though we performed a systematic procedure where we extracted the new tweets on a daily basis (see also Section 3.2), we cannot rule out the possibility that we missed relevant tweets due to this API restriction. However, since the restrictions only apply for much larger samples than ours (see, e.g., [34]), we are confident that our data-set includes the majority of the relevant tweets that have been sent during our extraction period.

In this context, it is important to mention though that our data-set includes *all* tweets of the two presidential candidates (@vanderbellen and @norbertghofer) that have been sent during the extraction period. We ensured this completeness by checking the tweets extracted via the API and manually added tweets that have been omitted by the Twitter API (see also Section 3.2). However, it was unfeasible to repeat the same procedure for all tweets (i.e. all tweets of the candidates' followers) since that would have meant to manually check several ten-thousand user profiles on a daily basis.

A second limitation comes with the tools that we used for sentiment analysis. In particular, we used SentiStrength and the NRC emotion-word lexicon. Even though these tools have been used in numerous related studies (see, e.g., [24,26,29]), we cannot exclude the possibility that some scores assigned by the tools are not appropriate. Thus, to mitigate such errors, a prior assessment of the tools (e.g., by deploying human raters) could improve the overall correctness of the assigned scores (see, e.g., [35]).

6. Related work

In [29], Stieglitz and Dang-Xuan applied the SentiStrength algorithm to study the spread of opinionated tweets during the German elections in 2012. In particular, they quantified the impact of positive and negative tweets in terms of the retweet count and the speed of retweeting. The 2016 US presidential elections have been a topic of study in [36]. The authors relied on SentiStrength to obtain positive, negative, or neutral sentiment values for over 3 million tweets related to the US presidential elections. The authors found that neutral tweets predominated over the negative or positive ones. In 2017, Paul et al. [37] also studied the 2016 US presidential elections to identify sentiments towards the democratic or the republican party at a state level by obtaining geo-tagged tweets. Unlike the previous papers which rely on SentiStrength,

[17] https://developer.twitter.com/en/docs/tweets/search/overview.

[37] proposes the use of Stanford's Twitter Sentiment (STS) corpus and distant supervision to train and validate sentiment analysis classifier. In [38], Diaz-Aviles et al. studied the public opinion about the presidents of 18 Latin American countries by applying sentiment analysis techniques to Spanish language tweets and short blog posts. To determine how people feel about each president, the authors carried out a part-of-speech tagging to extract the list of nouns and adjectives which they later mapped to a corresponding emotion score in the NRC emotion lexicon. Additional non-English language studies have been conducted for the Nigerian presidential elections 2011 [39], Indonesian presidential elections [40], as well as the Bulgarian presidential elections [27].

Some studies also combine sentiment analysis and social network analysis. For example, in [41] Bermingham et al. study jihadists' radicalization over social networks. They took a lexicon-based approach to identify sentiment polarities in YouTube comments and combined it with the network aspects of information sharing. In particular, they applied betweenness centrality to identify influential users in the YouTube sphere, reported the network density, and determined the average communication speed. Fornacciari et al. [42] examined the differences in opinions among Twitter communities by reconstructing a follower-followee network of over 60 Twitter channels and assigning sentiment polarity scores to each vertex (user).

Some studies merely focused on the application of network analysis methods. For example, in [43] Burgees and Bruns collected tweets about the 2010 Australian elections containing the *#ausvotes* hashtag. In particular, they investigated the topics people tweeted about and reconstructed a network of replies. The authors distinguished between a passive (broadcast only) and an interactive user behavior, and identified important users in the network by applying the betweenness centrality measure. In [16], Song et al. applied a latent Dirichlet allocation over a set of tweets to identify a list of topics discussed during the 2012 Korean presidential elections. They examined the occurrences of each topic within a time period and categorized them as a rising (trending) or a falling topic.

7. Conclusion

In this paper, we presented a sentiment analysis of the Twitter discussion on the 2016 Austrian presidential elections. We extracted and analyzed 343,645 German and English language Twitter messages that have been posted by the two presidential candidates, their followers, as well as other Twitter users. In particular, we specified, documented, and applied a systematic approach for analyzing social media user behavior (see [31]).

For the 2016 Austrian presidential election, we found that:

- the winner of the election (Alexander Van der Bellen) predominantly sent tweets resulting in neutral sentiment scores, while his opponent (Norbert Hofer) preferred emotional messages (tweets resulting in positive or negative sentiment scores);
- negative information about both candidates continued spreading for a longer time compared to neutral and positive information;
- there was a clear polarization in terms of the sentiments spread by Twitter followers of the two presidential candidates. While Van der Bellen's followers predominantly disseminate positive sentiments regarding Van der Bellen, with a comparatively small number of negative sentiments about Norbert Hofer, the followers of Norbert Hofer tweet mostly negatively about Van der Bellen. Such tweets even substantially exceed the positive tweets about Norbert Hofer;
- the winner of the election received considerably more likes and retweets, while his opponent received more replies;
- in their attempt to correct misinformation, the followers of Van der Bellen also substantially participated in the spread of exactly that misinformation about him.

In addition to the main findings summarized above, we also found that the two presidential candidates showed a tendency to tweet shortly before and after important events (such as TV discussions) which confirms previous findings from other elections [27]. However, aside from that we also identified increased social media activity that did not correlate with important events, but resulted from negative posts about a candidate.

Moreover, we conducted a regression analysis and found that emotional tweets positively correlate with the like, retweet, and reply count respectively. We also found that the number of hasthags and URLs in a tweet positively correlates with the like and retweet count. However, as for the reply count we only found a positive correlation with URLs – i.e. more hashtags do not increase the reply count for a tweet.

By applying natural language processing (NLP) techniques, we found evidence that both candidates used negative campaigning in order to get more supporters. In particular, our study distinguishes between misinformation and negative information, and we found that negative information in this particular presidential elections received a high retweet and like count. However, we also found evidence that the propagation of misinformation can backfire and have negative effects on the spreader.

With respect to the tweeting behavior of the candidates' followers, we used sentiment analysis and network analysis techniques to construct ego-networks of the candidates, and examined which topics social media users associate with each candidate. Our results show a clear distinction in how users' perceive both candidates. In particular, we found that hashtags carrying a negative connotation have predominantly been associated with Norbert Hofer. This phenomenon can be observed in both, the English and German language hashtag networks.

As part of our future work, we intend to further study the impact of different emotions on the spread of information [7,35].

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