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Design of a social media processing system for crisis response: extraction, management and delivery of relevant information for decision makers.

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Summary

Introduction

At the time of writing, humanity is in the second year of the COVID-19 pandemic, at the dawn of the Omicron variant. In its propagation, this virus has led the world in a crisis of a magnitude usually contained in History books. All the world countries are currently facing a multifaceted crisis involving public health, social and economic issues. However, suppose we detach ourselves from the current events. In that case, we realize two points: (i) that crises and society are historically two partners in the same dance, and (ii) that despite the prevailing fear and uncertainty, society is still very much present. In the heat of the moment, it is difficult to perceive our societies' extraordinary resilience, regardless of the times. This resilience is made possible by the individuals of the society who manage this crisis, each at their own level.

This event reminds everyone of the importance and difficulty of crisis management. Crisis management is, above all, a matter of making decisions with uncertain information and an uncertain environment. In this context, facilitating access to and processing of information becomes key issue. At the same time, accessing and processing information has never been easy. The democratization of social media and the development of Artificial Intelligence methods have allowed significant progress on these aspects.

How to automatically leverage information posted on social media during a crisis? From this interrogation, three scientific questions are extracted:

1. What information posted on social media is helpful for crisis response?
2. How can we automatically collect this information?
3. How to effectively deliver this information to the decision-makers in charge of the response?

These questions were explored during the ANR MACIV project (Management of Citizens and Volunteers: the social media contribution in crises). This project brought together different actors, both institutional (Direction Générale de la Sécurité Civile et de la Gestion des Crises, Préfecture de Police de Paris, Service Départemental d'Incendie et de Secours du Var), associations (VISOV: Volontaires Internationaux en Soutien Opérationel Virtuel) and academics (Centre Génie Industriel - IMT Mines Albi and Institut Interdisciplinaire de l'Innovation - Télécom Paris). This work also benefited from a welcome cultural diversity thanks to a one-year exchange in the United States at the College of Information Sciences and Technology of the Pennsylvania State University, which allowed us to observe and understand management issues in a context that is certainly familiar but nevertheless different. All of these actors have contributed to the reflection and the results of this work.

The latter is organized into five parts. The Figure refintroduction:big-picture outlines the organization by specifying the origin of the entries that allowed each contribution. The first two parts provide the reader with an understanding of the context and the issues surrounding the topic discussed. The following three parts break down the contribution of this dissertation into three parts: (i) characterization of the information need, (ii) automatic collection of this need, and (iii) integration of this collection within an information system.

Chapter 1 presents the general context of crisis management, social media, and automated language processing. A principal research question and three consecutive research questions are identified from this context.

Chapter 2 is a literature review of the research conducted around each research question in recent years. This literature review feeds into the reflections conducted in the following three chapters. Each chapter successively answers the research questions.

Chapter 3 identifies the actionable information available on social media for decision-makers when responding to an event. This information is then organized into an information model used in the following chapters.

Once information that composes actionable information is identified and organized, Chapter 4 proposes an automatic collection method. This method relies on a semi-supervised machine learning model identifying previous actionable information in messages posted on social media. The information present in the messages is then highlighted to facilitate the emergency staff's processing of the data stream.

Finally, Chapter 5 considers the processing of social media by the information system as a whole. In particular, it highlights the crucial role of the information system in both data and information processing. It argues that an information system containing machine learning models should be organized with two systems in mind: a data system and an information system.

The Conclusion summarizes the contributions and outlines the perspectives for future work.

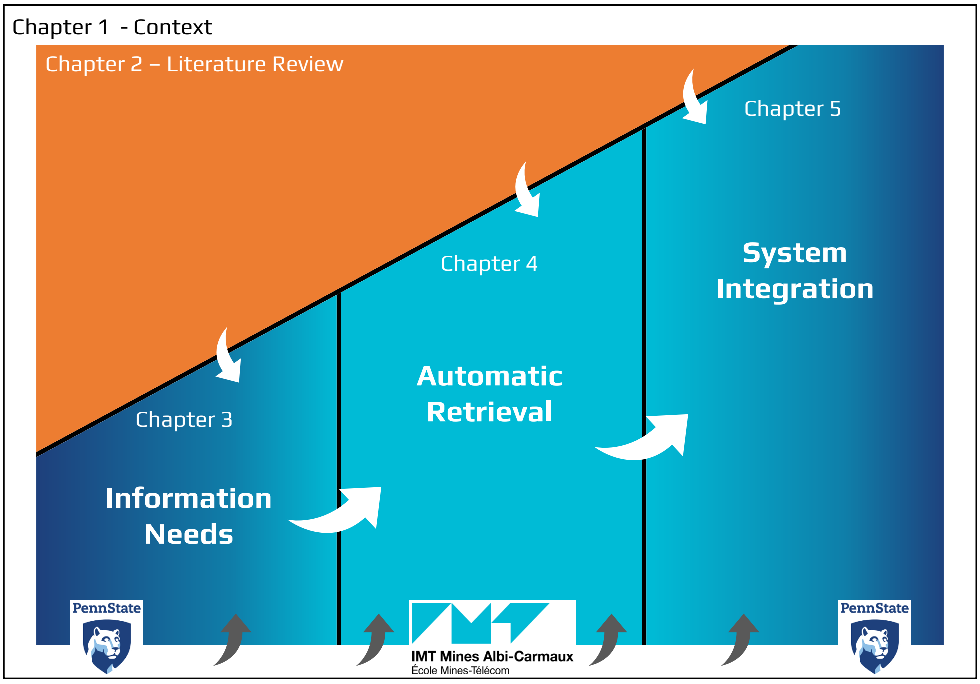

Figure 1: Overall organisation of the document. The arrows indicate the contribution of each part on the others.

1

Context

1.1 Crisis Management

1.1.1 A definition?

Defining the concept of crisis provides a hint of the challenges that lie within this domain. Although the term is widely adopted in everyday language, it is paradoxically challenging to give a precise and definitive scientific definition. The term is used every day for both financial crashes, natural or humanitarian disasters, or personal situations. Many researchers have tried to define this vague concept. Lagadec (1994) identified numerous attempts of definitions. Among them, Rosenthal (1986) proposed a taxonomy that would reflect the variety of types of crises:

- The "unimaginable" crisis requires that we question the unthinkable.
- The "neglected" crisis is caused by a lack of interest or care.
- The "almost inevitable" crisis, despite preventive action.
- The "compulsive" crisis results from inadequate management.

- The crisis sought by some, internal or external, actors.
- The crisis deeply desired by all parties.

In an almost similar way, Mitroff et al. (1988) proposed a classification of crises according to intrinsic characteristics. The authors use a 2D matrix to classify the different types of events. One of the components opposes the origin of the event (internal or external), while the other axis opposes the "social" or "technical" aspects. For instance, company bankruptcies are located in the internal/technical quadrant, terrorist attacks in the external/human quadrant, or natural disasters in the external/technical quadrant. Brief definitions have also been proposed to define the term itself. Hermann (1972) proposed that "a crisis is a situation that threatens the essential goals of the decision-making units, reduces the time available for decision-making, and whose occurrence surprises those in charge." More than a simple situation, Rosenthal (1986) will prefer to insist on the notion of crucial decision-making: "A crisis is a serious threat affecting the basic structures or the fundamental values and norms of a social system, which—in a situation of high pressure and high uncertainty—requires crucial decisions to be made." Nevertheless, crises are also periods of uncertainty and disarray of organizations, where rules and processes are blurred. Lagadec (1994), realizing the complexity of these phenomenons, abandoned the idea of a succinct definition. Thus, he proposed a more ambitious, complete definition through a higher-level viewpoint:

> A situation where multiple organizations, facing critical problems, subjected to strong external pressures, bitter internal tensions, are suddenly and for a long time projected on the front of the scene; all this in a society of mass communication, that is to say, 'live,' with the assurance of being on the front page of the radio news.

From the definitions given above, one can see the difficulty of defining the concept of crisis, as it is so diverse. This diversity in the use of the term reflects somewhat the very character of the crises. By nature, crises are a constantly renewing phenomenon. New causes, consequences, or ways to impact societies emerge. This constant innovation might be what prevents any final definition. In the end, crises seem to be the demons living in the dark face of our societies. Invisible and seemingly out of reach, societies only witness their sudden and brutal irruptions in the tangible phase of our world. These irruptions invariably result in an eruption of chaos. This metaphorical representation translates a personal vision of what a crisis is and the inherent complexity of the definition of this concept. However, while describing those "demons" seems a challenging endeavor, the irruptions themselves and their consequences possess common points. The following part discusses these points.

1.1.2 Characteristics of a crisis

It now appears that a fixed definition of the concept of crisis is difficult to achieve. However, if the concept of crisis remains vague, the effects and consequences are tangible and quantifiable. Victims, material damages, environmental destructions, and other more or less reversible consequences are tangible. A first characteristic extracted from the previous definitions is the emergence of chaos that creates a brutal rupture. Crises are thus to be distinguished from incidents, which are difficulties for which preventive measures allow to keep the situation under control. Without a definition, having an overview of the multi-dimensional consequences of crises is essential in building an adequate representation of the concept. The literature is rich in numerous efforts to list the manifestations of crises. Many authors, sharing the observation that it is difficult to define the phenomenon, even propose to define crises based on their consequences. Thus, for Milburn (1972), only an event that meets specific criteria would be eligible for the title of crisis. The characteristics they evoke are:

- Threat to assets identified as essential by managers.
- Need for quick decisions.
- Relatively short time frame for response.
- Lack of emergency measures available since it is an unforeseen situation.
- Need for innovation in solving the problem due to the absence of a pre-existing system.
- Information overload.
- Ambiguity.
- Increase in the number and importance of requirements.
- Internal conflicts in the organization.
- Considerable fatigue.

These first characteristics are discussed by Rosenthal (1986). The latter propose characteristics that frame the effects of a crisis. They consider that the previous characteristics do not sufficiently take into account all the facets of crisis. In particular, the authors consider that crises are also times that create opportunities for certain individuals. In a similar approach, Fink (1986) defines crises as situations that expose to risks. The risks he identifies include:

- Escalate;
- Attract significant media and administrative attention;
- Affect the regular operation of the company;
- Call into question the public image of the firm and its leaders;
- Reach the very foundations of the organization.

Lagadec (1994) summarizes the two previous authors through three main characteristics:

- Surge: A crisis is a tsunami. Information, issues, external actors involved, media attention, etc. Regular processing capacities are overwhelmed as everything is tenfold.
- Disruption: The universe in which the organization/system was is falling apart. Allies are disengaging. New, unusual actors (and, most often, unwanted) appear. An overall ambiguity is cast onto the system hit.
- Breakdown: The system is falling apart. The regularity is not anymore. All reference points, both internal and external, are disappearing. All the decisions are "no-win" for the organization.

These characteristics adopt a high-level point of view and encapsulate many concepts. They also provide valuable information to create a big picture of what a crisis is. Differently, Fertier (2018) proposed a set of four characteristics allowing to position crises relatively to each other:

- Geographic scope of the event.
- Duration (time between the first and last consequences, including replicas).

- The *severity* of the event (minor/major). Scale established according to the number of victims and or material damage.
- The *complexity* of the event, depending on the number of dimensions involved in the event, the number of layers and replicas of the crisis.

These criteria can be used as metrics to compare different events according to their impact. Also, it highlights how crisis events are composed of a wide diversity of consequences. Characterizing such events benefits from a multidisciplinary approach, as different viewpoints lead to a different picture of the crisis phenomenon. The following paragraph presents the different terms used in this manuscript and provides their semantics.

1.1.3 Schematic representation of the components of crisis

During nominal times, the *population* lives in an *environment* in which existing *systems* are composed of valuable *assets* managed by *organizations*. Usually, when one studies a crisis, the point of view of an organization is taken. The environment refers to everything outside of the system or organization of interest. The immediate environment can be composed of other assets part of other systems or organizations. It can be other companies, other cities, other countries, etc. In the environment, there are systems and their associated organizations that are impacted. The part of the population that suffers from the event is considered as the *victims* of the event. Among all these systems, there is one of particular interest when a crisis happens: the crisis management system, which is in charge of the response to the event. At crisis time, the organization in charge of crisis management creates a *crisis cell*. The United Nations Department of Humanitarian Affairs (UN Department of Humanitarian Affairs, 1992) defines a crisis cell as: "A facility officially designated for the direction and coordination of all actions in the response phase of a crisis." The crisis cell is composed of *operators* that gather, filter and share incoming information with the *decision-makers*. The latter make *decisions*, some of which are instructions to the *response teams*. The framework proposed is thus composed of four main entities: the environment, the system, the organization, and the decision-makers. The following sections describe each of the entities proposed.

The environment

The environment represents an area. This entity is linked to the geographical characteristic proposed by Fertier (2018). When an event occurs, the environment can be split into two parts: a part impacted by the event (the crisis environment) and a part not impacted. Some events can concern only a small industrial area, as in the case of water pollution, for instance, or have a worldwide scale, as in the case of the global pandemic that the world is facing at the time of writing this document. Events with different scales involve actors accordingly. A crisis can affect the environment in which systems and organizations exist in several ways. Part of what defines a crisis is this sudden change in the environment. Decision-makers find themselves disoriented. Infrastructures, resources, or actors that were supposed to be available are not anymore, or their status is unknown to the decision-makers. Crises reshape the environment, and consequently, the first step is taken once the organization realizes that they lost control of the situation is to figure out what this new environment is. However, not only is the system's environment reshaping, but the system itself is too.

The system

A system is a set of organizations that rely on resources that compose their stakes. In this definition, a city is a system composed of many organizations. The latter use different resources to function. A crisis affects a system if and only if the system's stakes are threatened. For instance, a volcanic eruption in the middle of a desert will probably not be considered a crisis event. On the other hand, a volcanic eruption near a city is a disaster event. The former would be a dramatic event, while the latter would probably modify a few air traffic lanes. Crises often result from a combination of different factors. The organization in charge of the systems is supposed to protect the known vulnerabilities of the system and prepare for the unknown ones. A crisis can emerge from a stressful event on one of those vulnerabilities. To illustrate those interactions, Benaben et al. (2014) propose a framework that illustrates the relationship between the different concepts Figure 1.1. According to the previous authors, the consequences result from an event on the different risks (which we call here vulnerabilities). These risks are, in turn, the result of dangers on stakes.

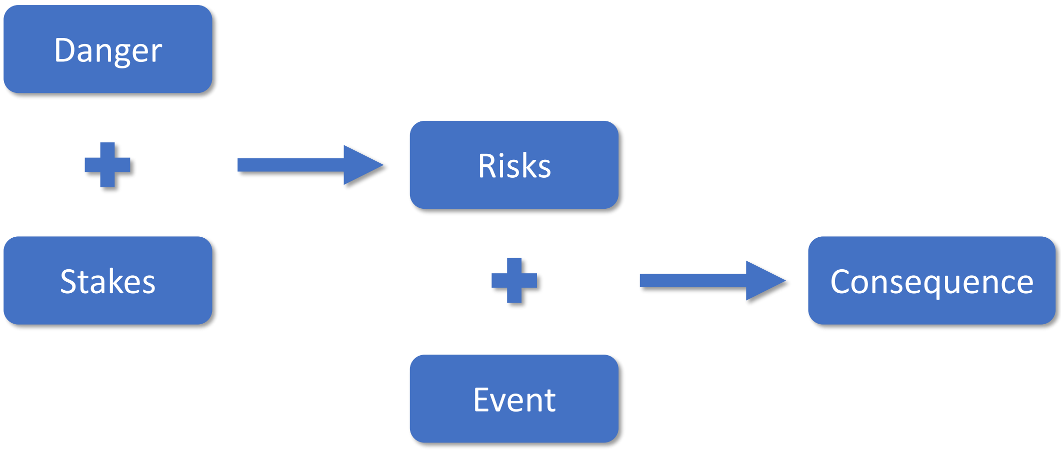

Figure 1.1: Crisis causality chain from Benaben et al. (2014)

Each consequence can, in turn, become a danger or an event that endangers the system. This phenomenon is referred to as the "cascading effect." With the dynamism explained before, the crisis is self-feeding and drags the system in its fall. The best known industrial example is undoubtedly the Chernobyl nuclear disaster. The cascading effect also joins the "surge" evoked by Lagadec (1994), which is based on numerous testimonies of people who were involved in the crisis management. In the end, a complete disruption of the system occurs. Regular operation is no longer possible. Existing processes are no longer valid. The historical partners are no longer available while unusual actors appear. One of the consequences of this disruption is the increasing complexity of conducting operations. Additional precautions are required for each decision and intervention that follows. Every action that was once trivial becomes uncertain. Most of the usual signals have disappeared, and the remaining ones are ambiguous. At the same time, the information requirements for each decision explode. The parts of the system that the event has not destroyed are then rendered inoperative.

The organization

An organization is a group of individuals who compose and manage a system. Companies, public services, NGOs, crisis management teams are considered as organizations. This definition is recursive: an organization can be considered as a system. Thus, the organization's services become the different organizations that compose the system. Each organization has to respond to the event that hit its system. They activate their services dedicated to crisis response. During response time, each organization attempts to protect its stakes and resources.

The activation of the response depends on how long it takes the organization to realize that the event is there. There may be a lag time between the first effect of the crisis and the activation of the response. By the time the response is activated, the crisis has already impacted a significant part of the system. From that moment, the state of the system is altered. This change plunges the organization into uncertainty and doubt. The system is no longer in a known state. The situational awareness has changed, and there is an urgent need to re-establish a coherent vision for further response operations. The importance of situational awareness is further developed in the second chapter. From that moment on, the organization will seek to obtain as much information as possible about its environment and its system. Each decision becomes crucial in the protection of the stakes. However, with the loss of knowledge about the system's state, every decision comes with much uncertainty.

To reduce uncertainty, the organization will seek to know the state of the system. It, therefore, requires reports on all aspects of the system. Information from automated parts of the system might be automatically retrieved if they are equipped with the appropriate sensors. Emergency services, such as the American 911, firefighters services, etc., obtain mainly their information from the response teams deployed and victims' calls. Similarly, external services (meteorological, specialists, etc.) can also provide external data to help the organization make decisions. However, the organization is rarely prepared to handle such a volume of information As a result, the decision-makers at the head of the organization become overwhelmed.

In addition to this, the initial information feedback is scattered and therefore ambiguous. The context in which each piece of information fits is absent or limited. The situation faced by the organization can be illustrated with a puzzle. However, we do not know the outcome of the puzzle, and the pieces are provided to us one after the other, in no particular order. We are also forced to place the puzzle pieces (i.e., make decisions) without knowing the following. Under these conditions, it is only possible to complete the puzzle when enough pieces are provided. To imagine the psychological consequences of such a way of completing the puzzle makes it obvious why we do not do puzzles in this way.

In addition to these internal difficulties, there is also external pressure. The event inevitably attracts the attention of regulators, higher authorities, and the media. The organization, sometimes unknown until then, finds itself under the spotlight. Its past is scrutinized, looking for previous mistakes that may have led (or not) to the current event. Its leaders and their decisions are dissected, and the inconsistencies are highlighted as soon as possible to feed the headlines. Damages caused to the organization are not limited to physical ones. Its image and reputation might also be impacted, especially if the management is not Thus, in addition to the physical impact of the crisis, the trust and the image of the organization are also weakened.

The decision-makers

The decision-makers are the people with responsibility in the organization. As most organizations are hierarchical, they have layers of decision-makers, each responsible for an area of the organization. Decisions made by some individuals thus take precedence over those made by their subordinates. During an ongoing event, this phenomenon might impede action.

Moreover, most of the decisions appear as "no-win" for the organization. Problems accumulate without solving any for fear of making the situation worse. The decision-makers, once in control of the situation, are getting paralyzed. With the knowledge of their environment gone, they find themselves stuck. Their perception is distorted, as much as their assumptions. They soon realize that the situation is incredibly complex, and yet they have to move on. All this is done in a hurry, created by the influx of requests and reports. Decision-making is further complicated because the usual processes and safeguards they used to rely on potentially no longer exist or have become irrelevant. Once feared, improvisation and innovation are now required to realize that inaction will be as, if not more, costly than action. The stress on the organization is hitting decision-makers hard. Under the urgency, stress, and fatigue, every decision becomes a battle to be fought in the war created by the crisis.

This first part of the chapter presents a personal vision of crises and what they imply. This vision will drive the manuscript, including the structure of the different concepts affected by a crisis - the environment, the system, the organization, and the decision-makers. The remainder of this section develops how organizations deal with these situations.

1.1.4 Crisis Management

Crises are not a question of "if" but of "when." This inevitability implies an upstream reflection on the part of organizations and a consideration of this problem within the systems. These practices are called *crisis management*. Crisis management is “The set of organizational modes, techniques, and means that allow an organization to prevent, prepare for and respond with the occurrence of a crisis, and then draw lessons from the event to improve procedures and structures with a forward-looking vision (Wikipedia, 2021).” This definition perfectly highlights two main characteristics of crisis management. First, crisis management is more a broad spectrum methodological toolbox than a set of recipes to be applied in an event. Secondly, it takes into account the different temporal phases of the crisis. In the following, we detail these two aspects.

The Crisis Management cycle

The crisis management literature identifies four major phases. These phases are most often represented in the form of a cycle. The 4 phases are :

- Prevention: phase aiming at preventing the appearance or reducing the effect of an emergency. This phase identifies potential hazards that threaten system vulnerabilities and appropriate measures.
- Preparedness: measures that facilitate the response to the disaster. It involves ensuring that resources are available and deployable, that response personnel are trained, and that the potentially impacted organization is psychologically prepared.
- Response: corresponds to the activation of the measures prepared previously.
- Recovery: the phase that follows the response to the crisis. It corresponds to the repair/reconstruction of the parts of the system impacted by the event. This stage is often accompanied by an analysis of the risks associated with the repairs to avoid creating a replica of the crisis.

In this cycle, only one transition between two phases is clear: the one between preparation and response. This transition occurs when the organization acknowledges the event and goes into crisis management. The other transitions correspond more to a period where two phases coexist. The prevention phase, however, leads to some debate. Benaben et al. (2014) argue that the prevention phase is, in fact, common to the whole cycle. Even during the response and the recovery, the organization observes prevention measures to prevent cascading effects. Therefore, prevention can be considered as constant. The crisis management cycle can be simplified with only three phases in crisis management: the preparation (before the event), the response (during the event), the recovery (after the event).

Also, it is possible to see beyond the cyclic representation. Today’s world is complex, tense, and deeply interconnected (Benaben et al., 2021). As a result, large organizations or countries possess a large surface vulnerable to potentially disruptive events. Then, instability and crisis management somehow become the norm. Small and large events trigger responses from the organization. However, these events are concurrent, and each is at a specific cycle phase. Consequently, looking at the global picture, these organizations are dealing with multiple crises simultaneously. Similarly, significant crises are often not directly dealt with at the global level. For instance, a local firefighters station will not deal with a whole hurricane by itself. Instead, it will take care of smaller, local events that are the direct consequences of the hurricane. In this example, the hurricane triggers the response phase in the cycle, but one could zoom into the "response phase" of the cycle. Each consequence of the hurricane can be imagined as a local crisis, each triggering its own cycles. As a result, there is a macro event (the hurricane) and several more minor and concurrent cycles happening simultaneously. The cycle representation of crisis management does not account for the scale or the complexity of events. It is, however, a good enough abstraction to represent the different times in an event.

Stakes in Crisis Management

Crisis management techniques are the set of tools used to respond to crises. They are used by crisis management organizations at the onset of an event. This organization faces various challenges in its mission to respond to the event. Fertier (2018, pp. 12–18) identifies five challenges for the organization:

- Collaborate with internal and external stakeholders.
- Recover a situational awareness of the environment and the system (see section 3.2.1).
- Manage data collection from multiple sources.
- Process the previous data to get relevant information.
- Have and maintain a system to automate the previous two points.

Batard (2021) also identifies two of the previous challenges as the top ones in crisis response: i) having sufficient situational awareness and ii) coordinating the different actors of the response. The author then proposes four axes to protect these two main stakes.

First, managing the multiplicity of data sources. Organizations in charge of crisis management are already used to taking into account several data sources. Feedback from the field from the staff allocated to the response and phone calls from victims or witnesses of the event are commonly used. However, new sources are emerging. The Internet of Things and the variety of sensors that compose it can provide records of interests. The rapid and global development of social media is also a potentially attractive source of data (Meier, 2013). The opportunities offered by this data source are detailed in section 1.2.3.

Secondly, automatically interpret these data to extract relevant information. This information should then be delivered in an adapted way to the decision-makers (Luokkala et al., 2014; Van de Walle et al., 2016).

Thirdly, the management of information systems adapted to the crisis management context. An IT system supports this information system to facilitate the response. This facilitation is enabled by delegating some of the tasks necessary to i) restore situational awareness and ii) coordinate actors to the IT system (Benaben et al., 2015).

Fourth, the information system and the computer system must be adaptable. This strong constraint results from the nature of crises. A crisis management system must therefore be able to detect changes in the situation and react to them in an adapted manner (Barthe-Delanoë et al., 2014; Charles et al., 2010).

The two previous analyses highlight primary challenges during crisis management.

1. Understanding the current situation and state of the environment.

2. Coordinate the actors' response fluidly, following their skills and needs.
3. Automatically collects and organizes available data.
4. Automatically manages the information obtained and distributes it efficiently to decision-makers.

Thus, the organization responsible for crisis management must first restore its knowledge using its available data. Secondly, it must manage the information obtained from these data to best coordinate its response with its internal and external actors.

1.1.5 Tools for Crisis Management

The previous section identified two major stakes from the information system point of view: the coordination of the actors and the restoration, then management of the situational awareness. The protection of these stakes by the system is of the utmost importance to allow an adequate response. Tools and practices have been developed to help organizations in charge of crisis response to address those issues.

Organizational modes

The response organization is one of the components of the preparation phase. During this phase, the different future actors of crisis response agree on the roles and responsibilities during the future event. For instance, in the response phase, the system dealing with the response uses a hierarchical organization layered with crisis cells. A crisis cell is a facility officially designated for the direction and coordination of all actions in the response phase of a crisis. They bring together the organization's decision-makers who implement and direct the various actors to respond to the crisis. Thus, the crisis units must have a high-level vision of the event and be close to the actors of the response they are managing. Large-scale crises (mobilizing many actors or a large territory, for example) will undoubtedly create a hierarchy of crisis units. While the "low-level" crisis units orchestrate the response, a "higher-level" crisis unit is responsible for transmitting information between the "low-level" crisis units and coordinating their responses. In France, this hierarchy and the role of each actor are described in the ORSEC plan [1]. The hierarchy itself is composed of 5 levels:

- European
- National
- Zonal
- Departemental
- County

Each of the crisis cells set up has its specificities, depending on the actors who compose it. However, all are constrained by the same need for collaboration (Benaben et al., 2020; Comfort, 2007) and information (Comfort, 2007; Endsley, 1995). It is precisely the role of the information system to manage and exchange situation-specific information between the different actors.

