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## The Role of Sentiment in Information Propagation on Twitter – An Empirical Analysis of Affective Dimensions in Political Tweets

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### Abstract

*Twitter is, among other social-media platforms, a service, which is said to have an impact on the public discourse and communication in the society. With the unique feature of “retweeting,” Twitter is an ideal platform for users to spread information. Besides their content and intended use, Twitter messages (“tweets”) often convey pertinent information about their author’s sentiment. In this paper, we examine whether sentiment occurring in politically relevant tweets has an effect on their retweetability (i.e., how often these tweets will be retweeted). Based on a data set of approximately 65,000 tweets, we find a positive relationship between the quantity of words indicating affective dimensions including positive and negative emotions associated with certain political parties or politicians in tweets and their retweet rate. We conclude by discussing the implications of our results.*

### Keywords

Twitter, Sentiment, Retweetability, Political Communication.

### INTRODUCTION

The last few years have witnessed a tremendous growth of different social media platforms. For example, more than 600 million people worldwide are now members of the Facebook network (Facebook 2011) while Twitter also counts more than 100 million users in total (Huffpost Tech 2010). Among various microblogging services, Twitter has gained most popularity. Due to its ease for real-time information sharing, Twitter is said to have an impact on the public discourse and communication in the society.

To enable more discussions on Twitter, the mechanism of “retweeting” has been adopted by users. As a result, Twitter is an ideal platform for users to spread information where the original tweet is propagated to a new set of audiences, namely the “followers” of the retweeter. By retweeting, users may not only share information but also entertain a certain audience or publicly agree or disagree with someone (Boyd et al. 2010). Until now, little is known about how and why certain information spreads more widely than others. In a large-scale study, Suh et al. (2010) addressed these questions and identified several factors that significantly impact retweetability of Twitter messages (“tweets”) including URL posting and hashtag inclusion as well as the number of followers and the age of user’s account.

In this study, we referred to the findings by Suh et al. (2010) and investigated the potential impact of sentiment or affective dimensions articulated in tweets on the diffusion of these messages through the network. Besides their content and intended use, tweets often convey pertinent information about their author’s emotional state or his/her judgement of a certain topic or the intended emotional communication by the author (i.e., the emotional effect the author wishes to have on the reader of the tweet) (Bollen et al. 2010). Previous studies from various disciplines have investigated and confirmed the relevance of sentiment or emotions expressed in online communication at different level of analysis (e.g., Bollen et al. 2010; O’Connor et al. 2010; Diakopoulos and Shamma 2010; Shamma et al. 2009; Tumasjan et al. 2010; Huffaker 2010; Joyce and Kraut 2006). However, to our knowledge there are no studies that have explicitly examined the potential impact of sentiment on the communication on Twitter.

Recently, microblogging and particularly Twitter have been viewed as having the potential for shaping political communication. In fact, Twitter has become a legitimate and frequently used communication channel in the political arena (Tumasjan et al. 2010). Besides being increasingly used for political deliberation, Twitter is said to

be capable of reflecting collective emotive trends and thus might have the predictive power with regard to political events (Bollen et al. 2010). Studies have also shown that sentiment of contemporaneous tweets is correlated with voters' political opinion and preferences (e.g., O'Connor et al. 2010; Tumasjan et al. 2010). Moreover, given the nature of political polarization which has been shown to also prevail in Twitter communication (Conover et al. 2011), sentiment associated with certain political topics, political parties or politicians might play an even more important role, particularly in times of elections. This motivates us to address our research question in a political context. More specifically, we want to know how the affective dimensions of tweets including positive and negative emotions associated with certain political parties or politicians affect the quantity of retweets that might be triggered. For that, we examined the communication on Twitter dealing with two specific political elections in Germany in 2011. We gained a data set consisting of approximately 65,000 politically relevant tweets for our analyses.

The paper proceeds as follows. We first give a short overview of microblogging with an emphasis on Twitter including related work. In the subsequent section, we provide theoretical background for our research question and derive hypotheses. Next, we describe our research methodology and present our empirical results. Finally, we conclude by discussing our results, pointing out limitations of our study, and giving potential research outlook.

