Big Data and Multi-platform Social Media Services in Disaster Management

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Contents

Abstract

The use of social media today is not only ubiquitous and an integral part of everyday life but is also increasingly relevant before, during, or after emergencies. Data produced in these contexts, such as situational updates and multimedia content, is disseminated across different social media platforms and can be leveraged by various actors, including emergency services or volunteer communities. However, the dissemination of several thousand or even millions of messages during large-scale emergencies confronts analysts with challenges of

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information quality and overload. Hence, crisis informatics as a research domain seeks to explore and develop systems that support the collection, analysis, and dissemination of valuable social media information in emergencies. This chapter presents the social media API (SMA), which is a multi-platform service for gathering big social data across different social media channels and analyzing the credibility and relevance of collected data by the means of machine learning models. Based on the lessons learned from both the implementation process and user-centered evaluations in multiple emergency settings, this chapter discusses core challenges and potentials of the SMA and similar services, focusing on (1) the multi-platform gathering and management of data, (2) the mitigation of information overload by relevance assessment and message grouping, (3) the assessment of credibility and information quality, and (4) user-centered tailorability and adjustable data operations.

Keywords

Big social data · Social media · Crisis informatics · Information refinement · Multi-platform services

Introduction

As of today, social media are not only well established for a variety of purposes in everyday situations (Robinson et al., 2017) but are also used during natural and man-made crises and conflicts as a valuable source of information (Reuter & Kaufhold, 2018; Riebe et al., 2021). Social media services coupled with smartphone technologies offer a permanent opportunity to create and gather valuable information, such as situation updates, eyewitness reports, multimedia files, or public mood information, anywhere at any time in large quantities. Thus, the multidisciplinary field of crisis informatics has combined knowledge, methods, and theories from computer and social science to investigate the effective usage and development of information and communication technology for the mitigation, preparedness, response, and recovery regarding critical situations (Palen & Anderson, 2016). Even though the emerging *big social data* (Olshannikova et al., 2017) has the potential to enhance emergency services' situational awareness (Vieweg et al., 2010) and establishes new bidirectional communication channels with both citizens and volunteer communities (Kaufhold & Reuter, 2016), the adequate deployment or implementation of *social media analytics* still presents a challenge (Stieglitz et al., 2018). Not only is relevant data scattered across numerous social media platforms (Hughes et al., 2014; Reuter et al., 2015a), but also technical or business-oriented restrictions limit data access (Reuter & Scholl, 2014), and the analysis of data must conform with the data exchange formats used (Reuter et al., 2016b). Furthermore, issues of chaotic use, serious information overload, and low information quality arise during emergencies and thus reduce potential contributions to emergency managers' situational awareness (Kaufhold, 2021; Kaufhold et al., 2019; Plotnick & Hiltz, 2018).

This chapter introduces related work on the challenges and potentials utilizing big social data by the means of social media analytics in the multidisciplinary field of crisis informatics. Based on this, it presents the architecture and development of the social media API (SMA), which is a multi-platform service for the gathering, processing, storage, and querying of social data from Twitter, Facebook, Flickr, Instagram, Reddit, Tumblr, and YouTube. The SMA has been deployed over several years in various application scenarios of the crisis management domain to evaluate its practical applicability, potentials, and limitations. Thus, this chapter continues with a discussion of our experiences and findings with respect to both the gathering of social media data across multiple platforms and their subsequent preparation for analysis. The results highlight that conversion and processing of heterogeneous social data into a unified data format are feasible (specification), although some metadata must be computed for comparative analysis if it is not provided by the source platform (comparability). It is shown how machine learning can be utilized to identify credible and relevant emergency information (classification), even though the context-dependent and highly individual character of information quality must be considered when analyzing social data (interpretability). In order to align tools with end-user objectives, sufficient search options and filter parameters (tailorability) using logical query operators (queryability) are required. Still, our findings show that social media platforms are subject to continuous change. Thus, frequent adjustments of social media tool implementations are required (adjustability).

Related Work

The increasing dissemination of mobile devices and the growing use of social media, such as Facebook or Twitter, led to the emergence of the term of *big social data*, which “is 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” (Olshannikova et al., 2017). In addition to the regular usage of social media platforms, a variety of application programming interfaces (APIs) render the automatic retrieval and processing of large quantities of data feasible. In response, social media analytics has emerged as a novel research field, which is concerned with the process of collecting, analyzing, and interpreting social media data with regard to involved actors, entities, and relationships (Choi et al., 2020; Stieglitz et al., 2014). To achieve these goals, different methods and tools are combined, enhanced, and modified for the analysis of big social data (Fan & Gordon, 2014; Holsapple et al., 2018; Lee, 2018; Stieglitz et al., 2018). Especially against the background of large-scale emergencies that result in the dissemination of vast quantities of messages on social media (Reuter et al., 2019), this research area becomes increasingly important as emergency services are faced with the issues of severe information overload and poor information quality. Information overload can be induced by a number of issues, including personal factors; characteristics and parameters of information, tasks, and processes; organizational design; or particular information technologies

