Topics in Social Media for Disaster Management - A German Case Study on the Flood 2013

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Abstract

The paper presents the results of a German case study on social media use during the flood 2013 in Central Europe. During this event, thousands of volunteers organized themselves via social media without being motivated or guided by professional disaster management. The aim of our research was to show and analyze the real potential of social media for disaster management and to enable the public organizations to get into touch with the people and take advantage as well as control of the power of social media. In our investigation, we applied state-of-the-art technology from *Natural Language Processing*, mainly topic modeling, to test and demonstrate its usefulness for computer-based media analysis in modern disaster management. At the same time, the analysis was a comparative study of social media content in context of a disaster. We found that Twitter played its most prominent part in the exchange of current factual information on the state of the event, while Facebook prevalently was used for emotional support and organization of volunteers help. Accordingly, social media are powerful not only with respect to their volume, velocity and variety but also come with their own content, language and ways of structuring information.

Keywords: social media analysis, crisis informatics, topic modeling, flood 2013 Central Europe, comparative corpus linguistics

1. Introduction

When in June 2013 the rivers Elbe and Donau bursted their banks and floodwaters were threatening the cities and villages in east and south Germany and Austria, a huge wave of readiness to help throughout the country was also on its way. During these days, not only the water levels and amount of rain set new records at many places, but also the engagement of volunteers was the highest ever known. Notably, these volunteers organized themselves mainly via social media.

There had been no concrete call to action and no guiding from the side of official public emergency management. But the new social media channels had created an opportunity to channel social energy and put into real action a valuable potential that might have been lost otherwise. And the viral effects of the open network made the movement rapidly spread and grow.

For instance, the public Facebook site 'Fluthilfe Dresden' founded by a young man, Daniel Neumann, on its own initiative, got about 12.500 followers after half a day only and reached 2.4 million people in one week. Before he knew how, the young man and two of his friends found themselves in a position to receive and answer about 60-80 messages per minute and coordinate as much as 50.000 people in overall (EIJK, 2015).

The high potential of social media platforms for emergency management is due to a number of properties. For instance, everybody can give and gain information directly and without barriers or information hierarchies to cross. The access is simple, stable and possible from everywhere, reach and coverage very wide, dissemination extremely rapid. The social aspects are inherent in the medium itself in form of interactivity, network building and multiplication of effects.

But in face of examples as 'Fluthilfe Dresden' it becomes obvious, that the powerful movement of privat engagement via social media urgently needs to be coordinated and guided by professional emergency managers (i.e., EIJK, 2015). Beside its great positive potential, self-dependent organization of volunteers can also bring dangers, as examples of misplaced and faulty actions during the flood 2013 showed. Volunteers and emergency managers both agree (ibid.) that state agencies should keep or regain information sovereignty and decision-making authority and that they have to assume ultimate responsibility in case of a disaster. This is only to be achieved by working hand in hand with volunteer's organizations and by *'going where the people are'* (Rutrell, 2010). That means, disaster management has to be present for gathering and giving information and for interactive communication on social media.

Currently, the idea to become actively involved into exchange of information and interaction on social media places a number of great challenges for the responsible bodies in German disaster management, though (i.e., Kirchbach Kommission, 2013; BMI, 2014). Two of them have been in the focus of the study presented in this paper.

- *Information flooding:* The digital room of social media is containing an overwhelming amount of information of great diversity and dynamicity.
- *New Modes of communication:* 24 hours of digital communication flow in an interactive many-to-many setting brings up new forms of communication together with new types of content.

The two problems mentioned are obviously interrelated, as the situation of information flooding in the social media space so far has been a great obstacle to all systematic investigations into its content and communicative characteristics.
With respect to the first problem, modern computer-based methods from the fields of text mining and information retrieval can automatically reveal content in very large collections of text and can enable disaster managers to efficiently search, sort and analyze relevant information. In our case study, we applied an up-to-date method for content analysis and clustering in order to test and demonstrate its usefulness in the given context. At the same time, with respect to the second of the above problems, our investigation was aimed at answering the following research questions:

1. What kind of communicative content is currently distributed by social media in context of a disaster?
2. Are their differences in content and language among several types of social media?

