End-User Development and Social Big Data – Towards Tailorable Situation Assessment with Social Media

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Abstract The amount of data being available is increasing rapidly. Based on the technological advances with mobile and ubiquitous computing, the use of social media is getting more and more usual in daily life as well as in extraordinary situations, such as crises. Not surprisingly, this increasing use is one reason why data on the internet is also developing that fast. Currently, more than 3 billion people use the internet and the majority is also registered with social media services such as Facebook or Twitter. While processing this kind of data by the majority of non-technical users, concepts of End-User Development (EUD) are important. This chapter researches how concepts of EUD might be applied to handle social big data. Based on foundations and an empirical pre-study, we explore how EUD can support the gathering and assessment process of social media. In this context, we investigate how end-users can articulate their personal quality criteria appropriately and how the selection of relevant data can be supported by EUD approaches. We present a tailorable social media gathering service and quality assessment service for social media content, which has been implemented and integrated into an application for both volunteers and the emergency services.

Keywords Social media · information quality · tailoring · End-User Development · emergencies

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1 Introduction

The amount of data has experienced exponential growth – data generation has been estimated at 2.5 Exabytes (=2,500,000 Terabytes) per day. The sources are manifold and include not only technical sensors, but also social sensors, such as posts to social media such as Facebook or Twitter. To handle this big data, new applications, frameworks, and methodologies arose that allow efficient data mining and information fusion from social media and new applications and frameworks (Bello-Orgaz, Jung, & Camacho, 2016). Usually, the data is called user-generated content, which is according to the definition of the Organization for Economic Co-operation and Development (OECD) (2007), "content that has been made publicly available via the internet".

Not only in daily life but also in recent emergencies, such as the 2012 hurricane Sandy or the 2013 European floods, both the people affected and volunteers alike used social media to communicate with each other and to coordinate private relief activities (Kaufhold & Reuter, 2016). Since the involvement of citizens is, still, mostly uncoordinated and the content is therefore not necessarily created in a structured way, a vast amount of resulting data has to be analyzed. Appropriate methods of valuation are essential for the analysis, whereby a consistent evaluation of the quality of information can be complex (Friberg, Prödel, & Koch, 2010). Especially in cases where a selection, whether by emergency managers or citizen volunteers, has to be made from a variety of information sources and formats under time-critical constraints, it is helpful if the evaluation can be simplified by applying situationally relevant quality criteria. Thus, our research question is how the concepts of End-User Development (EUD) can be applied to support individuals in extracting relevant social media information in the extraordinary and unique settings of emergencies.

This chapter explores the challenges arising from the integration of citizen-generated content and the analysis of information from social media focusing on EUD. Based on a review of related work in big data analysis, social media and EUD (Sect. 2), we present a design case study (Wulf, Müller, Pipek, Randall, & Rohde, 2011, 2015) on social media use in emergencies and its assessment by the tailorable weighting of information quality criteria. Accordingly, an empirical study on the use of citizen-generated content and social media by emergency services and the challenges, focusing on individual and dynamic quality assessments of social media data, informed the implementation of tools for platform-independent social media gathering (Social Media API) and quality assessment (Social-QAS) (Sect. 3). Furthermore, we have prototypically integrated and evaluated Social-QAS in two reference applications (Sect. 4). Finally, we draw conclusions (Sect. 5).

2 Big Data, Social Media and End-User Development

2.1 Big Data, Social Media and Data Analysis

Although – or because – big data is a buzzword, there is no unified definition of the term big data across various origins (Ward & Barker, 2013). According to the

Gartner IT Glossary, big data is "high-volume, high-velocity and high-variety in formation assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making." Dijcks (2012) distinguishes between different types of data: traditional enterprise data, machine-generated/ sensor data and finally social data, which are also known as *social big data*: it "will be based on the analysis of vast amounts of data that could come from multiple distributed sources but with a strong focus on social media" (Bello-Orgaz *et al.*, 2016). Reviewing current literature, Olshannikova, Olsson, Huhtamäki, and Kärkkäinen (2017) contribute with the definition of social big data as "any high-volume, high-velocity, high-variety and/or highly semantic data that is generated from technology-mediated social interactions and actions in digital realm, and which can be collected and analyzed to model social interactions and behavior." Ward and Barker (2013) explicitly research for a definition of big data and suggest that it: "is a term describing the storage and analysis of large and/or complex data sets using a series of techniques including, but not limited to: NoSQL, MapReduce and machine learning."

Ganis and Kohirkar (2012) consider that most big data is from social media: "Where is all of this big data coming from? It's produced within the many social media applications by a wide variety of sources (people, companies, advertisers, etc.)." Additionally, Bassett (2015) outlines that the existence of social media as big data was underplayed in the past, and, to bridge the gap to the domain of emergency management, Watson, Finn, and Wadhwa (2017) exemplify promising benefits of big data to support situational awareness and decision making especially before and during emergencies.

Data from social media contains complex dependencies and relationships within itself and this, combined with its – not to mention the characteristics of crises and emergencies – heterogeneous nature and imposes strong limitations on the data models that can be used as well as on the scope of information that can be discovered. In the case of current social media, the amount of data is increasing steadily as the data set is constantly supplemented. Data analysis or mining in the context of social media must continuously transform raw social media data into a processable form by selectively using specific characteristics needed for the upcoming analysis process. In the following, we will specify characteristics for the analysis process.

Big Data Paradox: Social media data has a huge amount of records consisting of different data types, like profiles, posts, groups, relationships and other. Therefore, enormous computing and storage capacities are required to process the data (Batrinca & Treleaven, 2014). However, little data exists for individuals, and conventional data mining techniques do not process relationships between profiles.

Obtaining Sufficient Samples: A wide range of data is accessible so that trends, indicators and patterns can be detected based on statistical information (Zafarani, Abbasi, & Liu, 2014). However, collecting data from social media has several limitations. In many cases one gets only a limited amount of data in a restricted period of time (Reuter & Scholl, 2014).