Table 1 Overview of existing mitigation techniques for information overload during emergencies, crises, or disasters

Technique	Description
Keyword search engine	Execution of simple keyword searches or complex searches using Boolean operators such as "AND," "OR," and "NOT," either in embedded web interfaces or by using search APIs (Imran et al., 2015)
Metadata filtering	Filtering of information by different types metadata, e.g., social media platform, language, time, or location, often in combination with search functionalities (Kaufhold et al., 2020b)
Interactive visualizations	Usage of interactive visualizations, e.g., timelines, charts, maps, or word clouds, that enable a reduction of the displayed data to a particular subset using a specific gesture (Onorati et al., 2018)
Message classification	Application of supervised machine learning models for the classification of information in terms of relevancy (Mohanty et al., 2021) or according to humanitarian categories (Alam et al., 2020)
Message clustering	Categorization of similar text documents into groups utilizing similarity metrics and unsupervised machine learning techniques (Bayer et al., 2021; Fahad et al., 2014; Huang et al., 2021)
Information summarization	Use of automated and real-time algorithms based on extraction or abstraction techniques to generate comprehensive information summaries of individual disaster events (Rudra et al., 2018, 2019)

(Eppler & Mengis, 2004; Roetzel, 2019). In light of the characteristics of information and technology, information overload can be defined as "[too much] information presented at a rate too fast for a person to process" (Hiltz & Plotnick, 2013). Research has identified numerous potential consequences of information overload (Bawden & Robinson, 2020), including the risks of getting distracted by data material irrelevant to the current task, as well as of processing and presenting data in an inappropriate way (Keim et al., 2008).

Past research in crisis informatics studied and developed multiple techniques and artifacts for the mitigation of information overload during large-scale emergencies (Table 1). An initial and intuitive step for the identification of relevant (and the exclusion of irrelevant) information is the utilization of *search engines* that enable searches with basic keyword-based or complex Boolean queries. Whereas these are directly accessible to regular users of social media platforms, platform search APIs enable developers the integration of acquired results into more advanced third-party applications (Imran et al., 2015). These types of applications frequently enhance search engines with the option to *filter information* by different types of metadata, including social media platform, language, time, or location (Kaufhold et al., 2020b). Furthermore, *interactive visualizations* (e.g., timelines, charts, maps, or word clouds) facilitate the reduction of the displayed data using specific gestures (Onorati et al., 2018).

Furthermore, machine learning algorithms may offer assistance for the identification of relevant information after data collection. For instance, supervised machine learning techniques are often applied for *message classification* tasks, such as the binary classification of information relevancy for a specific type of emergency (Habdank et al., 2017; Mohanty et al., 2021) or the classification of information according to humanitarian categories, including infrastructure and utilities, donations and volunteering, affected individuals, sympathy and support, caution and advice, other types of useful information, or not applicable (Alam et al., 2020; Burel & Alani, 2018; Pekar et al., 2020). Still, these techniques are often not universally applicable (i.e., designed for specific events), and their performance is dependent on the time-consuming labeling of data as well as the adequate training of models. In contrast, *message clustering* techniques categorize similar messages into groups utilizing similarity metrics and unsupervised machine learning techniques, thus not requiring labeled data for training (Bayer et al., 2021; Fahad et al., 2014; Huang et al., 2021). Existing research found that the "chunking" of messages from social media by distinct tools can have a positive effect on the disposition of emergency managers to utilize social media in emergencies (Rao et al., 2017). Since clusters often are not self-explanatory, they require a useful summary of the clusters' contents or a descriptive labels (Gründer-Fahrer et al., 2018). Thus, automated and real-time algorithms using extraction or abstraction techniques for *information summarization* can be applied to generate summaries of entire datasets or subsets of events (Rudra et al., 2018, 2019).

Besides the rich availability of techniques to deal with issues of information overload and quality, a market study of 45 tools for social media analytics (Kaufhold et al., 2020b) highlights that most solutions are designed for commercial purposes and thus are not tailored for the objectives of the emergency management domain. Although they often provide multi-platform capabilities for communication and monitoring, they lack algorithms for detecting credible or relevant information in emergencies. While expert tools such as AIDR permit the annotation of data, enable the classification of disaster-relevant information in Twitter (Imran et al., 2014), and can be combined with an interactive monitoring dashboard to enhance situational awareness (Aupetit & Imran, 2017; Onorati et al., 2018), it still requires multi-platform tools – tested in user-centered evaluations – to support (I) the coordination of emergency response in volunteer communities, (II) the interaction between emergency services and volunteer communities, and (III) the situational awareness of emergency services.