[1] https://www.gouvernement.fr/risques/dispositif-orsec

Techniques and Methods

The organization mentioned above is only effective if the actors coordinate their actions. This coordination requires the communication of information available to the different actors. The organization's information system is in charge of this aspect.

This dissertation uses the following definition of information systems.

> An information system (IS) is a formal, sociotechnical, organizational system designed to collect, process, store, and distribute information. From a sociotechnical perspective, information systems are composed of four components: task, people, structure (or roles), and technology. Information systems can be defined as an integration of components for collection, storage, and processing of data of which the data is used to provide information, contribute to knowledge as well as digital products that facilitate decision-making ("Information System" 2021).

This definition mixes the definition provided by (O'Hara et al., 1999; Piccoli et al., 2019; Zwass, n.d.). Thus, the organization's information system is the cornerstone of information management. It can be digitalized or not, depending on the needs and practices of the organization, as it reflects how the information is processed in the physical organization. The information system is an abstract concept that encompasses many aspects of the organization. The development and maintenance of the information system are performed during the preparation phase. During this phase, hardware and software must be deployed, tested, and used for training to ensure smooth operation during the response. The hardware aspects are outside the scope of this manuscript, which is mainly interested in the software and social part of the information system Figure 1.2.

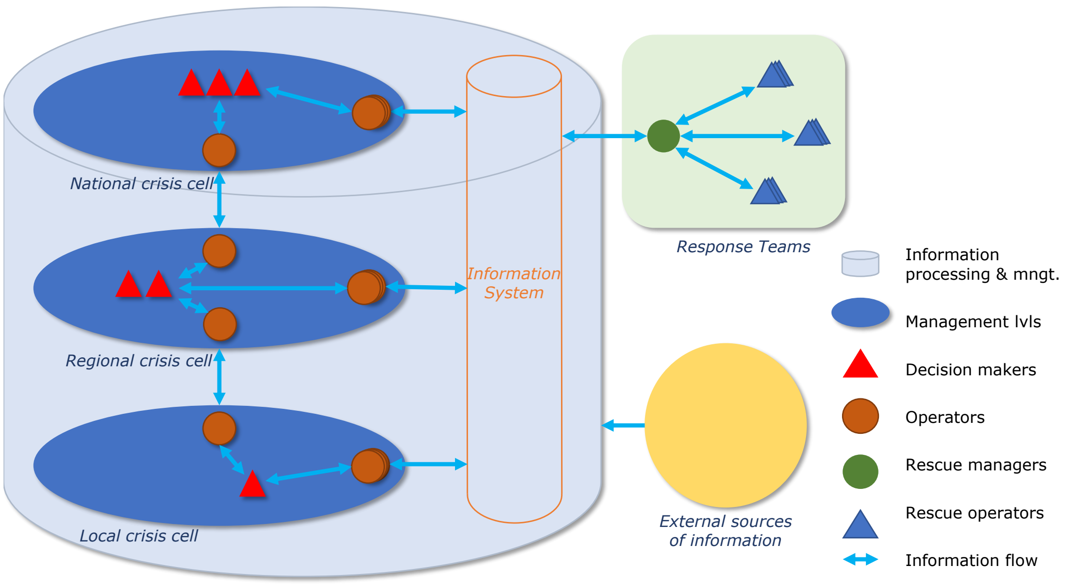

Figure 1.2: Representation of a crisis information systems and its interaction with the different members of the organization

The role of an information system is, according to the definition, to collect, process, store and distribute information. The information systems then allow their users to enter information into the system. This information is then consumed through interfaces. The information is automatically stored and processed by the system. In France, Morel et al. (2010) indicate that fire department services mainly receive their information from three sources:

- Victims' calls made from emergency numbers.
- The crews deployed to respond to the crisis.
- Other organizations involved in crisis management.

One thing all this information has in common is that none of it is first-hand. Moreover, how this information is collected is not necessarily representative of the situation experienced by the population. These collection methods result in a relatively small volume of information compared to the number of people affected. The information, therefore, does not systematically reflect the emergency experienced by the population.

The last part detailed the way crisis cells are organized in crisis response and the hierarchy built to scale decision-making with the size of the event. Each actor of this hierarchy comes with its own internal information system. However, to enable the coordination between all the different actors, information has to flow between each of them. Nevertheless, two challenges arise. First, the actors have to share a common vocabulary to communicate. Secondly, the information system has to be designed to allow communication.

Misunderstandings between the different actors often hamper the distribution of information. The latter often have different skills, responsibilities, and roles. Therefore, each actor builds his own vocabulary and terminology to designate his field of action elements. If this facilitates daily operations during an event, it complicates the collaboration and communication between the actors Opach et al. (2020). Therefore, the preparation phase is an opportunity to identify the actors who will potentially be brought to collaborate during an event and bring them together to be familiar with each other's culture.

Standard format and representations of the information between all the actors are needed to build a shared understanding of the situation. From a technical point of view, the different actors can decide to set up a "Common Operational Picture (COP)." The U.S. Department of Homeland Security defined a COP as (U.S. Department of Homeland Security, 2014):

> A representation that is established and maintained by collecting, collating, synthesizing, and disseminating information among the different participants. It allows the different actors to have access to the same information regarding the availability and location of resources and the status of different requests for assistance.

This representation is often cartographic, allowing the geographic component of information to be easily represented. Geographic information is also information that is equivocal among all actors. The COP is, therefore, a tool that allows to initiate and build a dialogue between the different actors of the response. It is also the visible face of the information system. The COP benefits from all the advantages that the rest of the information system provides. The COP can be automatically fed with the data mentioned above. Thanks to this data, the information system can then produce helpful information for the decision-makers and automatically make it available on the COP Fertier (2018). One of the problems currently faced by COPs is their inability to communicate with each other most of the time due to mutually exclusive software, which does not offer the possibility of dialogues between them Opach et al. (2020).

Finally, the COP is an asset for building and maintaining adequate and shared situational awareness among all actors. As we saw earlier, the restitution of situational awareness is one of the challenges of crisis management, as is the coordination between the different actors. The COP is an asset because it is a tool that allows both issues to be addressed simultaneously.

[2] https://research-gi.mines-albi.fr/display/RIOSUITE/Welcome

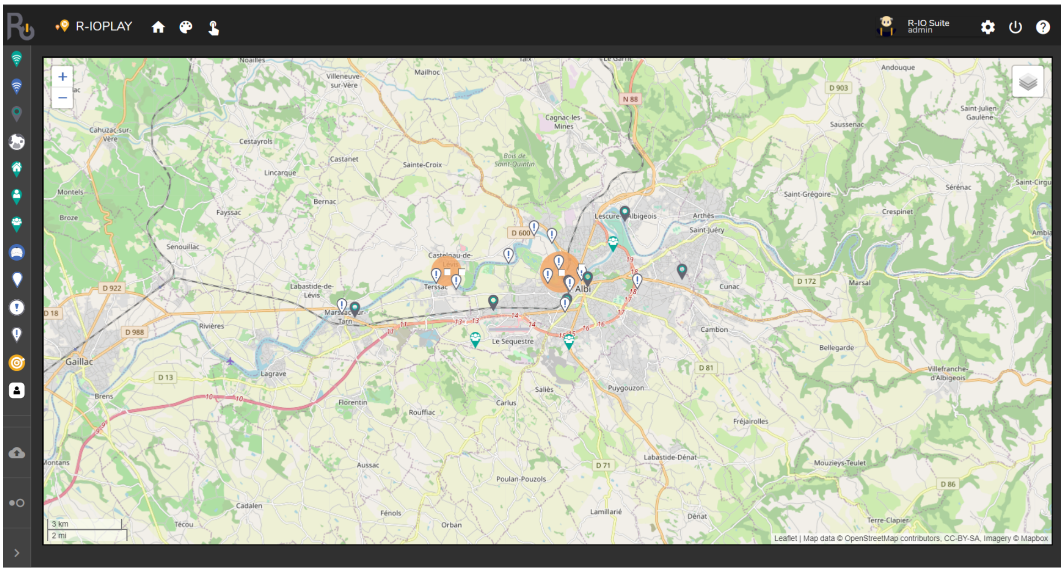

Figure 1.3: Cartographic display of the R-IOSuite software in a flood scenario in France[2]

Crisis management is a challenging domain. By nature, crises events are uncertain and hard to define. Nevertheless, patterns emerged from this uncertainty, especially regarding information management. Regardless of the event, decision-makers are in dire need of information about the event's impact on their system and organization. Tools and methodologies have then been developed to assist the decision-makers from the different organizations in coordinating and understanding the situation. Research and development around digital tools to support information management occur in the crisis informatics domain (Palen et al., 2020). One of those tools is the Common Operational Picture. The COP is a map shared between the different actors, with standard and specific information displayed. This visual representation aims to be the interface between shared information systems used by the different actors. However, the COP comes with its own challenge, as each information system has to share information with the common one. Also, the different actors have to agree on common representations and terminologies used.

1.2 Social Media

1.2.1 What are Social Media?

The previous section highlighted the challenges faced in decision-making during crisis events. At the same time, and somewhat paradoxically, our societies have never had that many ways and platforms to exchange information. Among these platforms, social media have recently appeared. Social media are Internet platforms that appeared during the Web 2.0 era. The term Web 2.0 was developed between 2003 and 2007 by T. O'Reilly. This terminology was initially born to revive the Web economy after the explosion of the dot com bubble formed during the development of Web 1.0, consisting mainly of web portals. Web 2.0 reflects the development of the community web and is organized around platforms that allow their users to connect in order to co-create and share content O'Reilly (2007). Social media fits into this definition. Kaplan et al. (2010) identify six types of social media: *blogs and micro-blogs* (e.g., Twitter), *social networking sites* (e.g., Facebook), *collaborative projects* (e.g., Wikipedia), *content communities* (e.g., Youtube), *virtual social worlds* (e.g., Second Life) and *virtual game worlds* (e.g., World of Warcraft). Social media are now essential websites and platforms that have up to one billion users, in the case of Facebook. It is difficult to grasp their full dimensions like the crises we mentioned earlier. These platforms, often global, connect users worldwide, forming a digital twin of our societies. The multitude of cultures, communities, languages, and codes that coexist in a single place has no equivalent in the history of humanity. Opportunities and threats accompany the disproportionate size of these platforms. Social media are indeed an excellent gateway to the world, allowing us to connect with an incredible number of people around the globe. It is also an efficient way to share information and exchange with other users through many formats. If the majority of social media users are consumers of content, a significant portion of them also creates content (Fuchs, 2021). Content creation on these platforms is thus their cornerstone, so much so that some of these platforms do not hesitate to pay their users who contribute, thus making a new profession emerge: content creator.

However, with this opportunity to unite humanity in a few hubs on the Internet comes many challenges. False information spreading, harassment campaigns or state disinformation are some of the problems associated with social media. If all these problems are not exclusive to these platforms, their dimensions and dynamics amplify them greatly. The following sections emphasizes two components of social media: *social network* and *viral information*.

1.2.2 Social Media characteristics

Social Network

Most people live in a community. Family, friends, neighbors, colleagues, all of these circles form an individual's social network. The social network is an integral part of one's life. Some researchers have looked into what the social network of different individuals could be.

The mathematician Erdös et al., while studying random networks, discovered that each node of the network is on average separated from any other node by six intermediate nodes (Erdös et al., 1960). More surprisingly, this result is little affected by the size of the network. These theoretical results found a concrete application in social sciences a few years later. Milgram (1967) verified the validity of the previous results within a population of individuals. By measuring the number of intermediaries required to send a letter to a targeted person, Milgram validated Erdös et al. results. In this experiment, each individual corresponds to a node in the network, and the edges are the relationships between the different individuals. Their results obtained in this physical experiment validated the theoretical results on random networks. This property is now known as the "six degrees of freedom" and refers to the average number of connexions required to link all nodes of the network.

Watts et al. (1998) sought to deepen the understanding of the six degrees of freedom and discovered on this occasion the structure in small worlds of social networks. So if people meet each other by chance, as in Paul Erdös' model, the social network itself is instead composed of small communities, with many links between individuals and very few links between communities. This model is called a "small-world network" as very few intermediaries connect most individuals, regardless of their distance or the community to which they belong.

Similarly, Barabási et al. (1999) deepen Paul Erdös' random model by discovering another property of social networks. Indeed, the random model predicts that the distribution of the number of friends among individuals must follow, by construction, a normal distribution. However, this is not what they discover experimentally. The distribution of the number of friends among individuals follows a power law. This property thus forms a scale-invariant network, where individuals connect preferentially to the most influential nodes.

In reality, both models have their properties verified. Therefore, we can consider, as a first approximation, that the two models coexist. Therefore, a social network can be modeled through three main properties:

- Each individual can be linked with any other, using only a few intermediaries (six on average), whatever the size of the network
- The network is structured in communities that are very connected to each other.
- The communities are connected by a few individuals who act as hubs.

These properties are illustrated in Figure 1.4.

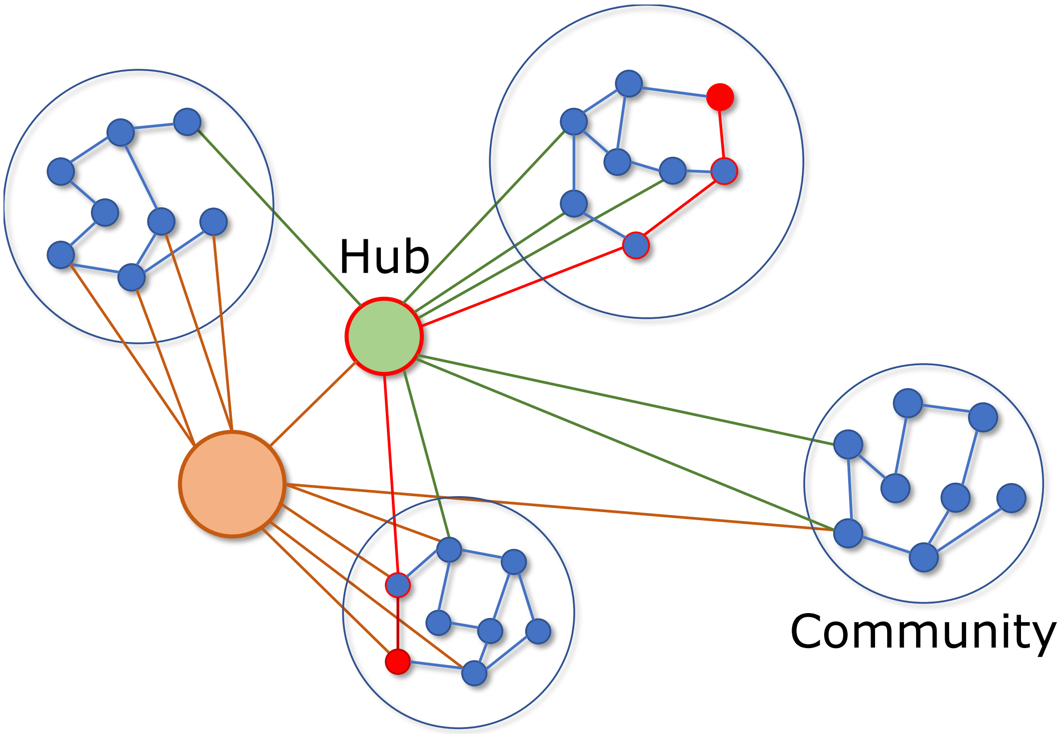

Figure 1.4: Illustration of the combination of both social network models from Watts et al. (1998) and Barabási et al. (1999). The red path illustrates how two members of different communities can still be linked through few intermediaries.

These properties are valid whether the social network is "real" or virtual - many of the experiments in the previous publications were obtained by studying social media. Thus, social media can be seen as many communities linked together by hubs (influencers). Having the structure of social networks in mind allows us better to understand the propagation of information within a social network. This brings us to the following section and a topic familiar to all social media users: viral information.

Virality

The propagation of information, true or false, within a community is experienced daily by everyone. However, this characteristic of information sharing is exacerbated in the case of social media for two reasons. First, social media brings together a vast number of users in one place. Second, they provide their users with several tools that aim to make information sharing much more straightforward. Social media put information and content sharing at the center of their strategy by construction. However, in a social network, each user can easily reach any user in very few intermediaries, regardless of the size of the network. Moreover, information can quickly reach many users if it is shared through network hubs.

This speed of dissemination is thus unusual, as are the results that such propagation can generate. Therefore, research teams are interested in understanding what viral information is and how this virality is characterized. By studying chains of information propagation, they identify that the phenomenon of virality is quite rare. Large content cascades are the exception, not the rule. 99% of posts are reposted less than ten times, while 0.001% of the posts create cascades of more than 1,000 reposts. Viral content is therefore rare, but it is seen by many users when it goes.

Recently, the notion of virality on social media has been widely associated with the term "fake news." Fake news is a concern that grew with social media platforms themselves. Notably, in the 2016 U.S. election context, the involvement of Russia in the process through disinformation campaigns (Senate, 2017). brought even more attention to that problem. D. M. Lazer et al. (2018) define fake news as "fabricated information that mimics news media content in form but not in organizational process or intent." The authors warn about the stakes and threats posed by fake news on our societies and call for more efforts to understand these dynamics, which are still largely misunderstood. Also, viral content cascades depend on the veracity of the content they propagate. Thus, to more people, false information spreads faster for longer with an essentially vertical structure (friends of friends relay the information). On the contrary, accurate information spreads more slowly, to fewer people, with slower kinetics and an essentially horizontal structure (the sender's followers essentially share the information). Deriving from the previous results, Vosoughi et al. (2017) built a system that assesses the veracity of one piece of information based on the way this information is propagated.

Finally, the understanding of the propagation of information on social media remains largely marginal. The call to link more independent research to the platforms of D. M. Lazer et al. (2018) remains anecdotal mainly, effectively hindering progress in this field. In the following section, we explore the different opportunities for crisis management in light of the few elements presented so far on social media.

1.2.3 Opportunities and Threats posed by Social Media for Crisis Management

The previous sections highlight how social media were similar to a digital twin of society. These platforms offer a point of view never seen before.

Significant events have long had an imprint on the Internet. In the aftermath of the September 11 attacks in New York, web pages for exchanging information about people were created (Palen et al., 2007). The relationship between crisis events and social media is now well established. The case of the ditching of the U.S. Airways Flight 1549 on the Hudson River in New York City in January 2009 is often used as an example of the impact that social media can have in essential situations. The information of the ditching had indeed been relayed on social media before all the traditional media (Murthy, 2018). Other studies have highlighted the reaction of social media during crises, as in the case of tornadoes in the United States (Blanford et al., 2014).

However, crisis management requires data and information to be able to achieve its objectives. Social media appear as a potential source of information for emergency services (A. H. Tapia et al., 2011). Moreover, where phone calls were the only link with the population, this digital twin of society offers a real-time overview of the conversations and feelings of the people who are affected by the event. These platforms thus make available a wide variety of data, which can help emergency services. As content creation platforms, users can use the wide range of tools at their disposal to share information about the ongoing event. Texts, photos, and videos can help crisis decision-makers better understand the event, even in places with no resources deployed. Social media can also bring back information that other actors within the organization may have missed. Finally, users of these platforms not directly impacted may decide to help the victims. These volunteers, digital or not, could be mobilized to assist the emergency teams deployed on the scene of the event (Batard, 2021).

The full potential of social media is yet to be discovered. However, these platforms come with challenges. As mentioned in the previous section, fake news is a current problem with social media (D. M. Lazer et al., 2018; Oshikawa et al., 2018; Vosoughi et al., 2018). This phenomenon is also mentioned in crisis management and attracts some interest from the scientific community (Sell et al., 2020; Starbird, 2017). However, while misinformation and the sharing of false information we see on social media in crises, it is not necessarily indicative of their uses alone. Bubendorff et al. (2021) present the small amount of information involved and the self-correcting effect of the crowd, which ultimately reduces the impact of false information. Despite this, emergency services remain cautious about the use of information from social media. A. H. Tapia et al. (2014) investigate their fears and what motivates this behavior. In particular, the previous authors highlight that social media do not necessarily provide more misleading information than phone calls. Their fears stem mainly from the relative novelty of social media and the lack of understanding of their universe.

Social media are Internet platforms that provide content creation tools to their users, generating and sharing data. Altogether, Twitter, Facebook, Reddit, Instagram, Youtube, and many others, have billions of users worldwide who share their everyday life, creations, and feelings with their communities. These digital twins of the society are resourceful and possess valuable information for crisis management. However, the dynamic of these platforms remains hard to understand for individuals. Also, in light of the recent controversies that have sprung, many are questioning their utility to ease crisis response. Social media provide a vast amount of

1.3 Natural Language Processing

1.3.1 On Natural Language Processing

Hirschberg et al. (2015) introduces Natural Language Processing the following way: “Computational linguistics, also known as natural language processing (NLP), is the subfield of computer science concerned with using computational techniques to learn, understand, and produce human language content.” As "learn, understand, and produce human language content" is a broad objective, the field is subdivided into many primary tasks such as:

- Language recognition
- Machine translation
- Sentiment analysis
- Question answering
- Text summarization
- etc.

The rest of this section presents the concepts and terminologies used in NLP.

NLP is concerned with textual data. There is no lack of such data, as this format is used extensively to share information on the Internet (wikis, emails, messages, etc.). To a computer, text is a sequence of ASCII or UTF-8 entities, called *characters* in the format of bytes (or eight bits). A set of textual data is called a *dataset* or a *corpus* (both terms will be interchanged throughout this manuscript). Corpora are most of the time composed of two parts: the *metadata* and the text itself. Metadata provides the context in which the data exists (e.g., a timestamp, recipient, receiver, etc.) The text in the corpus can be *tidy* or *raw* and, in the latter case, will require a step of *preprocessing*. The characters in the sequence are grouped in units called *tokens* during a process called *tokenization*. Tokenization depends on the language. Western languages can split tokens using white spaces or punctuation. However, this way of splitting text cannot be used for Japanese (that does not contain any space) or Turkish (an agglomerative language). Contiguous multitokens are called *spans* and are used to represent high-order tokens for specific tasks such as *chunking* and *named entity recognition*. For instance, in the sentence "Bob scored a goal," we might want to extract the noun "Bob" and the verb "scored." Named entity recognition aims at a similar objective, but with *named entities*, a string mention of a real-world concept such as locations, organizations, persons, etc. All the unique tokens form the *vocabulary* or *lexicon* of the corpus, and individuals are called *types*. These types can be either *content words* or *stopwords*, the latter mainly being used for grammatical purposes instead than for conveying information. Also, words have one or more meanings. The *senses* are all the meanings of a word. The WordNet project intends to catalog the senses of the words in the English language (Miller, 1995). As of writing (2021/07/19), WordNet contains more than 150.000 words and their senses.

NLP is mainly achieved through 3 main approaches (Hirschberg et al., 2015):

- Rule-based approach: rules are written to match specific tokens or groups of tokens
- The statistics-based approach: a statistical model is trained to recognize patterns in a set of features provided by the users.
- The deep neural network approach: a statistical model is trained to recognize word distributions and find them in new entries.

The revival of deep neural networks, driven by the explosion of available data volume and computational power, has found a place in NLP. The ability of these models to build subtle abstract components of the data patterns has allowed significant progress in NLP. These advances are apparent in the semantic part of the text. Once one relied mainly on the structure and syntax of the text, deep neural networks now allow us to add an essential semantic component to the processing.

1.3.2 NLP and Social Media: A natural match

The section dedicated to social media highlighted that these platforms provide tools to their users to create content. Content creators use these tools to share their content with their communities easily. As a result, a significant amount of data is created. These platforms embed data types such as text, images, and videos. Also, all the content possesses metadata that provides context at processing time and, in turn, leverages many opportunities. A large portion of this data is textual data. This amount of data can hardly be processed by human agents alone. Thus, the need for an automatic processing method, such as NLP.

However, most NLP methods and tools are developed using textual data from news articles and books primarily written in English. Social media data rarely look like this type of data, as they are more informal, conversational. Messages on social media often use emoticons, non-standard spelling, and abbreviations, making tokenization even more challenging. As an example, tweets (messages published on Twitter) can contain @handles, #hashtags https:urls, and smileys :-) that need to be processed. Thus, the medium, or even the platform, can require a specific tokenizer. The lack of grammar also complicates syntactic analyses. The absence of punctuation also makes detection of sentence boundaries challenging.

Social media are also a very noisy source of data. Posts from users are mostly direct reports of their current thoughts. Hence the use of "status" to mention social media posts, as users share with their community their instant feelings. Messages are also more subjective than news articles, where the objectivity of the information matters.

Much research has been done to explore the possibilities of social media in a wide variety of domains. highlight in their fourth chapter different use case in several domains:

- healthcare: tracking of depression, post-traumatic stress disorder, schizophrenia, pharmaceutical side-effects or flu season
- financial: computation of socio-economic indicators based on the sentiment of the general population, monitoring of financial community boards
- political: predicting voting intentions
- media monitoring: tracking of news worldwide
- security and defense: pre identification of possible threats, tracking of incident reports
- etc.

Natural language processing provides valuable tools to those who want to process textual data. More essentially, it allows automatically processing a large amount of data and making sense of it. On the other hand, social media are platforms that contain large amounts of textual data posted by millions of users worldwide. Processing this amount of data requires automatic processing. Thus NLP and social are two domains that naturally fit together.

1.4 At the crossing paths of the domains

The previous sections described three domains: i) the crisis domain, ii) the social media domain and, iii) the NLP domain. Also, as presented earlier, these domains intersect. Crisis management requires information to operate. Social media produce data, which can be converted into information. NLP tools provide ways to extract information from textual data. Thus, there is an intersection between the different areas (Figure 1.5).