Answering the first question will help to better assess the real potential of social media for disaster management. The results of our investigation into the second question will support disaster managers to find out the most promising place where to search for and where to place certain kinds of information and the most appropriate way to communicate with the people in each context.

2. Data and Methods

2.1 Data

In our case study on the flood 2013, we investigated messages from two big social media platforms - Facebook and Twitter. Covering the time span of the core event from May to July 2013, we collected German data from both platforms via their public API, respectively.
For the Facebook flood corpus we retrieved data from public pages or groups containing the words *Hochwasser (flood)* or *Fluthilfe (flood aid)* in their names. Our sample trainings corpus consisted of 35.6k messages (1.2M word tokens) from 264 public pages or groups. Preprocessing of the corpus included deletion of punctuation marks and stop words, tokenization and lemmatization; numbers were mapped on a generic reference (*num_ref*).
For the Twitter flood corpus we retrieved a current version of the research corpus of the project *QuOIMA* (QuOIMA, 2013) on basis of tweet IDs. The *QuOIMA* corpus had been collected from the public Twitter stream and filtered by 65 hash tags coming from research of the Austrian Bundesheer and by 29 names of manually chosen public accounts connected to disaster management and flood aid. The current version of the corpus comprises 354k tweets (4M word tokens). The preprocessing was the same as in case of the Facebook corpus but additionally included removal of Twitter names, URLs and Hashes from Hash tags as well as deletion of retweets.

2.2 Methods

The technique we applied to reveal the hidden thematic structure in our corpora was topic modeling. Topic models (e.g., Blei, Ng, & Jordan, 2003; Blei, 2012; Griffiths & Steyvers, 2002) are a family of statistical models based upon the idea that documents are mixtures of topics. Each topic is defined in form of a probability distribution over words. These weighted topic words, that pick out a coherent cluster of correlated terms, allow for an intuitive interpretation of the topics. Topic model techniques are a very useful new way to search, browse, summarize and cluster large collections of text.
The specific type of topic model we applied in our investigation of social media content was a *Hierarchical Dirichlet Process* in form of a *Chinese Restaurant Franchise Sampler* (HDP CRF) (Teh and Jordan, 2010). Unlike more standard algorithms like LDA (*Latent Dirichlet Allocation*), HDP CRF is a nonparametric algorithm which automatically uncovers the number of topics based on the data characteristics. The benefit of this is that we have greater flexibility in adapting to the peculiarities of social media data and are able to formally define Bayesian priors, even if we do not know, how the appropriate prior probability distribution should look like.
We took an additional step to improve interpretability of topics for the following reason. Common terms in the corpus often appear near the top of the ranked word list for multiple topics, making it hard to differentiate the meanings of these topics on basis of the most probable terms according to the topic model. In order to meet this problem, we used *relevance* (Sievert, Kenneth, 2014) as our method of ranking topic terms. *Relevance* is defined as the weighted average of a term's probability within a topic and its *lift* (Taddy, 2012). The *lift* generally decreases the ranking of globally frequent terms, being the ratio between a term's probability within a topic and its marginal probability across the corpus. The following definition of *relevance* by Sievert and Kenneth (2014) uses a parameter λ (where $0 \leqq \lambda \leqq 1$) which determines the weight given to the probability of a term w under topic k relative to its *lift* (measuring both on the *log* scale).

