

Analysis of Twitter Communication During the 2017 German Federal Election

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Abstract—Even before 2016 elected US president Donald Trump made the microblogging service Twitter a tool for political campaigning and broadcasting, the online service with millions of users gained attention in public events, scandals or sport events. The question still remains open to what extent the analysis of Twitter communication reveals insights into to political discourse during elections. This study uses the context of the 2017 German federal election to investigate the political communication within the Twitter network during 10 weeks leading to the election in September 2017. Almost 1,500,000 million tweets are analyzed using three different lexica: SentiWS, Linguistic Inquiry Word Count (LIWC) and German Political Sentiment Dictionary (GPSD). In order to gain deeper insights, the users producing the tweets are investigated. The results show that users strongly differ in their activity on the network and perform statistical tests to evaluate differences among the user groups.

Keywords—Social Media; Twitter; Sentiment; Elections

I. INTRODUCTION

Political communication via social media and especially microblogging services, such as Twitter have intensified in recent years. Digital platforms are used by numerous actors to inform themselves politically and to exchange thoughts and ideas [1]. In many countries, social media are used by politicians and political parties more frequently as a medium for election campaigns and political marketing [2]. Especially negative political statements can often attract people's attention and gain high efficacy and attention [3].

As the popularity of social media increases, so does the likelihood that people will find ways to abuse them for their own purposes. One type of abuse in the political online debate is the so-called Astroturf, in which politically motivated individuals and organizations use several remote controlled accounts to give the appearance of broad and spontaneous support for a candidate or opinion [4]. Symptoms include various types of unlawful use, such as spam infiltrating social networks [5]. In addition, in recent years, political actors around the world have begun to use the digital power of automated programs called social bots [6]. They purposefully mimic human behavior, actively engage in the opinion-forming process and have the potential to distort discussions in social networks and manipulate public opinion [7], [8].

Twitter, in particular, has become an ideal destination for exploiting automated programs through its growing popularity and open nature [9]. Automated accounts are often characterized in Twitter by high activity in terms of large tweets, which are generated in connection with political events during very short timespans.

From the growing need to identify highly active, opinion-forming actors in the digital political discourse, the task of this work is to quantify the message traffic in the context of the 2017 German federal election on Twitter and to quantify

the influence of highly active users on the general mood in the election campaign debate. Important questions include the contribution of highly active users to political communication for the 2017 federal elections and their potential influence on other users. In addition, it should be determined whether the generated mood of highly active users, in polarity or strength, agrees with or differs from the majority tonality of the users. The question is whether highly active users differ significantly in their behavior from other users. This is especially interesting due to the fact that a new party, called the "Alterantive für Deutschland (AfD)", entered the stage of German politics and vies for attention.

The paper is organized as follows. In Section II we will provide the research background on election analysis in twitter and the special features to this subject. Section III we will lay out the research method and details of the data collection. Furthermore, the different lexica used in this work are introduced. Another aspect is the measurement of user activity, which is also addressed in this section. The results of the analyses are presented in Section IV. The result presentation is divided into a descriptive analysis, results from investigating the different user groups and the sentiment investigations. The work concludes with a summary and interpretation of the results and gives indications of future investigations.

II. RESEARCH BACKGROUND

In our study, we use 1,475,838 tweets published in the months leading up to the federal election of the national parliament in Germany in 2017. The election took place on September 24th 2017. The elections in 2017 are entering a new chapter in the history of the Federal Republic of Germany, as in this election for the first time a new party, the *AfD*, by many considered a "right-wing" or populist party enters the stage [10], [11]. The German party landscape consists of 7 relevant parties, Social Democratic Party *SPD*, Christian Democratic Union *CDU*, Christian Social Union in Bavaria *CSU*, Alternative for Germany *AfD*, Free Democratic Party *FDP*, The Left *LINKE* or *DIE LINKE* and Alliance 90/The Greens *GRÜNE*, where *CDU* and *CSU* form a federal union called *CDU/CSU* or short *Union*. The strongest group in the new Bundestag, with a share of 32.9%, was the *CDU / CSU* parliamentary group. The *SPD* reached 20.5%. The *AfD* made its first entry into the Bundestag with 12.6%. The *FDP* managed with 10.7% to return to parliament. The Left achieved 9.2% and The Greens 8.9% of the votes [12].