## TWITTER NETWORK

Among various microblogging platforms (e.g., Tumblr, Jaiku, and Google+), Twitter is said to be the most popular service. Microblogging is understood as a type of blogging in which entries typically consist of short content such as phrases, quick comments, images, or links to videos (Boyd et al. 2010; Java et al. 2007; Zhao and Rosson 2009). Twitter is a microblogging service, which allows users to send and read 140-character short messages known as "tweets", enabling users to share and discover topics of interest in real-time to a network of followers. There are different modes of communication on Twitter (e.g., answering or drawing attention to external content), which are signified by user-accepted norms, such as annotating their tweets with different characters. One of the most important features of Twitter is "retweeting" which refers to the practice of resending a tweet posted by another user. When users find an interesting tweet written by another Twitter user and want to share it their followers, they can retweet the tweet by copying the message, typically adding a text indicator (e.g. "RT", "via", or "by") followed by the user name of the original author in @username format. Users often add more content or slightly modify the original tweet when retweeting. To make conversations, the @-sign is used to mark the addressee of a message. For example, posting a message including @username indicates that the message is intended for or somehow relevant to a specific user. Tweets can also include so-called hashtags, where the # character is used in conjunction with a word or phrase in order to connect the tweet to a particular theme. This use of the #-sign allows users to search the "Twittersphere" for specific topics of interest and to follow threads of discussion.

Since its creation in 2006, Twitter has gained popularity worldwide. Kwak et al. (2010) conducted a large-scale study to analyze the topological characteristics of Twitter and its power as a new medium of information sharing. From Twitter's public timeline, Java et al. (2007) examined the topological and geographical properties of Twitter's social network. They identified a number of usage categories such as daily chatter, conversations, sharing information/URLs, and reporting news. Honeycutt and Herring (2009) employed a grounded theory approach on their sample and found 12 distinct categories of tweets: about addressee, announce/advertise, exhort, information for others, information for self, meta-commentary, media use, opinion, other's experience, self-experience, solicit information and others. As studies indicated, one of the most popular usages is for users to inform others and to express themselves. For example, Naaman et al. (2010) examined the content of 3,379 tweets by manually coding the messages collected from the public timeline, finding that 80 percent of the 350 users they studied posted messages relating to themselves or their thoughts, as opposed to sharing general news.

### Political Communication on Twitter

Researchers have analyzed the role of social media in shaping political debate in the U.S. as well as in other countries (e.g., Bennett 2003; Benkler 2006; Sunstein 2007; Farrell and Drezner 2008; Aday et al. 2010; Tumasjan et al. 2010; O'Connor et al. 2010). Given the tremendous growth of social media, in particular Twitter and Facebook, it is argued that from the perspective of politicians and political parties it is important to actively participate in the political communication based on the use of social media, especially during election campaigns. In this regard, U.S. politicians are said to have a leading role with the most prominent example of Barack Obama being able to successfully employ social media within his last election campaign (Wattal et al. 2010).

A number of studies focusing on different parliamentary uses of Twitter have been published of which the majority have dealt with the U.S. For example, Golbeck et al. (2010) focused on the U.S. Congress and analyzed the contents of more than 6,000 tweets from Congress members. They found that Congress members consider Twitter a vehicle for self-promotion as they are primarily using Twitter to share information, particularly links to news articles about themselves and to their blog posts, and to report on their daily activities. In a study of

250,000 politically relevant tweets from the six weeks leading up to the 2010 U.S. congressional midterm elections, Conover et al. (2011) demonstrated that the network of political retweets exhibits a highly segregated partisan structure, with extremely limited connectivity between left- and right-leaning users while for the user-to-user mention network, which is dominated by a single politically heterogeneous cluster of users in which ideologically-opposed individuals interact at a much higher rate compared to the network of retweets. In a study of approximately 100,000 messages containing a reference to either a political party or a politician in the context of the 2009 German federal election, Tumasjan et al. (2010) showed that Twitter is extensively used for political deliberation and that the mere number of party mentions accurately reflects the election result suggesting that microblogging messages on Twitter seem to validly mirror the political landscape offline and can be used to predict election results to a certain extent.