Relevance: $r(w, k \mid \lambda) = \lambda \log(\phi_{kw}) + (1-\lambda) \log(\phi_{kw} / p_w)$,

where ϕ_{kw} denotes the probability of the term w for topic k and p_w the marginal probability of w across the corpus.
In order to investigate inter-topic differences within a corpus, we computed the distances between topics (*Jensen Shannon divergence*) and then applied *Multi-dimensional Scaling* (*Principal Components*) to project the distances onto two dimensions (compare Chuang et al., 2012). As our visualization system, we used *LDAvis* (Sievert, Kenneth, 2014).
In order to complement the results of our main analysis using topic modeling we conducted two supplementary comparative studies.
First, we did mutual comparison of equal sized samples of the flood corpora from the two different social media, aiming at differences in content and language between them. We analyzed differences in relative frequency of

keywords from one corpus to the other using *Log-Likelihood Ratio Test* (Dunning, 1993).
Finally, we investigated emotional involvement in flood-related messages in Facebook and Twitter. We compared relative frequencies of sentiment words for each case using the *SentiWS* resource from the University of Leipzig NLP group (Remus et al., 2010), a list of German positive and negative sentiment bearing words.

3. Results

The results of our investigation to be discussed in the remainder of the paper, are presented in the following figures and tables.
Table 1 and Table 2 summarize the results of the topic model analysis for the Facebook and the Twitter flood corpora. We have proposed a title to each topic on basis of the words that received high probability under the topic. For each topic, the 8 most *relevant* topic terms, according to the above definition, are displayed in decreasing order (together with their English translation in brackets). We chose $\lambda=0.4$ for Facebook and $\lambda=0.3$ for Twitter to balance term's probability within the topic and its *lift*. For each corpus, the topics are ordered by their *topic frequency*, calculated as the sum of topic probabilities over all documents, normalized by the length of the respective document.
The relative size of all topics according to this measure is displayed in a topic wheel in Figure 1 and Figure 2.
Another global view on the topics in each flood corpus is revealed in Figure 3 and Figure 4 on the lefthand side in form of the results of multi-dimensional scaling. On the righthand side of these figures there are the most relevant terms for an example topic, namely topic 1 in each case, together with the corresponding term frequencies within this topic and overall term frequencies within the corpus.
Table 3 lists the 12 most significant terms of the mutual differential analysis in decreasing order. The terms in the first row characterize the Facebook content when compared to Twitter; the terms in the second row, are the differentiating lexical features of Twitter when compared to Facebook.
Finally, results of sentiment analysis are displayed in Figure 5, showing the relative frequency of sentences containing positive and negative sentiment markers (as a percentage), respectively.

