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Editorial

Using AI and Social Media Multimodal Content for Disaster Response and Management: Opportunities, Challenges, and Future Directions

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ABSTRACT

People increasingly use Social Media (SM) platforms such as Twitter and Facebook during disasters and emergencies to post situational updates including reports of injured or dead people, infrastructure damage, requests of urgent needs, and the like. Information on SM comes in many forms, such as textual messages, images, and videos. Several studies have shown the utility of SM information for disaster response and management, which encouraged humanitarian organizations to start incorporating SM data sources into their workflows. However, several challenges prevent these organizations from using SM data for response efforts. These challenges include near-real-time information processing, information overload, information extraction, summarization, and verification of both textual and visual content. We highlight various applications and opportunities of SM multimodal data, latest advancements, current challenges, and future directions for the *crisis informatics* and other related research fields.

1. Introduction

During disasters and emergencies, getting a quick understanding of the situation as it unfolds is a challenging task for formal response organizations. Members of the public, humanitarian organizations, and other concerned authorities search for pertinent information either to prevent the crisis or to help victims as early as possible. However, traditional approaches to gain situational awareness (i.e., understanding a bigger picture of the situation) are time-consuming and labor-intensive (Hiltz and Plotnick, 2013). Widespread adoption of non-traditional information sources such as Social Media (SM) platforms has created numerous opportunities to gather relevant information in a timely manner to improve disaster response. Research studies show that the general public uses SM platforms during disasters and reports critical information such as early warnings, cautions, damages to infrastructure such as roads, bridges, and buildings (Castillo, 2016; Imran, Castillo, Diaz, and Vieweg, 2015; Vieweg, Castillo, and Imran, 2014). Moreover, SM is considered as a potential source to perform urgent needs assessment of the affected population after a major disaster (Vieweg et al., 2014). Research has also shown that many real-world events, including crises, are first reported on social media compared to traditional media outlets such as TV and radio (Kalyanam, Quezada, Poblete, and Lanckriet, 2016).[1]

Despite these benefits, processing SM data is not trivial. The various types of content available on SM platforms such as text messages, images, videos, are considered noisy and less formal compared to standard Web data, such as news articles or images published with those articles. Therefore, data analysis techniques trained and built for standard Web data often do not work well on SM data. For instance, text messages on Twitter or Facebook cannot exceed a fixed length and thus contain shortened words such as “2moro” instead of “tomorrow” in addition to other issues, including misspellings and use of slang. Studies revealed that techniques, which are specifically trained and built to process SM content, seem to work better than the ones trained for the processing of standard and well-structured data (Singh and Kumari, 2016). However, this highlights the need for in-domain labeled data, which is usually scarce.

Despite the lack of labeled data, the *crisis informatics* research community has continued to show advancements in different SM data processing tasks. Among others, these include data parsing, classification, extraction, summarizing, ranking, and

[1] https://latimesblogs.latimes.com/technology/2008/07/twitter-earthqu.html

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recommendation. Several of these research lines have been struggling to perform until the recent breakthroughs in the field of Artificial Intelligence (AI), especially deep learning, have shown promising results. Deep learning techniques have recently been used by both Natural Language Processing (NLP) and Computer Vision (CV) communities to show substantial performance improvements over traditional machine learning approaches for several data processing tasks.

This special issue provided an opportunity to researchers working on crisis informatics topics using NLP, CV, ML, and AI methods to publish their latest and novel research works. We focused on the use of AI and SM multimodal content for disaster response topics. In total, we received 13 papers, which were rigorously peer-reviewed. Based on the expert reviews, four articles were finally accepted and summarized in Section 5. In the next section, we highlight the applications of SM textual content and techniques aiming at different processing tasks. Section 3 highlights applications of SM imagery content and how the CV community is addressing various challenges for crisis response, followed by a discussion on multimodal learning as a potential future research direction in Section 4. We conclude the editorial in Section 6.