Palen et al. (2007) highlighted in 2007 the role of information and communication technologies (ICT) in crisis response. A few years later, social media were considered as an opportunity in crisis management (S. Vieweg et al., 2010). This work started the social media branch of crisis informatics (Palen et al., 2020). NLP was then used to automatically retrieve information from the flow of social media data (Caragea et al., 2011; Verma et al., 2011). This allowed scaling the analysis to the high volume of content that social media have to offer. Most of the early work was spent in ways to identify crisis-related text messages automatically. Since then, many efforts have been added to explore other opportunities, such as images. Variations on different crises, NLP techniques, and features used to represent the data were developed and used. Imran et al. (2020) identify several remaining challenges in the domain of social media in crisis informatics:

- Crisis event detection: detect the apparition of an event by detecting characteristics messages.
- Eyewitness detection: determine whether a direct or indirect eyewitness posts a message.
- Situational awareness: identify text messages that contribute to restoring the situational awareness of crisis management organization

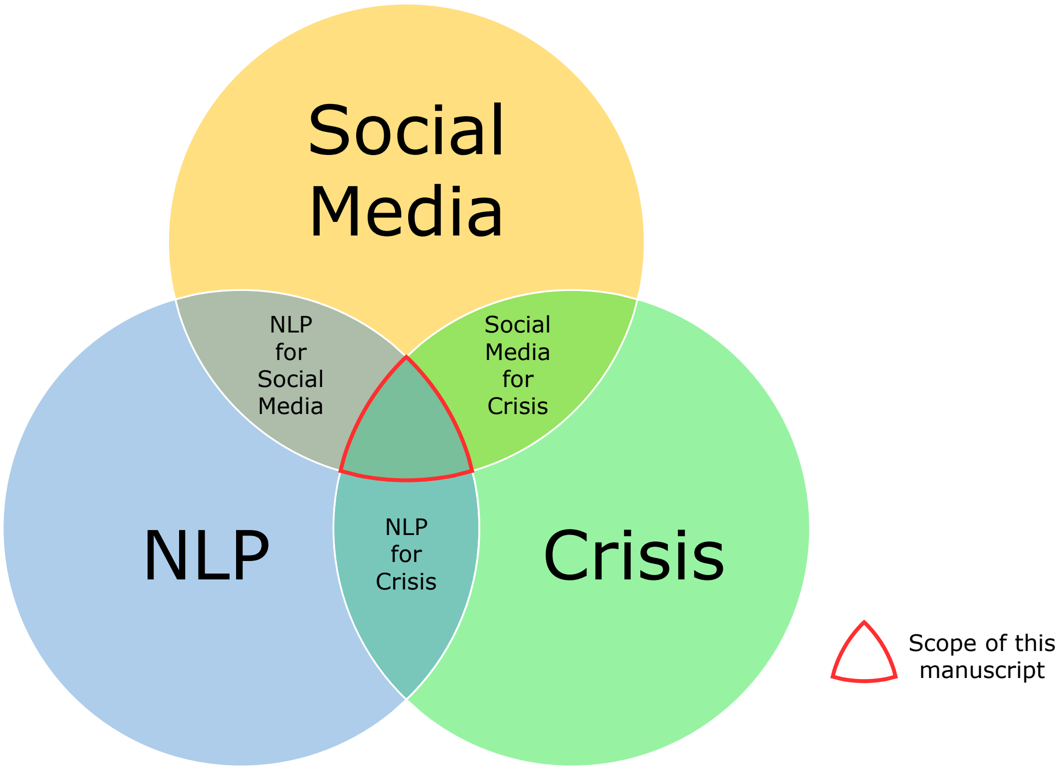

Figure 1.5: Intersection between the domains of Social Media, Crisis Management et Natural Language Processing and the positioning of the research presented in this manuscript.

- Actionable information gathering: a collection of information that facilitates decision-making
- Damage assessment: methods to determine the extent of the damage caused.
- Crisis communication: tools to facilitate crisis communication to the general public
- Understanding public reaction: tools to help understand the general public reactions to an event
- Information veracity: evaluation of the relevance of the information collected

All these challenges aim at extracting information from social media. They necessarily involve artificial intelligence to identify at scale the mentioned information. However, as mentioned earlier, social media data are subjective, fuzzy, and prone to rumors. At the same time, the outcome of NLP models is never 100% accurate. Thus, uncertainty is the norm among the information extracted from social media data. Also, all this information, once created, need to be stored, managed, and distributed to provide valuable insights. Thus, the following research question:

Primary research question:
How to design an information system for crisis response that can automatically manage and deliver actionable information from social media data?

This primary research question is then decomposed into three sub-research questions.

1.4.1 Challenges consecutive to the primary research question

Three consecutive challenges arise. In order to collect actionable information, the first step is to define what is actionable information in our context. Hence,

> *Research question 1:*
> What can decision-relevant information from social media be processed automatically?

Using the previous results, i.e., the actionable information for the decision-makers, leads to the automated recovery of this information. Hence, the second research question:

> *Research question 2:*
> How can the actionable information available on social media be automatically retrieved during crisis response?

Finally, obtaining this information allows us to answer the automatic information retrieval part. The last part is thus interested in the aspects of management and distribution of information. In particular, how should this system be designed if it uses machine learning models to obtain information? Leading to the third research question:

> *Research question 3:*
> What challenges are faced by an information system dedicated to crisis management that embeds machine learning models?

1.4.2 Research context

This chapter has presented three scientific topics whose main research question is at the intersection. This Ph.D., whose subject is at the border between social sciences and information sciences, has brought together three main academic actors. These three partners reflect the multidisciplinary approach taken during this Ph.D.

The MACIV project (Management of Citizens and Volunteers: the social media contribution in crises) brought together a variety of actors from different institutions around the issue of the adoption of social media in crisis response. The project studied the opportunity offered by volunteers in crisis management, emphasizing contributions on social media. This project, funded by the Agence National de la Recherche (ANR), was composed of both scientific actors — Télécom ParisTech, IMT Mines Albi and —, institutional actors — Direction Générale de la Sécurité Civile et de la Gestion des Crises, Préfecture de Police de Paris, Service Départemental d'Incendie et de Secours du Var — and associatives actors — the VISOV (Volontaires Internationaux en Soutien Opérationel Virtuel) association. Under the principal supervision of Dr. Caroline Rizza from Telecom Paris, this collaboration was illustrated through three different real-world exercises. These exercises were an opportunity to meet, observe and exchange with crisis management practitioners in France. The MACIV project has also seen the completion of two doctoral degrees. The first one was presented and defended by Robin Batard (Batard, 2021). The second one is currently in front of the reader. The former was interested in the role played by citizens in response to an event and how they could be integrated into the official organization. His findings and observations inform this paper, particularly on the contributions related to the social sciences.

This Ph.D. also involved PennState University, through the co-direction of Pr. Andrea Tapia. Although this project was conducted primarily in France, a year-long visit to the

U.S. considerably benefited this work. This exchange was an occasion to understand the challenges of the research question through the point of view of the social sciences, which informs chapters three and five. It also created the opportunity to meet several actors of the American emergency services, such as the Charleston County 911 Center and Cincinnati 911 operators, among others. These meetings provided valuable insights as well as a different perspective on the organization of crisis management.

Finally, this work was mainly conducted in France at IMT Mines Albi under the direction of Pr. Frederick Benaben and supervision of Dr. Aurélie Montarnal. PennState University provided valuable insights on the social science side of the research topic. However, this Ph.D. focus is in information sciences. Chapters four and five reflect the body of work conducted at IMT Mines Albi. Most importantly, the research topic emerged from a reflection on connecting the R-IO Suite software to social media. The R-IO Suite software[3] is "a dedicated set of tools to support efficiently inter-organizational collaborations." The software is articulated around an information model that represents the different concepts handled by the software. As several scenarios exist in which inter-organizational collaborations can happen, the model is declined in several flavors. This model related to crisis management is further explained in section 3.2.1. R-IO Suite is composed of various services that handle different aspects of inter-organizational collaborations. Its services are visually represented in Figure 1.6.

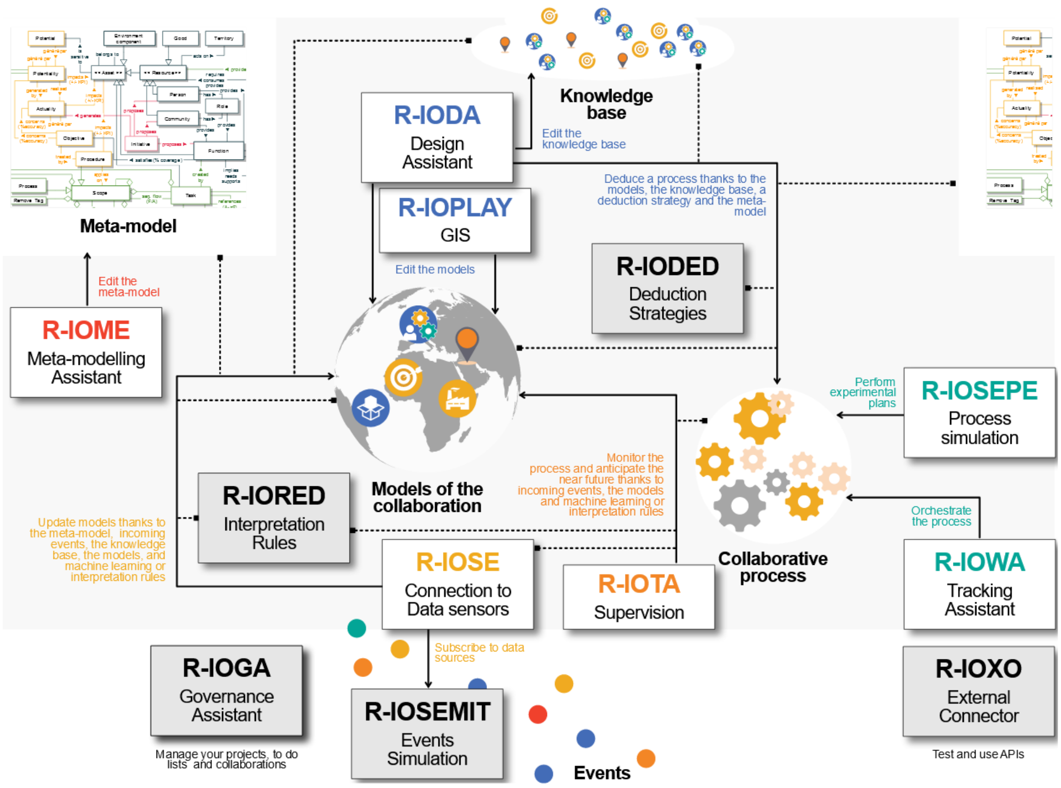

Figure 1.6: Services that compose R-IO Suite.

The main services are:

- R-IOPLAY: provides a Common Operational Picture
- R-IODED: proposes strategies to address certain aspects of the event

[3]https://research-gi.mines-albi.fr/display/RIOSUITE/R-IOSuite+Home

- R-IOSE: connects to a variety of data sources
- R-IOSEMIT: performs simulations of the outputs of R-IOSE
- R-IORED: is in charge of processing the data provided to instantiate the classes of the information model
- R-IOME: the editor of the information model
- R-IOGA: the main interface of R-IO, manages the different projects and use cases available

1.5 Structure of the document

The purpose of this manuscript is to advance the issue of improving situational awareness and collaboration between actors during the response to a crisis event, which was one of the issues identified in the crisis management section. Thus, adopting the point of view of decision-makers, and in the scope of the information system, the principal research question is:

How to design an information system for crisis response that can automatically manage and deliver actionable information from social media data?

The scope and consecutive research questions of the primary one are illustrated in Figure 1.7.

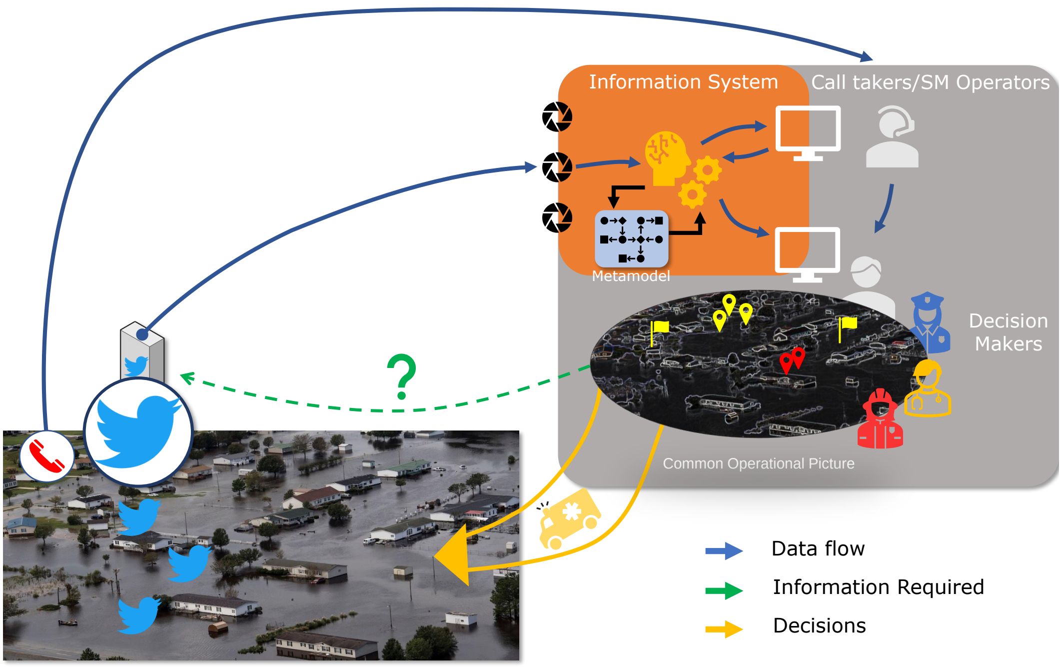

Figure 1.7: Overview of the context of this dissertation.

The following chapter, Chapter 2, is a literature review that explores the scope of each research question. Chapters 3 to 5 are the contributions associated with each research question.

- Chapter 3 narrows the scope of the information system designed by identifying its users and their information needs from an operational point of view.

- Chapter 4 describes an algorithm to identify the information needed while maintaining the user in the information extraction process.
- Chapter 5 embeds all the previous contributions in software architecture for a crisis information system, allowing to structure and produce further information.

The final chapter, chapter 6, provides conclusions and discussions about this work.

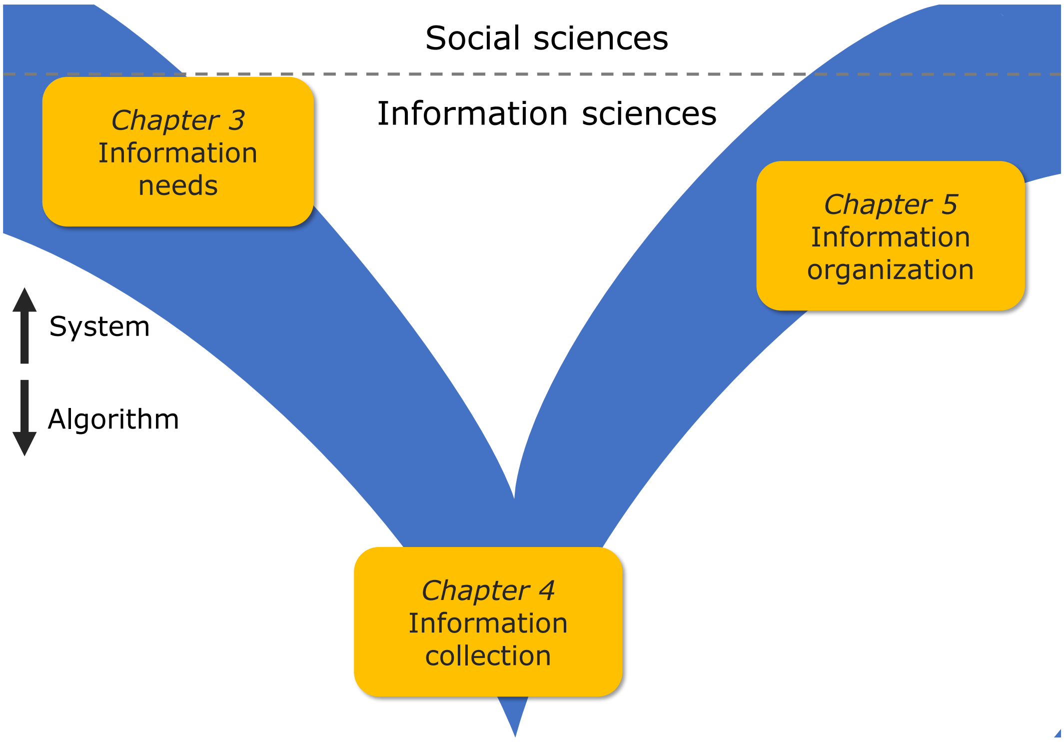

Figure 1.8: Organization of the different contributions presented in this dissertation.

2

Literature review

Introduction

This chapter presents and discusses previous conducted works related to the three research questions driving this dissertation. The research questions previously identified are:

1. What can decision-relevant information from social media be processed automatically?
2. How can the actionable information available on social be automatically retrieved during crisis response?
3. What challenges are faced by an information system dedicated to crisis management that embeds machine learning models?

Each research question has its dedicated section. Each section presents the evolution of the associated fields and the trends that have guided their development. The review of this literature allows for the identification of research directions for the following chapters. The remainder of this section presents the methodology used for the literature review and the research hypotheses.

Methodology

A mixed approach was taken to capture the evolution of work related to each research question First, the scope of the literature review is defined through research hypotheses. Once these hypotheses are created, the queries are made on Scopus [1], a bibliographic database.

The results obtained are then be analyzed from several angles. First, the evolution of the volume of publications returned by the query to attempt to represent the interest in the topic. Secondly, an analysis of the keywords is made through VOSviewer [2] "a software tool for constructing and visualizing bibliometric networks." Especially VOSviewer allows visualizing bibliographic features such as the networks of authors or keywords. The keywords used by the different articles fetched by request provide valuable insights into the evolution of a given field, especially its interdisciplinary aspect. Finally, the results of the most cited articles are discussed. This methodology should make it possible to show the evolution of the scientific community's interest in the topics explored.

Hypotheses

This sub-section establishes the scope of the research conducted in the rest of the chapter. First, the only data source considered is social media. As mentioned in the previous chapter, social media data present a set of specificities that differ from other data sources such as newspapers. Secondly, the literature review is scoped to the crisis management context. Finally, it is assumed that facilitating decision-making necessarily improves disaster response. Thus, the following working hypotheses delimit the work presented.

1. Social media data: social media data have a low ratio of information/noise.
2. Crisis management: the crisis management context is particular, and this manuscript focuses on the response phase and its context.
3. Improving the decision-making process leads to better disaster response.

These hypotheses guide the literature review around the research questions outlined above. Thus, the first section presents previous works on systems that automatically process social media for crisis response. Then, the second section explores the first research question and develops on previous representations of information created. The third and final section overlooks the different attempts to process social media data using Natural Language Processing methods. As the third research question also refers to systems for processing social media data automatically, it shares the insights of the first section.

2.1 Information systems for crisis response fed with social media data

The first chapter identified the opportunities offered by social media to support crisis response. Many researchers explored these opportunities and proposed various systems and architectures to process social media data automatically. The ultimate goal of these researches is to provide valuable insights to decision-makers. This first part of the literature review highlights the main systems built for this purpose. The research question this part aims to answer is: *What are the existing social media processing system developed for crisis response over the years?*

[1]https://www.scopus.com/
[2]https://www.vosviewer.com/

The request run on the Scopus database is broken down in table 2.1. It returns 96 documents published between 2011 and 2021. The beginning of this domain of research corresponds to the democratization of social media, with the development of social media platforms happening during the 2000-2010 period (Figure 2.1). Naturally, the field has developed, driven by the need of crisis management organizations and the public interest benefit it promises.

Table 2.1: Overview of the bibliographic request related to information systems.

Type of request	Keywords	Explaination
SUBJAREA	*comp*	Articles in the Computer Science domain
TITLE-ABS-KEY	*crisis management* OR *crisis response* OR *contingency* OR *disaster response* OR *disaster management*	Articles related to crisis management
TITLE-ABS-KEY	*system* AND *processing*	And concern systems processing information
TITLE-ABS-KEY	*social media* OR *twitter*	Using social media sources. Twitter is specifically indicated because of its prevalent use in the research community.
EXCLUDE-DOCTYPE	*re* OR *cr*	Reviews and conference tracks introductions are excluded

The network provided by VOSviewer (Figure 2.2) does not reveal any significant cluster of keywords. The youth of the domain can explain the structure observed, as no prominent direction as been created yet. However, the publication timeline (represented by the color variation) provides insights into the direction of the domain. Years around 2016 mainly were focused on data analyses of the different datasets available. Then, the following years saw the development of more and more automation. Artificial intelligence, machine learning, and natural language processing appeared in that chronological order, coinciding with the progress made in these areas. More recently, deep learning models to process text and images are appearing, as well as new opportunities created by the internet of things and the development of the concept of smart cities. It is also worth noting that social and computer sciences are blended in this big picture.

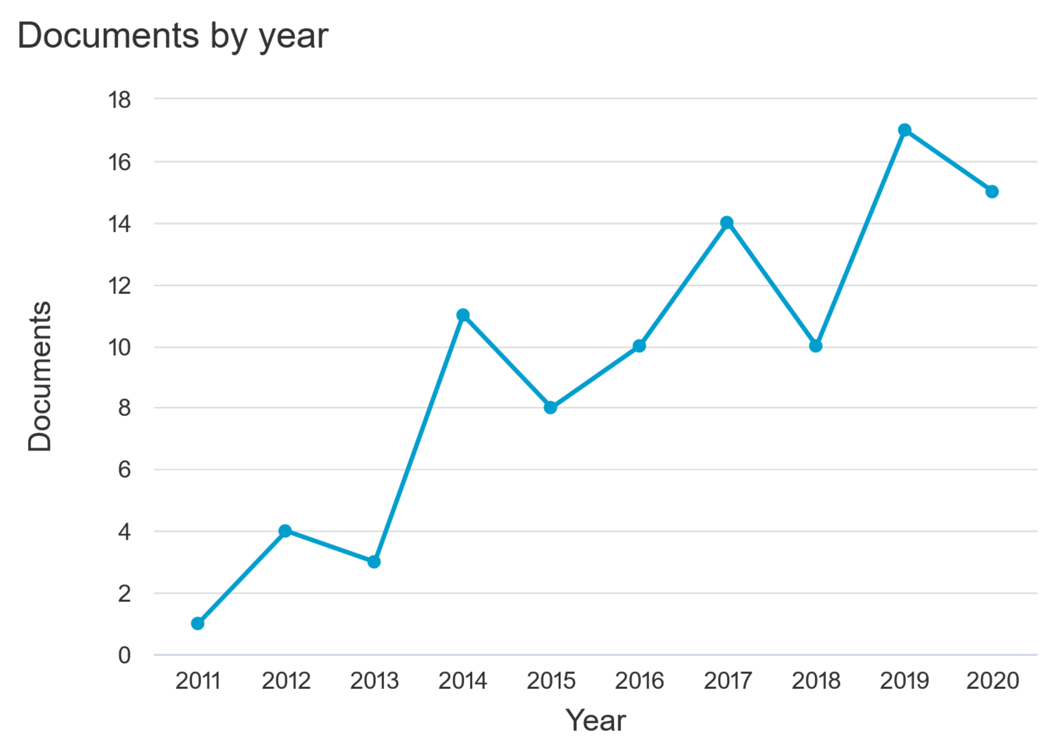

Figure 2.1: Timeline of the volume of contributions per years for the crisis informatic domain. The year 2021 is excluded because the year is not complete at the time of writing.

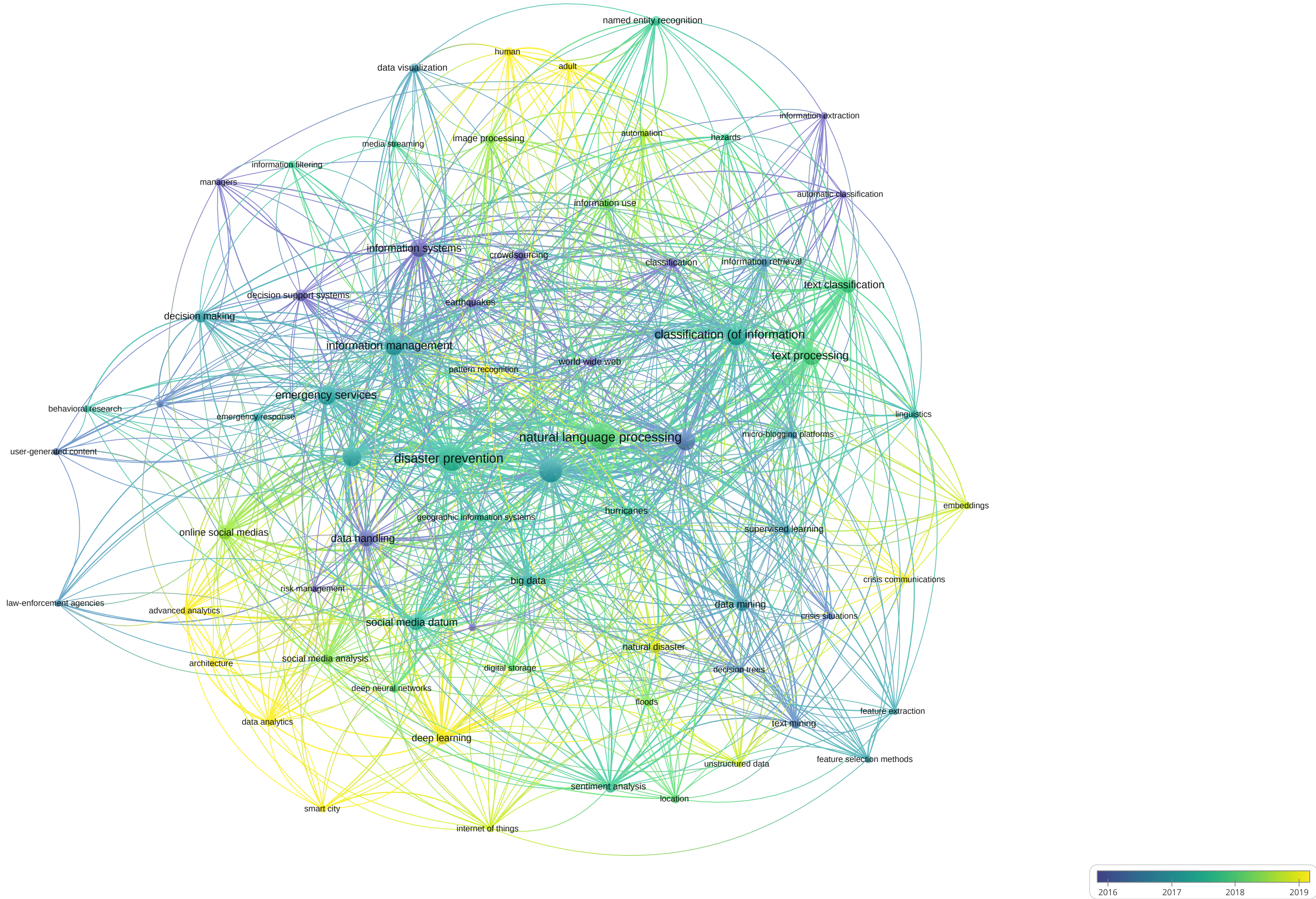

Figure 2.2: Distribution of keywords with more than 3 occurrences among the articles from the query on crisis informatics.