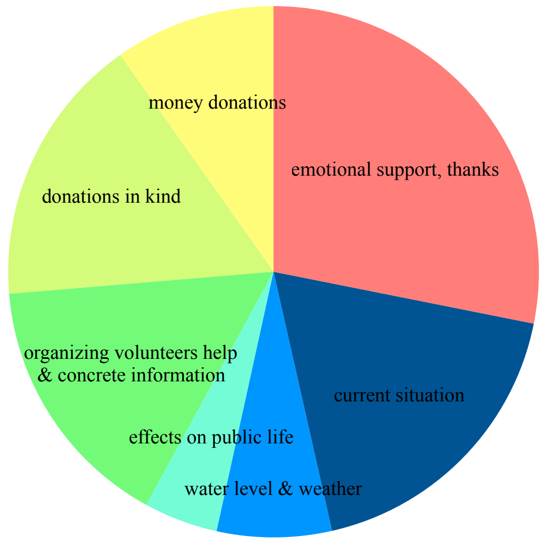

Figure 1: Facebook Topic Wheel Flood 2013

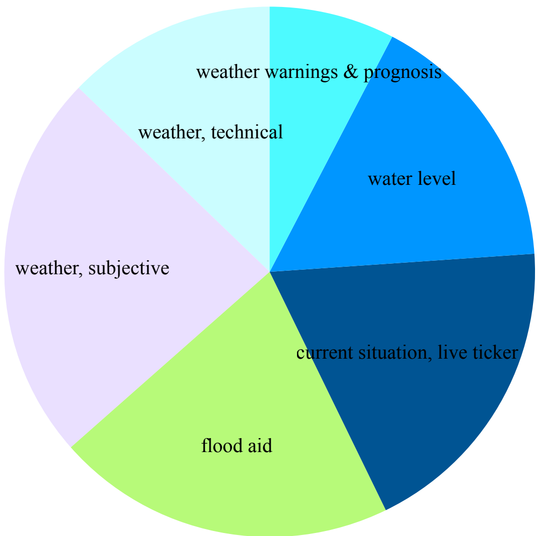

Figure 2: Twitter Topic Wheel Flood 2013

1	emotional support and thanks	*mal* (*times* or modal particle spoken language), *danke (thank you), vielen (many), Dank (thank), Menschen (people), Seite (site), schon (already* or modal particle spoken language), *viele (many)*
2	current state	*Wasser (water), Quelle (source),* num_ref, *Elbe* (river *Elbe), Deiche (dikes), Evakuierung (evacuation), Deich (dike), Landkreis* (administrative district),
3	donations in kind	*Sachen (things), Kleidung (clothes), melden (report, volunteer), Sachspenden (donations in kind), spenden (donate), bitte (please), abzugeben (to be given away)*
4	organizing volunteers help and concrete information	*Helfer (volunteers), jemand (somebody), Sandsäcke (sand bags), benötigt (needed), weiß (know), Hilfe (help), gebraucht (needed), tomorrow (morgen)*
5	money donations	*Euro,* num_ref, *Hochwasser (flood), Konto (bank account), BLZ (BIC), Soforthilfe (emergency aid), Betroffene (people affected), Deutschland (Germany)*
6	water level & weather	num_ref, *Uhr (o'clock), Pegelstand (water level), aktueller (current), html, Tendenz (tendency), steigend (rising), Pegel (water level)*
7	effects on public life	*Grundschule (primary school), Unterricht (classes), Straße (road), gesperrt (closed), Schulen (schools), Zwickau* (city in Saxony), *Mülsen* (town in Saxony)*, ZOB (Central Bus Station)*

Table 1: Facebook Topics Flood 2013

1	weather, subjective	*Regen (rain), mal* (*times* or modal particle spoken language)*, schon (already* or modal particle spoken language)*, schön (nice), gut (good), Sommer (summer), endlich (finally)*
2	flood aid	*Hochwasser (flood), Hilfe (aid), Hochwasserhilfe (flood aid), Euro, helfen (help), Merkel* (German chancellor)*, Helfer (volunteers)*
3	current situation, live ticker	*Hochwasser (flood), Lage (current situation), Magdeburg* (city in Saxony), *Hochwasser-Ticker (flood ticker), Webcam, Hochwasserlage (flood situation), Live-Ticker*
4	water level	num_ref, *Stand (state, level), Pegel (water level), gefallen (fallen), Pegelmw (mean water level), gestiegen (risen), Minuten (minutes)*
5	weather, technical	num_ref, *kmh* (metric measure of speed)*, hPa* (metric measure of pressure)*, temp* (abbreviation for temperature)*, Wind (wind), Luftdruck (air pressure), /m²* *(per square meter)*
6	weather warning	*Starkregen (heavy rain), Unwetter (severe weather), Gewitter (thunderstorm), Wetterwarnung (weather warning), Unwetterwarnung (thunderstorm warning), schwere (heavy), Vorhersage (forecast)*