Architecture and Deployment of a Multi-platform Social Media API

The SMA enables the gathering and processing of big social data. Using the underlying social media platforms as foundation, it comprises several services that can be leveraged by different client applications. Though initially intended as an enabling technology for emergency management, its design enables the support of a multitude of use cases in different application domains. To facilitate the acquisition of big social data and subsequent analysis, our initial step was the specification of a service for the gathering and processing of social media content. *Gathering* in this context refers to the capability to conduct one-time searches or to continuously aggregate social media activity (e.g., posts, news, or photos) from multiple platforms (Twitter, Instagram, Facebook, Reddit, Flickr, YouTube, and Tumblr) in a uniform

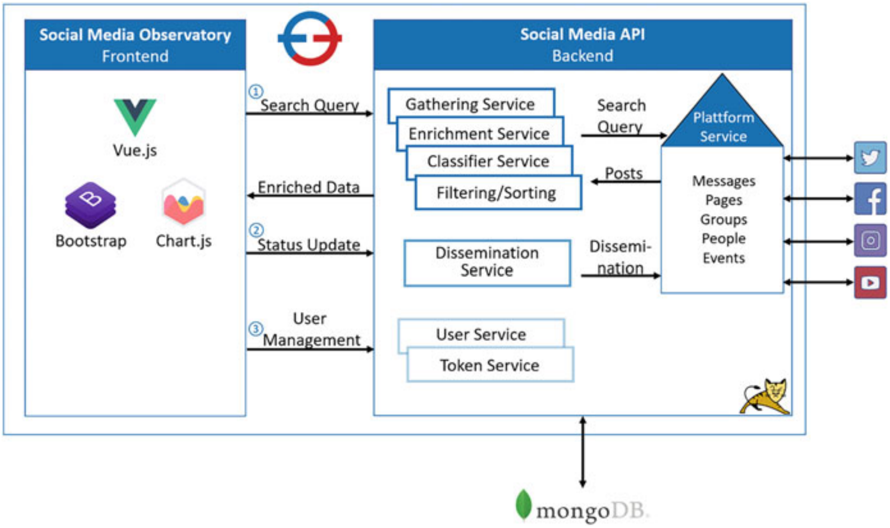

Fig. 1 Social media API architecture in conjunction with the Social Media Observatory client application. (Kaufhold et al., 2020a)

manner leveraging multiple search queries or filtering criteria. Moreover, *processing* refers to the SMA's capability to access, manipulate, enrich, store, and disseminate social media activities.

The SMA is implemented as a web-based application following a service-oriented architecture (Fig. 1). Designed as a Java Tomcat application, it utilizes the Jersey Framework for REST services and the MongoDB database for document-oriented data management. The underlying social media platform APIs, such as the Twitter Search API or the Facebook Graph API, are integrated by means of multiple libraries. To accommodate the diversity of data access and structures, the Activity Streams 2.0 Core Syntax (AS2) is used to process and store all gathered social media activities. Moreover, the SMA leverages Java interfaces that enable standardized implementations of additional social media, provided their APIs offer suitable data access. Although there are multiple service templates, developers must apply the *message service interface* as the basic template, which requires the implementation of four methods to search for multiple messages as well as to get, modify, or delete a single message. The SMA serves as foundation for multiple client applications which were deployed for three different scenarios.

Scenario I: Coordination of the Emergency Response in Volunteer Communities

Independently of the actions taken by official emergency services, volunteer communities often spontaneously emerge and complement relief efforts by performing tasks such as dike building and the distribution of material donations (Kaufhold &

Reuter, 2016). These tasks are increasingly coordinated across multiple social media. Therefore, a Facebook application named XHELP was developed allowing users to gather and disseminate information across media (e.g., Twitter and Facebook) and across channels (e.g., Facebook pages and groups) (Reuter et al., 2015a). It is specifically designed for digital moderators in emergency contexts who coordinate volunteers and material resources by providing an overview of their own joined groups, liked pages, and published posts. The central dashboard "My Posts" (Fig. 2) displays an overview of the user's communication threads, comprising not only posts created with XHELP but also comments and posts set up on the source platform. The user has the options of (1) collapsing or expanding comments on a communication thread, (2) responding to any or deleting own comments, and (3) removing or finalizing own communication threads. The finalizing functionality offers the user the opportunity to draft a posting to notify relevant groups, media, and pages (e.g., if an emergency-related problem is solved). Subsequently, the post will disappear from the central dashboard but will still be accessible from the navigation bar. In addition, the cross-media search enables looking for publicly and privately (e.g., if the user belongs to a closed Facebook group) shared Facebook and Twitter posts and filtering them by time, geolocation, and radius. Due to the Social-QAS integration, the user may also sort their search results according to particular evaluation criteria.