2. SM text processing: opportunities, challenges, and future directions

Many SM platforms provide access to their data through APIs. Textual data available on SM is different in many aspects from other Web-based sources such as news articles. Typically, these messages use less formal language. They may contain words from multiple languages. They may also have various grammar and spelling mistakes. The length of the messages varies greatly, so does their content. They are mostly unstructured, fuzzy, and short in length (often due to a platform's restricted character length[2]). For example, the length restriction on Twitter results in shortened words, slang, and sometimes self-made abbreviations. Moreover, during disasters and emergencies, SM platforms receive millions of messages, often within a short time-span. These issues pose challenges for NLP techniques to parse, analyze, and extract information useful for disaster response.

Over the last several years, the crisis informatics community has shown promising progress on many fronts. Extensive research has been conducted, and novel computational methods and techniques have been proposed to address challenges ranging from crisis event detection to actionable information extraction and damage assessment. In this section, we focus on SM textual content and highlight various opportunities, challenges, and current status of relevant research fields.

Crisis event detection: Text messages shared on SM contain multifaceted information ranging from personal opinion, mundane discussion, and emotions to newsworthy events, as well as reports of crisis events. Users of SM platforms report real-world events much faster than traditional news media. More importantly, these reports reach millions of users instantly through followers, friends, and resharing. The current literature around crisis event detection can be categorized as “large event detection” and “fine-grained event detection”, where the former represents detection of large-scale events such as earthquakes (Poblete, Guzmán, Maldonado, and Tobar, 2018), floods (Eilander, Trambauer, Wagemaker, and Van Loenen, 2016), wildfires (Sousa, Moutinho, and Almeida, 2020), riots (Alsaedi, Burnap, and Rana 2017) whereas the latter focuses on identifying small-scale events such as “power outage” (Pourebrahim, Sultana, Edwards, Gochanour, and Mohanty, 2019, “critical infrastructure damage”, “airport shutdown”, especially during disasters (Arachie et al., 2019). Several past works employ traditional machine learning techniques, including pattern matching, classification of data streams, locality sensitive hashing, and clustering to detect large events (Zhou and Chen, 2014). More recently, deep learning has emerged as a promising approach (Burel, Saif, Fernandez, and Alani, 2017; Xiang and Wang, 2019). However, despite these advancements, identification of small events remains a big challenge mainly because SM streams are extremely noisy, and often small events do not represent a spike—a popular indicator used by many event detection techniques. Moreover, given the fact that only 1-3% of SM content is geotagged, event detection techniques face challenges to geolocalize the identified events—a factor that minimizes their utility.

Understanding public reaction: Monitoring public reaction and sentiment during a crisis does not only help to understand the issues that the public is facing but it also is useful to assess if the government response to an issue is slow or not well perceived among masses. SM platforms give freedom to everyone to express their views and reactions. Therefore, formal disaster response organizations are becoming more dependent on SM, especially during a crisis situation, to understand public sentiment and response to a particular issue (Suran and Kilgo, 2017; Utz, Schultz, and Glocka, 2013). Despite these advantages, most of the existing research works mainly focus on sentiment analysis, and less attention has been given to developing techniques that automatically get a sense of public reaction on a specific issue. To achieve this goal, techniques that can first identify pressing issues of a community and then segregate public opinion, reactions, and sentiment around them would be most beneficial for response organizations (Beigi, Hu, Maciejewski, and Liu, 2016; Chae et al., 2014).

Eyewitness identification: To validate occurrence of a disaster event and understand the scale of damage it caused, firsthand information plays a vital role for response organizations. Moreover, these organizations can rely on information from eyewitnesses to understand the urgent needs of affected people and accordingly plan relief operations. While sending personnel to disaster-hit areas, e.g., to perform field assessment, could take several hours or days, eyewitness reports on SM platforms can help agencies gather important information within minutes (Truelove, Vasardani, and Winter, 2015; Zahra, Imran, and Ostermann, 2020). Compared to the benefits of obtaining eyewitness data during an event, little focus has been given to developing techniques to identify them from SM automatically. Only a handful of research works have focused on this promising research topic (Tanev, Zavarella, and Steinberger, 2017; Zahra, Imran, Ostermann, Boersma, and Tomaszewski, 2018).