Table 2: Twitter Topics Flood 2013

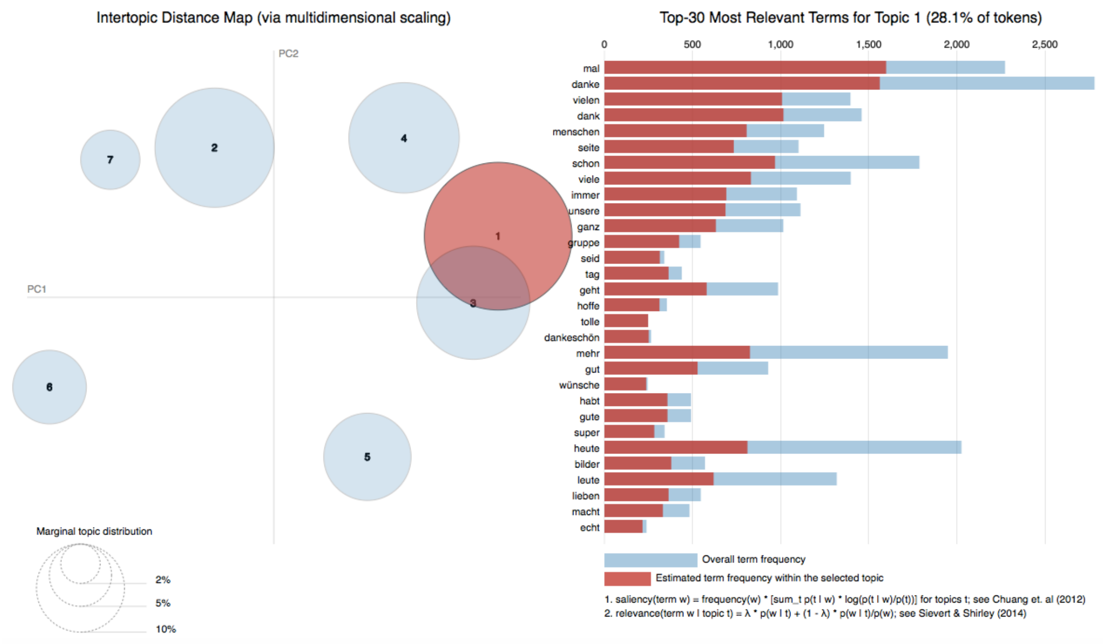

Figure 3: Facebook Topic Global View (λ = 0.4)

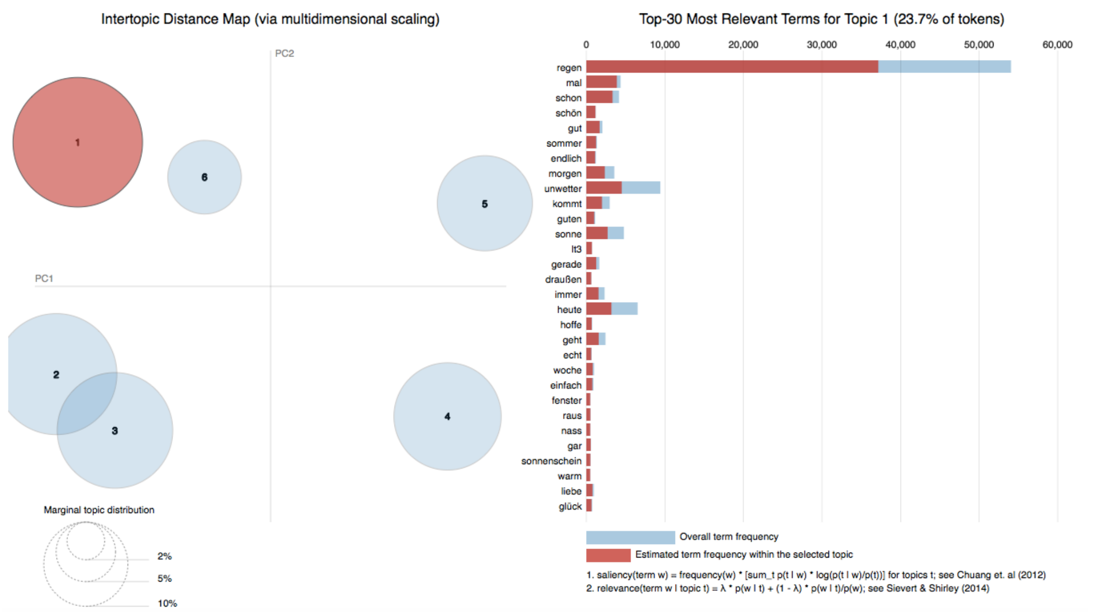

Figure 4: Twitter Topic Global View (λ = 0.3)