The bar diagram (Figure 2.3) provides a representation of the distribution of the occurrences of the different keywords. From the most used keywords, two areas of interest seem to emerge. The first one is the automatic processing of social media data. The type of data appears to be primarily textual, according to the prevalent use of *natural language processing* and *text processing* is no more important than the use of this automation. *Disaster prevention*, *situation awareness*, *information management* and *emergency services* highlight the importance of the applications of the results.

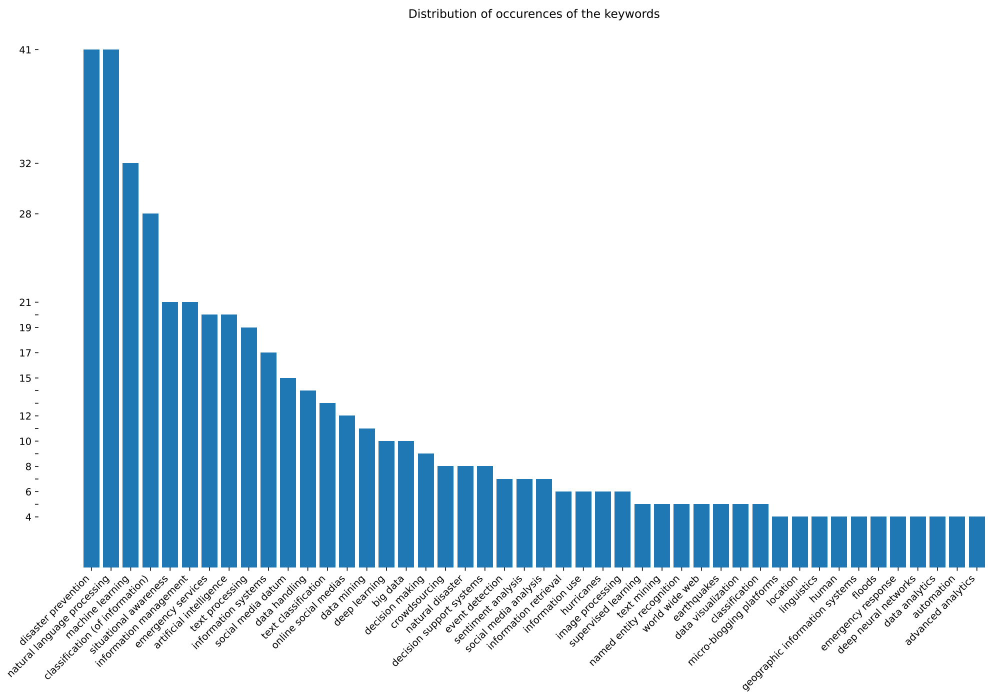

Figure 2.3: Distribution of keywords with more than 3 occurrences among the articles from the query on crisis informatics.

As mentioned in the first chapter, automatically processing the content of social media to extract information is a new and promising scientific venue. Thus, many attempted to create systems to achieve this goal, proposing features to improve usability. Table 2.2 presents the results of the previous query that mention a processing system that uses social media as a data source and that has been cited at least ten times are shown. The right column of the table summarizes the main features proposed by the authors.

Among the features identified, the trend towards automation observed earlier is clear. The first iterated systems were mainly relying on crowdsourcing to identify relevant information from messages posted on social media (Backfried et al., 2012; Imran et al., 2014; Schulz et al., 2012). The following works were interested in automating the previous tasks to reduce the dependence on human resources and improve massive data processing. Problems related to the detection of occurence of events and their related information on social media, have been explored using different approaches (Avvenuti et al., 2014; Gibson et al., 2014; Imran et al., 2014; Middleton et al., 2014). In parallel, experiments were conducted to identify the best ways to organize and disseminate the information obtained (Avvenuti et al., 2016; Gründer-Fahrer et al., 2018; Huang et al., 2015; Middleton et al., 2014). Building on its successes, the field has continued to develop by relying on other available data formats and in particular images (Agarwal et al., 2020; Alam et al., 2017; Nguyen et al., 2017). Beyond the data, new questions have emerged, following feedback from the emergency departments involved in the experiments. The detection of sub-events and the different concerns of the impacted population is added to the results of previous works (Gründer-Fahrer et al., 2018; Ragini et al., 2018; Wu et al., 2018). More recently, teams with a broader vision are interested in the integration of such systems within smart cities (Shah et al., 2019). The multiplication of sources and formats naturally leads to the need for unified processing methods for data and fusion of information obtained by the different channels (Alam et al., 2020).

This introductory section presented previous works around crisis informatics. More particularly, it highlighted the development of the field over time. This development is directly reflected in the different systems developed and their features. An interesting trend to note is the move towards more and more automation in systems. First, using crowdsourcing for initial data labeling, the following systems used machine learning to classify the data into different categories. Currently, automation was further extended to other valuable data types and ways to merge the information acquired.

Table 2.2: Articles retrieved from the previous request which propose social media processing systems or methods with at least 10 citations.

Reference	Type of event studied	Features
Schulz et al., 2012	None	Crowdsourcing
Backfried et al., 2012	None	Crowdsourcing, Automatic processing
Imran et al., 2014	None	Crowdsourcing, Information categories, Message filtering
Middleton et al., 2014	None	Common Operational Picture, Location inference
Avvenuti et al., 2014	Earthquake	Event detection
Gibson et al., 2014	None	Formal concept analysis, Rule-based method
Glasgow et al., 2014	None	Death-related content detection
Huang et al., 2015	None	Big Data, Common Operational Picture
Avvenuti et al., 2016	Earthquake, Flooding	Event detection, Message filtering, Disaster management
Alam et al., 2017	None	Image processing, Infrastructure damage
Fersini et al., 2017	Earthquake	Message filtering, Information management
Nguyen et al., 2017	None	Image processing, De-duplication, Image filtering
Ragini et al., 2018	Flooding	Sentiment analysis
Shah et al., 2019	Earthquake, Tsunami	Smart Cities, IoT integration
Gründer-Fahrer et al., 2018	None	Topic modeling, Disaster management
Wu et al., 2018	None	Subevent detection, Clustering
Agarwal et al., 2020	None	Damage identification, Severity detection
Alam et al., 2020	Hurricane	Information fusion

2.2 Decision-making in crisis situation

This part of the literature review explores the bibliographic context around the first research question: *What can decision-relevant information from social media be processed automatically?* Decision-making is at the heart of the response during a disaster. Ideally, the right decisions need to be made at the right time. This expectation is theoretical. This section is split into three parts. The first part presents the previous attempts to represent the context of crisis management. The second part highlights the challenges faced by decision-makers when responding to disasters. The third and final part refines the previous findings on those which consider social media.

2.2.1 Organization of information during crises: crisis models

With the advent of computers to delegate tasks, many have thought of charging some parts of crisis management to machines. However, in order to delegate these tasks to computers, they must first be provided with a representation of these tasks. In the context of crisis management, these are representations of the environment of this management. These representations will be called crisis models in this dissertation. Two paths to represent crisis' concepts have been taken: ontologies and metamodels. Ontologies and metamodels have very close definitions. Both methods aim at creating a controlled vocabulary to define the entities and their relations in a given domain. These two methods differ in what they seek to produce (Assmann et al., 2006). On the one hand, ontologies *define* concepts, providing a vocabulary and a grammar for manipulating the concepts studied. On the other hand, metamodels *represent* computationally the studied concepts, preferably using a standard modeling language. More precisely, they seek to represent the information associated with the concept. Therefore, metamodels and information models will both be used interchangeably in the following. Standard modeling languages such as the Unified Modeling Language (UML) are preferred as they ease the distribution and development of these representations. As the backbone of model-driven engineering, Metamodels tend to be developed with interoperability between different systems in mind. Ontologies and metamodels have been both applied to crisis management. Due to the tremendous variety induced by crises themselves, many ontologies and metamodels have been proposed to represent different aspects of crisis management. Consequently, ontologies and information models emerged to represent the informational concepts manipulated during an emergency. This sub-section aims at retrieving from the literature the different key informational concepts useful for decision-makers during crisis response. The query used to explore this domain is summarized in Table 2.3.

Table 2.3: Overview of the bibliographic request related to crisis models.

Type of request	Keywords	Explaination
SUBJAREA	*comp*	Articles in the Computer Science domain
TITLE-ABS-KEY	*crisis management* OR *crisis response* OR *disaster management* OR *contingency* OR *disaster response*	Articles related to crisis management
TITLE-ABS-KEY	*ontology* OR *metamodel*	And methods to represent and model information
EXCLUDE-DOCTYPE	*re* OR *cr*	Reviews and conference tracks introductions are excluded

The request returns 205 documents published between 1998 and 2021. Figure 2.4 shows the evolution of the volume of publication during this period. According to the Scopus database, the field has emerged around 2000 and progressed over ten years to reach a plateau of fifteen articles on average per year. The objective of this research was to identify and organize the information and knowledge used in crisis management. As mentioned before, the final goal is to delegate part of the management of this information to computers. For this, it is necessary to structure the required information and knowledge.

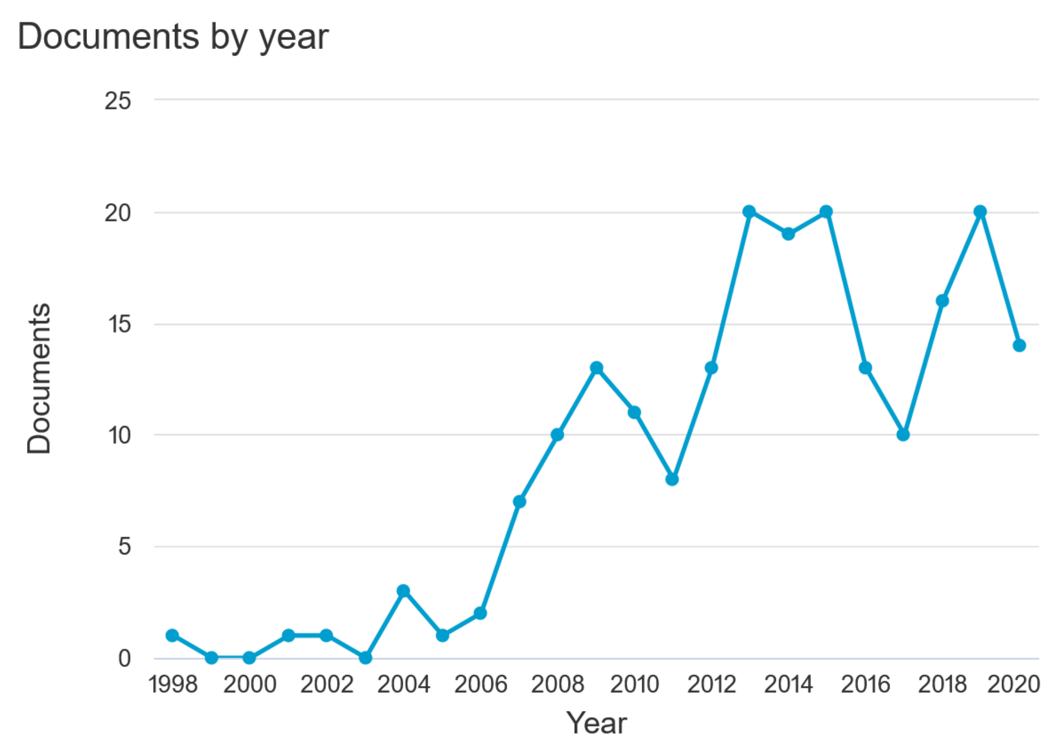

Figure 2.4: Timeline of the volume of contributions per years for the crisis-situation models domain. The year 2021 is excluded because the year is not complete at the time of writing.

Following the same methodology as in the previous section, Figure 2.5 provides a visual of the evolution over time of the different keywords used in the fetched articles. The overlay indicates three clusters: a major one and two smaller ones. The primary cluster focuses on the literature review topic, while the two smaller ones mainly refer to outlier topics (the petroleum and medical sectors). As in the previous section, the evolution (represented by the color variation) of the keywords hints at the direction of the domain over time.

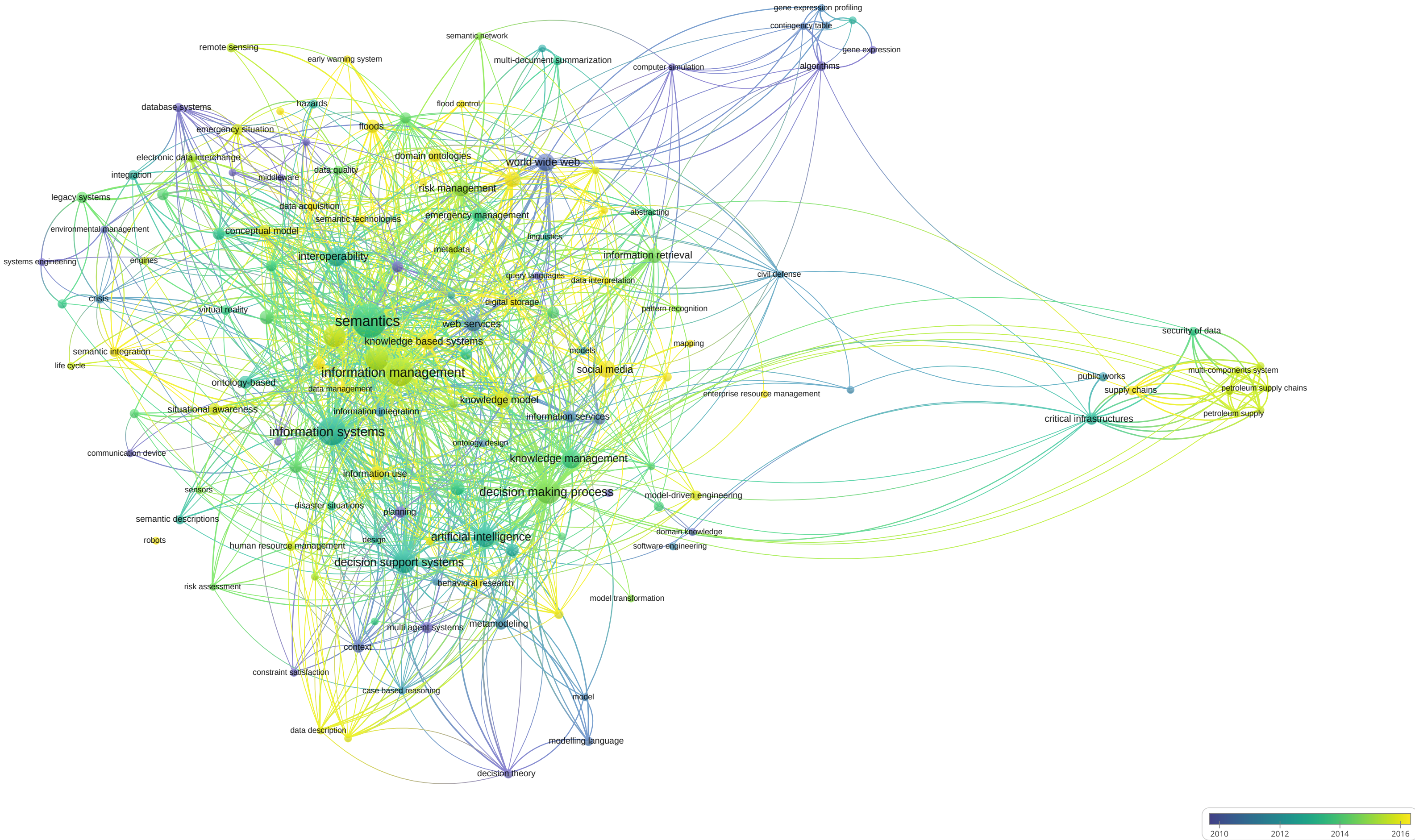

Figure 2.5: Distribution of keywords with more than 3 occurrences among the articles from the query on crisis-situation models.

The overlay spans from 2010 to 2016, as it filters keywords with less than three occurrences. By cross-checking this information with the previous histogram, one understands the reason for this short period. The histogram shows a low number of publications between 1998 and 2006, while the overlay shows an important variety of keywords used. This pattern reflects the novelty of the domain. The stop of the overlay in 2016 can be explained by the loss of interest in this topic from 2015. Also, according to the histogram, the field regained interest in 2017, indicating that it is on a plateau overall.

Despite this short covered span, it is possible to identify keywords use trends similar to those in crisis informatics. The older keywords used, such as *SOA*, *simulation*, *multi-agent systems*, and *systems engineering*, show an interest centered around the core of what we're used ontologies and metamodels for—model-driven engineering and information management. Then, the field knew a pic of interest, as the previous histogram showed. This period reflects on Figure 2.6, where one can observe that most of the most important keywords are located between 2012 and 2014. As explained previously, the years between 2012 and 2014 were the most prolific. These years were primarily focused on the idea of crisis management systems powered by artificial intelligence for decision support. Artificial intelligence would automatically create the information representations needed by systems. As these representations would have been written in a standard way, these systems would have adapted to new models, providing greater interoperability quickly. After this period, the interest in the field decreases a few before coming back with new approaches. Knowledge-based systems and knowledge management started to appear and a reborn of metamodel and ontologies creation, powered by improvements in machine learning.

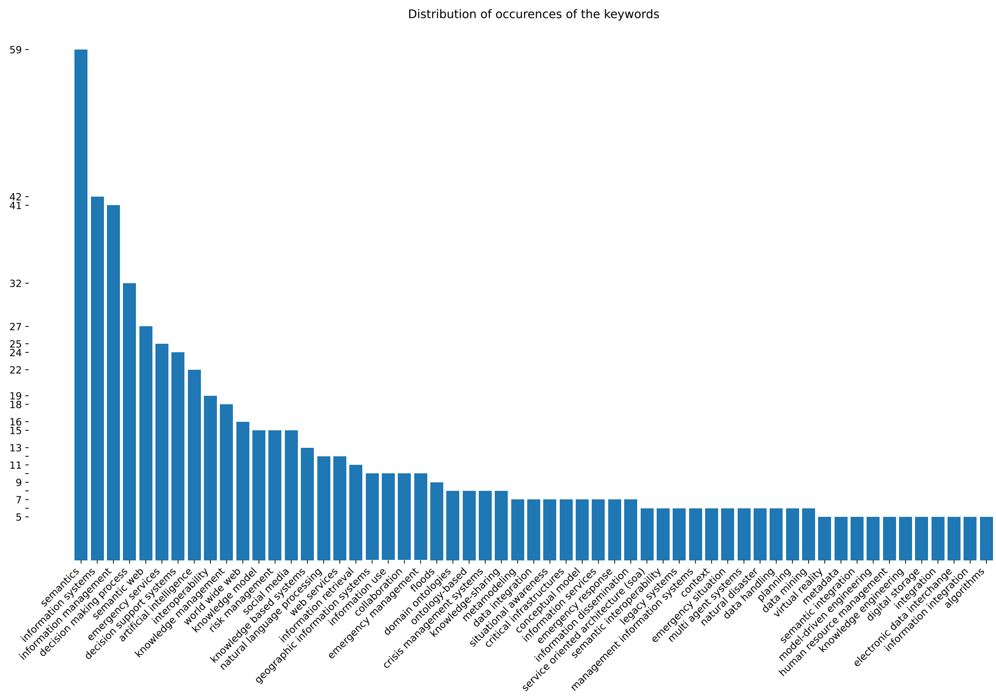

Figure 2.6: Distribution of keywords with more than 4 occurrences among the articles from the query on crisis-situation models.

In association with the previous qualitative review of the field, Table 2.4 presents the needs of the decision-maker identified in the articles from the previous request with at least 25 citations. Duplicates and unrelated articles (e.g., gene ontologies) are also excluded. This review of the main articles highlights the diversity of approaches covered by ontologies and metamodels. Some of these ontologies are specific to certain events (Jung et al., 2015; Qiu et al., 2017; Xu et al., 2014). While these models effectively deal with the type of disaster they are designed for, most of their concept representations do not fit with other types of events.

As mentioned in the first chapter, a proper collaboration between crisis management actors is crucial for disaster response. Thus Bénaben et al. (2008) and Othman et al. (2014) propose metamodels to represent the collaboration between several actors, independantly of the type of crisis. The metamodel proposed by Bénaben et al. is further developed in section 3.2.1.

Others have also focused on emergency organizations and proposed improving their functioning. Chou et al. (2011) proposed a way to automatically create websites to disseminate information related to an ongoing event. As reports are an essential concern and participate in information overload, Li et al. (2010) created an ontology to assist in report summarization. Disaster management software is inherently complex. Thus, Babitski et al. (2011) proposed an ontology to assist and guide the development of the software. As disaster management systems grow, they become intricated and complex. Madni et al. (2014) proposed an ontology to facilitate their integration into a functioning system of systems.

All the systems mentioned above require data. Fortunately, sensors are excellent ways to keep emergency responders informed of specific characteristics of their environment. Poslad et al. (2015) and Babitski et al. (2009) proposed ontologies to better integrate sensors data into crisis cells. Finally, another type of sensor considered is humans, acting as social sensors whose data can be automatically gathered from social media platforms. Purohit et al. (2014) proposed an ontology to identify victims' requests and volunteers' capabilities from tweets. Being able to geolocate individuals behind social media posts is critical for emergency services. Therefore, Ghahremanlou et al. (2014) built an ontology to help resolve this issue.

Table 2.4: Articles retrieved from the previous request which propose social media processing systems or methods with at least 25 citations.

Reference	Decision-makers needs addressed
Bénaben et al., 2008	Collaboration
Babitski et al., 2009	Sensor integration
Li et al., 2010	Reports summarization
Babitski et al., 2011	Disaster management software usability
Chou et al., 2011	Automatic web sites creation
Ghahremanlou et al., 2014	Location retrieval
Madni et al., 2014	System integration
Othman et al., 2014	Collaboration
Purohit et al., 2014	Identify victims and volunteers
Xu et al., 2014	Earthquake management
Jung et al., 2015	Landslide prevention
Poslad et al., 2015	Sensor integration
Qiu et al., 2017	Flood management

This part identified the different approaches to model information in crisis response from a decision-maker point of view. Yet, most of these approaches are top-down, and few conducted interviews to identify decision-makers' needs directly. The following section focuses on articles in the literature that used a bottom-up approach to identify the needs mentioned above.

2.2.2 Business needs of emergency services

Emergency management teams are tasked with novel and complex decisions. Information collection is one of the levers that ease decision-making and facilitate crisis management. Knowing the different elements that hinder emergency management teams from achieving their goals and what could ease information gathering is of the utmost importance to improve crisis management. Researchers in social sciences have been interested in studying the challenges faced. This section aims to highlight the main issues identified in the literature.

The request summarized in Table 2.5 returns 219 documents published between 1995 and 2021. The domain follows an increasing trend similar to the previous ones studied. Interest in the study of emergency services has been multiplying since the 2000s. This interest grew relatively steadily until today, where about 20 articles are published per year on the subject (Figure 2.7).

Table 2.5: Overview of the bibliographic request related to challenges in crisis management.

Type of request	Keywords	Explaination
SUBJAREA	*comp* OR *soci* OR *deci*	Articles in either Computer Science, Social Sciences of Decision Sciences domains
TITLE-ABS-KEY	*information gathering* OR *interview?*	Articles that conducted interviews or identified the information collected by the services
TITLE-ABS-KEY	*emergency responders* OR *emergency services* OR *dispatchers*	Interviews were conducted by emergency services
EXCLUDE-DOCTYPE	*re* OR *cr*	Reviews and conference tracks introductions are excluded

The overlay of the keywords generated from the articles retrieved (Figure 2.8) spans from 2010 to 2018. It reveals two clusters: one centered on medical issues and another centered on information systems. The medical cluster focuses on staff well-being and, in particular, on psychological aspects. The other cluster focuses on emergency services and events management information systems. This last one is more in connection with the objective of this manuscript; the next analysis will be focused on it.

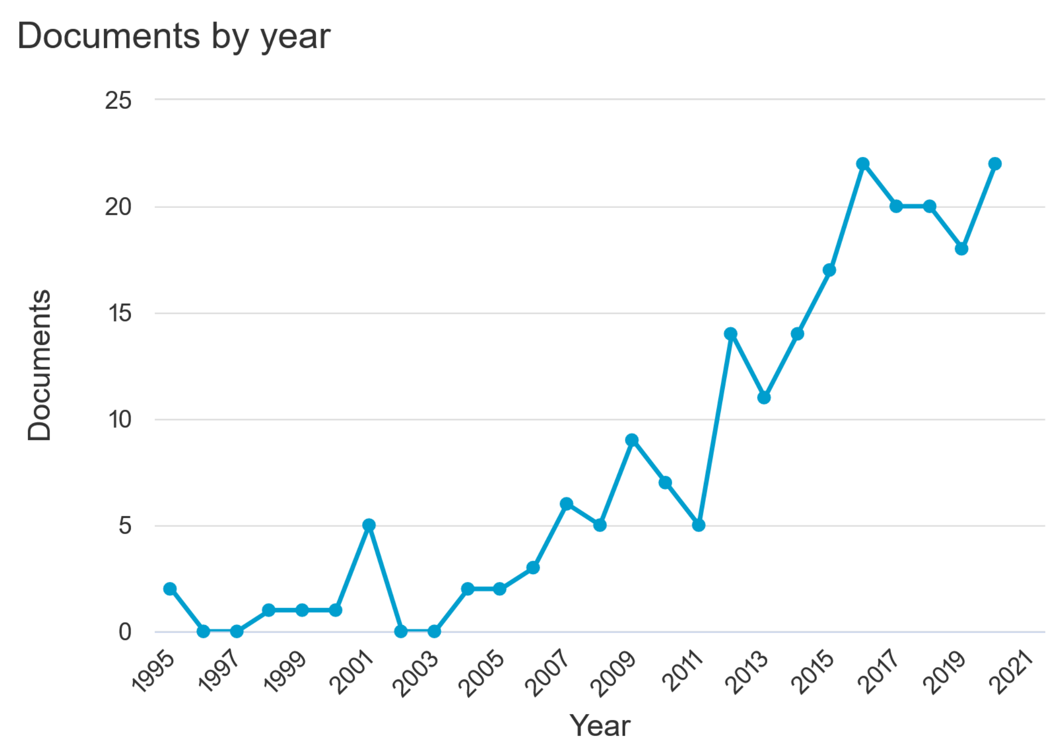

Figure 2.7: Timeline of the volume of contributions per years for information needs of crisis responders. The year 2021 is excluded because the year is not complete at the time of writing.

