2011

Analysis of Sentiments in Corporate Twitter Communication – A Case Study on an Issue of Toyota

Stefan Stieglitz
University of Muenster, stefan.stieglitz@uni-muenster.de

Nina Krüger
University of Muenster, nina.krueger@uni-muenster.de

Analysis of Sentiments in Corporate Twitter Communication – A Case Study on an Issue of Toyota

Stefan Stieglitz
Department of Information Systems
University of Muenster
Muenster, Germany
Email: stefan.stieglitz@uni-muenster.de

Nina Krüger
Department of Information Systems
University of Muenster
Muenster, Germany
Email: nina.krueger@uni-muenster.de

Abstract

Knowing about communication of specific issues in social media has become increasingly important for the reactive and proactive stakeholder-communication of enterprises. Tools have been designed to monitor social media sites and to aggregate data of discussions in social media. However, these tools do not consider the dynamics of discussions and are not able to reflect sentiments within these discussions. In our contribution, we address these aspects by analyzing a data set of around 730,000 Tweets published in a time frame of 19 weeks. Within this data set, we analyzed those Tweets dealing with the corporate crisis of Toyota in 2010. We classified sentiments by using a linguistic approach. In this context, we identified and investigated specific stages of communication ("quiet stages" and "peaks"). Additionally, our study concentrates on the sentiments found in Tweets of the ten most active participants of the discussion.

Keywords

Social Media Monitoring, Sentiment, Twitter, Toyota, Issue Management.

INTRODUCTION

Background

Since 2006, microblogging has become a new and widely used concept for communication in the Internet. Twitter, as one of the first and most popular microblogging providers, counts 106 million users, according to their own statements. On average, 180 million Tweets (short messages with up to 140 signs) are posted each day (Twitter 2011). In contrast to social networking sites (SNS) such as Facebook, the range of communication in Twitter is usually not limited to a specific group (e.g. friends). Each Internet user is able to create public postings to initiate discussions, to participate in debates, and to follow the communication of others. Twitter users adapted different methods to increase the efficiency of this form of communication by classifying their contributions (postings), e.g. as an answer (retweet), direct message or mention. This new way of public communication also affects enterprises because (1) customers can frequently and rapidly share experiences about companies and certain products, (2) enterprises may adopt social media as a new channel to communicate with customers, and (3) the user-generated content can be tracked and analyzed to extract relevant and innovative ideas.

As a consequence, the traditional "speaker role" of enterprises in public communication becomes blurred by the emergence of social media. Traditionally, the external communication of companies mainly took place in a one-way fashion, from the company to the customer (i.e. via traditional mass media such as television, printed media or radio). It has been shown that this kind of communication may have a direct impact on customer's decision-making processes (Kolo and Heinz 2010; Mühlenbeck and Skibicki 2009). Furthermore, it is becoming increasingly important for enterprises and other organizations to recognize relevant issues early on and to intervene in discussions if necessary. For this reason, it is relevant to learn more about the dynamics of public discussions in social media. One indicator to get a deeper understanding about those discussions is to analyze sentiments (moods), which can be observed in social media artefacts (e.g. postings).

Research Questions

In our research, we seek to analyze the dynamics and sentiments of Tweets that deal with a specific corporate issue. To identify an appropriate issue (crisis), we referred to an inductive approach. We then monitored the related discussion in Twitter for several months. Based on literature of traditional public communication, we expected that the dynamics of this discussion in Twitter show some "quiet stages" (continuous communication that is characterized by a low frequency of postings) as well as “peaks”, when significantly more contributions are published (Röttger 2002). Since other studies show that a high frequency of sentiments in a posting cause more retweets on average than neutral Tweets do (Stieglitz and Dang-Xuan 2012), we investigated whether power-tweeters (most active participants of discussion) use sentiment words more frequently than other users.

In this paper, we will address the following three research questions (RQ) for the specific case we analyzed:

RQ1: Are crisis-related long-term discussions in social media characterized by “quiet stages” and “peaks”? Do involved users of a specific issue generate more contributions (postings) in peak stages than in quiet stages?

RQ2: Are discussions in peaks characterized by “stronger” emotions (sentiments) than in quiet stages?

RQ3: Is there a difference between sentiments in Tweets posted by power-tweeters (PT) and the sentiments in Tweets posted by all participants of the sample?

Answering these research questions will provide a deeper understanding of communication in public social media. Furthermore, it expands our own work in this field, e.g. regarding the behaviour of power-tweeters (Stieglitz and Krüger 2011). As earlier studies have shown, sentiments are an influencer of dynamics of discussions and can therefore become a critical factor for organizations. In further steps, our results may be beneficial to develop improved mechanisms of social media monitoring and help enterprises to understand and participate in this kind of communication.