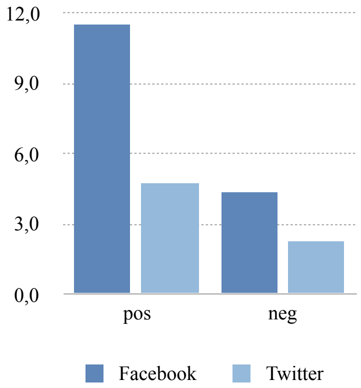

Figure 5: Comparative Sentiment Analysis

Facebook compared to Twitter	*helfen (help)* *bitten (please)* *melden (report, volunteer)* *bitte (please)* *gerne (gladly)* *benötigen (need)* *Sachspende (donation in kind)* *abgeben (give away)* *sache (thing)* *Gruppe (group)* *gebrauchen (use)* *Hilfe (help)*
Twitter compared to Facebook	*Hochwasser (flood)* *Stand (state, level)* *Pegel (water level)* location_city (location marker) *kmh* (metric measure of speed) *hpa* (metric measure of pressure) *Pegelmv (mean water level)* *Elbe* (river *Elbe)* *Wind (wind)* *Unwetter (severe weather)* *Regen (rain)* *temp* (abbreviation for *temperature*)

Table 3: Mutual Differential Analysis[1]

3.1 Facebook

The focus of the content in the Facebook flood corpus is on social interaction and help. In Figure 1, the socially relevant topics are market in red, yellow and green colors and take about three-quarters of the overall topic space of the corpus.
The most prominent topic is concerned with giving emotional support to the affected people and thank the helpers. Furthermore, there is a large topic on offering, asking for and coordinating volunteer's help and concrete information and two topics on organizing donations in kind and money donations, respectively. In Figure 1, the topics that include current information on the factual level of the flood event, i.e., general situation, water levels, weather conditions, are marked in blue colors and only take about one-quarter of the overall topic space. Even on the factual level, the social perspective occurs in topic 7 that is concerned with current effects of the event on public and social life.
In line with this consideration, the main division of lexical semantic space according to *Multi-dimensional Scaling* in Figure 3 appears between social topics on the right and factual topics on the left. For the vertical dimension one might suggest an interpretation in terms of formal content of the topics, with topics 5 and 6 ('money donations' and 'water level & weather') being he most formal ones and set apart from the other, more informal topics.
As the most dominant content of Facebook flood-related messages is related to empathy and social interaction, the prevalent language is emotionally involved and informal in style, often showing elements of spoken language (i.e., certain modal particles, as shown in Table 1, topic 1).
High empathy and emotional involvement is also proven by the results of *Sentiment Analysis* in Figure 5. The fact that especially high values appear in case of positive sentiment markers is reflecting the efforts of the public to provide emotional support, encouragement and motivation. In comparison, Twitter does not even come close to achieving similar high rates in positive sentiment.
The differentiating terms of Facebook compared to Twitter (in Table 3) all hint to social interaction and help.
In overall, the Facebook communication seems to be taking the perspective of the affected people.

3.2 Twitter

When moving from the Facebook to the Twitter flood corpus, the semantic focus just switches. As can be read off the topic wheel in Figure 2, the main focus in case of Twitter is on current information on the event.
The topics related to factual information with respect to the general situation, water level, weather, weather warnings and prognosis are marked in blue colors, and they are taking about 80 percent of the overall topic space. Social engagement and organization of help is also

1 For differential analysis, all location markers where mapped on the string 'location_city'.

present in Twitter but appears as subordinated.

Likewise, emotional involvement is relatively rare here (Figure 5), and it mostly appears in the prominent topic 1 were people show their sentiments with respect to the weather rather than in the context of empathy and emotional support as it was in Facebook.

The division of lexical semantic space according to *Multi-dimensional Scaling* seems to be between weather topics in the upper and topics related to flood and water level on the bottom. The vertical dimension may be interpreted as dividing between more formal language style on the right, and less formal and colloquial style on the left.

The prevalent language of Twitter is situative reporting and factual. It shows examples of colloquial style but also includes topics that show very technical language.