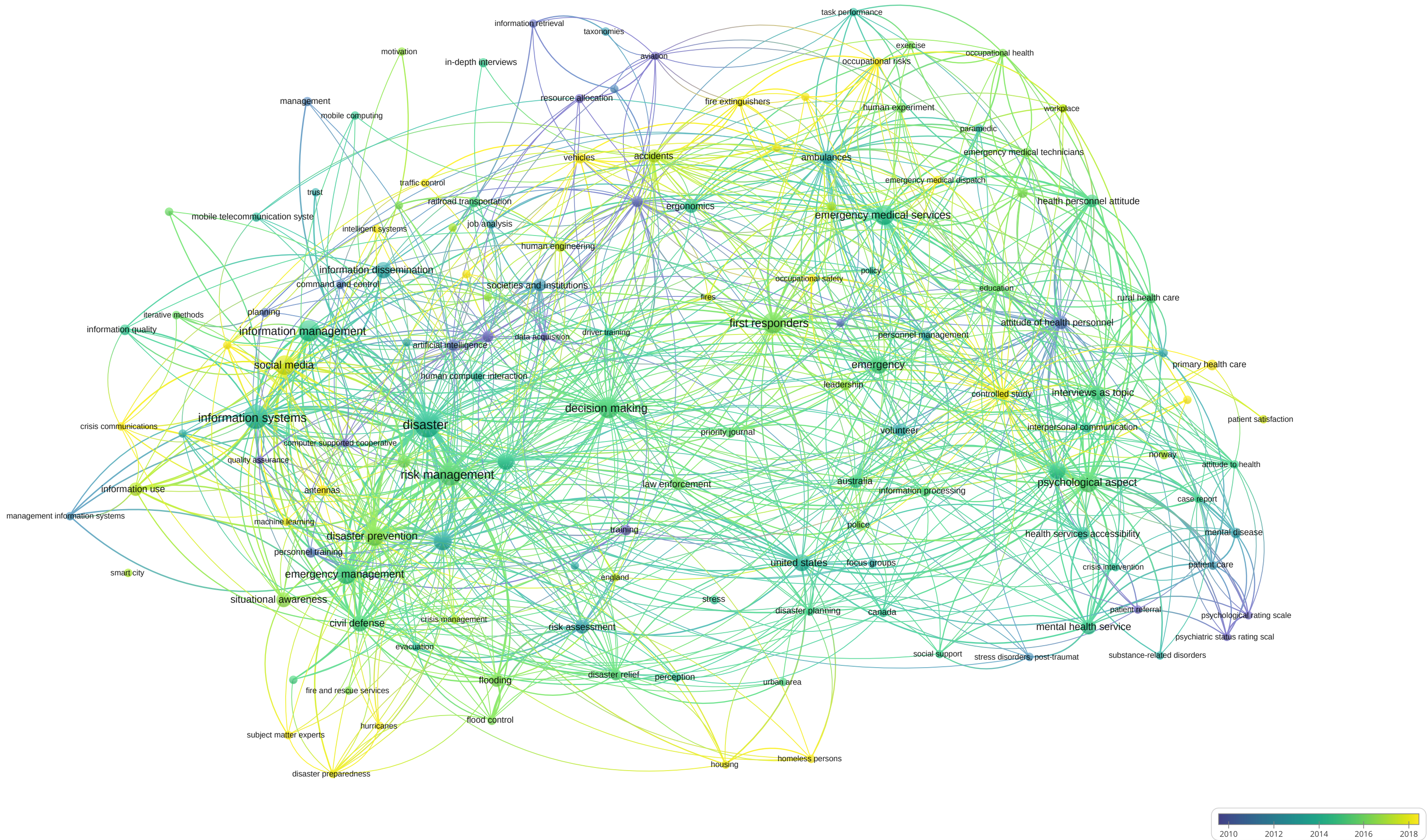

Figure 2.8: Distribution of keywords with more than 3 occurrences among the articles from the query on information needs of crisis responders.

The left cluster is composed of the most common keywords used in the fetched articles. Keywords such as *disaster*, *information systems* and *risk management* (Figure 2.9) are the most prominent ones and seems to be mostly used circa 2014. Before that period (between 2010 and 2014), the field was primarily focusing on resource or training planning. But the field took a shift towards data processing to support *decision-making* during emergency events. The collision with the other domains explored in this chapter seems to happen around 2018, with the use of keywords such as *machine learning*, *social media* or *situational awareness*.

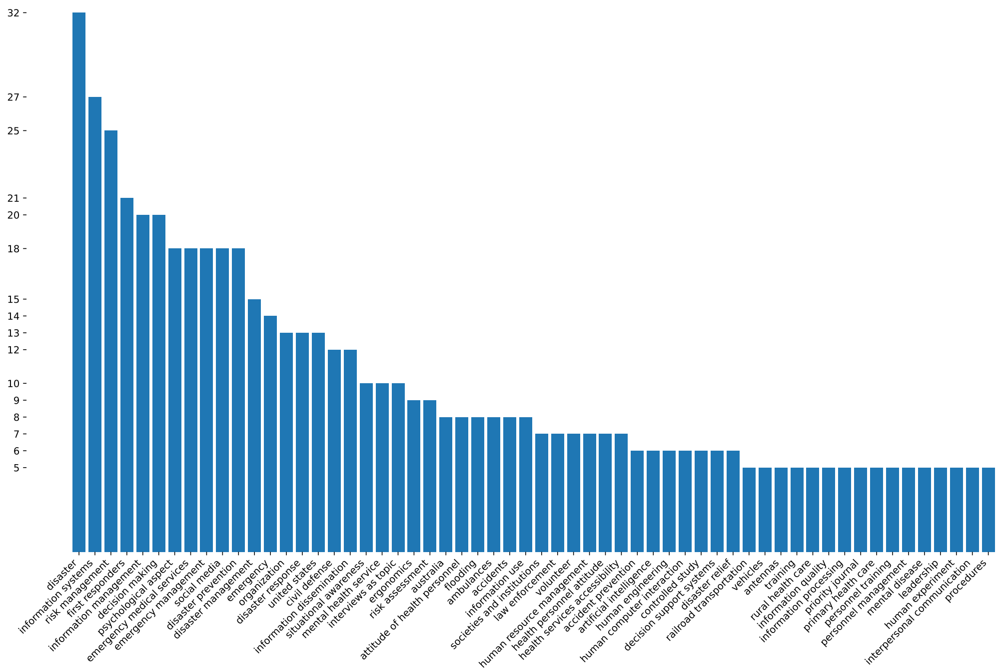

Figure 2.9: Distribution of keywords with more than 3 occurrences among the articles from the query on information needs of crisis responders.

Table 2.6 provides a summary of the responder's needs identified in the most prominent articles in the field. Articles were selected if at least 25 citations were published in 2010 or after, are located in the information systems cluster, and are not duplicates. The articles retrieved provide insights on some of the pain points of emergency organizations.

Some studies are event-specific due to a governmental request or a gap in the emergency preparation cover. Lindell et al. (2010) is interested in tsunamis management on the US east coast and Cabrera Aguilera et al. (2016) tackle oil spill. Neither study addresses any particular point in managing this type of event. Instead, they implement the entire crisis management cycle for these events, which were not considered until their work. Unfortunately, no specific information needed for decision-makers emerges.

On the other hand, others articles are most focused on the specific needs of emergency organizations. Collaboration, information sharing and joint preparation exercises are one of the concerns raised (Berlin et al., 2011; Parker et al., 2011). The increasing complexity of crisis events asks for a broader range of skills. As no organization can possess all the required skills simultaneously, other actors must be involved. Crisis management organizations acknowledge that an unexpected collaboration between actors yields poor outcomes during the response. Thus, exercises and discussions are critical during the preparation phase, and an adequate

Table 2.6: Articles on informational needs of emergency responders retrieved from the previous request with at least 25 citations.

Reference	Business need identified by the authors.
Lindell et al., 2010	Tsunami training
Aloudat et al., 2011	Communication to the public
Berlin et al., 2011	Collaboration between the different actors
Parker et al., 2011	Create conversations between unusual actors during the preparation phase
Yang et al., 2012	Increase situation awareness, Identify key information [3]
A. Tapia et al., 2013	Accounting for informal sources of data (such as social media)
Cobb et al., 2014	Big data processing methods adapted to social media data
Cabrera Aguilera et al., 2016	Oil spill preparation

means of communication between the actors during the response are needs identified by the studies.

Yang et al. (2012) highlight an interesting and well-mentioned need for crisis response: situation awareness. Situation awareness corresponds to the representation of the state of the environment that surrounds the emergency response organization during an event. This representation directly guides decision-making. Consequently, it is critical to build the best and most accurate representation possible at the event's start. In there are articles, Yang et al. emphasize 4 critical pieces of information for situational awareness:

1. Environmental conditions such as the building infrastructure, number of occupants, and the exact location of any hazards;
2. Information on the response participants such as who is involved in the response, what skills they could offer, and what resources they bring to the scene;
3. The status of any casualties, the accident location, cause, and severity; and
4. The available resources, including equipment and food.

As per the authors, "timeliness, accuracy, and completeness are the critical dynamic attributes of these four categories of information." The next chapter (chapter three) will dive deeper into this concept.

The issue with building an accurate situation awareness is the need for information. With the disruption of regular communication and information channels, decision-makers are shrouded in darkness. According to Cobb et al. (2014) and A. Tapia et al. (2013), some emergency centers acknowledge the benefit of social media as a potential information source. However, the issue identified is the lack of tools and methods, similar to those built for calls for social media.

Finally, the last need identified among the extracted items is communication to the public. Aloudat et al. (2011) insist on the potential yielded by modern communication means such as cell phones and social media to share information with the public during an event. People are not always close to a radio or a TV. Hence, they often miss critical messages during fast-moving events (floods, fires, etc.), resulting in casualties. On the other hand, (almost literally) most of the population carry a cellphone nowadays, and the critical messages could be distributed faster and with a better viewing rate than traditional methods. Text messages or notifications from social media could be more effective communication channels that emergency response teams should use.

2.2.3 Gathering information on social media?

The previous two subsections focused on (i) the representations proposed to describe crises and (ii) the challenges organizations face in charge of crisis management. The overview of these aspects has remained relatively general. This sub-section, therefore, proposes to refocus the previous analyses on the articles that specifically mention social media. It also provides insights on the initial research question: What information can be obtained from social media relevant to decision-makers in crisis response?

The keywords "social media" and "Twitter" have been added to the previous queries to refocus on social media. In the case of the query on crisis models, 18 articles mention social media among 205 initial documents. The following presents the different information that authors seek from social media. Thus, ten of the 18 articles do not specify what information they hope to collect but only mention social media as a potential source. The findings from the remaining articles are summarized in Table 2.7. he table highlights the main information that the authors wish to use to implement the ontologies they propose. Information about the event, such as its type and effects, is the most common information required. Victims' information is also mentioned in several studies. Interestingly, the studies seem to fall into two groups. In the first group, ontologies are created before retrieving posted messages. In this group, the authors thus seek to filter the messages that correspond to the ontologies they use (Coche et al., 2019; Gaur et al., 2019; Moi et al., 2016b; Montarnal et al., 2017; Narayanasamy et al., 2019). The second group follows a similar approach but proceeds to the first phase of message collection, whose content feeds the ontology construction. The ontologies thus obtained are then "closer" to social media by "moving away" from crisis management (Kawtrakul et al., 2012; Kemavuthanon et al., 2020; Lee et al., 2013).

Table 2.7: Articles on informational needs of emergency responders retrieved from the previous request with at least 5 citations.

Reference	Information authors are looking for from social media
Purohit et al. (2014)	Victims' needs and people offering resources.
Gaur et al. (2019)	Location, Event type and impact, Victims, Resource, Actors involved, Status
Ghahremanlou et al. (2014)	Geographic location
Bhatt et al. (2014)	Victims' needs
Zavarella et al. (2014)	Event type, Event impact, Location, Weapon inolved, Organizations involved
Coche et al. (2019)	Location, Event type, Weapon involved, Victims
Montarnal et al. (2017)	Crisis related messages, Event type, Time of publication
Lee et al. (2013)	User name, Time of publication, Location, Event type

The same methodology is then applied to the needs of crisis management organizations. Adding the keywords *social media* and *Twitter* indicates that 21 of the 219 articles previously retrieved are related to these topics. Unlike the studies retrieved in the previous query, these rarely consider categories of social media information. Table 2.8 summarizes the different approaches considered in the main articles. Among these articles are common interests that can be grouped into three categories. First, the involvement and consideration of volunteers in crisis management (Cobb et al., 2014; Grace et al., 2018; Nielsen, 2019; Smith et al., 2018). Another group of studies focuses on filtering information from social media to reduce the volume of information reaching decision-makers. The aim is to avoid an information overload that would be detrimental to the conduct of the response (Kaufhold et al., 2020; Moi et al., 2016a; Norri-Sederholm et al., 2017; Oneal et al., 2019) Finally, the last group focuses on the veracity of social media content and the information they expose to response organizations. As such, two of the four publications highlight the usefulness of this content for the response, while the other two call for more caution (Mehta et al., 2017; A. Tapia et al., 2013; A. H. Tapia et al., 2014; Van Gorp et al., 2015).

Table 2.8: Articles on informational needs of emergency responders retrieved from the previous request with at least 5 citations.

Reference	Approach to information from social media
Cobb et al. (2014)	People requiring or providing resources
Grace et al. (2018)	Consideration of citizen reports posted on social media
Kaufhold et al. (2020)	Reducing information overload through social media filtering
Mehta et al. (2017)	Evaluation of uncertainty of information coming from social media
Moi et al. (2016a)	Reducing information overload through social media filtering
Nielsen (2019)	Considering volunteers in crisis management
Norri-Sederholm et al. (2017)	Importance of information flow to reduce information overload
Oneal et al. (2019)	Image classification to detect rescuers and rescuees
Smith et al. (2018)	Social media use of volunteers during disaster
A. H. Tapia et al. (2014)	Evaluation of uncertainty of information coming from social media
A. Tapia et al. (2013)	Evaluation of the usefulness of social media content
Van Gorp et al. (2015)	Evaluation of the usefulness of social media content

This section has gone through different aspects of the research question: *What can decision-relevant information from social media be processed automatically?* The first two sections have explored information processing in crisis management globally along two axes. The first axis is the crisis models designed and proposed by computer sciences. We have seen that a great diversity of models have been proposed. This diversity mainly results from the granularity or scale adopted by the authors or the type of disaster studied. The second axis has adopted the point of view of the social sciences on these issues. The latter has allowed us to understand the numerous issues of emergency organizations in managing their information. The final part of this section focused on the studies from both approaches that considered social media as a source of information. In this context, most of the research from the computer science community focused on implementing different ontologies proposed. The teams that presented the information that was attempting to retrieve mostly focused on the following information:

- Event type
- Event consequences

- Victims status
- Victims needs
- Location

On the other hand, social studies are less interested in what information is processed but rather in how it is processed. Three main topics appear from the set of studies highlighted in this part. First, consider physical and digital volunteers in crisis response and include them in the official process. Secondly, managing the flow of information to avoid information overload. This research group is directly aligned with the views of the computer science domain. The final research group focuses on assessing the value of social media information for crisis management. Interestingly, each axis has a different approach to managing social media information during crisis response. The first axis took a top-down approach by thinking about representations that are then confronted with reality. The second axis took the other direction, with a bottom-up approach, where authors interview practitioners to identify points of interest. This section highlighted the need and previous attempts to automate the collection and management involved in crisis management. Also, it showed that social media are a source of valuable information that requires appropriate means of processing. Thus, the following section discusses existing means of identifying and mining information from social media.

2.3 NLP methods for information extraction from social media data

The first chapter presented the Natural Language Processing (NLP) domain. Through the development of this domain, many tools, algorithms, and methods have been developed to process textual data. With the emergence of social media, a new source of textual data appeared, and with it, its own challenges. This chapter explores the following research question: *How can this information be obtained in the context of crisis informatics?* Social media data are used as a data source in various use cases. This section is broken down into two parts, and it aims to explore two directions. First, for which applications is NLP used on social media data? Secondly, what are the methods used to extract information from social media? Each question is treated in a sub-section. To explored these two direction the following request is run:

This section will only consider surveys published in the domain. This choice is made to filter the numerous publications in this area. Without this constraint, the request returns 4231 documents. This large volume of publications, which reflects the popularity of the field, makes it challenging to analyze the field's evolution. However, restricting the results in this way should not prevent reporting on trends in the field. The request presented in Table 2.9 returns 217 surveys, published between 2011 and 2021 (Figure 2.10). While being a relatively recent research venue, the interest in NLP uses on social media data has increased over the years.

The surveys retrieved appear as a single cluster (Figure 2.11). This overlay was created by aggregating synonyms, removing the keywords from the query, and some keywords with a low value for our study ("state of the art, large amounts, codes (symbols), research questions, text"). Despite the field's youth, its evolution is swift, both in applications and methods used. Circa 2011, the field was centered around epidemiological applications and statistical analyses. From this point on, a kaleidoscope of applications and methods was used. They are detailed in the following two subsections.

Table 2.9: Overview of the bibliographic request related to challenges in crisis management.

Type of request	Keywords	Explaination
SUBJAREA	*comp*	Articles in either Computer Science, Social Sciences of Decision Sciences domains
TITLE-ABS-KEY	*natural language processing* OR *information mining*	Articles focus on natural language processing or information mining
TITLE-ABS-KEY	*social media* OR *Twitter*	To process social media data
TITLE-ABS-KEY	*survey*	Only surveys are considered in this section
EXCLUDE-DOCTYPE	*re* OR *cr*	Reviews and conference tracks introductions are excluded

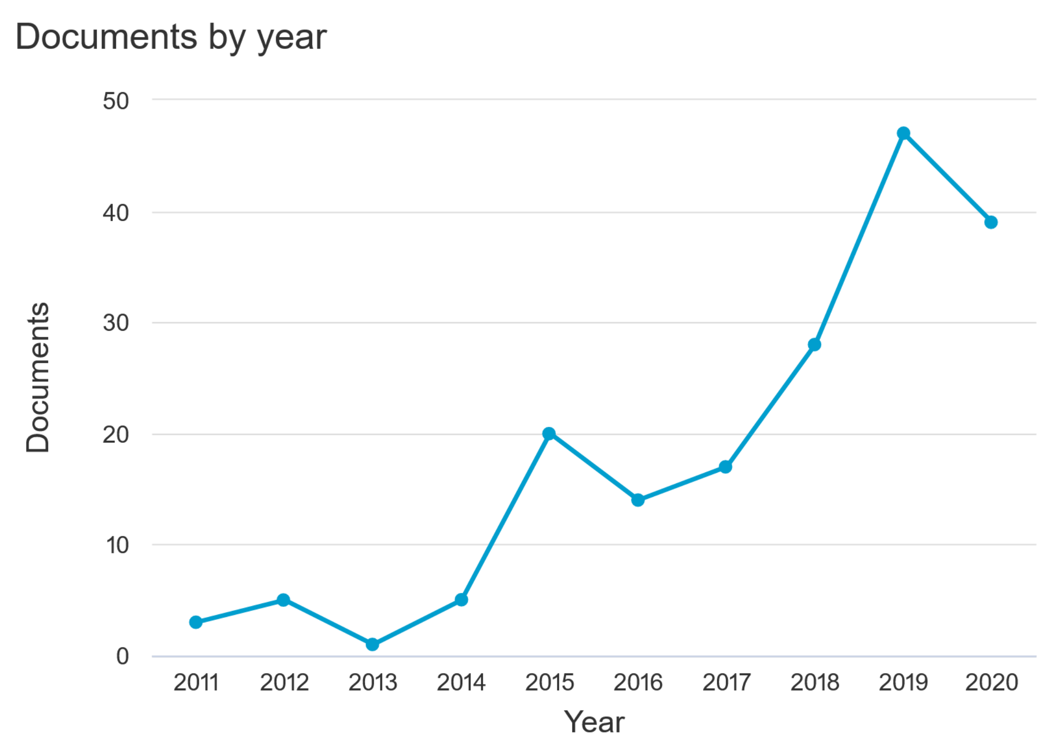

Figure 2.10: Timeline of the volume of contributions per years for the application of NLP methods to social media data. The year 2021 is excluded because the year is not complete at the time of writing.

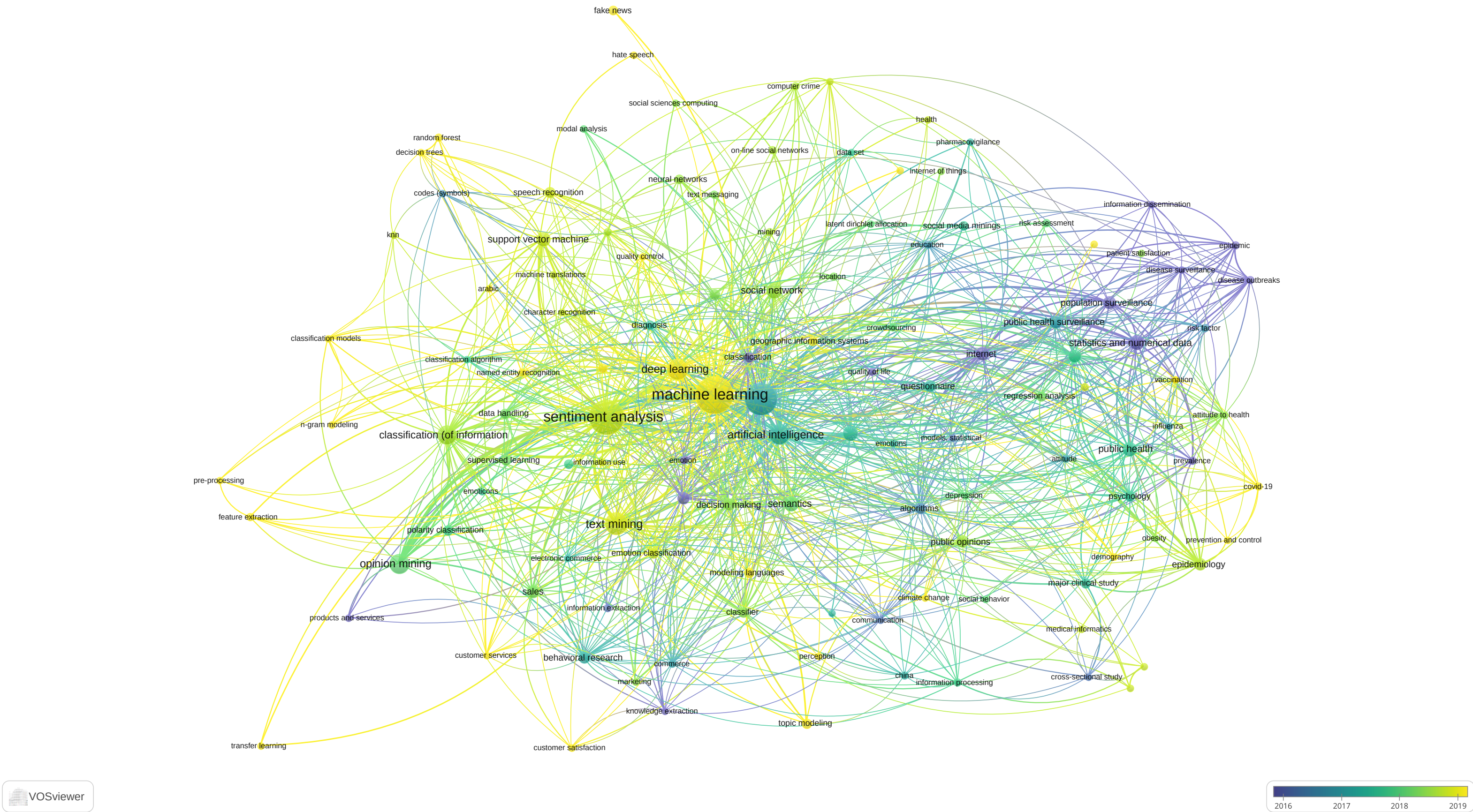

Figure 2.11: Distribution of keywords with more than 3 occurrences among the articles from the query on NLP applied on social media data.

However, some keywords trends have been more prominent during these years than others. On the application side, *sentiment analyses* is by far the most studied application (73 mentions of this keyword) (Figure 2.12). Mining applications are second with *data mining* (mentioned 61 times), *text mining* (30 times) and *opinion mining* (mentioned 21 times). On the method side, *artificial intelligence* (mentioned 25 times), and especially *machine learning* (85 times, almost half surveys) methods (such as shown with the appearance of *deep learning*) are heavily mentioned as well in the surveys. These methods illustrate the importance of the applications of machine learning methods in natural language processing.

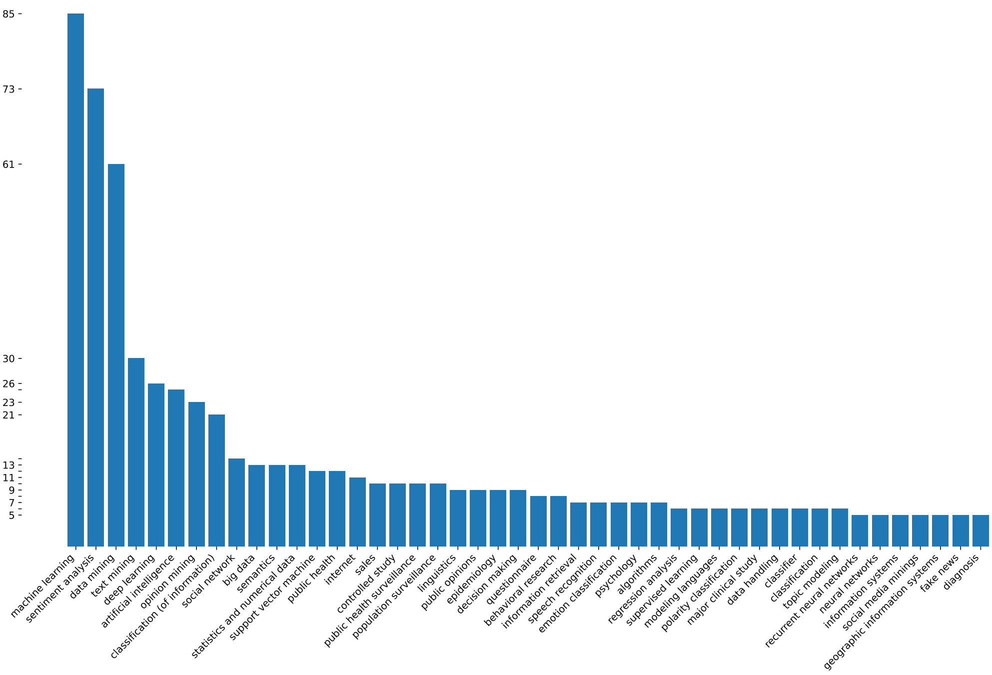

Figure 2.12: Distribution of keywords with more than 4 occurrences among the articles from the query on NLP applied on social media data.