Context and User Dependency: A large part of data from social media is generated and consumed by users and, from the interactions between different actors and the environment, new metadata such as time, location, groups, hashtags and other variables arise. When analyzing data it is important to mention that the data that is being processed originates from a variety of sources (e.g. third-party applications) which have their own use context and purpose (Mislove *et al.*, 2007).

Structured and Unstructured Data: Profile data, the number of likes or retweets are structured data and can easily be compared with each other. In contrast, user-generated text is usually in an unstructured form and varies in quality and quantity (Stieglitz, Dang-Xuan, Bruns, & Neuberger, 2014). This is a challenge because data mining requires the identification of *high-quality* information in the large data sets (Agichtein, Castillo, Donato, Gionis, & Mishne, 2008).

Importance of Metadata: Metadata represent an essential part of the social media's information content. They provide the interaction context of users such as a specification of time and location. Because a large set of metadata is available in almost any situation, it may be possible to draw conclusions on the user intention and situation. The in-situ context influences user behavior significantly and is formed by activities, time, place and conversations of the respective user (Church & Oliver, 2011).

Historicity of Data: The historicity of data can be represented not only by the data and metadata itself but also through the interactions between social media. A snapshot can be created in the virtual space of social media including all dependencies. Here it is vital that the collected data is stored persistently because the access to data from social media such as Twitter is volatile, particularly at high-traffic events such as crises.

Type of content: Social media is strongly characterized by the use of images, videos and sounds and by text comments and annotations from users and therefore important contextual information may be present. Hence, data mining of social media usually includes natural language processing (NLP). A major problem with NLP on social media is non-standard language (Ritter, Clark, Mausam, & Etzioni, 2011; Xu, Ritter, & Grishman, 2013). Social media reports frequently contain non-standard grammar (punctuation, capitalization, syntax) and vocabulary (including non-standard spelling) (Eisenstein, 2013).

2.2 The End-User Development Perspective in Data Analysis

Referring to situation assessment during emergencies, it is important to have information available at the right time, the right place and in the right format (Ley, Pipek, Reuter, & Wiedenhoefer, 2012). Endsley (1995) makes a distinction between *situation awareness* as a "state of knowledge" and *situation assessment* as the "process of achieving, acquiring, or maintaining" that knowledge; he defines information gathering as a selection procedure which results in the construction of a mental model pursuant to individual goals. Since several emergencies are extraordinary and time-critical, they require a demand for unpredictable information. It is therefore essential to have instantaneous access to as many sources as possible. Still, it is not easy to dispose of all the necessary information (Turoff, Chumer, van de Walle, & Yao, 2004). Simultaneously, it is very important to prevent a possible information overload so that the decision making is not affected (Hiltz & Plotnick, 2013).

In crisis management, situation assessment and decision making are supported by information systems (van de Walle & Turoff, 2008). Of course, it can come to difficulties, particularly when dealing with seldom used technologies within emergencies and while assessing social media. Adjustments of these technologies and especially of the considered information are essential and play a big role at 'use-time' (Fischer & Scharff, 2000; Pipek & Wulf, 2009; Stevens, Pipek, & Wulf, 2009).

EUD supports flexible adjustments by making it possible for end-users to tailor and rearrange information systems independently (Lieberman, Paterno, & Wulf, 2006). EUD can be defined as all "methods, techniques, and tools that allow users of software systems, who are acting as non-professional software developers, at some point to create modify or extend a software artefact" (Lieberman *et al.*, 2006). One essential part of EUD, with regard to the change of a "stable" aspect of an artefact, is adapting (Henderson & Kyng, 1991). Nonetheless, for some people it is "tailoring," for others it is "use." An essential part of software with regard to its establishment in practice definitely is tailorability. EUD uses mashups to combine services or information from various sources (Cappiello, Daniel, Matera, Picozzi, & Weiss, 2011). The metaphor of a "bazaar" has therefore been used (Doerner, Draxler, Pipek, & Wulf, 2009). While component-based architectures in software engineering enable tailorable systems (Won, Stiemerling, & Wulf, 2006), intuitive notions as well as interaction designs are needed to support end-user articulations (Hess, Reuter, Pipek, & Wulf, 2012). Pipek (2005) argues that tailoring might lead towards appropriation support to support the users.

2.3 Existing Approaches in EUD and Emergency Management

There are existing approaches and models (Costabile, Member, Fogli, Mussio, & Piccinno, 2007; Doll & Torkzadeh, 1988; Grammel, 2009) to deal with data analysis using EUD: Wong and Hong (2007) argue that there is "a tremendous amount of web content available today, but it is not always in a form that supports end-users' needs." Addressing this, their EUD tool enables end-users to create mashups that re-purpose and combine existing web content and service. In the domain of social networks, Heer and Boyd (2005) present a case study of the design of Vizster, an interactive visualization system for end-user exploration of online social networks. Resulting techniques include connectivity, highlighting and linkage views for viewing network context, X-ray mode and profile search for exploring member profile data, and visualization of inferred community structures. Coutaz and Crowley (2016) present their "lived-with" experience with an EUD prototype deployed at their home.

Considering the domain of visual programming, Borges and Macías (2010) present a visual language and a functional prototype, called VISQUE, providing an easy-to-use mechanism to create SQL queries for non-programmer professionals, such as engineers, scientists and freelancers. With VISQUE the users can build the queries through a web-based visual interface to explore and analyze data without the need of SQL skills. Ardito *et al.* (2014) conducted a study to identify end-user requirements for accessing and customizing web-services and APIs. Based on their findings, the authors present a prototype, which enables people without programming skills to create a dashboard of widgets. With the help of a wizard the users can create a widget to combine data from different services and APIs and choose a visualization format. In addition, FaceMashup (Massa & Spano, 2015) is an EUD environment that "empowers social network users, supporting them in creating their own procedures for inspecting and controlling their data."