Despite the content management features of XHELP, it is often hard for volunteer communities to find high-quality information that is tailored according to their specific situational needs. A social quality assessment service (Social-QAS), which strives to facilitate the assessment of social media content through the customizable weighting of information quality criteria, was developed and integrated into the

Fig. 2 Social Media Volunteers-Coordination (XHELP) for community interaction and dissemination of social media messages

SMO to mitigate these issues (Reuter et al., 2015b). Since the diverse circumstances of emergencies necessitate differing methods of assessment, the opportunity to combine these techniques could contribute to the improvement of quality assessment practice (Ludwig et al., 2015a). The concept encompasses 15 methods for the assessment of social media content, subdivided into four groups: metadata (author frequency, temporal proximity, local proximity, followers/likes, media files), content (frequency of search keywords, stop words), message classification (sentiment analysis, negative and positive sentiment, named entities, emoticons, slang), and scientific methods (term frequency-inverse document frequency, Shannon information theory). Social-QAS allows end users to determine the subjective information quality by selecting and weighting several evaluation methods. As part of an exemplary implementation in XHELP, users have the option of searching for information based on various quality parameters in order to conduct a quality assessment (Fig. 3). For this purpose, users can select and weigh assessment dimensions by the means of sliders.

Scenario II: Improving the Interaction between Emergency Services and Volunteer Communities

Although volunteer communities have the potential to make valuable contributions to crisis response, the sometimes chaotic and dangerous activities of citizens initiated via social media may lead to an increased complexity of tasks, uncertainty, and

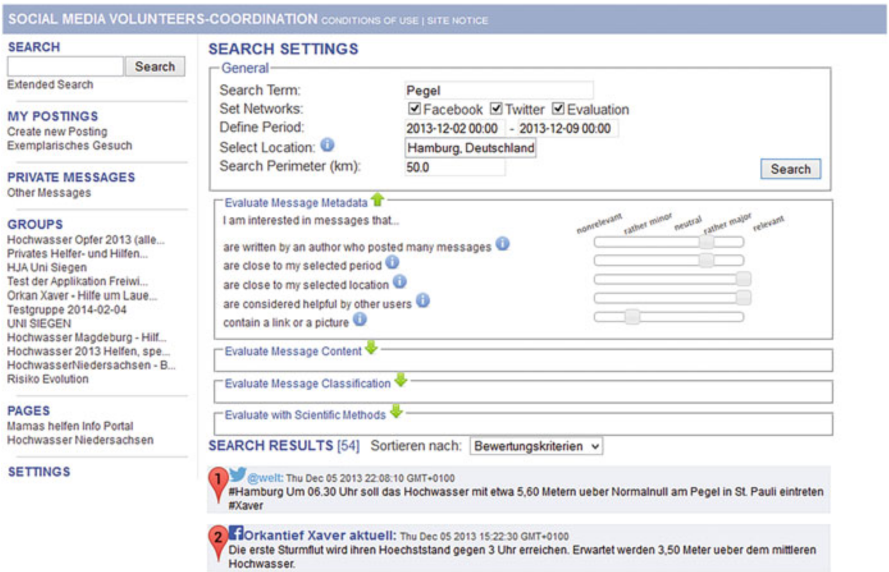

Fig. 3 The social quality assessment service (integration in XHELP) for tailorable data assessment during gathering and post-processing

pressure for emergency services (Perng et al., 2012). Thus, it is of utmost importance that the activities of both emergency services and volunteer communities are well-aligned. In an effort to improve their interaction, the web application CrowdMonitor (Fig. 4) was designed to enhance the meaningfulness of spontaneous volunteers' activities for emergency services during emergencies (Ludwig et al., 2015b). One challenge in crisis management is to gain awareness of activities of spontaneous volunteers and to coordinate these activities with those of the formal emergency services. To this end, the tool combines collective processes tracked through social media by the SMA with individual activities sensed by mobile devices. First, CrowdMonitor applies the SMA to allow responders the passive collection and display of information from social media (generated by ordinary people without their knowledge). Second, requests for specific information or targeted alerts can be created, which subsequently can be sent to users of a corresponding mobile app (within a specified area). Thus, CrowdMonitor combines the potential of a synchronized view of mobile-gathered data and information acquired on social media with additional capabilities to interact with people in order to provide situation pictures and reports during emergencies.

In long-term and large-scale emergencies (e.g., forest fires or floods), a large number of volunteers come together to help those affected. On the one hand, the helpers coordinate online within social media, but on the other hand, they travel physically to the site, where a number of local activities are also required. While CrowdMonitor is an interface designed for emergency services, important information about the ongoing event as well as current offers and requests for help must be disseminated to both the affected population and volunteers on-site. To this end, the public display application City-Share (Fig. 5) maintains a robust infrastructure for