Table 2.10 presents the main surveys, their focus, and the associated field of application. Specifically, 27 surveys cited more than 25 times appear. These 27 documents are divided into seven topics:

- Sentiment analysis
- Epidemiology
- Health
- Text mining
- Social Network
- Uncertainty

Nine surveys compose the sentiment analysis topic (Chamlertwat et al., 2012; Chaturvedi et al., 2018; Hawkins et al., 2016; Hemmatian et al., 2019; H. Jiang et al., 2016; B. Liu et al., 2012; Ravi et al., 2015; Yadav et al., 2020). It is a well-discussed topic as surveys span from 2012 to 2020. The main objective of sentiment analysis is usually to detect if a message is positive or negative about the topic of the message. Emotion detection is the next step after sentiment analysis. It can be more challenging, as it is required to classify text messages to a large variety of emotions that are notably hard to capture (Poria et al., 2017; Sailunaz et al., 2018). These two subjects make up almost half of the volume of publications highlighted. Eight articles are related to medical topics. Four are using social media to study the spread of diseases among the population such as influenza (Kagashe et al., 2017; Santillana et al., 2015), Ebola (Odlum et al., 2015), and opioids (Chary et al., 2017). Three others survey the public behavior related to depression (Khzam et al., 2018; Yazdavar et al., 2017) and to inflammatory disease (Martinez et al., 2017). Four surveys identify the various approaches available and used in different contexts. Salloum et al. (2017) review different existing methods, while Paul et al. (2016) focuses on applications to public health, S. Wang et al. (2015) on air quality and Collier (2012) epidemiology. NLP applied to social media also provides valuable insights on social media themselves or the social network of its users. Three surveys are focusing on these aspects, with Bail (2016) studying advocacy groups and Vázquez et al. (2014) consumer behavior while Bontcheva et al. (2014) identify semantic relationships between the users. Finally, the last two surveys remaining study the uncertainty and ambiguity of information posted on social media, with Hariri et al. (2019) discussing uncertainty at large in big data and Lin et al. (2015) emphasizing on uncertainty on growdsourced reports.

The following sub-section explores the applications mentioned by the surveys obtained from the request.

2.3.1 Social media information extracted using NLP

Social media data contain valuable information for a wide range of applications. The recovered surveys reflect the diversity of application areas. Table 2.11 presents the keywords used to build the overlay in Figure 2.11. These keywords are then associated with domains similar to the previous table. Here, broader categories are used to account for the more extensive diversity. For instance, as *sentiment analysis* is used as a keyword, it can hardly be used as a category itself. Also, some keywords are generic, hence common to multiple domains. For instance, *attitude* is used both in health and business-related surveys. *quality of life* is used in urban issues, breast cancers, depression detection, and opioid side effects. Other keywords that did not belong to any significant category have been grouped separately. These applications are then grouped into major domains of applications. This results in seven major application domains identified:

- Epidemiology: efforts to track and document an outbreak through social media
- Health: tracking of symptoms, psychological distress or drugs mentions
- General Public: uses of social media as part of the smart city to prevent crime or collect the public's opinions
- Social Media/Social Network: social studies on social media platforms themselves or social interactions through social media
- Business: uses of social media for product marketing or maintaining a relationship with consumers.
- Information Science: general topic related to extraction and management of information from social media in general
- NLP Tasks: a set of tasks related to natural language processing such as translation, speech recognition, etc.

The following details some of the most prominent keywords retrieved. NLP applied to social media is used for a variety of medical applications. Epidemiology, which studies the distribution and frequency of diseases, uses social media to monitor symptoms related to an epidemic to infer future propagation. This includes, of course, the COVID-19 outbreak or the 2009-2010 influenza outbreak. Broader medical applications are labeled under "Medical Informatics." It contains applications using the same methodology but applied to other diseases or conditions, such as *depression*, *obesity* or *pregnancy*. Social media are also considered for *pharmacovigilance* to monitor secondary effects (*patient satisfaction*, *opiate addiction*). The behavior of the urban population (*smartcity*, *computer crime*) or society in general (*demography*, *population surveillance*) can also be observed through social media. Their feelings about events or political decisions can then be quantified and analyzed. As digital twins of society, social media are also environments that bring some reflections of their own. The phenomenon of *fake news* in particular has taken many actors in society by surprise and is an issue that attracts a lot of attention. How information spreads within the *social network* of users or its very structure are also topics of research. Marketing departments and Public Relations firms are also naturally very interested in the insights available on social media. The management of the content of social media and especially the *information extraction* and *knowledge extraction* part are challenges for the information science domain. Social media data also come with specific challenges for the NLP domain. Social media content is noisy, informal, and often comes with its own use of grammar. Consequently, most of the methods applied to other texts are disrupted with social media data. *machine translation*, *named entity recognition* and other tasks are then explored and improved in this context. Alongside improvements on several tasks, social media are also widely used to *sentiment analysis*, *topic modeling* or *polarity classification*. In the final category, interesting topics appear, such as *crowdsourcing*. Indeed, instead of exploiting social media, some social scientists leverage their power to achieve goals and then study mechanisms that can encourage positive actions. Of course, *climate change* is also an application mentioned, considering the importance of this topic.

Table 2.11: Grouping of the main keywords returned into domains.

Keyword	Domain
COVID-19	Epidemiology
disease outbreaks	
disease surveillance	
vaccination	
epidemic	
epidemiology	
influenza	
opiate addiction	
opioid-related disorders	
depression	Health
diagnosis	
psychology	
public health surveillances	
health survey	
risk factor	
major clinical study	
medical informatics	
obesity	
pregnancy	
patient satisfaction	
pharmacovigilance	

prevention and control	
quality control	
risk assessment	
controlled study	
prevalence	
social behavior	General Public
models, statistical	
computer crime	
public opinion	
population surveillance	
demography	
smart city	
risk assessment	
internet of things	
facebook	Social Media/Social Netword
social media mining	
social network	
fake news	
modal analysis	
data mining	
information dissemination	
opinion mining	
perception	
crowdsourcing	
surveys and questionnaires	
commerce	Business
customer services	
sales	
communication	
electronic commerce	
marketing	
products and services	
knowledge extraction	Information Science
information systems	
classification (of information)	
gis	
decision-making	
information extraction	
information processing	
spatiotemporal analysis	
machine translations	NLP Tasks
speech recognition	
polarity classification	
location inference	
text mining	
automated detection	
named entity recognition	
arabic languages	
linguistics	
topic modeling	
emotion analysis	
sentiment analysis	
emoticons	

modeling languages	
quality of life	No specific domain
china	
education	
climate change	
attitude	

2.3.2 Overview of NLP's methods

The previous sub-section presented the different applications of NLP on social media data. The surveys retrieved also mentioned algorithms, methods, or models related to NLP. This sub-section aims to present the different methods mentioned briefly. Table 2.12 shows the keywords used in the surveys and groups them according to the different fields of artificial intelligence to which they belong.

The many applications above require many different algorithms capable of meeting different needs. As already mentioned in the first chapter, data from social media are particular, compared to corpora composed of books and national newspapers. The data are then thus pre-processed, in a step named*pre-processing* Pre-processing refers to the different steps taken to normalize the data. For instance, one can lower the sentence, remove punctuation, etc. The data are then provided to the processing algorithms. Most of the algorithms mentioned in the survey are machine learning algorithms. These algorithms build *statistical models* based on the distribution of tokens in sentences to provide results. There are different categories of algorithms for other use cases. *Classification algorithms* are algorithms designed to assign data to a category. On the other hand, *regression* algorithms provide a value in a numerical range. These models can be either *classifiers* or regression models. Most of these models are *supervised*, meaning that they require a dataset where all the data are labeled. Models can also be semi-supervised (only a portion is labeled) or self-supervised (the model learns its own label from scratch). Neural networks are also machine learning algorithms and can be stacked in layers to build deep neural networks able to learn complex and abstract patterns.

In addition to the overview of the NLP's field provided through the previous keywords, many algorithms are also directly mentioned. The following summarizes their applications and the reasons for their mention in the surveys. The *K-Nearest Neighbors*, as its name suggests, it uses the K-nearest neighbors of a data point to infer the label associated with the data point considered. It can be used to identify the most similar messages in a corpus. *Decision trees*, and its ensemble version *random forests*, are classifiers/regressors algorithms that build decision paths to classify the incoming data. *Support Vector Machine* (or SVM) achieves the same result by creating a decision boundary between the different sets of data using a kernel chosen by the user. The boundaries created by SVM are usually more subtle than those produced by decision trees, resulting in better results in complex datasets. These models are used for sentiment analysis, polarity detection, attitude, opinion analysis, and language identification. The *Latent Dirichlet Allocation* algorithm allows to identify the topic in a collection of documents and is thus used in topic modeling.

Deep *neural network* models are used for applications that rely on the semantics of words rather than their distribution. *Convolutional neural networks* are a specific type of neural network composed of neurons that use a kernel, or convolution matrix, to detect patterns in sentences. These neural networks are used for classification applications. *Recurrent Neural Networks* are another type of neural network that uses a recurrent structure. It uses specific neurons that carry information from previous data points to build a new understanding of the data. Neural networks are also used for classification applications, such as machine translation or named entities recognition. Finally, once these models are trained, they can reuse their knowledge for other applications. *Transfer learning* consists in reusing a model trained on a task to solve similar ones, completely re-training a model from scratch.

Social media processing applications have widely benefited from recent improvements in machine learning. This trend is visible in how this field evolved towards statistical models and later deep neural networks. As applications are numerous and opportunities offered by the NLP domain significant, the two meet in the middle, and several research teams explore the different paths offered. The surveys retrieved provided valuable insights to answer the original problem of this section: *How can this information be obtained in the context of crisis informatics?* The results are twofold.

The first sub-section identified the main applications of NLP on social media data. The main uses that have emerged are:

- Health: tracking of symptoms, psychological distress or drugs mentions
- Epidemiology: efforts to track and document an outbreak through social media
- Business: uses of social media for product marketing or maintaining a relationship with consumers.
- Population study: uses of social media to understand and communicate with the public

The second sub-section reviewed the most prominent algorithms used to process social media data and linked them to previously identified applications. Table 2.12 reviewed the most prominent methods used to tackle the challenges in the domains previously identified. Social media processing systems in disaster response are constrained due to the context in which they are used. Consequently, systems and algorithms need to adapt to this environment. Chapters 4 and 5 will provide a deeper view of the literature associated with the processing at the algorithm and system levels, respectively.

2.4 Literature review outcomes

This chapter explored the literature around the main problem of this manuscript: *How to design an information system able to automatically manage and deliver relevant information extracted from social media data during crisis response?* For this purpose, the literature review was articulated around three main research axes:

1. Axis 1 explored the main social media processing systems for crisis management previously built. Many systems have been developed on this occasion, with a trend towards increasing automation, data collection, and processing. Also, many different issues have been addressed (different types of crises, different types of data, etc.), often with different approaches proposed. The most recent advances are focused on more and more sophisticated data processing (images, the fusion of information obtained, etc.). However, these systems focus on succinctly described problems, leaving many unanswered questions about the problem addressed.
2. The second axis of research was interested in the needs in identified information to which the preceding systems are supposed to answer. Two points of view were confronted on this occasion: (i) the top-down vision of the modelers who tried to represent and organize the information exchanged during an event between different actors and (ii) the bottom-up approach of the sociologists, who sought to collect through interviews

the information needs of the actors in charge during a crisis. Both approaches have their advantages and disadvantages. The first one organizes the information in a computerized model but does not consider the actual need. The second approach, on the contrary, collects the needs expressed by the first concerned but rarely proposes a result that computers can exploit. However, both points of view agree on the importance of information management in crisis management.

3. Finally, the third axis explored previous work that automatically exploited data from social media using NLP. The different applications have been summarized, both from the point of view of the application domain and the problem that the approach allowed to solve. This was also an opportunity to review the main algorithms mentioned in the articles obtained and to correlate them with the problems. Many current approaches rely on supervised machine learning, which consists of training an algorithm to perform a specific task by providing it with labeled data. This approach has some limitations, further developed in chapter 4. This axis highlighted the possibilities offered by the richness of the data available on social media.

Additionally, Table 2.6 presented the challenges in crisis management that drew more attention. It cross-references the identified information needs with the available social media information previously mined. Therefore, the integration of data from these sensors is outside our scope. Finally, social media deliver by nature large volumes of data. This need is therefore implicitly considered when considering social media due to the very nature of these platforms. The remaining needs are, therefore:

- Collaboration: the need for information to support coordination between partners
- Situational awareness: the need for information that enables the identification of the elements that make up the environment
- Public communication: the need for information to understand the population's feelings regarding the event and facilitate public relations.

An interesting point to note is that not all needs are similar. For instance, social media accounting and sensor data integration provide data that contribute to situational awareness and consequently ease the collaboration between the different actors. This chapter highlighted past achievements in the field of crisis informatics. One interesting trend to note is the convergence of the interest and methods of all the fields studied. It also revealed the steps that are still ahead and the unresolved issues. In particular, it was pointed out that previous systems did not systematically build on existing work on information needs assessment. Chapter 3, therefore, addresses this aspect and focuses on this need and its computational modeling. The following chapter is also the occasion to emphasize the interdisciplinary discussions which took place during this research, conducted at the border between sociology and computer science.

Table 2.10: Articles on applications of NLP on social media data retrieved from the previous request with at least 25 citations.

Reference	Topic of the survey (application domain)
Yadav et al. (2020)	Sentiment analysis (methods)
Hemmatian et al. (2019)	Sentiment analysis (methods)
Hariri et al. (2019)	Uncertainty (big data analytic)
Sailunaz et al. (2018)	Emotion detection (methods)
Chaturvedi et al. (2018)	Sentiment analysis (methods)
Yazdavar et al. (2017)	Public health (depression)
Salloum et al. (2017)	Text mining (methods)
Poria et al. (2017)	Emotion detection (methods)
Martinez et al. (2017)	Public health (inflammatory bowel disease)
Kagashe et al. (2017)	Epidemiology (influenza)
Chary et al. (2017)	Epidemiology (opioid)
Paul et al. (2016)	Text mining (public health)
H. Jiang et al. (2016)	Sentiment analysis (infrastructure projets)
Hawkins et al. (2016)	Sentiment analysis (quality of care)
Bail (2016)	Social network dynamic (advocacy groups)
Bahk et al. (2016)	Sentiment analysis (vaccines)
S. Wang et al. (2015)	Text mining (air quality)
Santillana et al. (2015)	Epidemiology (influenza)
Ravi et al. (2015)	Sentiment analysis (methods)
Odlum et al. (2015)	Epidemiology (ebola)
Lin et al. (2015)	Uncertainty (growdsourcing)
Karmen et al. (2015)	Public health (depression)
Vázquez et al. (2014)	Social network dynamic (consumer behavior)
Bontcheva et al. (2014)	Social network dynamic (semantics)
B. Liu et al. (2012)	Sentiment analysis (methods)
Collier (2012)	Text mining (epidemiology)
Chamlertwat et al. (2012)	Sentiment analysis (consumer behavior)

Table 2.12: Main NLP algorithms and techniques that appear among the keywords

High-level category	Keywords used in the surveys
Data management	Big Data
	Pre-processing
	Feature Extraction
	N-gram Modeling
Artificial intelligence	Artificial Intelligence
	Algorithms
	K-Nearest Neighbors
Machine learning	Statistical Model
	Regression Analysis
	Classification Algorithms
	Classifiers
	Supervised Learning
	Decision Trees
	Random Forests
	Support Vector Machine
	Latent Dirichlet Allocation
Deep learning	Neural Networks
	Classification Models
	Convolutional Neural Networks
	Recurrent Neural Networks
	Transfer Learning

3

Crisis model distillation to extract actionable information from social media

Introduction

The context presented in the literature review highlighted the importance of information management during an emergency event. Improving the response requires better coordination between the different actors. However, a coordinated response can only be performed if all the partners easily share information. The first chapter used the example of the Common Operational Picture (COP) as a visual medium for information sharing. The COP makes it possible to display certain information with a vocabulary common to all actors. However, this approach requires that all the actors agree beforehand on the information of interest. During the preparation phase, COP is a way to create a shared Situational understanding between the different actors (Steen-Tveit et al., 2021). Also, the integration of information obtained from social media into this interface remains a challenge. The previous chapter identified three aspects that could use a better information input using social media data:

- Collaboration: the need for information to support coordination between partners
- Situational Awareness: the need for information that enables the identification of the elements that make up the environment
- Public communication: the need for information to understand the population's feelings regarding the event and facilitate public relations.

These needs are directly linked with the first sub-problem mentioned in the first chapter, namely: *What decision-relevant information from social media can be processed automatically?* The current chapter seeks to identify this relevant information to identify what could be automatically collected. There are, therefore, at least two needs that must be considered: i) the information needs of decision-makers ii) the information required by the information system used to support the response. As a result, the approach is twofold. The first section considers the information needed from the point of view of a crisis management organization. In particular, it identifies the profile of the people who deal with social media and the information sought. This section is then based on the literature, meetings, and interviews with crisis management practitioners. The second section focuses on previous crisis models proposed to digitalize crisis response. These crisis models consist of abstract but automatable representations of the information during crisis management. Thus, this section aims to identify the information needed to implement such models. Finally, the third and last section is a conclusion that crosses the needs identified previously. It presents the information that can be automatically handled by a computer to support decision-making.

3.1 Information expected by practitioners

This chapter thus draws on previous research and works realized alongside social studies conducted during the research project by social scientists. This section is split into three parts. The first part focuses on social media processing in crisis management organization. It aims at answering the question *Who is processing social media content in these organizations?* The second part focuses on the information already identified in the literature. Finally, the last part presents the first set of information corresponding to the information sought by decision-makers.

3.1.1 Social media processing in crisis management organizations

Crisis management organizations are composed of several actors with well-defined roles. As the first chapter mentioned, crisis management involves multiple actors, and not all of them pay attention to social media content. While decision-makers benefit from the insights coming from these platforms, they do not perform the collection themselves. This section reports on the place of social media in different organizations observed in this study. The research question that this part aims to answer is: *RQ: Who is in charge of social media handling in crisis response organizations?* The observations and interviews with practitioners associated with previous results from the literature contribute to answering the previous RQ.

Method

The multidisciplinary and multicultural context of this study allowed to meet and exchange with a wide variety of crisis management actors. This variety is welcome since, as presented in the next section, the treatment of social media in management knows no standard. At least five occasions (summarized Table 3.1) provided valuable insights into the scope of the study.

In the U.S., Grace et al. (2019) conducted role-plays at the Public-Safety Answering Point (PSAP) of Charleston (South Carolina). This PSAP is tasked with answering calls from citizens and dispatching resources during emergencies. The particularity of this PSAP is its adoption of a system allowing it to consider text messages (SMS) and reports from Internet platforms (social media) in addition to calls. One of the objectives of these role-plays was to define with the call-takers and dispatchers what a perfect social media could be for them (Kropczynski et al., 2018). The study in the U.S. took place in the context of the development

Table 3.1: Overview of the different meetings with practitioners.

Occasion (Location)	Participants profiles	Methodology
PSAPs Role Play (Charleston, SC)	Call takers, Dispatchers	Role-plays
Early Adopters Summit (Charleston, SC)	25 local 911 professionals (PSAPs Managers, Call-takers, Dispatchers, and IT technicians)	Focus groups
Exercise 1 MACIV (Var Département)	Professional and volunteer firefighters	Exercise observation
Exercise 2 MACIV (Vienne Department)	The staff of the Prefecture 86, a communication officer, two representatives of the police, firefighters, and gendarmerie	Exercise observation
Exercise 3 MACIV (South-West Zone)	Southwest Zone and six of the twelve associated Préfectures (the 79, 47, 40, 17 ,23 , 87). The Préfectures had a similar composition as the one in exercise 2.	Exercise observation

of Next-Generation 911. As per the authors: “Next-Generation 911 (NG911) infrastructure will replace analog systems designed to support voice services for landline 911 callers with digital, IP-based systems that will allow smartphone users to "call" 911 via voice, text, image, and streaming video.” The objective of these role-plays was to document how call center operators processed the incoming call to obtain information. This study ultimately aimed to reflect this processing to social media messages. This exercise highlighted many aspects of call center operations. First, there are two types of operators who interact with information: call-takers and dispatchers. Call-takers are responsible for receiving calls and getting the correct information from the callers. The answers are shared with the dispatchers through the Computer-Aided Dispatch (CAD). The CAD system allows for the entry of notes associated with the call. The call-takers teams also use a CAD plugin called ProQA. ProQA is an integrated expert system that provides a support function through question proposals and classifications for the event. Protocols, as interpretive frameworks, shape information gathering and filtering. The information pipeline in the case of the PSAPs was the following:

1. A *Caller* calls the PSAP through the 911
2. The *Call-taker* receives the phone call, asks questions to the Caller to obtain as much information as possible about the event. They then record their findings on the CAD system.
3. The *Dispatchers* receive an alert from the CAD that a new event is in progress. They then consult the notes provided by the call-takers to dispatch resources.
4. The *Responders* follow the instructions provided by the dispatcher to intervene on the scene of the incident.

The 2019 911 Early Adopters’ Summit provided the opportunity to meet 911 practitioners on the topic of NG911. This summit was composed of many different profiles: managers of PSAPs, but also call-takers, dispatchers, and I.T. technicians. The participants met during this event, as early adopters, were largely in favor of changes in emergency response. Grace et al. (2020) report their feelings and opinions through a Strengths-Opportunities-Weaknesses-Threats (SWOT) analysis (Gao et al., 2011) on NG911. The SWOT analysis lasted an afternoon and implied 25 participants, all of them being 911 professionals. This type of analysis allows identifying of strengths and weaknesses (internal or external) of an organization. The goal was then to reflect on these factors in the case of NG911 through the lens of this method. The summit was also the occasion to capture the diversity of configurations of PSAPs that exist in the U.S. Indeed, the setup documented during the Charleston role-plays is not standard, and each PSAP center is free to organize as it prefers. So, depending on the constraints applied to the center, its structural organization might be different. The call center can report to a remote dispatch center, along with other call centers, for instance.

In France, the MACIV exercises were opportunities to observe how professionals respond in practice to a situation. Figure 3.1 illustrates the organization of the institutions in charge of the crisis response. It is a hierarchical organization. The hierarchy is based on the size of the area affected by the event. The higher layer is the National level (not represented in the figure), then the Zonal level, the Départemental level, and the Communal level.

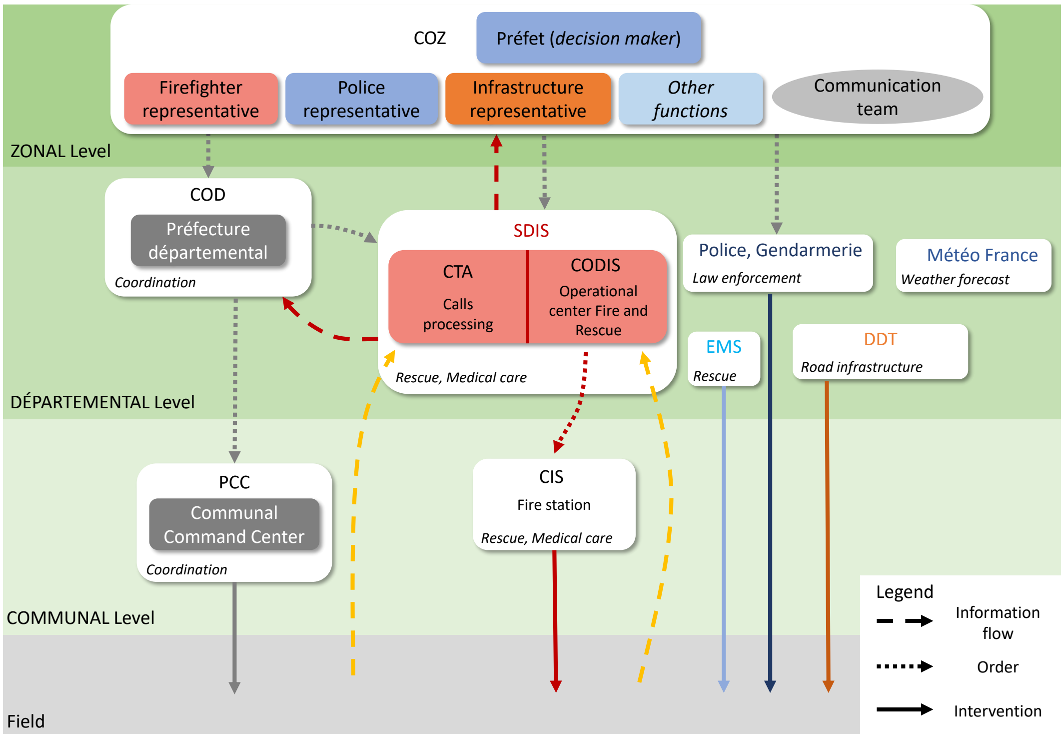

Figure 3.1: Diagram of the organization of the different French institutions involved during the response to an event of zonal scale. Illustration adapted from Batard (2021)

The Zonal and Départemental levels are governed by Préfectures (administrative institutions in charge of representing the government authority). The services in charge of crisis response in these institutions are the Centre Opérationnel de Zone (COZ) and the Centre Opérationnel Départemental (COD). The Départemental level also includes the highest representation of the response actors (firefighters, police, emergency services, etc.). Among them, the Service Départemental d'Incendie et de Secours (SDIS, for *Departmental Fire and Rescue Service*) oversees managing the rescue teams according to the priorities fixed by the COD. The SDIS serves two functions: i) organized the rescue units and ii) handled phone calls. The calls are handled through the Centre de Traitement des Appels (CTA, for *Calls Processing Center*). The organization and management of rescue teams is performed by the Centre Opérationnel Départemental d'Incendie et de Secours (CODIS). The Centre Opérationnel de Zone provides instructions to the Centre Opérationnel Départemental or directly to the SDIS (see definition below). The SDIS takes its orders from either the COZ or the COD. It provides orders directly to the commanders of the units deployed or officers in charge of sub-centers—the CIS. It receives back reports from the rescue teams and phone calls from victims. They provide the information they have to the COZ and COD. The last actor is the PCC, the crisis cell created in each Commune (the equivalent of Counties).