## **THEORETICAL BACKGROUND AND HYPOTHESES**

Previous research from different disciplines has investigated the role of sentiment in online communication at different levels of analysis. There is a growing literature dealing with the relationship between sentiment occurring in short-text messages and other real-world events or phenomena. For example, O'Connor et al. (2010) attempted to link measures of public opinion derived from polls to sentiment measured from Twitter messages. They found that sentiment word frequencies in contemporaneous Twitter messages do correlate with several public opinion time series such as surveys on consumer confidence and political opinion from 2008 to 2009. In a recent study, Bollen et al. (2010) found that events in the social, political, cultural and economic sphere do have a significant, immediate and highly specific effect on the various dimensions of public mood displayed in Twitter messages. Their findings suggested that large-scale analyses of mood can provide a "solid platform to model collective emotive trends in terms of their predictive value with regards to existing social as well as economic indicators."

In a study of political tweets around the 2009 German federal election, Tumasjan et al. (2010) showed that tweet sentiment (e.g., positive and negative emotions associated with a specific politician) corresponds closely to voters' political preferences. In addition, party sentiment profiles can reflect the similarity of political positions between parties. Other works such as studies by Diakopoulos and Shamma (2010), and Shamma et al. (2009) sought to characterize performances of political election debates by aggregated Twitter sentiment. They developed an analytical methodology and visual representations that could help to better understand the temporal dynamics of sentiment in reaction to the debate video. They demonstrated visuals and metrics that can be used to detect sentiment pulse, anomalies in that pulse, and indications of controversial topics that can be used to inform the design of visual analytic systems for social media events.

### **Research Question**

A number of other studies have dealt with the role of sentiment in the communication in newsgroups, discussion forums or in other contexts. The main results from these studies indicated that affective dimensions of messages (both positive and negative emotions) can trigger more attention, feedback or participation (e.g., Smith and Perry 1996; Huffaker 2010; Joyce and Kraut 2006). Further, studies have shown that emotional states articulated in messages might spread through different kinds of networks (e.g., Hill et al. 2010; Huffaker 2010). Hence, at this point it would be interesting to ask whether the diffusion of emotions also applies to the communication in social media, particularly Twitter, i.e., to investigate whether, and if so how, sentiment of tweets might disseminate through the Twitter network. To our knowledge, however, there are no studies that have explicitly examined the potential impact of sentiment on the communication on Twitter. This motivates us to address the following research question:

*RQ: Do affective dimensions of Twitter messages have an impact on how often these messages will be retweeted (i.e., retweetability)?*

### **Hypotheses**

Results from a study of online interactions (Joyce and Kraut 2006) suggested that negative affect of messages can actually trigger participation. This, however, seems to apply to negative affect in terms of anger rather than sadness or fear. Meanwhile, the same study found that positive affect in messages encourages continued participation in newsgroups by creating a sense of community among users. These results were confirmed in a large-scale study of online communities (Huffaker 2010) showing that people who use affective language in their messages receive more feedback than those who do not. This applies to both positive and negative emotions. Further, Smith and Petty (1996) showed that positive as well as negative framing of a message could create attention and cognitive involvement, in particular when the framing is unexpected for the recipient of the message.

Beyond triggering more attention or feedback, affects articulated in a message might diffuse through networks. Human populations are arranged in social networks that determine interactions and influence not only the spread of behaviors and ideas, but also emotions. Contagion theories seek to explain networks as conduits for "infectious" attitudes and behavior. In this sense, social contagion refers to the spread of affect, attitude, or behavior