Not only since the 2016 elected US president Donald Trump uses the online service Twitter to process political statements, microblogging services are in the focus of science [13]–[15]. Many researchers investigate the effects on the political landscape or the reflections of real world events in online social networks like Twitter [16]. It remains unclear

whether networks like Twitter either mirror or shape political discourses and if so, to what degree [17]. Despite this uncertainty, there is an ongoing discussion about the influence of possible bots or agents from other countries on local political events, such as the Brexit [17], [18] or the 2016 US elections [19], [20].

Despite the unique properties of tweets compared to other textiles, they have proven to be a reliable source for sentiment analysis. One of the earliest works in which Twitter data was used for sentiment analysis is by Go et al. [21]. They used tweets with emoticons to train a machine learning algorithm and were able to predict the mood in tweets with high accuracy (about 83%). Birmingham and Smeaton also announced in 2010 that classifying short microblogging entries is much easier than classifying longer blog entries [22]. Barbosa and Feng showed that the performance of sentiment analysis in Twitter can be improved by incorporating social relationships and connections, for example a user's followers [23] on Twitter. Further work has been done to introduce new automated methods of sentiment analysis and to optimize existing approaches to increase the classification accuracy of Twitter texts in a variety of contexts. This emphasizes the ability of Twitter sentiment analysis as a scientific tool to investigate human communication, hence, political communication. Tumasjan et al. found out that political sentiment towards parties and politicians can be linked to real events and political demands of the actors using sentiment analysis of the 2009 general election [16]. The results showed both, a lively discussion and conversations among the users. The study was further able to attribute the election result to the proportion of tweets which mentioned a specific party. Furthermore, research has shown, that Twitter usage varies significantly among its users [24].

In the political context regarding Twitter sentiment, negative moods are frequently identified. For example, news coverage of the 2008 US presidential election revealed negative sentiment rather than positive sentiment in response to specific political events, such as television debates [25]. Another work showed that the general mood of the Twitter debate on the 2008 US presidential election was also rather negative [26].

III. METHOD

The data used in this work was collected in a 10 week period leading to the federal elections in Germany on 24th September 2017 using the official Twitter API [27], [28]. During this period, all tweets containing at least one hashtag reference to one of the top parties *SPD*, *CDU*, *CSU*, *AfD*, *FDP*, *LINKE*, *GRÜNE* were collected. The resulting raw dataset comprised 1,475,838 tweets. Since only German tweets are evaluated, the tweets were extracted from the multilingual tweets for further use. Language recognition was performed using the N-gram based text classification of Cavnar and Tenkle [29]. The described speech recognition process classified 1,255,666 tweets as German. The dataset also included 225,371 entries with hashtags of the two chancellor candidates *Merkel* und *Schulz* which have been removed in this work, since we concentrate on party related content. The resulting dataset then comprised 1,030,295 entries. All relevant hashtags are listed in Table I. They are already subdivided into hash tag groups with subsequent hashtags.

In a further step, additional special characters and HTML elements, such as “&” were removed from the text corpus.

TABLE I. NUMBER OF HASHTAG ENTRIES BY HASHTAG

Party hashtag	Number of entries	Assigned hashtags
AFD	515,615	#AFD, #AfD, #afd, #TrauDichDeutschland, #traudichdeutschland, #noAfD, #NoAfD, #AFDwaehlen, #NeinZuAFD, #afdstoppen, #fckafd, #FCKAfD, #AberKeineAFD, #afdverhindern
SPD	154,397	#SPD, #Spd, #spd, #spdde, #EsistZeit, #esistzeit, #EsIstZeit
CDU	149,980	#CDU, #Cdu, #cdu, #fedidwgugl
FDP	71,570	#FDP, #Fdp, #fdp
LINKE	31,206	#LINKE, #Linke, #linke, #DIELINKE, #dielinke, #DieLinke, #Linken, #NURDIELINKE
GRÜNE	46,794	#GRÜNE, #Grüne, #Grueene, #Grünen, #Gruenen, #DieGruenen, #DarumGrün, #GrueeneVersenken
CSU	54,649	#CSU, #Csu, #csu

To determine the mood of a text by means of lexicon-based sentiment analysis, different dictionaries can be used. In the past, several such directories have been developed. Each with different strengths and weaknesses [30]. Due to the focus on a German text corpus, the use of dictionaries is limited to German lexica. In this work, three word-based sentiment lexica will be used: SentimentWS [31], Linguistic Inquiry Word Count [32] and German Political Sentiment Dictionary [33].