Another important player in these exercises was the VISOV association. The Volontaires Internationaux en Soutien Opérationnel Virtuel (VISOV, French equivalent of the *Virtual Operations Support Teams* — VOST) association is of volunteers. These citizens organize themselves to help the institutional actors to identify the information related to an event posted on social media. Their organization is further developed in Batard (2021, p.122–148).

The exercises involved three types of actors: an institutional actor, an association of volunteer citizens, and the research teams. These exercises took place in the following manner. First, preparation of the exercise (role of each actor, choice of the type of crisis, actors involved according to their availability, etc.) Then comes the exercise itself. During the exercise, the institutional actors play their roles and address the event as they would normally do. The VISOVs support the practitioners by processing the social media content provided for the exercise. Finally, the research teams shadow the practitioners in their roles. At the end of the exercise, an exchange phase allows the participants to give feedback on the exercise. The main purpose of these exercises was to document the information flow within the French emergency management institutions, and particularly, the way information coming from social media was considered. The types of events simulated were, respectively:

- Flooding event in the Var Department at the Service Départemental d'Incendie et de Secours du Var (SDIS83).
- Snow event and consecutive traffic jam in the Vienne Department at the Vienne's Préfecture.
- Chemical incident in the South West of France involving the Southwest Zone and six of the twelve associated Préfectures (the 79, 47, 40, 17 ,23, 87) and the CODIS 47.

The three exercises were an opportunity to observe different institutions and the way they approach social media. In the first exercise, social media were processed inside the SDIS83[1] by a Médias Sociaux en Gestion d'Urgence operator (MSGU, French equivalent of the *Social Media in Emergency Management* — SMEM). The setting of the SDIS is shown in Figure 3.2. The decision-maker was a firefighter officer in charge of the room. The officer was assisted by four firefighters managing the teams dispatched and their reports using a whiteboard. One of the firefighters was taking phone calls from victims. Directly to his right was a volunteer firefighter trained to gather social media information during the event. Behind these two operators, a specialized volunteer firefighter was overseeing the cartographic desk.

The social media operator was who is familiar with social media and communication. This operator was sharing a Google Sheet[2] document with the members of the VISOV association. A Google Sheet document is a tabular file identic to an Excel file, where multiple persons can modify simultaneously the document and see the changes in real-time. It is the possibility of having several actors collaborate in real-time on the same document that motivated the choice of this format. The VISOV association is mostly composed of volunteers with a background in public service, rescue operations, etc. These volunteers monitor social media on their own to identify information related to a potential or already ongoing event. This operator was monitoring social media and cross-referencing the information they could obtain with that provided by the VISOV volunteers. This live document is then shared with the

[1] Each French Department is associated with a number. In this case, the Var Department has the number 83

[2] https://www.google.fr/intl/fr/sheets/about/

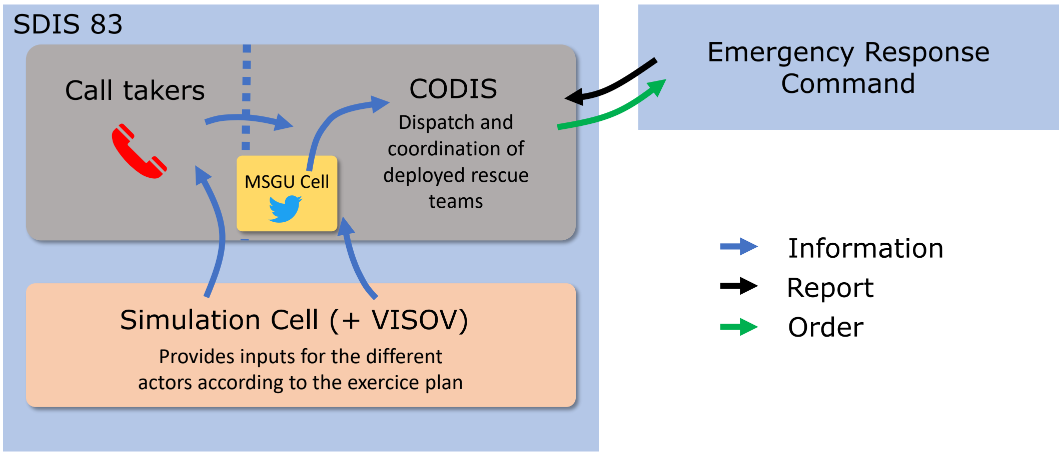

Figure 3.2: Organizational diagram of Exercise 1 MACIV at SDIS83 in the Var Department. Illustration adapted from Batard (2021).

person in charge of social media processing within official institutions. Using their own findings and the ones from the online document, the MSGU operator will then provide the information obtained when asked by the decision-maker in the room.

The second exercise took place in the Vienne Département at the 86 Préfecture in Poitiers. The institution studied was the Prefecture of Vienne through their COD and their communication cell Figure 3.3. The COD was composed of a decision-maker (played by a subordinate of the Prefect), a person in charge of communication, two representatives of the police, the fire department, the gendarmerie, and other services (cartography, road infrastructures, etc.). This institution uses software similar to the CAD software used in the U.S. to share information. This information system is named SYNERGI (SYstème Numérique d'Échange, de Remontée et de Gestion des Informations). The Prefecture did not have a dedicated social media handling service (MSGU) as in the first exercise. Instead, the VISOV association volunteers transmitted their findings directly to the communication unit. In this configure, the institution was more reliant on the processing realized by the VISOV association. The operators in charge of the social media in the Préfectures were persons from the communication team of each Préfecture. In this case, these persons were not familiar with emergency or rescue operations. They were mostly tasked with communication to the public using the official accounts of the institution they were part of. Monitoring of social media activity and information gathering were not the priorities of these operators.

The third exercise saw similar actors involved but on a bigger scale. Instead of one Préfecture, six were present under the direction of a Préfecture Zonal (see Figure 3.1). The setting of this exercise is illustrated in Figure 3.4. Each Préfecture involved the same organization as the second exercise (rescue team representatives, communication cell, specialized functions). Similarly there was no MSGU cell created by the institutions. As a result, they also relied on the VISOV association to obtain information from social media. Also, the participating Préfectures were using the SYNERGI to exchange official information.

Findings

The various exchanges with the practitioners allowed us to understand better their functioning, their problems, and their overall feeling on the issue of social media. The opportunity to carry out these observations in two different countries also allows us to understand better if some difficulties are local or shared between the two continents. This section thus presents the key findings of these interviews.

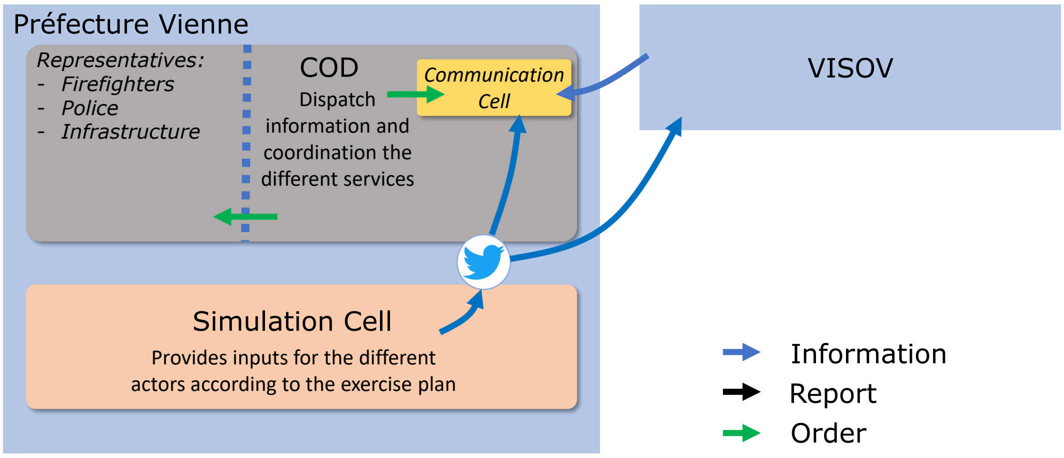

Figure 3.3: Organizational diagram of Exercise 2 MACIV at the COD in the Vienne Department. Illustration adapted from Batard (2021).

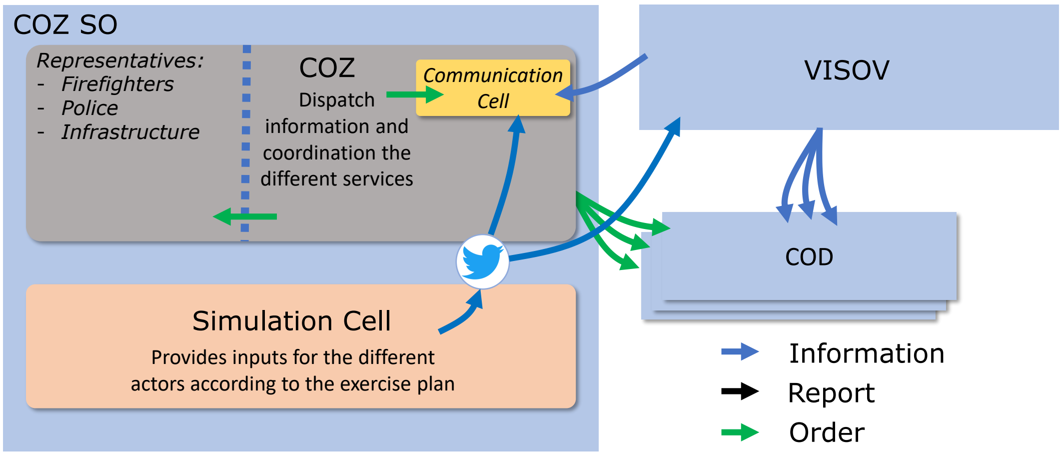

Figure 3.4: Organizational diagram of Exercise 3 MACIV in the different Préfectures involved. Illustration adapted from Batard (2021).

A lack of tooling for processing social media content The results of the SWOT analysis conducted during the Early Adopters Summit reveal that participants understand the value of this system. Participants cite an improvement in the resilience of their information pipeline, thanks to the inclusion of new information channels such as social media that allow cross-checking the information obtained. They also see NG911 as an opportunity to improve Situational Awareness of ongoing events. On the other hand, participants noted concerns mostly related to the digitalization of their work environment. Different platforms' volume, variety, and speed of data expose PSAPs to numerous threats such as misinformation and cybercriminals. Participants also mentioned privacy issues. The above threats require new protocols and tools for processing and new training for the personnel assigned to these new tasks. However, all these new features come at a price, and the cost was identified as one of the main concerns about NG911. Hence, social media processing systems, while they are wished by some practitioners, did not reach them yet. Practitioners also find themselves struggling with the CAD system sometimes. In the role-play conducted at the Charleston PSAP, Grace et al. (2019) reports that "the current system lacks flexibility. The operators reported 'breakdowns' in the information pipeline—corresponding to calls that do not provide the expected information or reported elements not relevant with an emergency." Similarly, in

France, the information system used in crisis response, SYNERGI, has some critics. Linot et al. (2018) report that the SYNERGI users suffer from:

- Its rigidity, which leads to system circumvention.
- Communication issues, caused by a lack of common vocabulary.
- The diversity of unprepared institutions involved, leading to poor coordination.
- Lack of context associated with the information shared, adding confusion.

Also, the SYNERGI system prevents the collection or sharing of social media information on this platform. The widespread use of the system and its official status hinders any rapid iteration of it. The only integration of social media in an institution in France was during the first exercise. But the system used was not official and was more like a homemade design that met a practical need. Thus, it appears that the early adopters are unfortunately not so much. Rather, they are individuals convinced of the value of social media in crisis management. However, due to the lack of tools offering the necessary capabilities, it is difficult to consider this technology ready to enter the early adoption stage.

Heterogeneous profiles of social media operators The different sessions also allowed us to understand the diversity of profiles of people who deal with social media in crisis management. The PSAPs encountered envisioned the role as an adaptation of call takers. Thus, either an operator would be dedicated to social media monitoring, or existing call takers would be provided with an interface to monitor the content of interest. In the past, when VOSTs were still in operation, some PSAPs (notably in the Colorado State) used these volunteers to assist them. This third-party operation was found during the MACIV project exercises. In France, media operators can be found at different levels in the hierarchy of response actors. For the time being, this distribution depends on the interest that each one has in social media. In the case of the first exercise, the SDIS had a dedicated operator alongside their call-taker and were cross-checking information. In the other two exercises, it was the communication cell of the Prefectures that was monitoring social media to provide information to the decision-makers. In all French cases, their operators were assisted by a third-party of volunteers, VISOV. Overall, the processing of social media in crisis cells is carried out in a relatively similar manner in France and the U.S. Both countries dedicated a person to the processing and kept this person in proximity with the decision-makers. For instance, in France, the social media operator was in each exercise in the same room as the latter. The organizations in charge of the response also rely (or have relied on) on a partner (the VISOV in France or the VOST in the U.S.). Consequently, the processing is not always directly made by the social media operator present in the crisis cell. Thus, there is currently one or more intermediaries between the fact and the decision-maker, as may be the case with telephone calls or reports made by response teams. Gathering information from social can then be challenging because of the current lack of framing in the process of information collection. Finally, the skill profile of the operators is also currently very diverse. In France, the profiles observed were those of communicators, while in the United States, the people considered would be specially trained. In the former case, these profiles translate a vision more oriented toward information dissemination rather than information collection. As reported in Castagnino (2019), French emergency organizations systematically assume information coming from social media as untrustworthy information. Thus, for them, social media is more a communication channel than a collection channel.

Framing information collection: the Six Ws The Role-Play session at the Charleston PSAP brought interest in the way the information collection is framed by call-takers (Kropczynski et al., 2018). “The "Six W’s"—Where, What, Weapons, Who, When, and Why—provide call-takers with a heuristic for questioning callers and entering only relevant information for each call." The call-takers from the 911 PSAP's frame their interviews with the callers through the Six W's. The goal of the Six W's is to obtain information that matches the information needs of the decision-makers. These Six W's are:

- *Where* is the assistance needed,
- *What* is the event taking place,
- *Weapon(s)* involved in the event (if relevant to the nature of the event),
- *Who* is involved in the event,
- *When* the event started,
- *Why* the event is happening.

These specific questions help the call-takers to acquire quickly detailed information relevant for decision-making. This information was previously identified as the most relevant information to respond quickly and effectively to an emergency.

3.1.2 A plurality of information needs in crisis management

It appears that in most cases, the information coming from social media passes through at least one intermediary before reaching the decision-maker. Thus, while decision-makers need information, but they are not the persons actively monitoring social media. The staff responsible for retrieving information from social media must therefore orient their research towards the needs of the latter. Several questions therefore arise:

- What information do decision-makers need?
- What information are the operators looking to retrieve?

The first question is at the heart of the crisis management system. The decision-makers needs have to be answered, and this is the role of the support operators (call-takers and social media operators) to fulfill these needs. The second question looks at the information that operators search for in the stream of social media messages. This question guides the development of the algorithms responsible for retrieving data presented in the next chapter. The remainder of this section develops the analysis of this need considering previous works that have defined concepts such as Situational Awareness and Actionable Information.

Situational Awareness

Situational Awareness is summarized as the understanding of the "big picture" of a situation. More precisely, it is the comprehension of the different aspects of an event, environment, and/or entities and how they are more likely to evolve in the near future. Sufficient Situational Awareness is a critical factor in decision-making. Each individual has their own Situational Awareness, depending on several factors such as experience, perception ability, training, etc. The group formed by individuals also carries its Situational Awareness. As described in Chapter 1, emergencies are confusing events that reset Situational Awareness. The decision-makers in charge of the response must therefore build an updated mental representation of their environment. This task is even more difficult as the context is unstable and may continue to evolve because of aftershocks or cascade effects. In addition, the amount of new information can be overwhelming, depending on the size or complexity of the event. In the described context, it appears crucial that decision-makers rely on adapted methodologies and tools to reconstruct adequate Situational Awareness for decision-making. This work and definition attracted the interest of the U.S. military, who embraced the concept, working permanently in a stressful and highly uncertain environment. Department of the Army (2021) compiles the doctrine they have built around the concept, including how it fits into the decision-making process and how Situational Awareness is influenced by the environment.

The currently dominant definition is seminal work presented in (Endsley, 1995). Endsley, propose a definition of Situational Awareness as well as a model to explain how it fits into the decision-making process. They define Situational Awareness as the: "perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future." This definition is associated with three levels: (1) perception, (2) comprehension, and (3) projection. Perception refers to an operator's ability to detect relevant signals through its senses. Level 2, comprehension, refers to the ability to interpret and make connections between the perceived signals. Finally, level 3 corresponds to the ability to anticipate future events based on available information. Figure 3.5 provides an overview of Situational Awareness in the decision-making process according to (Endsley, 1995).

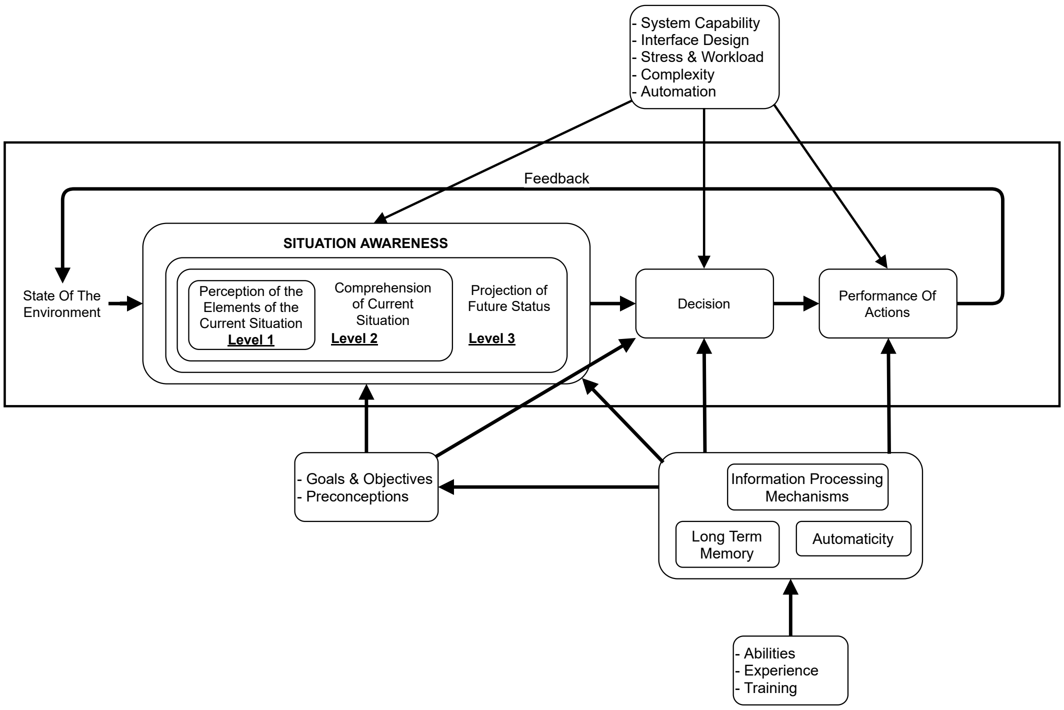

Figure 3.5: Adapted Situational Awareness model from Endsley (1995).

Endsley's definition of Situational Awareness has seen many developments in the field of crisis computing. Crisis models are one of these developments. These computerized representations of the crisis terrain indeed meet the need for Situational Awareness. For example, the model presented by Bénaben et al. (2008) provides an interface representing the different actors and what they are doing, the components of the event, and the environment. Later, Fertier et al. (2020) proposed a system to automatically implement such models using sensors data to improve the Situational Awareness of its users. S. E. Vieweg (2012) uses the previous definition of Situational Awareness to propose a coding scheme for messages posted on social media. This analysis highlighted that social media contain information that can improve Situational Awareness. The automated extraction of messages contributing to Situational Awareness is then proposed in Verma et al. (2011). Inspired by this proposition, many systems have been developed to classify messages according to certain categories of information (Ashktorab et al., 2014; Caragea et al., 2011; Imran et al., 2014). More and more complex approaches are proposed. For example, the processing is no longer limited to text only, but now also integrates the associated images Alam et al. (2017). The primary objective of this approach is to improve the classification results. But aggregating data sources also allows providing the user with more points of view of the situation. Having access to several data sources will also allow the user to cross-check the information from both channels to verify the information or complete certain aspects that would be missing on one of the channels.

Actionable information

Interviews conducted with crisis managers and operators of call centers revealed a need for information other than situational awareness (Kropczynski et al., 2018; Zade et al., 2018). The interviewees refer to the need for actionable information, i.e., information that enables direct decision-making leading to a physical response. During an event, a crisis management team can lack the critical information to take action. This situation can arise when teams do not have the information they need to act or when they have to analyze a large volume of information. This leads to a situation of paralysis of the decision-makers, despite the availability of the necessary information. Situational Awareness is an important part of the decision-making process. However, it does not specify what information is needed for the decision-making. Systems that seek to improve Situational Awareness (e.g., by retrieving information posted on social media) do not guarantee that this information will be relevant to decision making. Such an approach can even potentially contribute to the information overload mentioned above. Hence, the proper design of these systems is of utmost importance (see Chapter 5). The rest of this section focuses on this concept, its definition, and what it implies for the processing of social media data.

Actionable information can then be considered as a specific type of information. Yang et al. (2012) indicate that the fire response system they propose should focus on information that is (i) timely, (ii) accurate, and (iii) complete. For instance, information that provides the exact location of the event (accurate information) and the environmental conditions (complete information). Comes et al. (2015) call for a similar set of attributes to define the information needed in an information system for crisis response: (i) relevant, (ii) accurate, (iii) timely. Zade et al. (2018) conducted a survey and various interviews of emergency and humanitarian responders. They focused their research on the question: "how can the right information reach the right person at the right time?" In their approach to this research, they first asked practitioners to define actionability. They report: “participants described actionable information as anything which either they or their organization could use at that moment to assist, enact, or expedite the solution to a (potentially) identified issue.” More importantly, the authors report that the practitioners use a different definition depending on their organizational role and responsibilities. Zade et al. identified the same attributes as the previous authors. However, they also highlight the dependence of the definition of actionable information on the receiver of the information. Thus, information may lead a particular type of decision-maker to decide. In contrast, a decision-maker in charge of other aspects may judge the information provided as unimportant. For instance, a piece of information can be actionable for firefighters but not for EMS. The same authors also add the criteria of credibility. Information that is not convincing will not lead to any response from the decision-makers. As a result of all the points of view presented, a piece of information is actionable if it is:

- Accurate: contains a location
- Addressed to the right role: the right decision-maker receives the information
- Timely: it reaches the decision-maker at the right time, e.g., avoiding a danger.

- Credible: it is considered
- Complete: it provides sufficient context on the environment.

Kropczynski et al. (2018) relied on the Six W's previously presented to identify actionable information posted on social media. The concept of actionable information is indeed at the heart of the Six W's, which seek to obtain the information necessary to make decisions. The authors ,therefore, proposed to use the same approach for social media content. Later, the same authors proposed a refined version of this coding scheme (Kropczynski et al., 2019). They conducted an analysis of a corpus of tweets to determine the appearance of actionable information in social media posts. They coded 200 tweets using their proposed coding schema and reported the proportion of tweets that were fitting in these categories. Their results show that among the tweets, four of the categories (Where, What, Who, Why) were significantly present, while two (Weapon and When) were rare. With social media content, the Six W's might process is then slightly modified. Usually, there is no follow-up information to fill the missing attributes like in a regular phone call. A social media processing, therefore, must consider that specificity. It can be addressed by aggregating the pieces of information retrieved from both call-takers and social media operators within a unified system.

3.1.3 Location of Actionable Information in the Situational Awareness model

Situational Awareness is the initial building block of decision-making in crisis response. Information cannot be designated as actionable without the decision-maker having sufficient context to decide if that information is actionable. Therefore, crisis management starts by recovering an adequate perception of the elements/assets of the environment (level 1 of S.A.). From that perception, they will use their skills/training to understand (level 2 of S.A.) the current situation. Then, decision-makers evaluate the future status of their environment (level 3 of S.A.). In this picture, Actionable Information is information that can trigger a decision or focus from the decision-makers. This section aims to unify both concepts, starting from the Situation Awareness model.

Building Situational Awareness requires information and Actionable Information also depends on *Information*. Hence, both concept of Actionable Information and Situational Awareness relies on the definition of *Information*. Several definitions of *Information* have been proposed. Ackoff (1989) proposed a hierarchical framework where four concepts, Data-Information-Knowledge-Wisdom, are used. Later, Bénaben et al. (2016) refined this framework to embed the concepts of *Decision*. Here, the definitions of *Data* and *Information* are only used. The concept of *Data* refers to symbols that have no meaning beyond their existence. *Information* is built from *Data*, by structuring them. Therefore, *Information* is contextualized, organized, or structured *Data*. *Information* generally answers questions such as "who," "what," "where," and "when." Thus, the Call-takers interviewed in Kropczynski et al. (2018) are gathering *Information* through the Six W's. The remaining part of this section presents an interpretation of the place of Data, Information, and Knowledge in Situation Awareness and the role of Actionable Information. This interpretation is illustrated in Figure 3.6.

The first level of Situational Awareness described in Endsley (1995) concerns the perception of the "elements/assets" of the environment. These "elements" or "assets" can correspond to images or text messages in the context of social media processing during crisis response. This first step can thus be interpreted as the collection of *Data* points. These *Data* are then processed and cross-referenced with each other, with the help of prior *Knowledge*, to enable the understanding of the situation. This step can therefore be seen as the beginning of the construction of *Information* by the organization. This is this level of Situational Awareness that decision-makers are required to reach to be able to decide. Finally, the state of this *Information* can be projected into the future to anticipate the future status of the environment and the event. In this image, *Knowledge* intervenes in two places. First, it allows the interpretation of *Data* into *Information*. Second, it allows the projection resulting from the analysis of the *Information*.