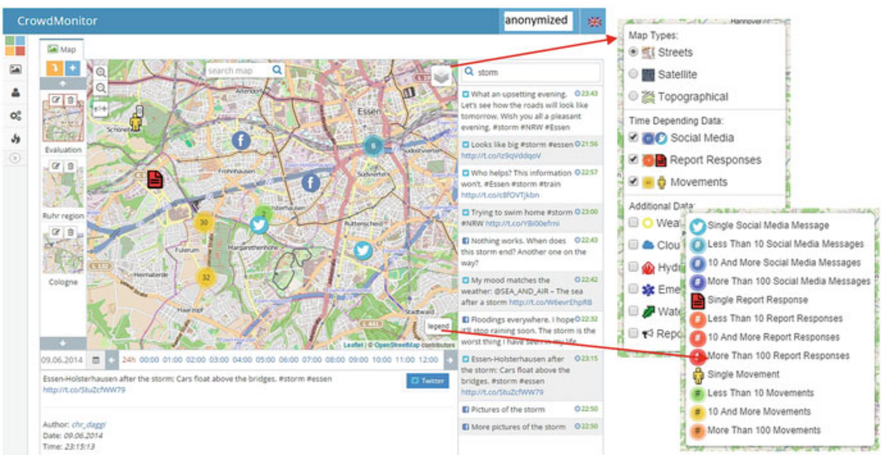

Fig. 4 The CrowdMonitor interface for combining social media content and emergent civil on-site activities

Fig. 5 The City-Share application for managing the tasks of spontaneous volunteers through public displays

communication and additionally incorporates situated crowdsourcing mechanisms to manage offers and requests related to on-site activities (Ludwig et al., 2017).

In this process, relevant information from social media is displayed based on the SME and is used to help coordinate volunteers. At the same time, important location-related information, such as warnings or assembly points, is provided. City-Share helps to improve disaster resilience in communities, particularly in terms of a collaborative type of resilience that emerges at the local level between official actors and spontaneous volunteers or involved citizens.

Scenario III: Enhancing the Situational Awareness of Emergency Services

Thousands of potentially relevant messages may be disseminated during an emergency, which can result in information overload. The Emergency Service Interface (ESI) was developed to improve emergency managers' situational awareness and decision-making by "transferring high volume, but unclear information content into low volume and rich content suitable for emergency services" (Moi et al., 2015). The central dashboard (Fig. 6) combines *app alerts*, which are received from a separate mobile emergency application (Kaufhold et al., 2018), and *social media alerts*, which are computed based on the data provided by the SMA (Kaufhold et al., 2020b; Reuter et al., 2016a), in a map and list view. Social media alerts consist of a set of classified messages with a similar context, which is determined by event type, platform, language, keywords, relevancy, quality, time, and location. Each alert

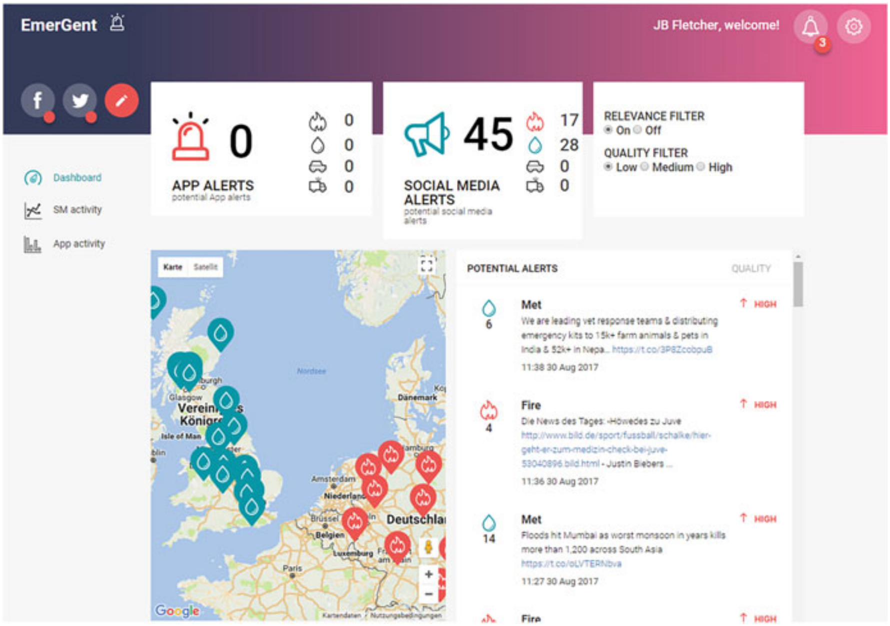

Fig. 6 Emergency Service Interface (ESI) for mobile and social media alerts

consists of multiple messages from different social media if they belong to the same setting. However, several steps are conducted before messages are grouped into alerts. After an initial data gathering and keyword-based filtering, relevance classifiers (e.g., for fire and flood scenarios) are used to reduce irrelevant information. Then, an information quality component measures the believability, completeness, relevancy, timeliness, and understandability of the remaining messages before they are grouped into social media alerts and directed to the interface. On the interface level, emergency managers can enable or disable both the relevance and quality filters and also click on alerts to investigate the individual messages.