from an “initiator” to a separate party, or “recipient”, where the recipient does not perceive an intentional influence attempt on the part of the initiator (Levy and Nail 1993). This exposure increases the likelihood that network members will develop beliefs, assumptions, and attitudes similar to those of their networks (Carley and Kaufer 1993). Perhaps due to the unconscious nature of social contagion, extant empirical investigations have rarely been realized to examine the diffusion of attitudes across networks. In a recent study, Hill et al. (2010) showed that, over long periods of time, emotional states spread in the same way as do contagious diseases across social networks. In various contexts, it has been shown that both positive and negative moods can be “infectious,” for example during workplace interactions (Barsade 2002), in negotiations (van Kleef et al. 2004), and among roommates (Howes et al. 1985). Furthermore, Huffaker (2010) showed that in verbal interaction, communication partners sync their wording, which would indicate that messages which contain positive (negative) emotions words are likely to receive verbal responses, which also express positive (negative) emotions. Further, Huffaker provided evidence for the concept of language diffusion in online communities as the more often people used words that express affect the more of the words they used were repeated in the subsequent replies. All of these findings lead us to conjecture a positive relationship between sentiment articulated in tweets and their likelihood to spread through the Twitter network.

*H1: The more words which indicate positive emotions a Twitter message contains, the more often it will be retweeted.*

*H2: The more words which indicate negative emotions a Twitter message contains, the more often it will be retweeted.*

## METHODOLOGY

### Data Collection

As discussed above, we want to address our research question in a political context. Therefore, we examined politically relevant tweets, which were published on Twitter’s public message board for a period of one week from March 21 to 27, 2011, prior to the two Landtag (state parliament) elections in the populous states Baden-Württemberg and Rheinland-Pfalz in Germany. Both elections took place on March 27, 2011. We systematically collected all tweets that contained the names of either the five most important German parties (CDU, SPD, FDP, B90/Die Grünen, and Die Linke) or the front-runners of these parties in the two Landtag elections. We consolidated our data set by ruling out redundant or irrelevant tweets (e.g., advertising tweets) as well as tweets in other languages than German. More importantly, to avoid confusion, tweets that contain multiple party or candidate mentions were also excluded from the analysis as the association of sentiment with a specific party or candidate might remain unclear. Finally, we obtained 64,431 tweets in total.

### Sentiment Analysis

We used the Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al. 2006; Tausczik and Pennebaker 2010) to objectively and systematically analyze tweets for emotional components of text samples using a psychometrically validated internal dictionary. LIWC is a text-analysis software program that places words from a text file into categories based on a series of built-in dictionaries. These dictionaries have over 4,500 words and word stems containing a total of 80 categories into which words may fit. These categories include descriptive dimensions (e.g., total number of words in text), linguistic dimensions (e.g., words in text that are pronouns or verbs), dimensions of psychological constructs (e.g., affect words, cognition words), dimensions of personal concerns (e.g., leisure, work), paralinguistic dimensions (e.g., fillers, assent), and punctuation. LIWC has been used widely for academic purposes in psychology and linguistics but also for topics related to political science and communication studies (e.g., Yu et al. 2008; Huffaker 2010). Further, LIWC-based analyses have also been conducted to examine shorter text samples such as instant message conversations or Twitter messages (e.g., Golder and Macy 2011; Tumasjan et al. 2010).

For our analysis, we used the LIWC categories “positive emotions” and “negative emotions” to profile sentiment of politically relevant tweets. These categories have either been successfully used in prior studies of political text samples or seemed best suited to profile messages in the political domain by covering emotions. We concatenated all tweets published over the relevant time frame into one text sample to be evaluated by LIWC. Since our sample consists of only German-language tweets, we processed our data by using the LIWC German dictionary. The accuracy and robustness of LIWC analysis for German-language text samples have been positively assessed by other studies such as Wolf et al. (2008). However, as our analysis deals with Twitter, where the use of short forms, acronyms and emoticons is prevalent, we performed the following steps to additionally ensure the validity of the measurement of sentiment. First, we added to the LIWC standard dictionaries a custom list of short forms and acronyms that might indicate sentiment as well as another list of emoticons. Second, we addressed the issue of potential ambiguity when classifying tweets according to the prevailing sentiment. For example, a tweet might contain both positive- and negative-emotion words, or a positive message might be retweeted but a nega-

tive tone might be added on. In such cases, two independent coders were employed to manually identify the overall sentiment. Inter-coder reliability constituted 0.95 ( $p$ -value < 0.000) suggesting a high level of agreement between the coders (Landis and Koch 1977).