Taking the case of emergency management, where social media is used for about 15 years (Reuter & Kaufhold, 2017), in addition to information that is provided automatically (meteorological data, water levels, etc.), there are two other kinds of information sources provided by people: emergency services in the field from whom information can be requested (Ludwig, Reuter, & Pipek, 2013) and other individuals and organizations not actively dealing with the emergency. In the case of a house coal for example, the (target) number of residents can be requested from the registration office, but the estimation of the fire's size and of the (actual) number of affected people can only be performed on-site. Unlike sensor data, information provided by citizens is not always objective. Sometimes citizen-generated content is accurate – illustrated at a comparison of Wikipedia and Britannica encyclopedia articles (Giles, 2005). In some cases, however, the subjectivity of citizen-provided reports can generate some sort of vigilantism (Rizza, Pereira, & Curvelo, 2013). Additionally, the misinterpretation of a situation – whether deliberate or not – can lead to potential misinformation; this can result from the reporter paying too little attention to some aspects of the situation or from an incorrect representation of the facts (Thomson, Ito, Suda, & Lin, 2012). However, some information cannot be obtained from other sources (Zagel, 2012). This subjectivity makes data analysis rather complex.

There are approaches concerning the selection and use of data from social media; these, however, do not support a complete quality assessment (Reuter, Ludwig, Ritzkatis, & Pipek, 2015): *Twitcident* (Terpstra, Vries, de Stronkman & Paradies, 2012) allows the user to select tweets by keywords, message types or users and display them on a map. Nevertheless, quality assessment based on meta-information such as the time of creation is not possible. *Alert.io*[1] offers individual trainable tonality analyses and thus first approaches to the integration of machine learning in the form of a learning process to be carried out by the end-user. *HootSuite*[2] emphasizes the design of the analysis by adapting and extending software artifacts. *Tweet4act* (Chowdhury, Amer-Yahia, Castillo, Imran, & Asghar, 2013) enables the tracing and classification of information on Twitter

[1] https://mention.com/en/

[2] www.hootsuite.com

by matching every Tweet against an emergency-specific dictionary to classify them into emergency periods. With *TwitInfo* (Marcus *et al*., 2011) information concerning a specific event can be collected, classified and visualized graphically including additional information about the (not adaptable) quality of the actual information. *Netvizz* is a "data collection and extraction application that allows researchers to export data in standard file formats from different sections of the Facebook social networking service" (Rieder, 2013) to allow quantitative and qualitative research in the application, mainly based on pre-defined categories. *Ushahidi* (McClendon & Robinson, 2012) enables citizens to exchange information. Additionally, emergency services can get access to the information. The direct communication and the spread of unfiltered information can cause an information overload, which forces the user to evaluate the information manually according to its quality.

To sum up, one can say that many studies and approaches about citizen-generated content exist, but concerning EUD in quality assessment of social big data, they are missing a tailorable tool for assessing social media information.

3 EUD in Social Big Data Gathering and Assessment

Based on the results of our literature review, an empirical pre-study and further analysis, we developed two tailorable services processing social media content. First, this section summarizes the key findings of the pre-study. Second, it introduces the "Social Media API" (SMA), which allows end-users to gather, process, store and re-access social media content and, third, it serves as a foundation of the "Social Quality Assessment Service" (Social-QAS) that facilitates the assessment of social media content by the tailorable weighting of information quality criteria.

3.1 Pre-Study: Social Media Assessment by Emergency Services

To gain a deeper understanding of the impact of citizen-generated content in social media on emergency services, we analyzed the data from a previous empirical study on the work practices of the emergency services (focus on fire departments and police) in two different regions of Germany. The results of this pre-study have already been published (Reuter *et al*., 2015; Reuter & Ritzkatis, 2014) and we aggregate the main results within this chapter.

The question: "Who is going to evaluate this now […] and is it really going to help us to assess the situation?" (I03) often appears in emergency situations. The sheer amount of citizen-generated content makes its use especially difficult: "Above all, 290 [messages] of 300 are trash. You can only get something from ten reports" (I02). The mass of information quickly raises the problem of how to handle it: "You have to read them all. Of course, it would be helpful if there was a preselection" (I02).

For this reason, automatic selection is recommendable: "It would be nice if there was a selection that separates the important from the unimportant" (I03). Nevertheless, information has to appear in a certain quantity to render it trustworthy for the emergency services: "It's a problem if I only have one source. It is certainly more reliable to have five sources than just one" (I15). External sources are especially susceptible to providing misinformation (I14, I15) and have to be verified (I15) because of this: You "have to be careful with the content because it does not always reflect reality" (I14) – "In such cases it becomes obvious that someone is trying to lead us up the garden path […] and we have to evaluate the information for ourselves" (I02). In these cases, misinformation is not always intended; potentially it can result from the subjective perception of the situation, which can appear very different to a neutral observer. In conclusion, the use of citizen-generated content from social media fails because of the need for assessment by the emergency services: "There is simply a bottleneck which we cannot overcome" (I02).

Overall it is noticeable that "the more precise information, the more relevant it is" (I02). This kind of precision can be achieved by assessment. There has to be some form of guarantee that the selected information is useful for the emergency services (I02, I03). Global selection also proves to be difficult because "it does not seem possible to me that we can select in advance what is important for the section leader. He might need the same information as the chief of operations – or not" (IM01). This therefore necessitates the possibility of flexible assessment criteria (I19). Due to the time-critical aspect of emergency situations, it is imperative that the personal selection of information be supported since every member of the emergency team has to decide "relatively quickly between the important and the unimportant" (I19).

The first impression has to include some amount of significance and has to be helpful for the situation assessment: "If someone takes a photo of a window, I know that he was really there. But where is that window exactly?" (I16). This shows that pictures need additional meta-information just as normal textual information does. Pictures can be especially useful for assessing crowds of people at huge events: "If someone had noticed that a relevant number of people were congregating in certain areas, you could have closed the entrance immediately with the help of the security" (I06). Even though this entails gathering a lot of information, "most people […] do not [know] what counts and what kind of information we need" (I02). There is therefore a risk that the information has no additional value and cannot be used in the emergency situation: "I do not believe that someone who is not connected in some way to the police or the fire service is capable of providing useful information in these stress situations" (I02). It is unusual for an untrained citizen to have knowledge of this sort. "You have to be very careful with this kind of information" (I14).

Ultimately, it is a member of the emergency team who has to assume responsibility for actions and who also has to decide if the information is utilized or not (I15). Misinterpretation is possible both by humans and through computer support.