Despite the generally positive reception of the ESI by involved emergency services, the tool lacked the capability to configure and tailor the analysis according to end-user requirements (Kaufhold et al., 2020b). The Social Media Observatory (SMO) is an interface that enables end users to monitor, analyze, and classify social media messages (Kaufhold et al., 2020a). More specifically, it facilitates the creation of social media datasets (based on one-time or continuous searches of the SMA), management of SMO users (e.g., to create, edit, or delete users), creation of machine learning classifiers, and dissemination of messages. In its first version, the SMO was simply an interface for the SMA to create and manage social media datasets (Reuter et al., 2016b). Now, its central feature is a real-time capable dashboard (Fig. 7) that displays characteristics of the loaded dataset (e.g., number of results, post frequency, sentiment, media, and language) besides visualizing posts on a map and in social feeds. If no exact location (green markers on the map) is given, named entity

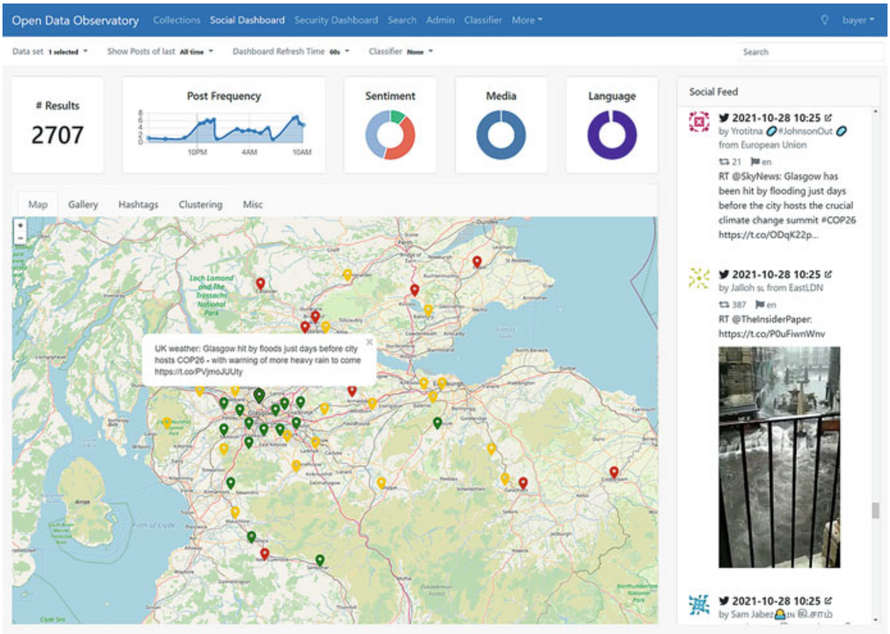

Fig. 7 Social Media Observatory (SMO) dashboard with interactive charts, feed, and list view

recognition is used to attempt extracting location information from either the individual post (yellow markers) or the author's profile (red markers). However, posts without a location will be displayed in the social feed only. Alongside with some basic settings (e.g., dashboard refreshing time), the dashboard supports visual interactive filtering (e.g., by clicking on the red part of the sentiment pie charts, only messages with negative sentiment are displayed in the interface). Furthermore, the SMO features an annotation tool to create datasets for machine learning classifiers. In this way, classifiers for credibility and relevance assessment can be designed and used to filter out unreliable and irrelevant information from the dashboard view. Additionally, the interface allows emergency services to correct algorithmic misclassifications to improve the classifiers' accuracy.

Discussion of Challenges

In order to evaluate these client applications individually, cognitive or scenario-based *walkthroughs* requesting participants to "think aloud" (Nielsen, 1992) were combined with follow-up semi-structured *interviews* to encourage the reflection on the evaluation procedure. For the results of both the walkthroughs and interviews, audio recordings and transcripts as material for a subsequent "open coding" analysis (Strauss & Corbin, 1998) were created. The evaluations' philosophy followed the

Table 2 Key evaluation topics for client applications of the social media API

	Multi-platform usage	Information overload	Information quality	Tailorability
XHELP (N = 20)	×			×
Social-QAS (N = 20)	×	×	×	×
CrowdMonitor (N = 28)			×	
City-Share (N = 27)	×	×		×
Emergency Service Interface (N = 33)	×	×	×	
Social Media Observatory (N = 12, D = 2)	×	×	×	×

notion of "situated evaluation" (Twidale et al., 1994) drawing on qualitative methods and the involvement of domain experts to derive conclusions about real-world technology usage. Furthermore, machine learning algorithms for credibility and relevance assessment were evaluated with regard to accuracy, precision, recall, and time (Kaufhold et al., 2020a, 2021a). In both cases, the most suitable models were integrated into the SMO. Based on the lessons learned, the upcoming section presents potentials and obstacles of the multi-platform gathering and analysis of social media data (Table 2).