SentiWS is a publicly available, German-language dictionary provided by the University of Leipzig and is suitable for sentiment analysis based on the German language [31], [34]. The words are weighted in the interval -1 to 1, depending on the level of expressiveness. *SentiWS* includes 1,818 positive and 1,650 negative words, or 16,406 positive and 16,328 negative word forms, and includes nouns and verbs in addition to sentiment-bearing adjectives and adverbs. *SentiWS* is based, among other enhancements, on the General Inquirer, a popular English language sentiment dictionary whose words have been systematically translated into German and then manually reworked [31].

The *LIWC* is a text analysis software with an integrated dictionary [32]. It was published in 2001 by Pennebaker et al. [35] and has been developed for the automatic analysis of texts in the one-word-procedure and provided by Dr. med. phil. Markus Wolf from the University of Zurich. With the aid of the stored dictionary, words are assigned to one or more predefined language categories. The language categories cover grammatical-linguistic characteristics of the text as well as thematic-content-related aspects, such as positive and negative emotions or the presence of social and cognitive speech content. The program also tracks how many words in a text could be assigned to categories and considers this in relation to the length of the text. The precision rate of the German *LIWC* dictionary was cited with 63% in the past while the English dictionary is cited with 73% [32]. In the context of the general election in 2009, the *LIWC* software was used in 2010 by Tumasjan et al. [16] for political sentiment analysis in Twitter.

The *GPSD* is a German lexicon by Haselmayer and Jenny [33] especially developed for the analysis of political communication. The words contained are weighted along a 5-step negativity scale from 0 (not negative) to 4 (very strong negative). Assuming swarm intelligence, Haselmayer and Jenny

used the crowd-coding method and had texts reviewed by a large number of anonymous non-experts. They achieved reliable results through crowd-coding and advocated the use of custom dictionaries.

To address the questions of user activity differences it is necessary to determine a users’ activity in the Twitter network. According to Bruns and Stieglitz, a user’s activity can be described in the simplest way by the number of tweets generated by a user for a certain hashtag [36]. If this activity is determined for all users, the relative contribution of users or user groups to the overall communication for a hashtag can be determined. User activity in communicative situations on Twitter and other platforms is likely to be described by a long-tail distribution: a comparatively small group of highly active users generate most of the content, while a much larger number of less-active users only account for a small amount of Tweets [37]. According to Bruns and Stieglitz, it is often meaningful to group the users into groups based on this law. They work with a 90/9/1 distribution established by Tedjamulia et al. [38], which allows users of social networks to be divided into the following three groups:

- The most active 1% of users
- The other, still very active 9% of users
- The remaining, less active 90% of users

In this way, it can be examined how dominant the most active 1% of users are within the entire hashtag conversation on Twitter and whether there are obvious differences between the activity patterns of these groups [39].

IV. RESULTS

A. Descriptive Analysis

As highlighted in Table I, the number of hashtag entries strongly differs by party (hashtag) and does not reflect the election outcomes. In particular, the hashtag group #AFD shows an extremely frequent occurrence with over 500,000 cases, which corresponds to a share of almost 50% of all entries, yet having an election result of 12.6% of the votes. On the other hand, the strongest group in the elections, the CDU/CSU union with 32.9% of the votes only accounted for 14.64% of the entries of party hashtags. As a short conclusion, the users mentioning the AFD hashtag are either very active or there is a big controversy around that hastag within the Twitter community. This is further highlighted in Figure 1 where the percentage of each hashtag of the 7 party hashtag groups is stacked upon reflecting the percentage of entries per day. The AFD hashtag dominates the whole timespan having numerous days when the percentage reaches values higher than 50%.

To assess possible activity differences, all users producing tweets where grouped in three activity groups. The classification of users based on their activity was based on the 90/9/1 distribution presented in Section III. The division of the data set into the three activity groups was realized by quantile division. For quantile formation, users were sorted by their tweet frequency (activity) in descending order, and then the 100%, 99%, and the 90% quantiles were determined to create the 1%, 9%, and 90% user groups. Each of the three subgroups of the activity groups created included the proportion of tweets generated by the Twitter users of each group.