To address our research questions, we first investigate related literature and present an overview in section 2. We then discuss the influence of social media, especially Twitter, on enterprises with a focus on the analysis of sentiments (section 3). Our research design is presented in section 4. In the next step, our suggested methodology is applied to the communication of an enterprise-related crisis, a product recall of the automotive-manufacturer Toyota. By conducting a keyword analysis, 732,000 Tweets were gathered over a period of 19 weeks. Based on this data set, we present and discuss the results of our empirical study. The paper ends with a conclusion and an outlook (section 5).

Related Work

Since 2005, the development of new Internet technologies and utilization concepts has led to a change and an extension of Internet-based communication (McAfee 2009; Sester et al. 2006; Sixtus 2005). Users are no longer restricted to be addressees of the provided content. Social media enabled them to publish user-generated content on their own (Mühlenbeck and Skibicki 2009). Gouthier and Hippner (2008) defined social media as those technologies, which provide a social interaction through the Internet such as blogs, discussion forums, wikis as well as social network sites (SNS), and microblogging platforms (Gouthier and Hippner 2008; Green and Pearson 2005; Zerfaß and Sandhu 2006).

Social media’s impact on the communication of enterprises and their stakeholders has been intensively discussed from the marketing point of view. With regard to the corporate communication, the main research has addressed the following aspects: Marketer-User-Interaction (MUI) such as RSS and viral marketing (Fösken 2006), Online Entertainment (Emrich 2002), and the creation of virtual brand communities (Frey 2002).

There is an increasing academic interest to get a better understanding of discussions in social media (Carrasco et al. 2003; Goyal et al. 2008; Palau et al. 2004). A widely used methodological approach is the social network analysis, which helps to get a picture of the entire structure of a network but can also be adapted to identify specific nodes (Getoor and Diehl 2005; Han and Kamber 2006; Kleinberg 1999; Knocke and Kuklinski 1982; Wassermann and Faust 1994). However, social network analysis is often used only to conduct static snapshots while neglecting the network’s dynamics (Lin et al. 2008). A few studies can be identified, which explicitly analyzed contents of social media (Adam 2008; Bakshy et al. 2011; Cha et al. 2010; Wu et al. 2011). In communication studies as well as in information systems, some contributions explicitly concerned the microblogging platform Twitter (Cha et al. 2010; Jansen et al. 2010; Kwak et al. 2010; Zerfaß and Sandhu 2006). Following Bollen et al. (2009), sentiment analysis can be used as a methodology to investigate the emotions of user-generated-content (Bollen et al. 2009).

Sentiment analysis focuses on classifying the emotional polarity of human recorded communication, e.g. a document or a sentence. Positive or negative opinions can be identified automatically if appropriate tools are adapted. Additionally, other emotions (sentiments) such as being "angry", "sad", or "happy" can be discovered.

Since 2002, different methods have been applied to detect the polarity of product reviews and movie reviews (Turney 2002). Currently, there are only a few studies, in which sentiment analysis is applied as an approach to investigate communication in social media. E.g. Cordis (2009) and Mitrovi’c et al. (2011) investigated the dynamics of sentiments in e-communities. In these studies, they used sentiment analysis to understand why certain e-communities die or fade away (e.g., MySpace) while others seem to continuously grow (e.g., Facebook) (Tumasian et al. 2010; Jansen and Koop 2005).

In a study about users and their behaviour in the Twitter network, Krishnamurthy et al. (2008) identified three types of users (broadcaster, acquaintances and miscreants) by analyzing a crawled data set that covered nearly 100,000 users. The broadcasters, also named power-tweeters, are characterized by a large number of followers as well as a large amount of self-created postings. One finding in this study was that these users update their status more often and post more Tweets than users of the two other categories.

Relevance of Twitter for Enterprises

Enterprises strive to influence the public opinion about products and their brand through a well-directed issue management. In particular, the issue management aims at an early and proactive re- and interaction. In this sense, issues are topics, which actually or potentially (relevance) concern the organization, which are addressed by heterogeneous expectations of stakeholders and of the organization (lack of expectation), and which can be interpreted in various ways. Furthermore, issues contain conflict potential (conflict) and are of interest for the public (Ingenhoff and Röttger 2008; Liebl 2000; Röttger 2002; Wartick and Mahon 1994).

An issue may evolve to a crisis, depending on the issue's relevance regarding enterprise's performance (Köhler 2006). Traditionally, the issue management focuses on observing mass media such as television, radio, and printed media. As a result of the growing number of users in social media, enterprise-related topics (e.g., brands or products) are increasingly discussed in the public.