Multi-platform Gathering and Management of Social Media Data

Keyword parameters represent a problem for querying data across multiple social media platforms since the APIs of different platforms support various differing notations and types of logical query operators, such as OR, AND, NOT, parentheses, or phrases. Thus, there is a necessity for a uniform query language and layer that facilitates the translation of the uniform parameters to their platform-specific equivalents. Whereas Twitter and YouTube employ a uniform query syntax for basic logical operators with their API, Instagram's API does offer a functionality for searching individual tags within media descriptions instead of keyword-based searches, and Facebook's Graph API is restricted to the AND operator. For both platforms, this necessitated a downstream implementation of logical operators using the parser generator ANTLR. For example, the conjunction OR was transformed into several individual requests to the API. However, this resulted in a faster quota limit exhaustion (Reuter & Scholl, 2014) due to the greater quantity of sent requests (OR) and the acquisition of irrelevant data (NOT). Particularly in the case of quota-limited APIs, such downward implementations can reduce the access to available data.

The diverse social media platforms not only provide numerous information types such as multimedia files text and metadata (e.g. the number of retweets or interactions) but are often subjected to differing standards (e.g. tweets are restricted to a maximum of 280 characters). During our research on a common and standardized approach for the representation and storage of gathered social media information the AS2 format in combination with MongoDB was found to be best suited for the task. While the flexibility of MongoDB's document-oriented approach enables the storage of clearly structured documents with a varying quantity of attributes AS2 follows an interoperable specification for the storage of attributes. However the possibility to compare and analyze social media activities is constrained with regard to diverging metadata. As it was impossible to map all attributes to the AS2 specification it was necessary to implement a custom class with divergent attributes for the mapping of platform-specific metadata such as the number of likes or retweets.

Besides, there exist two further valuable data types apart from publicly available data. First, data that is restricted to a distinct social media platform can be computed for the others. For example, there is the possibility to extract embedded mentions, hyperlinks, or tags from social media activities if not provided by metadata. Second, individual social media platforms lack some data required for quality assessment operations. Thus, the SMA is capable of manually computing classification attributes (slang conversion, emoticon conversion, positive or negative sentiment), content attributes (number of words, number of characters, words-to-sentences ratio, average length of words, entropy, number of syllables per word, number of punctuation signs), and metadata attributes (media files, location, tags, hyperlinks, language). Nonetheless, there are limitations to standardization, as it is uneconomical to map all available metadata attributes across all social media platforms into a singular specification. Against this backdrop, the storage of the native format as a string attribute per activity could be a feasible approach. This may also facilitate the transfer of data to client applications that support only certain native data formats.

Mitigating Information Overload by Relevance Assessment and Message Grouping

The presented client applications demonstrate several measures to reduce information overload during emergencies. For instance, a sophisticated information processing pipeline was established in the backend of ESI, which first gathers social data by keywords and metadata, then filters out irrelevant and incredible information using machine learning, and finally groups the remaining messages into social media alerts. By reducing social media content into alerts, the amount of displayed information on the ESI was reduced significantly. In their base implementation, social media alerts combine messages from all implemented platforms that are only connected by geographic and/or chronological proximity (i.e., Euclidean distance) since a more sophisticated clustering approach could not be realized within the scope of the project. A click on the alerts allows the user to inspect details on demand, i.e., to show the individual messages grouped into an alert. However, since the focus of the project was a human-centered evaluation of the tool, the used relevance classifiers were based on naïve Bayes, and the same classifier, which only achieved moderate classification accuracies, was applied to all implemented social media platforms (Kaufhold et al., 2020b). While the use of weak-performing classifiers might result in the overlooking of important information by emergency managers, another challenge lies in the time-consuming nature of annotating machine learning datasets – in our case, ideally for a high-classification performance across multiple platforms – under the time-critical constraints of emergencies.

To address these issues, first, a random forest algorithm with good performance during relevance classification that incorporates social media metadata into a batch learning approach and, second, a novel relevance classification approach that includes active, incremental, and online learning to achieve a reduction of the required amount of labeled data and a correction of algorithmic misclassifications using feedback classification were developed (Kaufhold et al., 2020a). With the second approach, a well-performing classifier was created that requires only a quarter of the labeled data in comparison to the conventional batch learning approach. Still, since the classifiers were trained based on data from a single social media platform, further research is required on how well these perform on multi-platform data or how to design classifiers based on annotated multi-platform datasets. Furthermore, based on an improved relevance filtering, the grouping of similar messages into alerts could be further improved by more efficient (e.g., based on word embeddings) clustering algorithms (Bayer et al., 2021).

The Context Dependency of Credibility and Information Quality Assessment

The evaluations revealed issues of credibility and overall information quality on different levels and for most emergency scenarios. For instance, it was questioned whether the content of a post is actually relevant to a specific situation, whether a social media post's author is credible, or whether the location attached to a posted message has a sufficient level of detail. Furthermore, the context dependency and highly subjective character of information quality notions became apparent. Therefore, it can be concluded that the "fit of information to specific tasks is more important than generic assessments of information quality" (Ludwig et al., 2015a). The credibility of social media data is one key dimension of information quality. The dissemination of false information and a varying credibility of authors frequently pose challenges for the analysis of social media messages. It is often challenging for inexperienced users to decide whether a social media message is reliable, trustworthy, and relevant.