Figure 2 shows the number of tweets by each user group. The results clearly show that 1% of the Twitter users in the

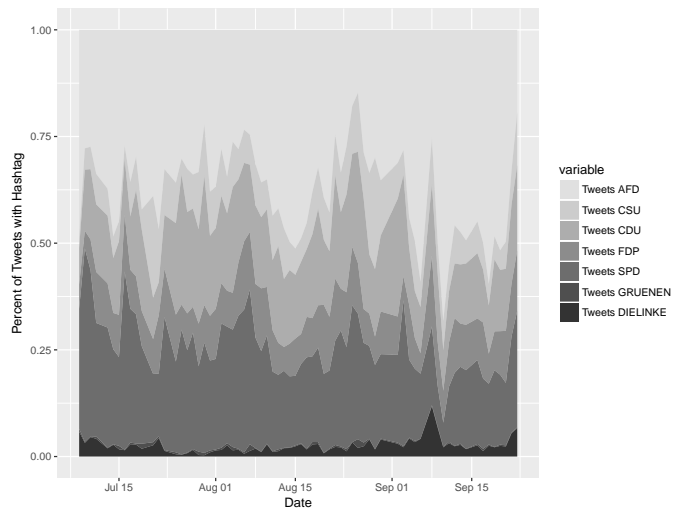


Figure 1. Hashtag share in tweets per day in percent

dataset account for the majority of all tweets in the dataset. The 1% group even accounts for more tweets than the lower 90% of the users. This confirms the presumption of the existence of a long tail in the user activity.

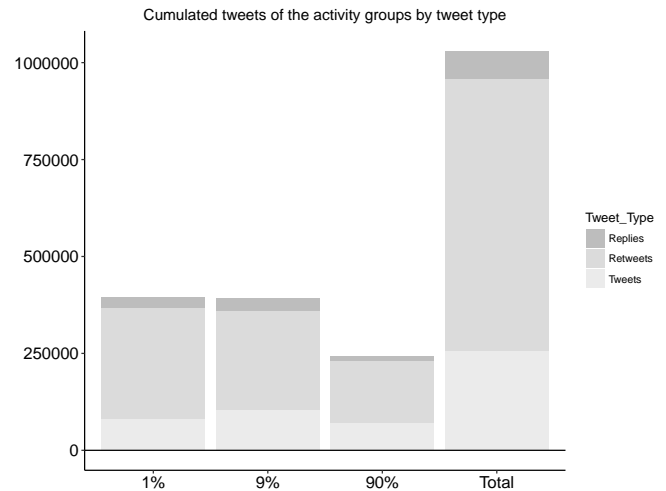


Figure 2. Cumulated tweets of the activity groups by tweet type

B. User Groups

TABLE II. USER AND TWEET PERCENTAGE OF USER GROUPS

Group	Users	Tweets per User	Tweets (%)
1%	1,043	160-3365	38.30%
9%	8,851	16-159	38.07%
90%	93,816	1-15	23.63%
Total	103,701	1-3365	100%

Table II lists the number of user per group and the percentage each group accounts for. To answer the question whether one user group shows a higher “reach” in terms of “Twitter reach”, the reach R has to be determined. The

potential reach R of an activity group was defined as the sum of the possible reach indicators of the Twitter API (number of followers, number of retweets and number of favorites) across all tweets of an activity group. Followers are the number of users subscribed to the twitter user posting a tweet. Figure 3 shows the mean potential reach of all user groups in terms of followers and retweets. The first group (1%) shows the highest numbers of average followers per tweet with 5097.46. Also the number of retweets is the highest in this group with a value of 0.83 retweets per tweet on average.

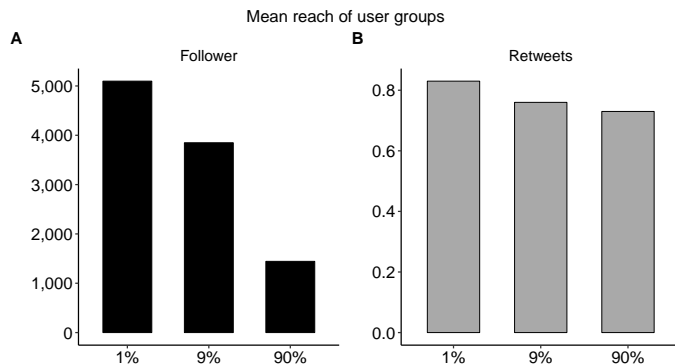


Figure 3. Mean reach of user groups

C. Sentiment of Election Tweets

As highlighted in Table III, the mean sentiment values of the activity groups SentiWS [-0.099; -0.073] and GPSD [-2.721; -2.591] were mainly in the negative and LIWC [1.302; 2.404] exclusively in positive territory. The difference between the activity groups was particular large in LIWC. The standard deviation (SD) was very high for all three procedures and for all activity groups. This was especially true for the lexica SentiWS and LIWC. It is noticeable that despite different scales of measurement, all three lexica displayed the same trend: the average sentiment value was highest in the 90% group of users, lower in the 9% group and lowest in the 1% group. This observation was significant at a level of $p < 0.001$ for all dictionaries.