The enterprise's issue management addresses this by identifying (scanning) and persistently observing (monitoring) streams of information to detect signals and sentiments as early as possible and to anticipate reactions (Ingenhoff and Röttger 2008). Even a proactive management of issues may be one goal of these activities (Mast 2006). Literature describes the issue "scanning" as a process of inductive observation on the Internet without a specific aim and without the concrete need for information of specific analyzing fields. In contrast, the issue "monitoring" is understood as a process of deductive observation on the Internet, which aims at supervising and following already known fields of interest (Köhler 2006). Based on the continuous execution of scanning and monitoring processes, organizations may identify and intervene proactively and reactively to manage the communication of enterprise-related issues.

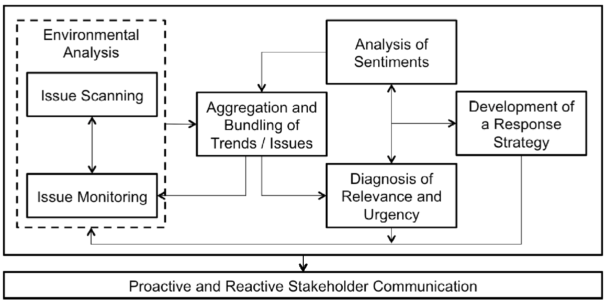

Figure 1: Phases of the Issue Management based on Liebl (2000)

Both scanning and monitoring are considered as ongoing processes, in which trends and issues are discovered, concentrated, aggregated and sorted according to their relevance. For complementing the process, it is necessary to analyze the sentiments in the identified communications and to let the insights influence the strategy choice (figure 1). In principle, it seems to be possible to analyze social media as a component of the issue management. Reasons for this are that topics may also be observed, players may be identified and the relevance of information may be evaluated. After the identification of enterprise-relevant issues and their descriptive analysis, research on sentiments in Tweets may help to react early and proactively to upcoming crisis situations.

EMPIRICAL STUDY

To answer our research questions, we attempt to identify an enterprise-related issue, which should be analyzed descriptively. Furthermore, we seek to study the dynamics of sentiments within this discussion. The main reasons for choosing Twitter as a data source, were (a) the high number of users and postings, (b) the application programming interface (API), which allows to download relevant Tweets, (c) the syntax of short messages, which allows to identify answers (retweets), and (d) the high topicality of Twitter-based communication (Milestein et al. 2008).

Methodology

We set up a methodological design consisting of three steps: (1) Inductive analysis to identify an appropriate issue, (2) data tracking and preparation, and (3) sentiment analysis.

Step 1: Identification of an Issue

For our study, we chose the communication about car manufacturers as a research subject because (1) there is a high public interest in car manufacturers, (2) they are easy to identify because of their unique names (brand, company name), and (3) the industry creates technically and economically sophisticated products, which are prone to be the subject of a crisis (Clark and Fujimoto 1991).

One critical factor in analyzing topics in the Twitter network is the identification of suitable keywords. Our goal is to identify an emerging issue as early as possible and to observe it over a longer period. Althaus and Tewksbury (2002) and also Ku et al. (2003) concluded that most topics are published in mass media first, and only then come up in social media (Althaus and Tewksbury 2002; Ku et al. 2003). Based on this perception, we identified topics related to the chosen automotive constructors in traditional print media. We chose the New York Times (NYT) for the analysis because of its high circulation and public importance. Furthermore, the NYT provides identical online editions, which can be utilized automatically. First, articles related to the automakers or their products were identified in a period of two weeks (11th and 12th week 2010). Based on the method of content analysis (Neuendorf 2002; Riffe et al. 2005), the articles were searched for mentioning certain automotive companies by name. After that, keywords were identified, which could be derived from those articles and which described a relevant topic for a company. A crisis-related issue could only be identified for Toyota. By analyzing NYT-articles about Toyota, we identified "recall" as a signal word, which is directly connected to a critical issue concerning the company. Therefore, in our further research steps we focus on that issue.

Step 2: Data Tracking and Preparation

As a second step, we gathered 732,003 Tweets that were published between the 13th and 31st week in 2010 and that contained the name of one of the automotive manufacturers as a keyword (e.g., Toyota).

We monitored, tracked, analyzed, and documented all those Tweets by using a software prototype. Every Tweet was archived with a time-stamp to provide the opportunity to analyze the data set dynamically. The collected data included the following metrics: Unique Twitter-ID, Time-Stamp, Author Name, Hashtags, Classification as Retweet, Full Content, and Hyperlinks. The data was stored in CSV format.

We consolidated different notations of terms in a Lucene-database to better prepare the data set. Furthermore, we were aware that not all of the 732,003 Tweets dealt with the corporate crisis of Toyota. Therefore, we extracted 37,323 Tweets, which contained the keyword-combination "Toyota" and "recall". We also excluded Tweets, which could be identified as being automatically generated (e.g., spam). Therefore, we received a data set consisting of 35,758 Tweets in English.