Thus, a multi-platform service that gathers and analyzes social media data should provide more contextual information by enriching existing data. This could be determined, for instance, by measuring retweets or likes (e.g., as in Social-QAS). Based on an analysis of relevant contextual data, three deep learning models for the real-time credibility assessment of Twitter posts, all performing well during evaluation, were designed within the scope of the SMO (Kaufhold et al., 2021a). However, if the data collected via multi-platform services is not sufficiently contextual or if the information is untrustworthy (e.g., because an author lacks credibility or the location is too narrowly defined), there must be additional means to validate the (semi-)automatically processed information. This could be achieved by means of individualized reports from the scene that broaden the knowledge base of situation awareness practices. The trustworthiness and quality of information can be increased by the implementation of preprocessed ranking and filtering of social media messages gathered across platforms as well as by the provision of advanced options for additional validation.

User-Centered Tailorability and Data Operations

Considering some SMA client applications (particularly SMO and Social-QAS), it also became apparent that a completely automated processing of big social media would not be sufficient to fulfill the end-user requirement of tailorability. Due to the subjective character of situational assessment, the SMA must possess a tailorability that allows the selection of relevant source platforms and quality assessment criteria. As a consequence, factors such as experience, personal feelings, and the situation itself have an impact on the information requirements. When gathering or analyzing information and developing information systems to support these tasks, one key question always arises: how can information systems be designed that, on the one hand, allow for automatic selection of relevant data and, on the other hand, give end users the freedom to customize this automation to enable a tailorable quality and relevance assessment in accordance with their requirements? This becomes even more important when application scenarios and work contexts vary and user practices evolve with time. Thus, concepts such as Social-QAS can facilitate the articulation of end users' requirements (Reuter et al., 2015b).

Providing suitable service endpoints with adequate filter parameters that remain consistent across heterogeneous social media is one major challenge. To some extent, the provided APIs determine the flexibility of filtering: whereas filtering by location (YouTube, Twitter) or time (YouTube, Twitter, Facebook) is supported by some social media APIs, this must be implemented manually for other platforms. Furthermore, social media platform APIs are subject to permanent development and a steady adaptation to changes is needed. Whereas minor and early announced changes, such as the temporary need for a Google+ account when using YouTube, can be accommodated more easily, others exert a significant influence on implementation. Major issues occurred due to Facebook's removal of the public post search (2015), which severely limited access to public data, as well as the shutdown of the Google+ service and YouTube's reduction of API request quota (2019). The progressively growing restrictions of researchers' data access are a constant challenge for developing and maintaining multi-platform social media services and were thus also labeled as an "APIcalypse" (Bruns, 2019).

Conclusion

Without doubt, social media are of great significance and interest to various stakeholders involved in emergencies, including official emergency services and communities of voluntary helpers. This chapter discusses the challenges and opportunities for utilizing big social data in emergencies and presents the development of an extensible

Table 3 Summary of the identified challenges for multi-platform social media services in emergencies

ID	Challenge	Description
C1	Specification	Most, yet not all, social media metadata can be stored in accordance with an interoperable specification, e.g., Activity Streams 2.0
C2	Comparability	The extraction or computation of metadata is sometimes necessary for cross-platform comparisons of (big) social data
C3	Classification	The creation of social media classifiers is time-consuming despite the time-critical constraints of emergencies, and classifiers must perform well on multi-platform datasets
C4	Interpretability	Interpretations of evaluative metadata, e.g., trustworthiness and information quality, are context-dependent and highly individual
C5	Tailorability	To address end users' objectives, the gathering of social data requires sufficient filter parameters (e.g., by location or time), which sometimes require a downstream implementation
C6	Queryability	Official social media APIs support a variety of logical query operators (e.g., AND, OR, and NOT), and the emulation of such operators often results in a high quota consumption
C7	Adjustability	Frequent modifications of official social media APIs, e.g., the Facebook or Instagram API, require corresponding adjustments or can cause the loss of data access

and standardized social media API (SMA), which supports the gathering, processing, and retrieval of acquired data from multiple social media platforms. The SMA has been deployed and evaluated in three scenarios to assist volunteers across social media (XHELP), facilitate the tailored quality assessment of social data (Social-QAS), combine social media with movements of volunteers for emergency services (CrowdMonitor), manage the tasks of spontaneous volunteers through public displays (City-Share), create social media alerts for emergency services (ESI), and filter for credible and relevant social data (SMO). Although the challenges for such multi-platform services are mostly determined by the research goals, client applications, and use cases, Table 3 outlines some of the challenges encountered in the evaluations.

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