It does not matter how good the assessment mechanism is: there "remains a risk and the person in charge has to bear it, it is as simple as that" (I15). That is the reason why the emergency services are so careful when using external information. In conclusion, it can be stated that "assessing information, assessing it correctly and dealing with it […] is a challenging task" (I15). Every single piece of information is an input to evaluate the whole situation: "You add more and more flesh to the skeleton you start off with so that in the end, you have a picture; not just a silhouette but a whole figure and any actions executed by the police are mostly based on that figure" (I16). Situation assessment influences the actions which in return influence the situation.

3.2 EUD in Social Big Data Gathering

Before assessing any social media data, ways of gathering relevant information must be established with the flexibility to support EUD applications, such as Social-QAS (Sect. 3.3). Thus, the "Social Media API" (SMA) allows its user to gather, process, store and re-query social media data (Reuter *et al*., 2016). Although it was developed as enabling technology for emergency management applications initially, its implementation enables the support of a variety of use cases in different fields of application, e.g. it allows its users to examine the impact of a product image within the field of market research (Reuter *et al*., 2016). Because it serves as the foundation of Social-QAS, we discuss its key challenges and concepts, implementation and tailorability in the following sections.

3.2.1 Key Challenges and Concept

To enable access to social big data and allow subsequent analysis, our first step was to specify a service for gathering and processing social media content. During the analysis, we agreed upon the following requirements, which are partly derived from Sect. 2.2 and enriched with considerations from conceptual and implementation viewpoints.

1. *Multi-Platform Support:* Relevant data during emergencies is spread across different social media services. Furthermore, depending on the participants, different services are used. As a result, it is required that a request allows access to multiple platforms. To obtain sufficient samples and reach most users, a further requirement is therefore to allow the gathering and posting of citizen-generated information spread widely on social media services.
2. *Extensible and Unified Data Format:* Both the multi-platform support and cross-platform usage imply the requirement of a standardized data format that is capable of mapping the diverse attributes, whether structured or unstructured content, of different social media content and providers. The possible emergence or relevance

of new attributes, which define the activity's and users' context, requires the extensibility of the data format.

3. *Gathering Service*: The historicity and volatility of social media content require the continuous capturing of citizen-generated information in nearly real time in order to accumulate a rich representation and allow post-analysis of the emergency. We therefore need to specify a service that constantly gathers the data over a defined period of time.
4. *Integration of Rich Metadata:* Literature not only identifies textual content but also images, sounds and videos as important information carriers during emergencies. Furthermore, location- and time-based information are very important metadata, because they provide interesting context-data to the information itself. Therefore, a requirement is that location- and time-based data are provided with the information itself.
5. *Flexible Query of Data:* Not only in the acquisition but also in the retrieval of already gathered data from database, sufficient filtering parameters are required to enable situated data analysis and provide a high degree of flexibility to support tailorable client applications or services.

3.2.2 Implementation of a Cross-Platform Social Media API

To gather and process social media content, we developed a REST web service called "Social Media API". With *gathering* we refer to the ability to uniquely or continuously collect social media activities (e.g. messages, photos, videos) from different platforms (Facebook, Google+, Instagram, Twitter and YouTube) in a unified manner using multiple search or filter criteria. *Processing* means that the API is capable of accessing, disseminating, enriching, manipulating and storing social media activities. The SMA is realized as a service following the paradigm of a web-based, service-oriented architecture (SOA). It is a Java Tomcat application using the Jersey Framework for REST services and the MongoDB database for document-oriented data management. Several libraries facilitate the integration of social media platform APIs such as Facebook Graph API or Twitter Search API. All gathered social media entities are processed and stored according to the ActivityStreams 2.0 specification (World Wide Web Consortium, 2016) in JSON format (JavaScript Object Notation). The SMA uses service interfaces, allowing a standardized implementation of further social media if their APIs provide suitable access to their data.

It comprises four main services, each providing a multitude of service functions: The *Gathering Service* comprises endpoints for gathering and loading social media activities. The main components are the Search service, enabling onetime search requests, and Crawl Service, which continuously queries new social media activities across a specified timeframe. Using the *Enrichment Service*, gathered social media activities are enriched with further computed and valuable metadata. Moreover, the *Dissemination Service* is a unified endpoint for publishing, replying

Table 1 Excerpt of source-based data attributes

Attributes	Facebook	Google+	Instagram	Twitter	YouTube
Date, Time	✓	✓	✓	✓	✓
Sender	✓	✓	✓	✓	✓
Age	✗	✓ (Age range)	✗	✗	✓ (Age range)
Location	✓	✓	✗	✓	✓
Real name	✓	✓	✓	✓	✓
Title	✗	✓	✓ (Caption)	✗	✓
Tags	✗	✗	✓	✗	✓
Replies	✓ (Comments)	✓ (Replies)	✓ (Comments)	✗	✓ (Google+)
Content	✓	✓	✓(Caption)	✓	✓ (Description)
Mentions	✓	✗	✗	✓	✗
Views	✗	✗	✗	✗	✓
Likes	✓ (Likes)	✓ (Plusoners)	✓ (Likes)	✗	✓ (Likes)
Dislikes	✗	✗	✗	✗	✓ (Dislikes)
Retweets	✗	✗	✗	✓	✗
Shares	✓	✓ (Resharers)	✗	✗	✗

to or deleting (multiple) social media activities (simultaneously). The *Data Service* provides structured database management operations. For instance, it encapsulates remote MongoDB operations to insert, load, update or delete data.

While working with SMA, based on the available type of social media, different data attributes are accessible (Table 1). The implementation or support of different attributes depends on the individual policies of social media providers. For instance, while it is certainly possible to add the age to a Facebook user account, the Facebook Graph API, which provides applications and developers access to Facebook data, does not allow retrieving the age of Facebook users. On the one hand, the flexibility of the document-oriented approach allows the social media users to store distinct structured documents with different numbers of attributes. Using ActivityStreams 2.0, the majority of attributes is stored according to a standardized specification. On the other hand, in terms of divergent metadata, the comparability and therefore analysis of social media activities is restricted. Therefore, it is not possible to apply all quality assessment methods in the same way. Also, because not all attributes can be mapped to the ActivityStreams 2.0 specification, we needed to add a custom property mapping our special metadata.