Step 3: Sentiment Analysis

One task of sentiment analysis (also named opinion mining) is to classify the polarity of a given text (e.g. document, sentence). This method is based on natural language processing, computational linguistics, and text analytics to identify and extract subjective information in different kinds of source materials.

To analyze sentiments in a large data set, computer algorithms have to be applied to automatically classify sentiments in digital texts (Turney 2002). Advanced methods differentiate between the affective state of the author and between emotions that are addressed at a named entity (Kim and Hovy 2006). To analyze the sentiments in our study, we decided to use the Linguistic Inquiry and Word Count (LIWC) Software (Pennebaker et al. 2006) since LIWC-based analyses have already been conducted to examine shorter text samples such as instant message conversations or Twitter messages (e.g., Tumasian et al. 2010; for a comprehensive overview of related studies, see Tausczik and Pennebaker 2010). LIWC is a text-analysis software program, which categorizes words into sentiments like positive, negative, sad, angry, glad, and happy. The program is based on a semantic dictionary search, including more than 4,500 words of moods or word stems and a total of 80 categories. The categories are built upon the combination of different dimensions: a descriptive dimension, which counts the total number of sentiment words in the text; a linguistic dimension, which focuses on the verbs and pronouns; a dimension of psychological constructs concentrating on the affect and cognition words; a dimension of personal concerns like leisure and work; and a paralinguistic dimension regarding the fillers and punctuation.

To emphasize the sentiments in our communication devolution about the Toyota-recall, we used the LICW categories "positive mood", "negative mood" and "neutral mood". The categories include all the above-mentioned dimensions to classify the accordant sentiment. The sentiment analysis was conducted for each week in the period of examination, which includes the weeks 13 to 39 of the year 2010.

Results

RQ1: *Are crisis-related long-term discussions in social media characterized by quiet stages and peaks? Do involved users of a specific issue generate more contributions (postings) in peaks than in quiet stages?*

Based on the time-stamps, the prepared data were separated in "peaks" and "quiet stages" for each week. We defined a peak as an area with a positive standard deviation above a value of 1.9 because of a 25% higher posting rate. Quiet stages are defined as those time periods where the standard deviation is below 2.0. Peaks are clearly identified with standard deviations of 6.1 in peak 1, 7.4 in peak 2 and 8.6 in peak 3.

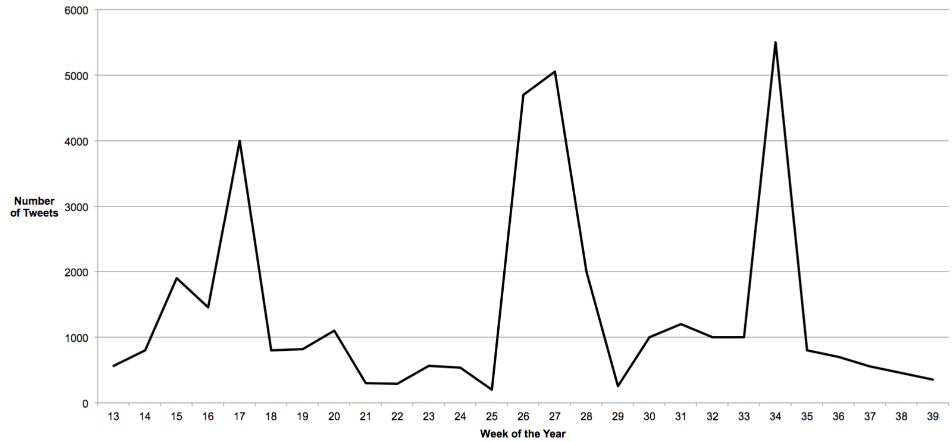

Figure 2: Number of Tweets for Keyword Combination "Toyota" & "Recall"
(13th to 39th week of 2010)

Figure 2 shows the dynamic issue devolution of the Toyota-recall in the weeks 13 to 39 in 2010. On average, 1,323.22 Tweets were published per week. As one can see, there are 4 "quiet stages" (Q1-Q4) and 3 peaks (P1-P3). Following our understanding of a peak and a quiet stage, we could identify 7 stages of discussion within the entire issue communication: Q1: week 13-16, P1: week 17, Q2: week 18-25, P2: week 26-27, Q3: week 28-33, P3: week 34, Q4: week 35-39.