Situational awareness: Understanding a crisis situation as it unfolds is of utmost importance to response organizations. The

[2] Twitter allows 280 characters (it was 140 until 2017), Facebook up to 63,206, and Instagram up to 2,200 characters.

concept of situational awareness mainly deals with the understanding of a high-level picture of a disaster, i.e., information about the overall scale of damage caused by the disaster in terms of causalities, injured people, and other affected individuals and their needs. For rapid situational awareness, no other medium can provide quicker access to such information than citizen reporting on SM platforms (Archie, 2016; Fan, Jiang, and Mostafavi, 2020; Wang and Ye, 2019). Many past works present automatic techniques to help response organizations gain situational awareness information. Since SM data is noisy, many works focus on developing machine learning models to identify relevant messages. Among many others, techniques for classification of SM messages into categories of interest (Mazloom, Li, Caragea, Caragea, and Imran, 2019; Ray Chowdhury, Caragea, and Caragea, 2019; Stowe, Anderson, Palmer, Palen, and Anderson, 2018) and summarization of large set of messages (Rudra, Goyal, Ganguly, Imran, and Mitra, 2019; Rudra, Goyal, Ganguly, Mitra, and Imran, 2018) are prominent. For a detailed survey on various techniques, see Castillo (2016); Imran et al. (2015). Although the progress made so far in this line of research seems promising, the community still lacks a system that consolidates all types of situational information and provides a comprehensive view of the situation for rapid decision-making.

Crisis communication: During all stages of a crisis event, the general public tries to engage with authorities and other peers, e.g., through hot-lines, ad-hoc SM or WhatsApp groups, to gain insights about an ongoing disaster, try to reduce uncertainties, and get information about unknowns (Lin, Spence, Sellnow, and Lachlan, 2016). On the other hand, studies report that official government organizations use SM platforms to communicate information about warnings and risks, encourage protective behavior, and tackle false rumors (Panagiotopoulos, Barnett, Bigdeli, and Sams, 2016; Stieglitz et al., 2017; Subba and Bui, 2017). Effective communication can reduce the community harm and prevent life losses. However, despite the fact that SM platforms can be a useful medium for crisis communication (Reuter, Ludwig, Kaufhold, and Spielhofer, 2016), limited focus has been given to developing tools to assist both general public and response organizations to effectively communicate with each other during times of emergencies.

Damage assessment: Assessing the impact of a disaster, especially damages to critical infrastructure such as bridges, roads, and important buildings, is essential for rapid restoration and recovery. However, response organizations rely on traditional approaches such as expert-based field assessment to gain an understanding of the impact of disasters. This is not only a time-consuming but also a laborious method. Research studies have shown that SM data contains reports of damages caused by disasters (Imran, Elbassuoni, Castillo, Diaz, and Meier, 2013; Kryvasheyeu et al., 2016; Vieweg et al., 2014). However, surfacing pertinent information from a trove of irrelevant content on SM is a challenging task. Most of the recent works for damage detection and damage assessment utilize imagery content shared on SM, which we discuss in detail in the next section. While images can be useful to assess the severity of damage, text messages can bring additional contextual information such as the location of the damaged object/building, what caused the damage (if unknown), and other consequences associated with the damaged object, e.g., road connection to a remote area is lost due to a bridge damage.

Actionable information gathering: While situational awareness perspective provides a general and agnostic approach to information available on SM, it may not be useful to fulfill varying urgent needs of the affected population. Several messages on SM contribute towards providing high-level information, however, other may contain urgent requests, e.g., people trapped under rubble seeking immediate help (Purohit, Castillo, Imran, and Pandey, 2018). Studies show that SM data provide such reports during disasters, which can help response organizations to act upon specific requests (Zade et al., 2018). Despite the importance of actionable information, only a small number of studies have focused on extracting pertinent information (He et al., 2017; Purohit et al., 2018). Among various factors contributing towards determining the actionability of text messages, location (i.e., where the aid is needed), the kind of help (e.g., medical assistance, shelter, or food), and its urgency are extremely helpful for responders to decide what is needed, where, and when (Zade et al., 2018). However, SM messages often miss these factors or they are ambiguous (i.e., incomplete location information), which makes the task of determining their actionability non-trivial. Future research focus requires automatic identification and disambiguation of pertinent information to help turn an ambiguous or unclear message into an actionable message.