Furthermore, as already discussed in Sect. 2.2, during implementation some technical and business-oriented limitations became apparent (Reuter & Scholl, 2014): Quota limits restricted the access to social media data and most data is publicly available for a limited time only. Consequently, especially with non-expensive approaches, it is possible to capture and process merely small portions of the high-volume social data. Concerning the historicity of data, another challenge arose: As social media activities are likely to be updated regarding, for instance, the number of comments, number of likes or the content itself, inconsistencies between the online data and the stored data occur.

Besides the available data, there are two kinds of additional valuable data: First, some data is only available in certain social media, but computable for others. For instance, embedded hyperlinks, mentions or tags can be extracted from activities to get a comparable amount of data from each social media. Second, some required data regarding the assessment of quality is not available in any social media. Therefore, the SMA computes classification attributes (negative sentiment, positive sentiment, emoticon conversion, slang conversion), content attributes (number of characters, number of words, average length of words, words-to-sentences ratio, number of punctuation signs, number of syllables per word, entropy) and metadata attributes (hyperlinks, language, location, media files, tags) manually.

3.2.3 Tailorability: Filtering Data during Gathering and Post-Processing

A key challenge of a tailorable SMA is the provision of suitable service endpoints with sufficient filter parameters that behave consistently over heterogeneous social media. Table 2 summarizes our implemented filter parameters of the *Crawl* and *Search* services. The flexibility of filtering depends on the providing APIs to a certain degree: While some social media APIs support location (Twitter, YouTube) and temporal (Facebook, Twitter, YouTube) filtering, it has to be realized manually for the other ones. However, given the quota limitations of social media, manual filtering always implies the prior gathering of results that do not match the filter criteria and is therefore less efficient than using native filter parameters. Another issue is the keyword parameter, because social media process keywords differently and support various types and notations of logical query operators (e.g. and, or, not, phrases). Here, the need for a unified query language and layer becomes apparent, which translates the unified query parameters into the platform-specific parameters.

Table 2 Parameters for social media search

Parameter	Type	Description
keyword	String	Required. The search term.
platforms	String	Required. A csv-list (Facebook, Google+, Instagram, Twitter, YouTube).
since	Long	Search Service. Lower bound of the searched timeframe (Unix time).
until	Long	Search Service. Upper bound of the searched timeframe (Unix time).
start	String	Crawl Service. Starting point of the crawl job (Unix time, default: now).
end	String	Crawl Service. Termination of the crawl job (Unix time, default: null).
latitude	Double	Latitude for geo search (decimal degree).
longitude	Double	Longitude for geo search (decimal degree).
radius	Double	Radius for geo search (km).

After data is gathered and stored into the database, the access becomes an important factor to allow loading and post-processing of data. Given the job id, social media activities of past crawl or search jobs can be loaded and filtered by count (amount of data returned) and offset (position of the first result to be returned) parameters. Alternatively, a list of activity ids allows loading the desired social media activities explicitly. However, to enhance the tailorability of SMA in order to increase the flexibility for consuming client applications, the implementation of additional parameters is planned, e.g. keyword, platform, location and time-based filtering, or language. In this case, the efficiency and flexibility of filtering is dependent on the underlying database management solution. Based on the SMA, the application Social Data Service has been implemented, which aims to allow the generation of data sets (Reuter *et al*., 2016).

3.3 EUD in Social Big Data Assessment

As our literature review suggests, citizens may provide emergency-relevant information via social media, but challenges regarding the quality of information, especially under time-critical constraints, persist. Moreover, our pre-study and further literature report on the relevance of quality-relevant metadata during emergencies, e.g., author reputation, location and time. That is why the "Social Quality Assessment Service" (Social-QAS) aims on facilitating the assessment of social media content by the tailorable weighting of information quality criteria. This section refers to content that has already been published in a research paper (Reuter *et al*., 2015), but is required to introduce the application's concept, depict its evaluation and elaborate the chapter's discussion.

3.3.1 Key Challenges and Concept

Our literature review and the empirical study have proved that the quality assessment of mass information and extractions of relevant information is a great challenge. Of course, various circumstances call for various assessment methods. That is why the possibility to combine these methods could help to improve the quality assessment practice (Ludwig, Reuter, & Pipek, 2015). Our concept allows the assessment of (social media) content with 15 assessment methods (Table 3), which are subdivided into four categories pursuant to their technical execution:

1. The *rating of metadata* consists of five assessment methods (author frequency, temporal proximity, local proximity, number of followers/likes, amount of metadata), in which either the discrepancy from the entered research criteria or the absolute appearance is defined by rating the difference.

2. The *rating based on the content* allocates two assessment methods (frequency of search keyword, stop words), which identify the occurrence of particular words (or their synonyms) from a list.
3. The *rating based on the classification of the message* supplies six assessment methods (sentiment analysis, fear factor, happiness factor, named entity recognition, emoticon, slang), which determine the occurrence of words applying word lists. Thus, information is sorted in different categories.
4. The *rating based on scientific methods* provides two assessment methods (Shannon Information Theory (Entropy), term frequency, inverse document frequency).

Table 3 Implemented quality assessment methods (Reuter *et al.*, 2015)

#	Method/Criterion	Description
A	**Assessment of metadata**	
1	Author frequency (Reputation)	Number of messages from the same author in the message set. The level of knowledge about the situation depends on the number of messages an author writes.
2	Temporal proximity (Currency)	Temporal proximity of the messages to the center of the search period. The information's importance depends on the proximity to the search moment.
3	Local proximity	Distance between the place where the message was created and the incident's place. Short distance stands for higher probability that the message is about the current disaster.
4	Followers/likes (Credibility)	It is assumed that credibility and the number of likes/followers conferred on a particular message/author grow proportionally.
5	Metadata (pictures/links)	It can be helpful to complement textual information with an image or other media material. With this assessment criterion the amount of data can be ascertained.
B	**Assessment based on content**	
6	Frequency of search keyword (Interpretability)	The keyword indicates the issue; it does not appear randomly in the message. The message is also searched for synonyms.
7	Stop words	Stop words such as "so" do not allocate any information as long as they do not increase the validity of the message. That is why the decrease of stop words increases message utility.
C	**Assessment based on classification of the message**	
8	Sentiment analysis (Impartiality)	The message is analysed concerning its emotional property. Emotional content, especially fear, can falsify the meaning.
9	Negative sentiment (Fear Factor)	Words that are related to the subject of fear are identified in the message; The Fear Factor determines the degree of expression of fear.
10	Positive sentiment (Happiness Factor)	Words that are related to the subject of joy are identified in the message; The Happiness Factor determines the degree of expression of joy.