The appearance of peaks can be explained by the upcoming of new information regarding the issue. This found resonance in the classic media as well as in the Twitter communication. In week 16, several articles about the second recall of the Toyota Lexus GX 460 Sort and about Toyota's conviction to pay a high fine (16,4 Mill.US-Dollar) were published (triggering peak 1). In week 26, another recall of 270,000 cars was announced (causes peak 2) and in week 34 Toyota recalled about 1.1 million 2005–8 Corollas and Matrixes as well as almost 162,000 Pontiac Vibes to fix a stalling problem (triggers peak 3). The quantity of Tweets in these peaks reached its highest point at 5,196 Tweets in week 34.

Table 1. Per Capita Posting Rate (PCPR)

Stage	PCP R	Tweets	Unique User
Q1: week 13 -16	1,5	4589	3050
P1: week 17	1,5	4076	2784
Q2: week 18-25	1,8	4786	2779
P2: week 26-27	1,8	9291	5131
Q3: week 28-33	2,5	5473	2392
P3: week 34	1,6	5196	3261
Q4: week 35-39	1,9	1220	2316

As table 1 shows, more contributions were published within the peak stages than in the quiet stages. However, the array also shows that the per capita posting rate remains nearly stable. This means that, in general, the active users do not post more Tweets in peaks than in quiet stages. Only one exemption in Q3 could be identified. In this case, the active users posted more Tweets than in any of the other phases.

Examining the allocation of active users and their posting-behaviour, this study confirms earlier research regarding participation in social media. We identified 14,119 different users and only few of them (10 power-tweeters / 0,07% of all user) authored more than 17,5% of all the Tweets we observed. Table 2 shows the top 10 users and the quantity of Tweets they posted within the analyzed period.

Table 2. Top 10 User in the Discussion Devolution

	Number of Tweets	Share of all Tweets
Toyota_recall	2,980	8.3%
Toy_Yoda	2,141	6.0%
Toyotacomplaint	385	1.1%
Toyotalinks	157	0.4%
Toyotadispatch	152	0.4%
Allairbagrecall	112	0.3%
Prius_Bat_Recon	90	0.3%
JaniceChase	84	0.2%
kulchawheels	82	0.2%
VehixCar	54	0.2%
Sum	6,237	17.5%

Based on our study, we can draw the conclusion that, even in peak stages, the number of Tweets per individual in our case study does not increase. However, it can be said that more users join the discussion in peaks and end their involvement during quiet stages.

RQ 2: *Are discussions in peaks characterized by "stronger" emotions (sentiments) than in quiet stages?*

To address the second research question, we separated the data set into four categories of sentiments: (1) positive, (2) negative, (3) neutral, and (4) ambivalent (table 3).

Table 3. Allocation of Sentiment Words (total period)

		negative sentiments					
	quantity	0 words	1 word	2 words	3 words	4 words	SUM
positive sentiments	0 words	23,588	7,293	599	36	10	31,526
	1 word	3,132	588	80	14	0	3,814
	2 words	321	61	6	0	0	388
	3 words	22	6	2	0	0	30
	SUM	27,063	7,948	687	50	10	35,758

Overall, we identified 35,758 Tweets, which contained the keyword combination ("Toyota" and "Recall"). Most of the Tweets (23,588) were classified as neutral because they contained neither positive nor negative sentiment words. 7,938 Tweets (23% of the whole sample) contained between 1 and 4 negative sentiment words but no positive expressions. 3,475 Tweets (10% of the whole sample) contained between 1 and 4 positive sentiment words but no negative expressions. 757 Tweets were classified as ambivalent, containing positive as well as negative sentiment words. To obtain better results about the influence of positive and negative sentiment words in Twitter discussions, we excluded ambivalent Tweets in our further analysis.

Table 4. Sentiments in the Issue's Devolution

Stage	Share of positive tweets	Share of negative tweets
Q1: week 13-16	38 %	62 %
P1: week 17	28 %	72 %
Q2: week 18-25	52 %	48 %
P2: week 26-27	9 %	91 %
Q3: week 28-33	41 %	59 %
P3: week 34	25 %	75 %
Q4: week 35-39	35 %	65 %

Regarding the sentiments in the peak and quiet stages, we discovered that a positive tinged peak is followed by a positive accented quiet stage (figure 3). Q1 is categorized as negative because of a 62% quote of negative tempered Tweets (only positive and negative tweets are considered here).

The following peak 1 with a quantity of 4,076 Tweets is highlighted as the only peak with a positive sentiment. 72% of the peak-communication contains positive sentiment words. The subsequent Q2 is also the only quiet stage with a low positive to neutral tendency (52 % positive emotions). After the negative affected peak 2 (91% neg) and peak 3 (75% neg), Q3 and Q4 followed with negative sentiment word quotes of 59% and 65%. Table 4 shows that there is a much bigger sentiment polarization in peaks than in quiet stages. The negative sentiment is significant especially in peak 2.