Information veracity: Even though incorporating SM as a complementary data source in established disaster response workflows could be useful, humanitarian organizations show concerns about the integrity of the information available on SM platforms. The trustworthiness of SM information is a major issue for both the general public and response organizations. Fake news, rumors, misinformation, and disinformation are common problems while considering SM data for any use, such as gaining situational awareness or informing a response (Plotnick, Hiltz, Grandhi, and Dugdale, 2019; Shu, Sliva, Wang, Tang, and Liu, 2017). Past works show the influence of various types of features in determining the credibility of a SM post. For instance, those characteristics and features include whether a post includes URLs or not, grammar correctness, number of followers, the credibility of those followers, among others (Castillo, 2016; Castillo, Mendoza, and Poblete, 2011). However, the problem of determining the trustworthiness of SM information is largely unsolved.

3. SM image processing: opportunities, challenges, and future directions

During emergencies, people may find it more convenient to capture the moment via images and share them online to inform others about impending hazards, damage to critical infrastructure, etc. (Liu et al., 2008). To that end, images can provide more detailed information about the severity and extent of damage, better understanding of shelter needs and quality, more accurate assessment of ongoing rescue operations, and faster identification of lost or injured people, among others. A survey study with 761 emergency service staff reveals that images posted on SM platforms during emergencies can provide significant information for disaster response (Reuter et al., 2016). Inspired by this phenomenon, early studies examine the value of analyzing SM images in various disaster contexts such as floods (Peters and de Albuquerque, 2015), fires (Daly and Thom, 2016), and earthquakes (Bica, Palen, and Bopp, 2017). However, potential implications of SM image analysis have not yet been fully explored, leaving it as a fairly nascent area of research. Therefore, in this section, we summarize existing research areas, hint at unexplored directions and opportunities, and discuss potential challenges.

Reducing information overload: Despite the ease of acquiring images from SM platforms, analyzing high-volume, high-velocity imagery content generated during a disaster remains to be a challenging task. Typically, emergency response agencies make a call for humanitarian organizations to inspect images *manually* for features of interest (e.g., blocked roads, collapsed buildings, damaged shelters, etc.). However, SM images are very noisy, i.e., contain a lot of irrelevant and redundant content. Human experts cannot afford sifting through this noise manually to identify pertinent information. Therefore, it is of utmost importance to develop robust filtering mechanisms (Nguyen, Alam, Ofli, and Imran, 2017a; Peters and de Albuquerque, 2015). In particular, Alam, Ofli, and Imran (2018b) presents how an image processing pipeline with duplicate removal and relevancy filtering mechanisms Alam, Imran, and Ofli (2017) is quintessential to reduce the time and effort needed by the humanitarian experts to analyze SM images. However, different humanitarian organizations have different information needs, and the definition of relevancy must satisfy particular needs of each organization. Therefore, rather than a generic mechanism that identifies just irrelevant and redundant content, there is need for more sophisticated methods for task-dependent retrieval of relevant images, which is known as content-based image retrieval (CBIR) in the computer vision domain (Lew, Sebe, Djeraba, and Jain, 2006). Adapting CBIR techniques from computer vision to crisis informatics domain can open new avenues for research.