(continued)

Table 3 (continued)

#	Method/Criterion	Description
11	Named entity recognition (NER)	Number of entities in the message. The relation between the information's content and another information source is indicated by an entity. The more entities, the higher the information quality.
12	Emoticon conversion	The possibility to make a message readable for different audiences by converting emoticons into language expressions.
13	Slang conversion	The possibility to make a message readable for different audiences by converting slang words into standard language.
D	**Assessment based on scientific methods**	
14	tf-Idf (term frequency – Inverse document frequency)	The appearance of individual search keywords (term frequency) with the frequency of appearance in all messages (inverse document frequency). Helpful if more than one single keyword is used since the occurrence of a fragment of the whole term, which only appears frequently in few documents, is weighted higher than the occurrence of a fragment, which appears in many documents but less frequently. $tf(t,d) = \frac{f(t,d)}{\max\{f(w,d) : w \in d\}}$
15	Shannon information theory (Entropy)	Shannon theory of information. The average amount of information contained in each message received. $I(p_x) = \log_a\left(\frac{1}{p_x}\right) = -\log_a(p_x)$

A subjective quality of information can be defined if the (non-specified) end-user of an application based on Social-QAS has the option to select various assessment methods. In addition to that, this selection and the classification enable further use of the quality assessment service within several scenarios.Generally speaking: Initially, the individual messages are analyzed absolutely regarding the specific method. Then the score of each message is determined. The message with the highest absolute score is rated with "1.0" (100%), the one with the lowest absolute score gets a "0.0" (0%). After that, an overall score is received by weighting the single scores. Further, to address both the requirements of querying multiple sources and enabling the subjectivity of quality assessment, the individual user gets the option to choose the desired social media sources.

3.3.2 Implementation of Social-QAS

The actual quality assessment service is conceived as a service that follows the paradigms of a web-based, service-oriented architecture (SOA). The use of such architecture enables a central rating and makes it possible to integrate it into

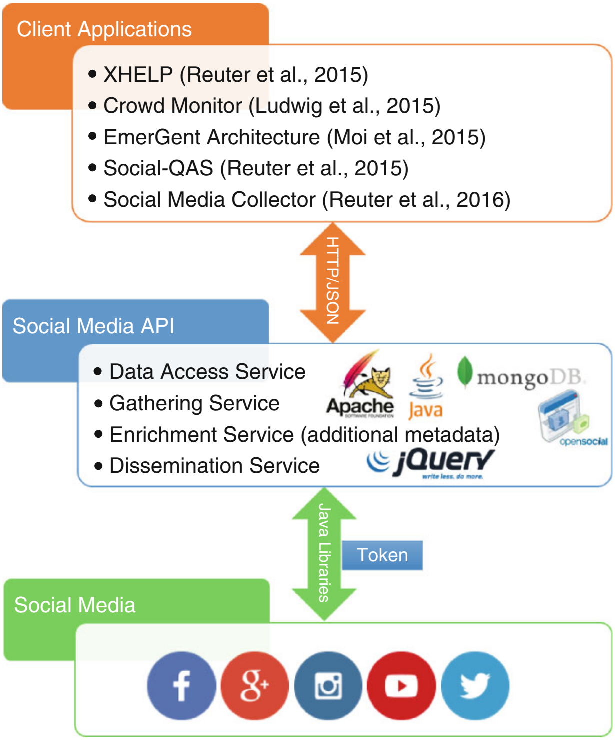

Fig. 1 Overall architecture of client applications such as Social-QAS that use the Social Media API to access different social media over a unified interface

various applications by allocating assessment results with the original data in JSON format (JavaScript Object Notation). The interface is called "via HTTP-GET" and the URL is complemented with query parameters, which are separated by "&". The client's processing load is supposed to decrease by the server-sided information rating. Via SMA, as illustrated in Fig. 1, the APIs of the particular social network providers are used to extract data from the social networks (Reuter & Scholl, 2014). In this context, especially Twitter and Facebook appear to be essential APIs: these APIs allocate many possibilities to both export and import data concerning the related social network.

To collect the semantic content of the message, one can apply a Named Entity Recognizer (NER) (No.11). The Stanford NER[3] is available as Java library for free. The corpus "deWac generalized classifier" was used for the NER because it works exceptionally well with German messages from social networks. The library Classifier4J[4] was utilized for the creation of a Bayes Classifier (No. 8) that enables

[3]http://nlp.stanford.edu/software/CRF-NER.shtml

[4]http://classifier4j.sourceforge.net/

the division of information into various categories since it can be skilled with lists of words. The list of synonyms (No. 6) was created by applying the Open Thesaurus web services[5]. One requires a geographical reference in order to visualize the information; however, in many cases the information does not contain any geographical metadata so that it has to be geocoded. The Gisgraphy Geocoder[6] is usable by web services and geocodes location information for any map material. To accelerate the process, there is a list of locations which have already been geolocated and whereof the coordinates can be defined without geolocation. GSON[7] is used for conversion since it allocates an automatic generation of a JSON object based on a java object model.

3.3.3 Tailorability: Integration of Social-QAS into a Web Application

To test the implemented service, we have integrated Social-QAS into a web-based application specified for emergency services as well as a Facebook-app "XHELP" to support volunteer moderators during disasters. In the following we will outline prototypically the implementation into XHELP, which allows information to be both acquired and distributed cross-media and cross-channel (Reuter *et al*., 2015).