The following examples provide a better understanding about the content of positive, negative, and neutral Tweets:

Tweets containing negative sentiments:

- M0019: "*Fucking hate Toyota. Don't give me attitude that I want my RECALLED car fixed now bc I'm taking time out of my day to drive it over here ugh*"
- MarleyLuv26: "*Damn Toyota is like a hot damn mess RT @cnnbrk: Toyota to recall about 50,000 Sequoia SUVs*"

Tweets containing positive sentiments:

- josereyesfl: "*Up for an early start, at central florida toyota hopefully they can fix the recall w the gas pedal. Let's just hope for the best!!!*"
- ay_bee: "*Sitting in the toyota customer center, finally getting my recall work done. (and a free carwash! Jovney will look so handsome!!!!)*"

Tweets containing neutral sentiments:

- Climateox: "*Toyota safety recall: Nasa called in*"
- Parkydust1: "*Toyota recalls 412,000 cars*"

RQ3: *Is there a difference between sentiments in* Tweets *posted by power-tweeters (PT) and the sentiments in Tweets posted by all participants of the sample?*

To answer this research question, we analyzed the usage of sentiment words by power-tweeters. As we found out, 33% of all 35,758 Tweets contained either positive or negative sentiment words.

Table 5. Sentiments in Tweets authored by power-tweeters

Account name	Background	Neutral Tweets	Tweets with sentiment words
Toyota_recall	Forwards news about cars	71,2 %	28,8 %
Toy_Yoda	Private blogger	79,5 %	20,5 %
toyotacomplaint	Private blogger	70,6 %	29,4 %
Toyotalinks	Forwards news about Toyota	66,6 %	33,4 %
Toyotadispatch	Forwards news about Toyota	69,2 %	30,8 %
Allairbagrecall	Posts about recalls and safety	11,1 %	88,9 %
Prius_Bat_Recon	Posts about Toyota Prius	20,5 %	79,5 %
JaniceChase	Private blogger	85,5 %	14,5 %
Kulchawheels	Kulchawheels official account	55,4 %	44,6 %
VehixCar	Vehixcar official account	60,4 %	39,6 %

As table 4 shows, only four power-tweeters published significantly more Tweets containing sentiment words than on average. To provide a better understanding of the power-tweeters, we analyzed their profiles and extracted some information about their background (table 5).

CONCLUSION

The results of the previous qualitative revision of the Twitter-content evidenced that there are vivid discussions about enterprise-related issues in the network. By addressing three research questions, we provided insights into the dynamics of issue discussions in Twitter. We found out that different stages of discussion can be identified: peaks and quiet stages. Furthermore, by analyzing a specific case, we learned that, even in peaks, users do not increase their frequency of postings significantly. Rather, more users enter the discussion. Regarding our sentiment analysis, we showed that, overall, the share of sentiment-expressions does neither increase in quiet stages nor in peaks. However, interestingly, the polarization of sentiment (positive and negative) increased strongly in all peak stages. Furthermore, we showed that in our sample only four power-tweeters used sentiment words more frequently than average users. As a further step, inspired by our results, we plan to investigate the sentiments of retweeters of those power-tweeters to analyze whether they adopt the sentiments of the power-tweeters. Clearly, the results only show tendencies within the observed discussion. However, considering the high number of Tweets and relatively clear characteristics of the study, we can assume that these results have a sufficient validity to support our conclusions.

This research is to our knowledge the first contribution, which analyzes sentiment in an enterprise-related issue dynamically in social media. However, some limitations have to be considered. Since we used a keyword approach to filter relevant Tweets, it can be supposed that some postings, which were also part of the analyzed issue, have not been considered because selected keywords were missing. In previous studies, LIWC was used to emphasize sentiments in text-based content. One further problem is that most sentiment analysis algorithms rely on us using simple terms to express our sentiment about a product or service. However, cultural factors, linguistic nuances and differing contexts make it extremely difficult to turn a string of written text into a simple pro or con sentiment. The fact that humans often disagree on the sentiment of text illustrates how big a task it is for computers to get this right. The shorter the string of text, the harder it becomes.

The shortness of Twitter-messages may therefore raise the margin of error. Considering this, we are aware that our findings merely show tendencies about sentiments of the dynamic communication. We are also aware that our conclusions are very specific and that results can not be generalized.

In a further study, we will concentrate on obtaining in-depth information about specific users and postings by conducting content analysis. Furthermore, we plan to conduct similar studies (e.g. different industries and issues) to draw comparative conclusions based on the results of several cases.

REFERENCES

Adam, S. 2008. “Medieninhalte aus der Netzwerkperspektive. Neue Erkenntnisse durch die Kombination von Inhalts-und Netzwerkanalyse,” *Publizistik* (53:2), pp 180-199.