Rapid damage assessment: This is an extremely important task for response organizations to perform immediately after a sudden-onset disaster to gain situational awareness and launch relief operations.[3] However, traditional approaches to acquire information in the occurrence of emergencies are labor-intensive and costly as they require field assessments by experts. Therefore, analysis of SM images can prove useful to gain a quick understanding of the severity and extent of damage. To that end, there are some studies analyzing image-level (i.e., scene-level) features to categorize severity of damage into discrete levels (Nguyen, Ofli, Imran, and Mitra, 2017b), or quantify the severity as a continuous-valued damage index (Li, Caragea, Zhang, and Imran, 2018; Nia and Mori, 2017). However, these methods are usually trained on sparse data with limited diversity, and hence, they do not generalize well to various types of real-world disaster scenarios. Some recent studies tackle the data scarcity issue by employing more sophisticated models such as adversarial networks (Li, Caragea, Caragea, Imran, and Ofli, 2019; Pouyanfar et al., 2019). Despite proving useful, image-level analysis is not enough to extract actionable information from images to answer queries such as what is damaged and where, what caused the damage, etc. For this reason, object-level understanding of images in disaster context is necessary. An important challenge in this direction is that disaster images do not share the same characteristics as those in the traditional large-scale image collections with clean annotations of well-defined object categories such as houses, cars, bridges, roads, etc. Therefore, it is essential to create large-scale collections of disaster images with object-level annotations to develop more sophisticated damage assessment models. This will allow for an in-depth understanding of disaster scenes ranging from detecting and localizing damaged objects and places to counting their instances, creating an inventory, and estimating overall damage cost for reconnaissance (Dashti et al., 2014).

Crisis event detection: SM platforms break news faster than official news channels and emergency response agencies. Therefore, continuous monitoring of SM platforms using automatic image analysis models can help detect disaster events around the world in real time. However, there are only a few studies that have explored this application in a limited context such as detecting fires (Lagerstrom et al., 2016), floods (Ahmad, Ahmad, Ahmad, and Conci, 2017; Feng, Shebotnov, Brenner, and Sester, 2018; Lopez-Fuentes, Farasin, Skinnemoen, and Garza, 2018; Zhao, Larson, and Oostdijk, 2018), and a few other common disaster types (e.g., earthquakes, droughts, landslides, cyclones, etc.) (Ahmad, Sohail, Conci, and De Natale 2018). In order to build more general models that can recognize a large variety of disaster types in various scene contexts, there is a dire need for large-scale disaster image datasets. More importantly, the models trained on such large-scale datasets should be robust enough to deal with highly skewed nature of the problem. That is, disasters are rare events, and oftentimes, SM images will not show *any* disaster scenes. These robust event detection models can then be integrated into map-based dashboards to provide real-time situational awareness updates to humanitarian organizations and emergency response agencies.

Information veracity: The fact that SM plays a big role nowadays in many people's lives has created opportunities for fake content to arise and spread faster (Vosoughi, Roy, and Aral, 2018), even during humanitarian crises such as natural disasters (Bica et al., 2017; Gupta, Lamba, Kumaraguru, and Joshi, 2013). Such content is often created for pure entertainment or advertisement purposes, but sometimes, it is also used for spreading disinformation. Therefore, checking veracity of information extracted from SM images is extremely important but largely unexplored for effective humanitarian response. An image may be deemed *fake* due to digital manipulation (e.g., cropping, splicing, retouching, etc.), and such examples are traditionally detected by image forensics techniques (Bayar and Stamm, 2016; Bayram, Avcibas, Sankur, and Memon, 2006; Carvalho, Faria, Pedrini, Torres, and Rocha, 2015; Stamm and Liu, 2010). However, more sophisticated techniques are needed to detect the recent deep learning-based fake imagery (i.e., deepfakes) (Dolhansky, Howes, Pflaum, Baram, and Ferrer, 2019; Verdoliva, 2020), especially on social networks (Marra, Gragnaniello, Cozzolino, and Verdoliva, 2018). Furthermore, an image may also be deemed fake (i.e., not authentic) because it does not originally occur in the time and place of the disaster. In this case, recent approaches use either accompanying text (Zhang et al., 2018) or the Web as a source of information for reverse image search Zlatkova, Nakov, and Koychev (2019) to identify if an image has been appropriated from another time and place. Information veracity on SM is a fairly nascent area and existing studies analyze SM images for fake detection in general context, however specific solutions are needed for more challenging disaster-related scenarios.