These very technical lexical features and the focus on the event itself also come out as the characteristic aspects of Twitter when compared to Facebook via differential analysis (Table 3). Surprisingly, Twitter hereby place itself in close proximity to professional reports rather than Facebook, as we have shown in Gründer-Fahrer, Schlaf (2015) on basis of *Latent Semantic Analysis*.

Generally, the communication in Twitter is mostly taking a factual perspective on the event.

4. Discussion & Conclusion

Our investigation we applied state-of-the-art techniques from *Natural Language Processing*, mainly topic modeling, in order to pursue a threefold aim.

First, we wanted to test and prove its usefulness in context of social media analysis for disaster management. The method generally revealed very meaningful and coherent clusters of content in the data examined. On basis of the inferred topic models, it is possible to filter, sort and semantically analyze huge amounts of social media data automatically and to open up efficient, computer-based access to this new source of information to professional disaster managers. For instance, the model can give an overview over the content of existing text collections and can point out the main topics under consideration there. Furthermore, new incoming text messages can be provided with topic labels and topic probabilities and can then be thematically ordered. This way of structuring and ordering the information makes it more comprehensible and available, and ready to be used according to different interests the managers may have when looking at the data. Additionally, the topic words can be used as search or filter terms for retrieval of data in each register. Finally, when tracking topics over time, one can get aware of overall developments and trends and of critical states in the factual or social dimension of the emergency situation.

An implementation of the topic model tested here is supposed to become part of the text analytical module of the disaster management software prototype that will be the outcome of the European project 'Slándáil'. This software prototype will be available for further testing and possible application to end-users then.

Second, our investigation at the same time was an analysis of social media content and its potential for disaster management. From the point of view of emergency management, a crisis has three basic dimensions: 1. the real event; 2. the actions of the involved organizations; 3. the perception of the crisis. Taking the flood 2013 in Germany and Austria as our case study, we revealed high potential of social media content for disaster management in all three dimensions. With respect to the real event, social media were intensively used for sharing of up-to-date information and for spreading warnings. In this way social media contribute to improvement of situational awareness and timeliness of early warnings. In the dimension of the activities related to the event and resilience, social media played an important part in the organization of volunteers activities and donations. Here the general potential was in improving social connectedness and concrete support. As for the perception of the crisis and its emotional processing, social media provided a good and frequently used possibility to directly show empathy, provide emotional support or practice emotional (self-)management. Like this it was a valuable resource for psychological self-help.

Finally, the third focal point of our investigation was a comparative analysis of social media content and language in context of a disaster. In our analysis of German language data from the flood 2013, there appeared striking differences in content between the two big social media platforms under investigation, Facebook and Twitter. According to our observation, the focus of Facebook content is on empathy and social engagement. The conceptualization generally takes the perspective of the affected people and the prevalent language is emotionally involved and informal. Twitter, in contrast, is mainly used for exchange of current and concrete information on the event. It takes a more factual point of view, and the characteristic language is situative reporting and factual, stylistically ranging from quite technical to colloquial. This means, among the dimensions of a crisis mentioned in the previous paragraph, Facebook dominates the dimension that includes activities related to the event and to resilience as well as the dimension concerned with the perception of the crisis and its emotional processing. To the dimension of the real event, Twitter contributes more and more precise information.

In result of this study, it can be stated that the arrangement of information in social media in context of a disaster, rather than being chaotic or arbitrary, reveals a clear order. And, interestingly, the different platforms, Facebook and Twitter, rather than being just coexisting or competing, perform a systematic and effective division of labor. These results can serve as an orientation point for professional disaster managers who seek to more successfully search for relevant information in social media. At the same time, the outcome of our study can support them to place their own information in the right context and in an appropriate style as to gain people attention and trust. Moreover, our results should be of interest to communication and linguistic studies as well as media research. It will certainly be interesting to extend this kind of analysis to different languages and social communities as to investigate commonalities and differences in the organization of public, collective and individual help, social behavior, sociolinguistics and media use.

5. Acknowledgements

The research leading to these results has received funding from the European community's Seventh Framework Programme under grant agreement No. 607691 (SLANDAIL)."

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