Althaus, S., and Tewksbury, D. 2002. “Agenda Setting and the „New“ News: Patterns of Issue Importance Among Readers of the Paper and Online Versions of the New York Times,” Communication Research (29:29, pp 180-207.

Bakshy, E., Hofman, J., Mason, W., and Watts, D. 2011. “Everyone’s an Influencer: Quantifying Influence on Twitter,” *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining* (WSDM’11).

Bollen, J., Pepe, A., and Mao, H. 2009. “Modeling public mood and emotion: Twitter sentiment and socioeconomic phenomena,” Arxiv preprint arXiv0911583, (arXiv:0911.1583v0911[cs.CY], pp 17-21.

Carrasco, J., Fain, D., Lang, K., and Zhukov, L. 2003. “Clustering of bipartite advertiser-keyword graph,” *Proceedings of the International Conference on Data Mining*.

Cha, M., Haddadi, H., Benevenuto, F., and Gummadi, K. 2010. “Measuring User Influence in Twitter: The Million Follower Fallacy,” *Proceedings of the International AAAI Conference on Web-logs and Social Media (ICWSM).*

Clark, K., and Fujimoto, T. 1991. *Product development performance: Strategy, Organization and Management in the world auto industry*. Harvard Business Press.

Cordis 2009. *Collective emotions in cyberspace (CYBEREMOTIONS)*, European Commission, 2009-02-03.

Emrich, C. 2008. *Multi-channelcommunications -und Marketing-management*. Wiesbaden.

Fösken, S. 2006. “Was ist dran am Web. 2.0?,” *Absatzwirtschaft* (9), pp 96-101.

Frey, B. 2002. “Virus-Marketing im E-Commerce: Von den Erfolgreichen lernen,” Frosch-Wilke D., and Raith, C. (eds.) *Marketing-Kommunikation im Internet: Theorie, Methoden und Praxisbeispiele vom One-to-One bis zum Viral-Marketing*. Wiesbaden, pp 234.

Getoor, L., and Diehl, C. 2005. “Link mining: a survey,” *SIGKDD Explor. Newsl.* (7:2), pp 3–12.

Gouthier, M., and Hippner, H. (2008): “Web 2.0-Anwendungen als Corporate Social Software,” Hass, B., Walsh, B., and Kilian, T. (eds.) *Web 2.0. Neue Perspektiven für Marketing und Medien*, pp 95f.

Goyal, A., Bonchi, F., and Lakshmanan, L. 2008. “Discovering leaders from community actions,” *Proceedings of the 17th ACM conference on Information and knowledge management*, pp 499–508.

Green, D., and Pearson, J. 2005. “Social Software and Cyber Networks: Ties That Bind or Weak Associations within the Political Organization?,” *Proceedings of the 38th Hawaii International Conference on System Science*.

Han, J., and Kamber, M. 2006. *Data Mining: Concepts and Techniques*.

Ingenhoff, D., and Röttger, U. 2008. “Issues Management. Ein zentrales Verfahren der Unternehmenskommunikation,” Schmidt, B. (ed.) *Unternehmenskommunikation. Kommunikationsmanagement aus der Sicht der Unternehmensführung*. pp 323-354.

Jansen, B., Zhang, M., Sobel, K., and Chowdury, A. 2010. “Twitter power: Tweets as electronic word of mouth,” *Journal of the American Society for Information Science and Technology* (60:11), pp 2169-2188.

Jansen, H.J., and Koop, R. 2005. “Pundits, ideologues, and ranters: The British Columbia election online,” *Canadian Journal of Communication* (30), pp 613-632.

Kim, S.M., and Hovy, E.H. 2006. “Identifying and Analyzing Judgment Opinions*,” Proceedings of the Human Language Technology / North American Association of Computational Linguistics conference (HLT-NAACL 2006)*. New York, NY.

Kleinberg, J. 1999. “Authoritative sources in a hyperlinked environment,” *Journal ACM* (46:5), pp 604–632.

Knocke, D., and Kuklinski, J.H. 1982. “Network analysis,” *Sage University Paper 28 Series on Quantitative Applications in the Social Sciences*.

Köhler, T. 2006. *Krisen PR im Internet. Nutzungsmöglichkeiten, Einflussfaktoren und Problemfelder*.

Kolo, C., and Heinz, A. 2010. *Wellenschlag in Social Media – Orchestrierung der Markenkommunikation zwischen Facebook, Twitter und Co. München*.

Krishnamurthy, B., Phillipa, G., and Arlitt, M. 2008. “A Few Chirps About Twitter,” *Proceedings of the first workshop on Online social networks (WOSN ´08)*.