Inside this application, it is possible to search for information by using different quality parameters in order to perform a quality assessment (Fig. 2). For this, the user chooses an assessment criterion with the help of a slider. Integrating the user in this way meets the requirements for a flexible and manageable quality assessment, as identified in the pre-study.

The search results are presented in a table and on a visual situation map. An abundance of meta-information such as the degree of completion of particular methods is illustrated as tool tips in the table. Simultaneously, the situation map makes it possible to directly determine the proximity of the information to the search location (Fig. 3). Thus, the user may select one mode in which s/he wishes to view the results; this method improves the flexibility of the application. This user interface is only one of several possibilities how Social-QAS can be applied.

To sum up, Social-QAS unifies the following functionalities (Reuter *et al*., 2015): Assessment takes place on the basis of metadata as well as on the basis of content. The user decides upon the weighting of each method. When all the assessments of every method have been combined, the subjective quality of a message develops. Social-QAS is very flexible since it makes it possible to expand the sources and assessment methods very easily. Due to the SOA-based implementation it is possible to integrate it and use it in other applications.

[5]http://www.openthesaurus.de/

[6]http://www.gisgraphy.com/

[7]https://code.google.com/p/google-gson/

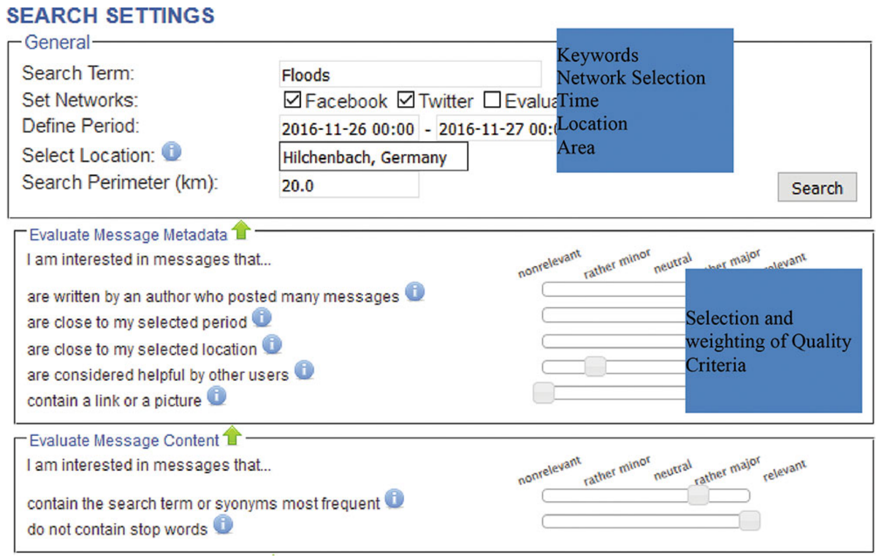

Fig. 2 Quality Assessment Service integrated into an application

Fig. 3 Search results (left), degree of completion (lower left) and map presentation (right)

4 Evaluation: Tailorable Quality Assessment

To answer the question how tailorable assessment services can be provided to users properly and how users can articulate the assessment criteria appropriately, Social-QAS has been evaluated by potential end-users.

4.1 Methodology

The philosophy behind the evaluation process was derived from the notion of "situated evaluation" (Twidale, Randall, & Bentley, 1994), in which qualitative methods are applied to draw conclusions about real-world use of a technology using domain experts. The purpose is to derive subjective views from experts about how useful and relevant the technology might be in use instead of measuring the relationship between evaluation goals and outcomes.

In order to obtain as much knowledge as possible about the potential of the service and the quality assessment of citizen-generated information, the evaluation consisted of a scenario-based walkthrough with a subsequent semi-structured interview. The participants were directed to tell us their thoughts according to the think-aloud protocol (Nielsen, 1993), enabling underlying reasoning and subjective impressions to be gathered. Each evaluation took about 45 minutes and was performed with 20 people in all (E1-E20). While, besides general knowledge on the use of social media, 15 participants were skilled technology experts, four participants had been initiators and moderators of Facebook pages during the European floods in 2013, and one was member of a voluntary fire brigade. Any participant who was not a volunteer using social media very actively had a role definition introduced to them, enabling them to place themselves in the position of a volunteer.

The scenario was supposed to show the participants a disaster's character and what volunteers do in crises (unless the participant was already an experienced volunteer). They worked on the basis of hurricane Xaver, which destroyed big parts of the German coast in December 2013. The participants got a general role description in order to know how to deal with the information demands of affected citizens with the help of Social-QAS embedded in XHELP (see Sect. 3.3.3). After that, the participants had the chance to get to know the application by solving a concrete problem: they were supposed to filter and search specific information about water levels. An evaluation mode was added to the search function for this purpose. The results of the search were assumed beforehand on preselected data records in order to be sure that the participants' results were comparable. In the following, semi-structured interviews were meant to support reflection on the evaluation process, on handling and the overall application's value. The questions were specialized in overall impressions concerning quality assessment, the advantages and disadvantages of Social-QAS, coverage of information demands, influence on information flow, potential overload and problems of cross-platform information acquisition. The interviews were evaluated and classified systematically. "Open" coding was employed, i.e. distributing data into adequate categories to reflect the issues raised by respondents relying on repeated readings of the data and its grouping into "similar" statements. The most remarkable classifications will be presented in the following.

4.2 Results I: How Much Tailoring? Quality Assessment Criteria

Many users considered the number of assessment criteria to be too high for effective use under the time-critical constraints of emergencies (E09, E07, E19). Nonetheless, the respondents agreed with the opinion that different situations require different assessment criteria (E12, E13, E08); and that a certain adjustment of the criteria to the situation is necessary: "There are many criteria, but I think that this is important, because different questions require different search keywords" (E13). Accordingly, the suggestion was made that the assessment criteria could be adjusted in such a way that allows the goal to be achieved more quickly (E12). Furthermore, other possibilities – for example the opportunity to search for a hyponym (E19) – were requested in addition to the various settings. The evaluation demonstrated that the biggest challenge to be overcome is the identification of criteria of appropriate quality. Although currency was an important criterion for all respondents, only a few understood the meaning of coordinate quality. The explanation of coordinate quality as a measure for the local proximity helped them to understand its meaning. One participant raised the question of the correlation between the author's number of subscribers and his reputation (E4).