Location identification: SM data do not always come with geolocation information. For instance, only 1-3% of all tweets have

[3] https://www.fema.gov/media-library/assets/documents/109040

associated geolocation information and images constitute even a smaller portion of this subset. Researchers in computer vision domain have studied the problem of inferring GPS coordinates from the visual content of an image (Hays and Efros, 2008; Vo, Jacobs, and Hays, 2017) and built systems that aim to perform this task at scale (Zheng et al., 2009). Other than landmark recognition, some studies have analyzed visual elements and attributes of certain geo-spatial areas (e.g., cities) to develop city-scale location recognition models (Doersch, Singh, Gupta, Sivic, and Efros, 2012; Schindler, Brown, and Szeliski, 2007; Zhou, Liu, Oliva, and Torralba, 2014). These studies have shown that image-to-location mapping is feasible to some extent in scene-centric images captured on a regular day. However, the task becomes much more difficult for disaster scenes. To tackle this challenge, domain adaptation techniques and image-to-image translation methods can prove useful to match damaged scenes to undamaged ones prior to geolocation inference.

Narrative summarization: There has been significant progress in image captioning (Bai and An, 2018; Hossain, Sohel, Shiratuddin, and Laga, 2019; Liu, Xu, and Wang, 2019) and narrative summarization of image collections (Chatterjee and Schwing, 2018; Liu, Fu, Mei, and Chen, 2017; Zheng, Li, and Wang, 2019). In light of these advancements, SM images collected during disasters can be analyzed to automatically generate a coherent summary report about an emergent event that can be distributed across different humanitarian organizations and emergency response agencies. Such summaries can also help with indexing and archival of collected SM images. However, similar to previous challenges, existing models need to be adapted to disaster context via large-scale annotated datasets and transfer learning techniques.

Missing, found, and displaced people: Recent advances in understanding person attributes (Bedagkar-Gala and Shah, 2014; Leng, Ye, and Tian, 2019) and recognizing faces in the wild (Kushwaha et al., 2018; Singh, Chawla, Singh, Vatsa, and Chellappa, 2019) offer new opportunities for analyzing SM images in the context of humanitarian crises such as detecting displaced people or human right violations (Kalliatakis, Ehsan, Fasli, and D McDonald-Maier, 2019a; Kalliatakis, Ehsan, Leonardis, Fasli, and McDonald-Maier, 2019b). Similarly, analyzing SM images to identify missing or found individuals can be of great value for search and rescue operations and emergency managers as well as for the distressed victims and family members of missing people.

4. Social media multimodal analysis

SM data have a multimodal nature, i.e., text messages, images, videos, and other meta-data appear together in general. These modalities oftentimes contain complementary information that, when analyzed jointly, can prove extremely useful to ascertain the big picture of a disaster situation at a greater level of detail (Alam, Ofli, and Imran, 2019; Alam, Ofli, Imran, and Aupetit, 2018c). For instance, a number of studies have shown the value of multimodal analysis as a better tool for relevancy filtering and reducing information overload (Chen, Lu, Kan, and Cui, 2013; Dewan, Suri, Bharadhwaj, Mithal, and Kumaraguru, 2017; Gautam et al., 2019; Yang, Ha, Fleites, Chen, and Luis, 2011). To that end, Alam, Ofli, and Imran (2018a) has recently presented a SM dataset to promote further multimodal research on several humanitarian tasks. There are also several studies leveraging multimodal content for damage assessment (Agarwal, Leekha, Sawhney, and Shah, 2020; Liang, Caverlee, and Mander, 2013; Mouzannar, Rizk, and Awad, 2018) as well as crisis event detection (Bischke, Helber, and Dengel, 2018; Jing et al., 2016; Kelly, Zhang, and Ahmad, 2017; Lopez-Fuentes, van de Weijer, Bolanos, and Skinnemoen, 2017). Similarly, geo-location inference for crisis mapping research has benefited from multimodal data (Choi et al., 2014; Luo, Joshi, Yu, and Gallagher, 2011; Stock, 2018). Last but not least, Layek, Pal, Saha, and Mandal (2018) presents how text and image data together can be used to generate multimedia summary of a disaster event. However, most of these studies present preliminary results on small-scale, home-grown datasets for specific disaster types. Therefore, collecting a large-scale benchmark dataset covering a large variety of disaster types with multimodal information is key to promote further exploration along various research dimensions discussed in previous sections.