TABLE III. MEAN SENTIMENT VALUES OF DICTIONARIES

Group	SentiWS	LIWC	GPSD
1%	-0.099 (SD 0.331)	1.302 (SD 9.242)	-2.721 SD(1.528)
9%	-0.089 (SD 0.328)	1.723 (SD 9.143)	-2.669 SD(1.504)
90%	-0.073 (SD 0.325)	2.404 (SD 9.283)	-2.591 SD(1.449)

D. Sentiment in Hashtag Groups

In this section, a sentiment comparison of the hashtag groups introduced in Table I was performed. Figure 4 visualizes the proportionate (A) and mean (B) sentiments of the hashtag groups. The generated sentiment of the hashtag conversations were very different. The highest sentiment was generated by the AfD (41.20%), followed by BTW17 (20.62%), SPD (12.31%) and CDU (11.33%) and again with a considerable distance FDP (4.89%), CSU (4.10%), GRÜENE (3.67%) and LINKE (1.90%). The proportionate sentiment of the hashtag conversations were related to their tweet proportions. For example, the AfD with 41.2% had the highest sentiment shares

and was with 39.98% the most sentiment-bearing Hashtag. The average sentiment per tweet slightly varied from -2.59 (LINKE) to -2.75 (AfD). The standard deviation was very high for all hashtag conversations.

Sentiment in Hashtag Groups

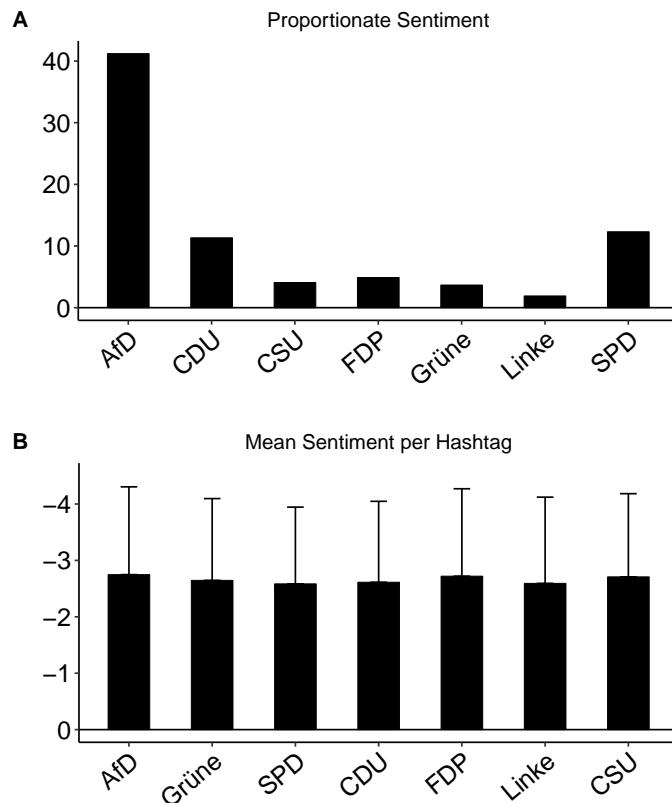


Figure 4. Sentiment per Hashtag Group

To investigate significant differences among the hashtag groups and the user groups in terms of sentiment, a Dunn test was performed [40] to compare group differences. Prior to the Dunn Test a Kruskal-Wallis test was performed to prove an existing effect of the activity and hastag groups on the sentiment. Table IV contains the associated p-values of the multiple mean comparisons.

TABLE IV. P-VALUES OF THE MULTIPLE MEAN COMPARISONS WITH THE DUNN TEST

Hashtag Group	1:9	1:90	9:90
AfD	0.349	0.047*	0.029*
CDU	0.018*	0.000***	0.000***
CSU	0.091	0.001**	0.017*
SPD	0.005**	0.000***	0.000***
LINKE	0.446	0.010*	0.002**
GRÜENE	0.188	0.225	0.329
FDP	0.000***	0.000***	0.180

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For CDU and SPD, there were significant differences in moods between all activity groups (see Table IV). The

sentiment becomes increasingly negative from the 90% group through the 9% group to the 1% group). For AfD, CSU and LEFT, the 90% group differed significantly from the other activity groups. Conversely, the pairwise comparisons of 1% and 9% showed no significant differences. For FDP, the 1% group differed significantly from the other two groups and for GRÜENE there were no significant differences between the activity groups.