## Variables

We built a predictive retweet model focusing on tweet sentiment as a factor that might impact the retweetability to examine whether articulated sentiment in political tweets, particularly those directly associated with a specific political party or politician, has an effect on their retweetability. We included further factors (as control variables) identified by Suh et al. (2010) representing content and contextual features such as the inclusion of hashtags or URLs, user's number of followers as well as age of his or her account. This leads us to construct the following variables for each tweet:

- The number of times the tweet has been retweeted: RT
- LIWC categories:
  - Number of words indicating positive emotions in the tweet: POSEMO
  - Number of words indicating negative emotions in the tweet: NEGEMO

Studies have shown that there are a number of other factors that also have an impact on retweet behavior on Twitter such as whether a tweet contains hashtags, URLs or user's number of followers (e.g., Suh et al. 2010). Therefore, we also included the following variables as controls:

- Dummy (binary) variable for whether or not a hashtag was included in the tweet: HASH
- Dummy (binary) variable for whether or not an URL was included in the tweet: URL
- User's number of followers: FOLLOWER
- Age of user's account (in days): ACCOUNTAGE

We conducted regression analysis to examine whether tweet sentiment has an effect on how often a tweet has been retweeted. As the dependent variable RT represents true-event count data, i.e., non-negative and integer-based, we employed Poisson regression model (Cameron and Trivedi 1998). Poisson regression relies on a log-transformation of the dependent variables and requires an exponential transformation of the coefficients of each predictor in the regression model to interpret the odds ratio, which is used to assess the effect size. The resulting regression models are as follows:

$$(1) \log(E(RT|*)) = \beta_0 + \beta_1 X + \beta_2 HASH + \beta_3 URL + \beta_4 FOLLOWER + \beta_5 ACCOUNTAGE + \dots$$

where  $E(RT|*)$  is the conditional expectation of RT, and X denotes each of the sentiment-related variables such as POSEMO and NEGEMO.

## EMPIRICAL RESULTS

### Preliminary Analysis

As a first step, we analyzed our data set regarding the distribution of different modes of communication. We found that about 23 percent of all tweets are so-called singletons, which represent ordinary tweets without an @-sign (Kwak et al. 2010). About 16 percent of all tweets in the total sample contain an @-sign, which is in line with previous research that has also suggested that the vast majority of @-signs are used to direct a tweet to a specific addressee (Honeycutt and Herring 2009).<sup>1</sup> A more conservative measure of direct communication is direct message to another user starting with an @-sign. About eight percent of the messages in our sample are direct messages, indicating that people are not just using Twitter to post their opinions but also engage in interactive discussions. The share of retweets is relatively high with roughly 33 percent. Also, more than half of the tweets contain a link to a website. These numbers indicate that people tend to share political information (e.g., political news) with their network of followers on Twitter.

The categorization of users according to their Twitter activity is illustrated in Table 1. It shows that political deliberation on Twitter is led by a few highly active users ("very heavy" users) who represent only about one percent of all users but account for almost 30 percent of all posted tweets. This is consistent with findings by Jansen and Koop (2005) and Tumasjan et al. (2010) who also found big inequality of participation for political deliberation on Twitter.

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<sup>1</sup> Note that retweets, which also contain an @-sign, are excluded from this statistic.

Table 1. User Activity

User Group	# Users (%)	# Tweets (%)
One-time (1)	8,155 (55.70%)	8,155 (12.66%)
Light (2-5)	4,443 (30.35%)	12,512 (19.36%)
Medium (6-20)	1,554 (10.61%)	15,363 (23.84%)
Heavy (21-50)	340 (2.32%)	10,143 (15.74%)
Very heavy (50+)	149 (1.02%)	18,258 (28.34%)
Total	14,641 (100%)	64,431 (100%)

Descriptive statistics for the total sample are presented in Table 2. On average, one tweet in our sample was retweeted 0.43 times. The average number of words per tweet reflecting positive and negative emotions is 0.19 and 0.33, respectively. For the purpose of comparison, a tweet contains at most 140 characters, which are equivalent to roughly 20 words. In our sample, a user has 403 followers on average and the age of his or her account is roughly more than one and a half year (576 days). Results of correlation analysis of all relevant measures suggested no multicollinearity concerns.