4.3 Results II: Broad Information Basis and Information Overload

In order to achieve a situational overview of an emergency setting, users especially regarded the opportunity to consider different information sources simultaneously to be an added value (E19, E15, E18): "Because public networks are used such a lot, it is much better to relate them to each other. That could really help to meet the information need" (E17). The number of sources should be steadily supplemented with further useful sources. What is more, not only social networks but also e.g. news sites should be taken into consideration. Furthermore, the interviewed persons were afraid of being confronted by a flood of information while searching for information in social networks during a large-scale emergency (E16, E19). This fear was soon quelled by sorting the results in Social-QAS. Most users did not want to go through the entire list of search results, but preferred to only look at the first few results on the list. Still it should remain possible for the user to see the additional results at will since some scenarios potentially require an inspection of the additional results.

4.4 Results III: Automatic and Tailorable Quality Assessment Necessary

The quality assessment of information proceeds automatically. Users accept this automatism as they have the possibility to control the assessment and are able to comprehend why something was assessed in a particular way (E08, E11). "As always, when something is evaluated, that does not replace your own opinion" (E10). Yet the general possibility to combine criteria was considered a benefit: "The default settings do not matter. That means if I do nothing, my search results will not change" (E13). "As a consequence, diverse combinations are possible, of course, which seems to me to be helpful" (E07). To counter negative impacts on actions, manual post-processing should be implemented, allowing the correction or recognition of defective entries.

Considering the possibilities and suggestions for improvement shown (E13, E19, E14), there is potential to improve the information flow in emergency situations. This could especially be realized by the classification of emergency situations and a preset of weightings based on this. Crucial temporal and organizational bottlenecks could be avoided by collecting information from local people (real volunteers) or the internet (digital volunteers) (Reuter, Heger, & Pipek, 2013) (E07, E16): "The benefits are that I can find things quickly, […] because it is possible to search specifically for something and that is really displayed on the different platforms, just how I want it. And I can weight very easily using the assessment criteria" (E18).

5 Discussion and Conclusion

From the perspective of EUD, many systems for analyzing social media offer more or less customization possibilities and are aimed at end-users who have little or no technical knowledge. However, the adaptability is largely limited to visualization elements, e.g. in form of a central dashboard. There, the presented figures are prepared in such a way that the end-user can scale and analyze along fixed dimensions. At another level of customization, there are systems such as HootSuite, which provide strong software extensibility by providing their own SDK. Expert users are able to create new functionalities available to all end-users. These extensions do not affect the design of the analysis process, thus, the end-user cannot tailor it to the individual preferences. The system alert.io with the structure of a learning process of tonality analysis shows approaches to such extensibility. An end-user trains this component based on his or her own situation understanding so that the machine learning algorithm can work independently on new data from a certain size of the experience data base.

This article demonstrates how it is possible to combine EUD and social big data. It discusses how situation assessment practices of crisis management actors, namely emergency services (Ludwig *et al.*, 2015) and informal volunteers (Reuter *et al.*, 2015), can be encouraged by tailorable quality assessment of citizen-generated information from social media. At the beginning, the results of an empirical study involving emergency services concerning the use of citizen-generated content and social media within their current work practices are summarized. With the help of literature and empirical findings we identified the need for different quality criteria and applied them on information from social media. We implemented an own Social Media API and a quality assessment service.

We come to three results that extend the current state of the art:

(1) An analysis of dealing with citizen-generated content in emergencies by means of an empirical study, which emphasizes the range and quality assessment of citizen-generated content in emergencies (Reuter & Ritzkatis, 2014).
(2) A concept for a tailorable social media gathering (Sect. 3.2.1) and quality assessment service (Sect. 3.3.1) for social media as well as a running

implementation which is SOA-oriented, tailorable and can be applied in various applications (Reuter *et al.*, 2015, 2016).

(3) A reference implementation of the gathering service (Sect. 3.2.2) as well as quality assessment service (Sect. 3.3.2) inside an existing web-based application for emergency services (Ludwig *et al.*, 2015) and an existing web-app for volunteers (Reuter *et al.*, 2015) (Sect. 3.3.3).

The contribution of this chapter is to show the process from data selection to use from an EUD perspective including pre-study, design, implementation and evaluation in order to generate findings to the field.

To sum up, it is useful to be flexible by tailoring options for source platform selection and quality assessment criteria since situation assessment revealed itself to be very subjective. Consequently, personal feelings, experience and the situation itself influence the information requirement. Our findings turned out to be interesting for other application fields as well. While gathering or analyzing information and implementing information systems to encourage the task, there is always one question that is hard to answer: How can we realize information systems, which enable the automatic selection of relevant data and, simultaneously, grant end-users the option to adapt this automation, thus allowing tailorable quality assessment pursuant to their requirements?

In terms of big data, some restrictions are apparent: Although social media provide high-volume, high-velocity and a high-variety (McAfee & Brynjolfsson, 2012) of social data (Dijcks, 2012), the access is limited allowing client applications such as Social Media API and Social-QAS to merely gather small portions of data (Reuter & Scholl, 2014). Even with continuously gathering new data and filling the database, the volume and velocity of data processing in client applications like those will be small compared to the daily data creation in social media (Kaisler, Armour, Espinosa, & Money, 2013). Therefore, in high-volume scenarios, valuable information according to the user-selected quality criteria may be missed. In future work, it is important to examine how the end-user can be better integrated into the analysis process by applying machine learning to ensure the adaptability and alignment of the analysis of social media in the dynamic context of end-users.

Our work still has some limitations. Not all the criteria that are relevant for quality assessment are included within Social-QAS. Furthermore, according to the context, the number of criteria might overburden the cognitive skills of end-users. It is, therefore, important to define standards and to allow end-users to adapt them, whereby different tailoring power might then require different skills, according to MacLean, Carter, Lövstrand, and Moran (1990); thus local developers may be required (Gantt & Nardi, 1992).

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