Ku, G., Kaid, L., and Pfau, M. 2003. “The Impact of Web Site Campaigning on Traditional News Media and Public Information Processing,” *Journalism & Mass Communication Quarterly* (80:3), pp 528-547.

Kwak, H., Lee, C., and Moon, S. 2010. “What is Twitter, a Social Network or a News Media?,” *Proceedings of the 19th International World Wide Web (WWW) Conference*.

Liebl, F. 2000. *Der Schock des Neuen. Entstehung und Management von Issues und Trends*. Hamburg.

Lin, Y.-R., Chi, Y., Zhu, S., Sundaram, H., and Tseng B. L. 2008. “Facetnet: a framework for analyzing communities and their evolutions in dynamic networks,” *WWW ’08: Proceeding of the 17th international conference on World Wide Web*, pp 685–694.

Mast, C. 2006. *Unternehmenskommunikation*. Stuttgart.

McAfee, A. 2009. *Enterprise 2.0. New collaborative Tools for your organizations´ toughest challenges*, Harvard Business Press: Boston.

Milestein, S., Chowdhury, A., Hochmuth, G., Lorica, B., and Magoulas, R. 2008. *Twitter and the micromessaging revolution: Communication, connections and immediacy – 140 characters at a time*. Sebastopol, CA: O`Reilly Media.

Mitrovi´c, M., Paltoglou, G., and Tadi´c, B. 2011. *Quantitative Analysis of Bloggers Collective Behavior Powered by Emotions*.

Mühlenbeck, F., and Skibicki, K. 2009. “Social Media-Marketing,” Eisinger, T., Rabe, L., and Thomas, W. (eds.) *Performance Marketing – erfolgsbasiertes Online-Marketing. Mehr Umsatz im Internet , Suchmaschinen, Bannern, Emails & Co*.

Neuendorf, K. 2002. *The Content analysis guidebook*. Sage: Thousand Oaks.

Palau, J., Montaner, M., Lopez, B., and de la Rosa, J. 2004. “Collaboration analysis in recommender systems using social networks,” *Cooperative Information Agents VIII, 8th International Workshop*, CIA, pp 137–151.

Pennebaker, J.W., Booth, R.J., and Francis, M.E. 2006. *Linguistic inquiry and word count: LIWC*. Erlbaum, Austin, TX, USA.

Riffe, D., Lacy, S., and Fico, F. 2005. *Analysing media messages by using quantitative content analysis in research*. 2nd Edition.

Röttger, U. 2001. *Issues Management. Theoretische Konzepte und praktische Umsetzungen. Eine Bestandsaufnahme*, pp 146.

Sester, A., Eder, B., and Scheichel, C. 2006. “Blessing or Curse? A Taxonomy for Virtual Product Communities,“ *Proceedings of the Twelfth Americas Conference on Information Systems*, Acapulco, Mexico.

Sixtus, M. 2005. “Das Web sind wir. Social Software und das neue Leben im Netz,” *Technology Review* (7), pp 44-53.

Stieglitz, S., Dang-Xuan, L. (2012): „Political Communication and Influence through Microblogging – An Empirical Analysis of Sentiment in Twitter Messages and Retweet Behavior,“ *Proceedings of the 45th Hawaii International Conference on System Sciences (HICSS)*.

Stieglitz, S., Krüger, N., and Eschmeier A. 2011. „Themenmonitoring in Twitter aus der Perspektive des Issue Managements," Meißner, K. and Engelien, M. (eds.) *Virtual Enterprises, Communities & Social Networks*, pp 69-78.

Tausczik, Y. R., and Pennebaker, J. W. 2010. "The psychological meaning of words: LIWC and computerized text analysis methods", *Journal of Language and Social Psychology* (29), pp. 24-54.

Tumasjan, A., Sprenger, T., Sandner, P., and Welpe, I. 2010. "Election forecasts with Twitter: how 140 characters reflect the political landscape," Social Science Computer Review. Advance online publication. doi: 10.1177/0894439310386557.

Turney, P. 2002. "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews," *Proceedings of the Association for Computational Linguistics*, pp 417–424.

Twitter 2011. http://twitter.com/about (2011-03-15).

Wartick, S., and Mahon, J. 1994. "Toward a substantive definition oft he corporate issue construct – a review and synthesis oft he literature," *Business and Society* (33), pp 293-311.

Wasserman, S., and Faust, K. 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press.

Wu, S., Hofman, J., Mason, W., and Watts, D. 2011. "Who Says What to Whom on Twitter," *Proceedings of the WWW'11 Conference*.

Zerfaß, A., and Sandhu, S. 2006. "Issues Management und Web 2.0: Monitoring der Meinungsbildung in der Blogosphäre," *PR Magazin* (38:9), pp 45-52.

COPYRIGHT