Table 2. Descriptive Statistics – Total Sample

Variable	Mean	Standard Deviation
RT	0.43	2.07
POSEMO	0.19	0.46
NEGEMO	0.33	0.61
FOLLOWER	403	221
ACCOUNTAGE (in days)	576	341

### Regression Analysis

In H1, we hypothesize that the more words which indicate positive emotions a Twitter message contains, the more often it will be retweeted. Results of the Poisson regression (see Table 3, Model (1)) show that messages featuring more words associated with positive emotions indeed tend to trigger more retweets, i.e., H1 is supported. The coefficient of POSEMO ( $b = 0.04$ ) is positive and statistically significant at the five-percent level ( $p < 0.05$ ).

H2 predicts a positive relationship between the quantity of negative-emotion words in a tweet and its retweetability. In fact, we also find support for H2 as the coefficient of NEGEMO is positive and statistically significant ( $b = 0.06$ ,  $p < 0.05$ , see Table 3, Model (2)).

The magnitude of the effects of the independent variables on the dependent one can be inferred from the coefficients. As Poisson regression was applied, the interpretation requires an exponential transformation of the coefficients to interpret the odds ratios. For example, the coefficient of NEGEMO of 0.06 means that a one-unit change in occurrence of negative-emotion words, on average, will trigger about six percent more retweets ( $\exp(0.06) = 1.06$ ). Comparing the estimates of POSEMO and NEGEMO reveals that the estimate of NEGEMO has a slightly larger effect size, i.e., tweets with negative sentiment tend to induce slightly more retweets on average. In all three models, control variables (HASH, URL, FOLLOWER and ACCOUNTAGE) are each significantly positively related to the frequency of retweets, which is in line with findings from the literature (e.g., Suh et al. 2010). Overall, all  $p$ -values corresponding to  $t$ -statistics are below 0.01 implying that our model and corresponding specifications are well-fitted.

Table 3. Poisson Regression Output

Independent Variable	Dependent Variable: RT	
	(1)	(2)
POSEMO	0.04**	
NEGEMO		0.06**
HASH	0.82***	0.82***

URL	0.26**	0.26**
FOLLOWER	0.0004***	0.0004***
ACCOUNTAGE	0.0009***	0.0009***
$p > \chi^2$	0.0001	0.0001
Pseudo- $R^2$	0.21	0.21

*Note that \*, \*\* and \*\*\* indicate significance level at 10%, 5% and 1%, respectively, with robust standard errors in parentheses. Note that this data set includes 43,081 observations of tweets (where retweets are excluded) which contain either the name of a politician or that of a party.*

## CONCLUSION

In this paper, we have addressed the research question whether affective dimensions of Twitter messages in terms of positive and negative emotional states have an impact on the quantity of retweets that might be triggered (i.e., retweetability). Given the growing relevance of social media, particularly Twitter, in political communication, we investigated the relationship between sentiment of political Twitter messages associated with certain political parties or politicians and their retweetability. We found that tweets containing words that reflect emotions tend to be retweeted more often than those, which do not contain such words. More specifically, both positive and negative emotions articulated in tweets make them more likely to spread through the Twitter network. This way, not only information but also sentiment in political context could be disseminated, which might influence the political opinion-making process.

As an implication, it is important for politicians and political parties to identify the most influential users and follow the discussions including sentiment occurring within their peers, particularly during periods of election campaigns. To attain that, political parties and politicians might follow the approach of social media intelligence, which has been widely used in the corporate context to systematically monitor and analyze user-generated contents in social media for specific purposes.

Our results also showed that the intensity of participation and contribution within political discussions on Twitter is unequal among the users. Therefore, as another contribution, we investigated the role of power users in political discussions and identified opinion leaders in the German political Twitter network (see Stieglitz and Dang-Xuan 2012).

As future work, we intend to extend our study to a much larger scale and more general context, i.e., we will not limit our investigation only to political events, which represents a limitation of this paper. For example, it might be interesting to see how generalizable and applicable our proposed model would be in the context of microblogging for business or marketing purposes. In addition, our analysis should not be restricted to a certain language as is the case in this study.

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