5. Special issue and accepted article summaries

In total, this special issue received 13 submissions. Of all, two were desk rejected. The remaining articles went through a rigorous reviewing process where all the articles were reviewed by at least three expert reviewers followed by a meta-review performed by one of the guest editors. Finally, four articles are accepted, which we summarize next.

5.1. Summary of article 1

The article titled “VOST: A case study in voluntary digital participation for collaborative emergency management” presents insights into the decision-making processes of a virtual operations support team (VOST) that was integrated into an emergency management agency’s (EMAs) workflow. The authors identify structural and procedural requirements for a successful collaboration between 20 digital volunteers embedded in a VOST and EMA and analyze technical requirements of existing tools for real-time SM monitoring in a time-critical environment. This study discusses organizational, structural and technical implications for future systems used in the decision-making process of the emergency operation center (EOC). Finally, this work identifies and reports challenges, which arose during the close inter-organizational collaboration between a VOST and an EMA during the Grand Départ of Tour de France 2017 (Fathi, Thom, Koch, Ertl, and Fiedrich, 2019).

5.2. Summary of article 2

The article titled “Identifying crisis-related informative tweets using learning on distributions” proposes to consider the distribution of words in SM posts to identify informative messages during disasters. Based on the distributional hypothesis, the authors show that each crisis-related tweet can be considered as a "distribution." Using the recent development in machine learning, namely, learning on distributions, each object of learning can be considered as a distribution. Finally, the authors show that learning on distributions achieves better results in identifying informative tweets about a crisis incident (Ghafarian and Yazdi, 2020).

5.3. Summary of article 3

The article titled "Automatic identification of eyewitness messages on twitter during disasters" presents an approach to effectively identify eyewitnesses from SM stream during disasters. The authors identify three types of eyewitnesses: (i) direct eyewitnesses, (ii) indirect eyewitnesses, and (iii) vulnerable eyewitnesses. Moreover, they investigate various characteristics associated with each eyewitness type. They report words related to perceptual senses (e.g., feeling, seeing, hearing) tend to be present in direct eyewitness messages, whereas emotions, thoughts, and prayers are more common in indirect witnesses, which they use as features to train several machine learning classifiers. Their experiments on several real-world Twitter datasets reveal that textual features (bag-of-words), when combined with domain-expert features, achieve better classification performance (Zahra et al., 2020).

5.4. Summary of article 4

The article titled "Rapid relevance classification of social media posts in disasters and emergencies: A system and evaluation featuring active, incremental and online learning" presents a system for SM monitoring, analysis and relevance classification. The paper also presents abstract and precise criteria for relevance classification in SM during disasters and emergencies. The authors perform the evaluation using the Random Forest algorithm for relevance classification incorporating metadata from SM into a batch learning approach with a fast training time. Furthermore, they present an approach and preliminary evaluation for relevance classification including active, incremental, and online learning to reduce the amount of required labeled data and to correct misclassifications of the algorithm by feedback classification (Kaufhold, Bayer, and Reuter, 2020).

6. Conclusion

SM during time-critical situations such as disasters and emergencies is considered as a vital resource for responders and decision-makers. Text messages and images shared on SM during such events contain situational as well as actionable information. Despite their usefulness, majority of this pertinent data is not available to humanitarian organizations during disasters, mainly due to several data processing and data quality challenges. This editorial provides a brief review of challenges and opportunities brought about by the use of SM in disaster management and response. Specifically, challenging tasks that can be addressed with artificial intelligence and machine learning techniques are described together with a brief overview of the state of the art in those tasks.

Some of the tasks discussed have been addressed independently with natural language processing techniques, using text content, and/or with computer vision techniques, using images. However, as discussed in the editorial, multimodal approaches that can handle text and images together are desirable. Directions for future work on combining different modalities of the data are highlighted.

Finally, summaries of the papers included in this special issue are provided. The summary of a paper highlights the main task and describes the approach used in the paper.

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