E. Interpretation

The 10% of the most active users (1% and 9% together) generate more than three quarters of the content, while the remaining 90% together make up just under a quarter of the tweets. Reach via followers and retweets increases with user activity: the mood of highly active users (1% group) reaches on average more followers and their tweets are retweeted more often than those of the other activity groups. Tweets from the 9% group are most often favored. Around 68% of the total tweets produced are retweets, just under 25% are tweets and about 7% are answers. The sentiment polarity for the 2017 general election is positive after evaluation of the LIWC software and negative according to the results from SentiWS and GPSD. The sentiment between the activity groups shows significant differences and becomes more negative as users become more active. This trend is evident in all dictionaries. Especially the hashtag groups on CDU and SPD follows this observation, while other hashtags do not always show significant results. Although the sentiment differences are highly significant, the overall effect is rather low.

V. CONCLUSION AND FUTURE WORK

We analyzed over one million tweets during the pre-election phase of the German federal elections in 2017. The overall results show that twitter is indeed an online platform for political discussion.

First, it will be discussed which spectrum of activity, expressed in terms of tweet share and reach, of highly active users on the political discussion on the 2017 German federal election on Twitter. The participation of highly active to active (1% - and 9% - group) and less active users (90% - group) is in the ratio 3: 1 (see Table II). 75% of the content is thus generated by a small, very active group. A similar trend was also observed in other political debates on Twitter: For example, in the Twitter debate on the 2009 general election, more than 40% of the news was produced by only 4% of the users [16]. This effect has been shown multiple times in past. News tweets comprising the standard political hashtag for political discussions #auspol in Australia, more than half were generated by the 1% most active users, while the majority of users remained inactive [36]. Howard and Kollanyi's (2017) Brexit referendum investigations also found that less than 1% of accounts accounted for almost one third of all content [17]. This strong imbalance in users' communication shares, which seems to emerge in political discussions on Twitter, can also be seen during the communication to the 2017 general election. The participation of the users in this dataset most likely seems to follow the rule that Bruns and Stieglitz refer to: A small minority of Twitter users dominate the discussion with their content.

However, the user groups not only generate different numbers of tweets, their contents are also differentially visible to

the Twitter community: the average reach in terms of followers and retweets increases with the activity of the groups and peaks in the highly active user group. This suggests that highly active users may pass the generated mood to more users than the less active users due to the higher number of followers. Their content is also retweeted more frequently, reaching more potential readers. The level of influence of highly active users on the Twitter community about their increased reach therefore seems to be higher than that of less active accounts.

The SentiWS and GPSD lexicons produced negative averages for mood in the dataset, while the LIWC software was positive. It can be assumed that negative tweets and thus negative moods dominate the data set and the general communication surrounding the election. As described in Section II, there seems to be a trend towards negative overall attitudes in political debates on Twitter. This trend was largely confirmed in the present work. Negative sentiment during the election campaign could be attributed to the fact that negative campaigns against parties, and in this case against their party-specific hashtags, seem to have proven effective considering Twitter reach.

In contrast to Tumasjan et al. [16], this study could not directly link the amount of tweets posted to election results. Nevertheless, the study shows that Twitter can serve as a tool to study the political debate during an electoral phase. Since the hashtags in all hashtag groups contain both, positive and negative sentiment, the sole number of hashtag per group is a limited predictor for election outcome. The study has, however, several limitations. The integration of other linguistic methods, which take into account sentence structure, part of speech and word location (part of speech tagging, negation, reinforcing words) would be another step to increase the classification accuracy.

In addition, sentiment values could be calculated on the basis of fixed expressions and phrases instead of words. It might also be useful to introduce special adjustments to informal texts and the Twitter-specific language by, for example, incorporating common typos, urban speech, speller and Twitter-specific vocabulary into the algorithm. Samples from the data set in this context gave the impression that only few spelling and grammatical errors were made. This could be related to the seriousness of the issue: Actors in the political discussion want to preserve their reputation and credibility through clear and correct language.

Furthermore, emoticons could be investigated, since they have already been successfully embedded in the sentiment analysis of Twitter data in other works [21]. In the tweet texts, however, no significant amount of emoticons could be identified, which may be related to the fact that the political discussion is a more serious topic in which emotional expressions about emoticons are rather avoided. In order to increase the accuracy of classification, the calculation of the sentiment values at the sentence level could also be varied by calculating not the sum of all values, but the mean value. This standardization could more accurately capture the polarity of the text. At the same time, however, the information about the intensity of the mood would be lost.

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