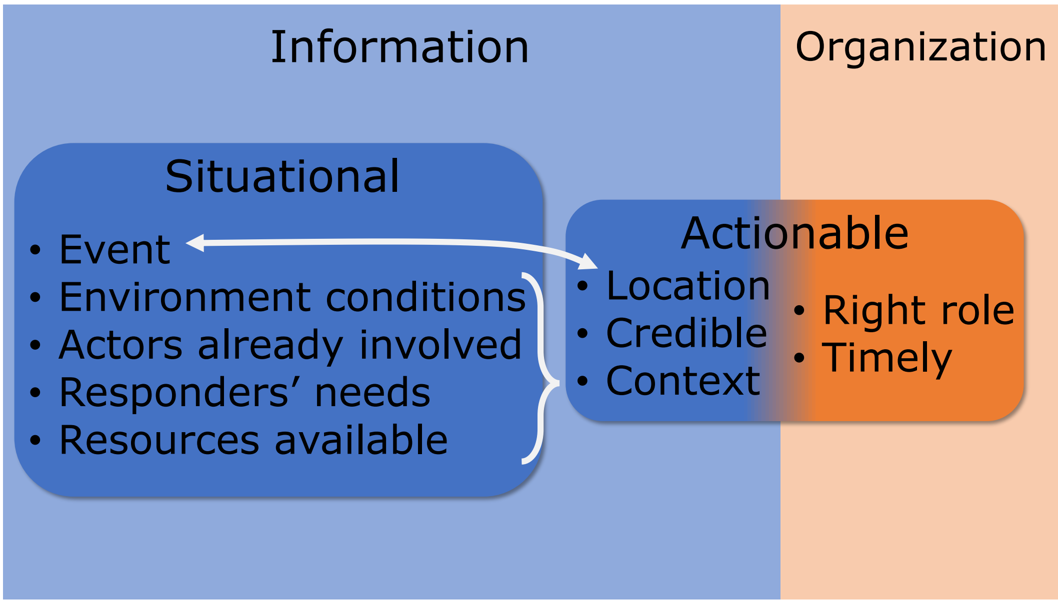

Figure 3.6: Location of Data-Information-Knowledge concepts in the Situational Awareness model

Situational Awareness is built upon any *Data* or *Information* about the current state of an environment, and that is delivered to the decision-maker. Using the previous proposition, we are now able to envision a relationship between Situational Awareness and Actionable Information. As Actionable Information is a type of *Information*, it is then embedded in the second level of Situational Awareness. The difference with regular *Information* is that Actionable Information is the missing piece of the puzzle that allows the decision-makers to decide. As a result, Situational Awareness is the puzzle comprised of pieces of *Information* that decision-makers try to assemble during the event. Actionable Information constitutes the final, missing pieces of that puzzle necessary to comprehend the whole. Actionable Information is then a specific piece of *Information* in the Situational Awareness model.

3.1.4 Information needs of a crisis management organization

This last section seeks to answer the question: *What information do decision-makers need?* The previous section showed that they need two types of information: information that improves their Situational Awareness and Actionable Information. To provide a more concrete answer we rely on the results of the observations made during the research project as well as on the literature. Figure 3.7 summarizes the relationship between Situational Awareness and Actionable Information.

Situational Awareness requires information about the event environment. First, they need constant and specific information—What is the emergency? Where is the emergency? What are the conditions at the location? Any information related to the event is potentially interesting. However, to avoid overloading the teams with information, it may be advantageous to restrict the type of information sought. Jackson (2006) thus proposes the following information to describe an event:

- Location of event, type, cause, and severity.
- Environmental conditions (buildings, population density, potential hazards, and their location, etc.).
- Information on the response participants (responders already involved, their skills, resources, etc.).
- Current and future needs of the responders (number of casualties, their status, etc.).
- The available resources for the event (qualified actors, appropriate equipment, etc.).

This information is used to describe the context of the event. This information also corresponds to the type of information that the Six W's are looking for. Yang et al. (2012) also used this information in the design of their firefighting system. In a second step, we also seek to obtain Actionable Information of interest to the crisis management teams. Actionable Information is a piece, or the last missing piece, that enables decision-making. As seen previously, Actionable Information is information that meets the following criteria, ordered by importance:

1. is located;
2. is directed to the right role;
3. is timely;
4. is credible;
5. provides context.

In addition, certain information allows for the de facto fulfillment of certain criteria. For example, a message that mentions deployed units fulfills the context criterion. Another example is a message that indicates the address of the event, thus fulfilling the location criterion while being a piece of information referring to an event.

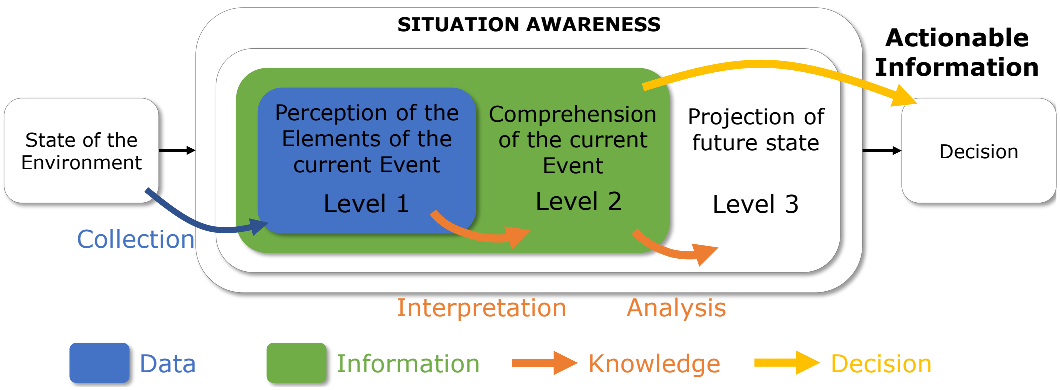

Figure 3.7: Information contributing to the Situational Awareness and criteria for a piece of information to be actionable and how they relate to each other.

This section sought to answer two questions:

- Who is processing social media during an event?
- What information do decision-makers need?

The first question was answered during the various meetings and observations of this research project. Thus, it appears that decision-makers are not directly involved in social media processing. This is done by dedicated operators, with various profiles that often correspond to the perception that organizations have of social media. These operators then act as intermediaries between social media and the decision-maker. The exploration of the second question showed that decision-makers use two types of information. First, information that allows them to improve their Situation Awareness during the event. Second, the need for Actionable Information, which allows for decision-making. This section, therefore, concludes with a set of information that feeds the first need and a set of criteria that define whether an information is actionable. The approach taken in this section can be characterized as bottom-up. The next section takes the opposite approach, focusing on the needs identified for the design of information systems for crisis management.

3.2 Information expected by information systems

The previous section consisted of a bottom-up approach to obtaining the information needed. This section takes the opposite direction, i.e., top-down, starting from the need identified during the conceptualization of the crises and the information deemed necessary to resolve them. As in the previous section, this approach also seeks to bring out a set of information relevant to crisis management. The previous chapter (Chapter 2) provided a history of the information models developed for crisis management (section 2.2.1). These models provide a computer-readable representation of the information used by the different actors. They then provide assistance through an information system that facilitates the distribution and manipulation of this information. Two models are emerging in the context of improving collaboration between different crisis management actors (Bénaben et al., 2008; Othman et al., 2014). Othman et al. (2014) propose four metamodels for disaster management, one for each phase of crisis management: mitigation, preparation, response, and recovery. Their proposition is presented in Figure 3.8. Their model is constituted of four principal entities:

- Disaster
- Rescue
- Emergency Management Team
- Response Organization
- Emergency Operation Center

An *Emergency Operation Center* latter is a *ResponseOrganization* that controls the *EmergencyManagementTeam*. A *ResponseOrganization* is composed of groups of *Aids* and *Resources* at its disposal and is organized according to an *EmergencyPlan*. It supports the *Rescue* teams in their efforts to rescue *Victims* according to their *Situational Awareness* and their *Exposure* to the *Disaster*. The *Rescue* teams are managed by an *EmergencyManagementTeam*. This team oversees defining a set of *ResponseTask* according to given *ResponseGoal*. It follows *Command*, requires *Coordination*, and uses means of *Communication*.

On the other hand, the metamodel proposed by Bénaben et al. (2016) focuses on collaboration during the response phase. This metamodel is split into five packages:

- Core
- Partners
- Context

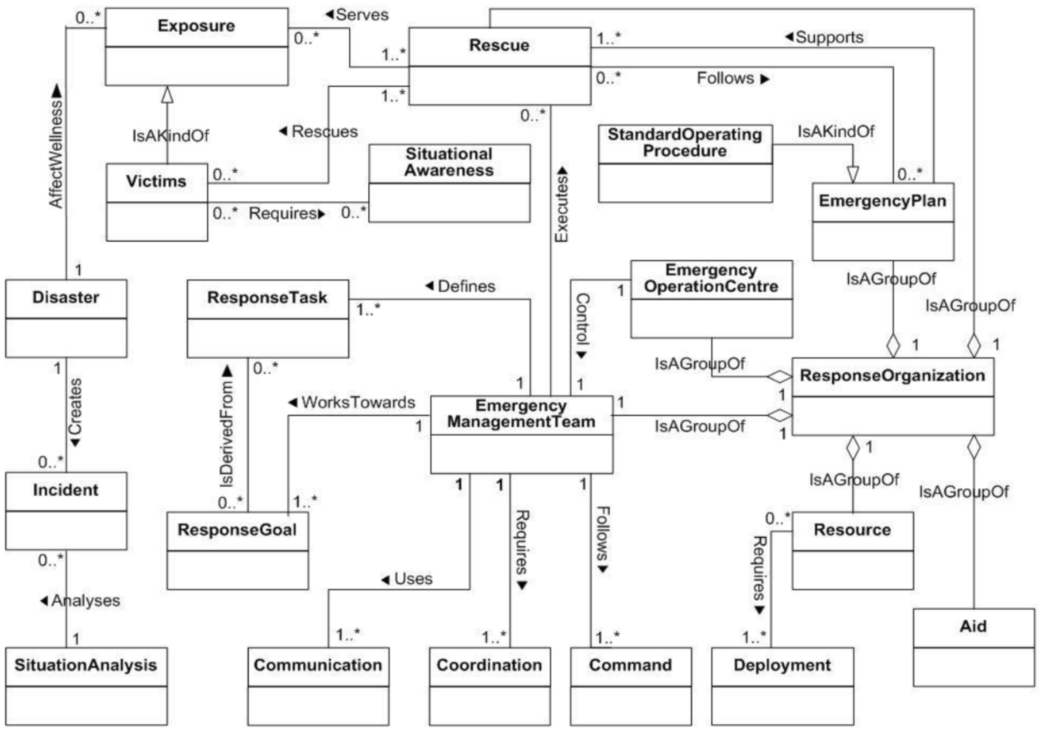

Figure 3.8: Metamodel proposed by Othman et al. (2014, Fig.4) for the response phase of a disaster event.

- Objectives
- Behavior

Figure 3.9 represents the four main packages: **Core**, **Partners**, **Context** and **Objectives**. The **Behavior** package is excluded as it is solely used to implement a process model of the collaborative behavior using the Business Process Model and Notation (BPMN) representation. The **Core** package describes the collaborative process. This package is composed of five sub-systems: Context, Objectives, Partners, Performance, and Behavior. Each system represents a specific aspect of collaboration. These sub-systems correspond to the five previous packages, as each package provides crisis-specific entities to its corresponding sub-system. The collaboration happens in a given *Context* that contains *Characteristics* and *Threat/Opportunities*. *Partners* collaborate in this *Context* according to their Resources, and Capacities in response to an Event. The different *Partners* collaborate towards *Objectives*. During their collaboration, they review their *Performance* in achieving their *Objectives*. This package is generic to any collaborative endeavor. Thus, the metamodel is specified to crises through the surrounding packages.

The Context package provides additional classes to represent the disaster environment. It is composed of:

- *Good*: human-made elements such as roads, buildings, etc.
- *People*: a group of persons
- *Natural site*: natural elements such as forest, lake, etc.
- *Civilian society*: social actors such as media, institutions, etc.

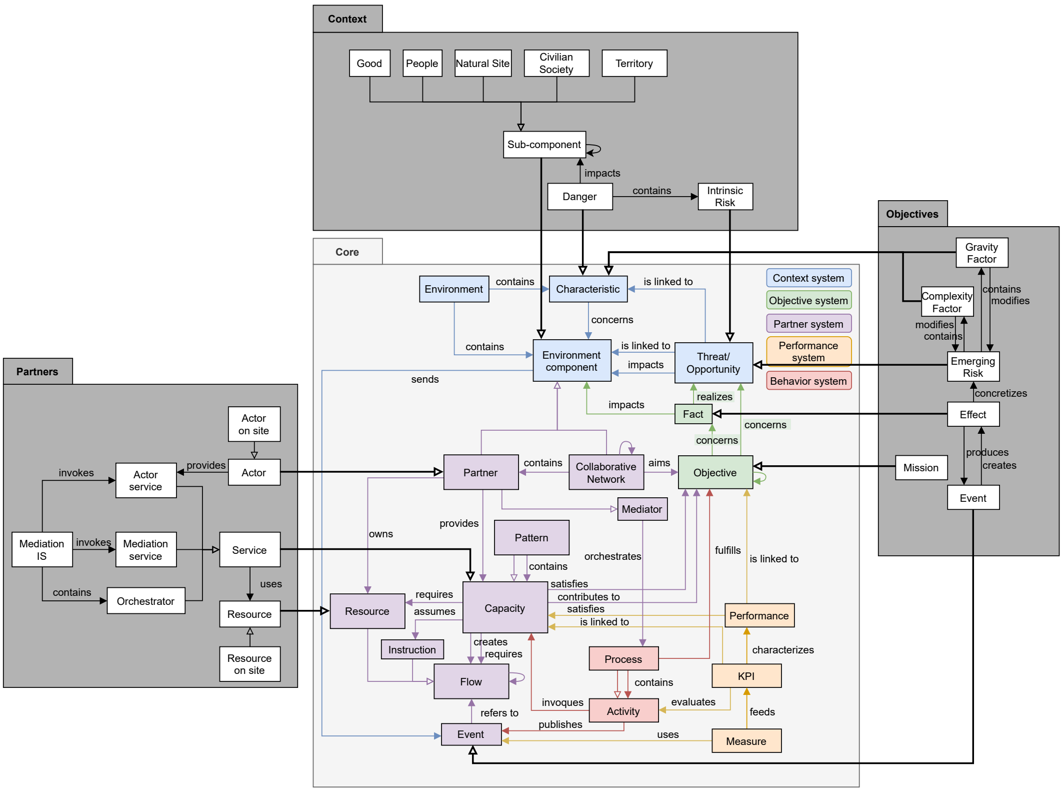

Figure 3.9: Metamodel proposed by Bénaben et al. (2016) for the response phase of a disaster event.

- *Territory*: administrative area such as a county, region, etc.
- *Danger*: dangerous characteristics linked to the environment such as seismic area, social instabilities, etc.
- *Intrinsic risk*: risk linked to the previous dangers identified which, in the previous example, would correspond to earthquake and riots.

The Partners package contains:

- *Actor*: emergency responders such as firemen, EMS, etc.
- *Resource*: resource used by actors such as a truck, an ambulance for the previous actors
- *Service*: capabilities of actors, which correspond to evacuate people and treat injured ones.
- *Actor service*: service specifically provided by actors.
- *Mediation service*: services provided by the information system used by the partners.

The Objectives package:

- *Emerging risk*: risk resulting from the event itself (e.g., the collapse of a building, panic, etc.).
- *Effect*: a direct consequence of the crisis itself (e.g., 10 injured people, fire, etc.).

- *Mission*: objective directly linked to identified risk or effect.
- *Event*: event occurring during crisis management that must be considered as triggering an effect.
- *Gravity factor*: characteristic of the current situation that may increase or decrease the gravity of the crisis (e.g., rain or wind on a large fire).
- *Complexity factor*: characteristic of the current situation that may change the type of the crisis.

The objective of both metamodels is to represent the collaboration between the different actors of the response. However, they differ in their approaches. On the one hand, the metamodel proposed by Othman et al. (2014) is a model that is part of a comprehensive crisis management model. This model, therefore, seeks to maintain continuity and coherence with the other models, at the cost of less granularity in the description. It thus focuses essentially on the collaboration between the different actors, leaving aside the description of the context in which this collaboration takes place. Some entities may appear insufficiently detailed. For example, the environment is only described by the class *Exposure* and the event through the *Disaster* class. On the other hand, the model proposed by Bénaben et al. (2016) focused solely on the response phase of the crisis. This makes it possible to explore more broadly the information needs of the actors regarding the context. The modular structure through packages allows specifying each aspect of the crisis. It allows for a more precise description of essential concepts for Situation Awareness and Actionable Information. The following presents the identified information, grouping it according to four categories: Actors, Environment, Event, and Collaboration. The **Core** package of Bénaben et al. (2016) is not considered, as its concepts are too abstract for crisis management. Information from the latter author are shown in magenta and the ones from Bénaben et al. (2016) are in cyan.

Actors

- Actor which includes Aid, EmergencyManagementTeam, EmergencyOperationCentre, ResponseOrganization
- ActorOnSite which includes Rescue
- Resource which includes Resource
- ResourceOnSite
- Service
- ActorService which includes Communication, Coordination, Command, Deployment, SituationAnalysis
- MediationService

Environment

- Good
- People
- NaturalSite
- CivilianSociety
- Territory
- Danger
- IntrinsicRisk

Event

- EmergingRisk which includes Exposure, Victims
- Effect which includes Incident
- Mission which includes ResponseGoal
- Event which includes Disaster, Incident
- GravityFactor
- ComplexityFactor

Collaboration

- EmergencyPlan
- StandardOperatingProcedure
- ResponseTask
- SituationalAwareness

This approach has made it possible to highlight numerous entities that correspond to information manipulated in the response to a crisis. However, it is also very exhaustive and essentially puts forward information necessary for the computer representation of the situation. The next section, therefore, overlaps the information needs of an information system, with the ones of decision-makers.

3.3 Actionable Information for decision-makers that can be processed automatically

Interviews and meetings with crisis management practitioners have shown that social media handling is currently done mostly manually. Despite the proven usefulness of this communication channel, it is questionable whether resources should be allocated to such a manual task. Aware of this issue, some organizations have chosen to delegate it to a third party (VISOV or VOST). Nevertheless, being able to process the available content on a large scale requires at least partial automation of this processing. The challenge in automating this processing is to ensure that it does not cause harm instead of solving the original problem. In particular, the overload of irrelevant or useless information is an issue of such an approach. The systems developed should require minimal attention from the operators on the menial tasks while keeping them engaged. This issue leads to this section, which links the information needs of decision-makers with the information needs of crisis management information systems.

The first section of this chapter identified the following information needs:

- Location of event, type, cause, and severity.
- Environmental conditions (buildings, population density, potential hazards, and their location, etc.).
- Information on the response participants (responders already involved, their skills, resources, etc.).
- Current and future needs of the responders (number of casualties, their status, etc.).

- The available resources for the event (qualified actors, appropriate equipment, etc.).

This information helps define the context of the crisis and contributes to the situational awareness of the organization in charge of the response. As explained in the first section, knowing the context is considered necessary but not sufficient for practitioners to make decisions. Their primary need is to have access to Actionable Information, on which decisions can be made. Information is considered Actionable if it meets the following criteria:

- is located
- is directed to the right role
- is timely
- is credible
- provides context

In the case of the information system, some of these criteria are challenging to take into account. Defining what is the right role to deliver a piece of information or the right time is difficult. To overcome this problem, the information system must guarantee access to information for as many decision-makers as possible, as soon as possible. Hence, in the scope of this work, an information is considered actionable if it: i) is located, ii) is credible and iii) provides context. This information is the information sought by the teams in charge of the response. It then remains to determine which information that meets the previous criteria can be manipulated by an information system. This requires an information model capable of representing the information that responders need (Comes et al., 2015). These pieces of information are the ones sought by the teams in charge of the response. It then remains to determine which information that meets the previous criteria can be manipulated by an information system.

Information on the **Collaboration** is, for instance, not retained in the final model This information is used to represent the interactions with the actors and therefore does not meet their needs. In the same way, the classes *GravityFactor* and *ComplexityFactor* intervening in the representation of the **Event** are not retained. These concepts are linked to the functioning of the Bénaben et al. (2016) metamodel and do not represent directly exploitable information. Finally, the class *MediationService* in the actor package is not considered since it is linked to the organization's information system.

The final model is then composed of sixteen entities:

- *Event*
- *Effect*
- *Emerging Risk*
- *Good*, *People*, *Civilian Society*, *Natural Site* and *Territory* are specific *Environment Components*
- *Danger*
- *Intrinsic Risk*
- *Actor on Site* is a specific *Actor*
- *Actor Service*

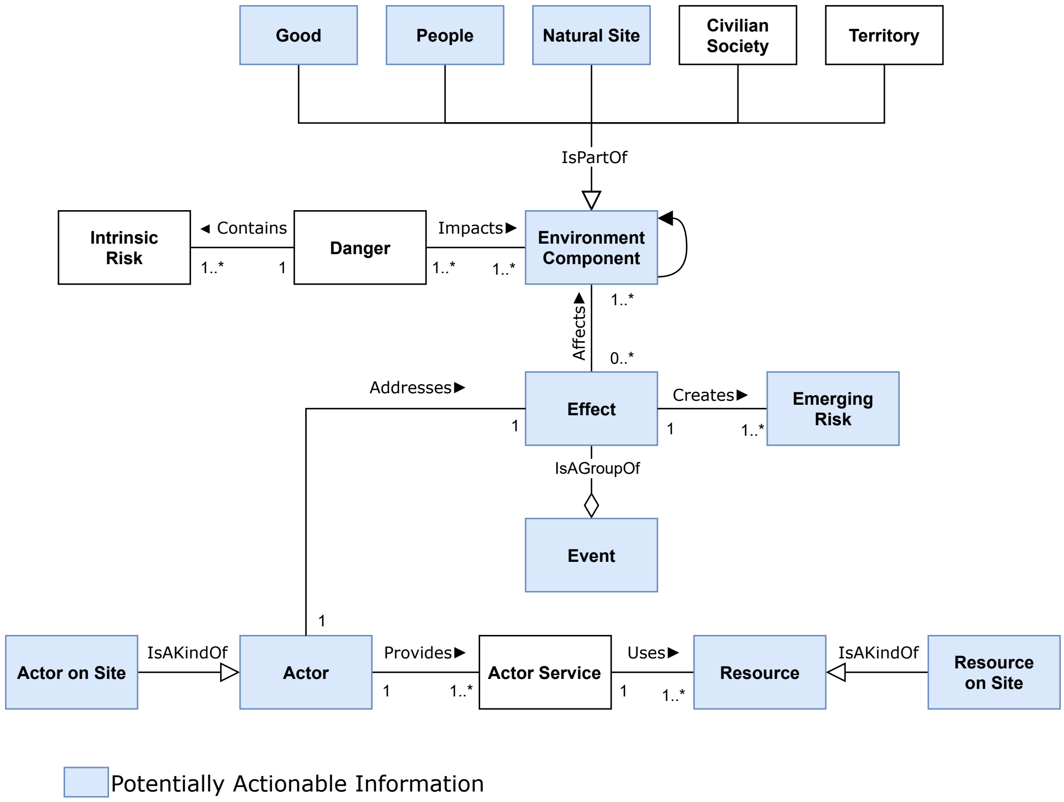

Figure 3.10: Proposed information model, produced after reviewing the information needed by decision-makers and fitting into an information system for crisis response. The information in blue qualifies as Actionable Information.

- *Resource on Site* is a specific *Resource*

This information model is illustrated in Figure 3.10 and described in the following.

It is centered around the concept of *Event*. The latter is visible through a group of *Effects* it has on the different *Environment Components*. These *Environment Components* can be either *Good*, *People*, *Civilian Society*, *Natural Site*, or *Territory* entities. These components are localized on potential *Danger* which contains *Intrinsic Risk*. These risks can be triggered by the *Event* which creates new *Effects* in their turn (see the relationship between Danger, Risk, and Event proposed in section 1.1.2.2). The consequences of these *Effects* create in their turn new *Emerging Risks* that are potential hazards to the rescue teams. The latter are represented through the *Actor* entity. These actors can either be organizations involved in the response or be *Actors on Site* who physically address the *Event*. Each *Actor* provides a set of skills or services (*Actor Services*). The skills often require *Resources* that might need to be deployed, in which case they are *Resource on Site*. Some of this information can be localized and thus qualify as Actionable Information if they match the previous three criteria considered (highlighted in blue in the figure). There are however, five information from the proposed model that cannot be localized. An *Actor Service* cannot be localized as it refers to the skills or capabilities (such as the ones proposed by Othman et al. (2014) previously). *Civilian Society* and *Territory* are respectively human organizations (such as a company or media) and geographical entities (such as a state or a region) that are too general to be localized. A *Danger* refers to an inherent characteristic of the environment that should be identified before an event happens. This characteristic is also thought to be a wide concept or a geographical area (such as in the example of a seismic zone). Similarly, *Intrinsic Risks* are latent concepts that do not correspond to a pinpoint on a map. This information must, therefore, be preferentially identified and located in the crisis environment. The information identified in this section is reused in the next chapter, which focuses on the automatic collection of some information.

Conclusion

The initial objective of this chapter was to identify what information from social media that is relevant to decision-making can be processed automatically. This question was split into two parts, each of which was addressed in a section. Each section presented the information needs of decision-makers and the information needs of a crisis management information system, respectively.

The first section is therefore devoted to the processing of social media in organizations responsible for crisis response. Our first finding is that social media are essentially treated as an auxiliary channel to that of calls and delegated to dedicated operators. This processing is essentially done manually by these operators or by third parties. The rest of the first section then presented two concepts adopted in the crisis informatics community: Situational Awareness and Actionable Information. Situational Awareness refers to the capabilities to perceive, understand and anticipate the state of the environment. On the other hand, Actionable Information refers to a piece of information that allows immediate decision-making. In the second part, we have taken the definition of these two concepts and developed how they interact with each other. In particular, we note that Situational Awareness is a prerequisite for the identification of Actionable Information. To determine whether a piece of information is actionable, it is first necessary to know the context in which this information is found. Finally, using interviews conducted and a review of the literature, a set of information that contributes to Situational Awareness and criteria for defining whether the information is actionable were presented.

The second section presented the information needed to implement a crisis model. Crisis models are computer representations used by information systems to manipulate information. These representations are necessary to automate the processing of information by the system. Here, we have examined the two most relevant models in the context of our study. Then, we have listed all the entities of interest for the automated collection of information. This list thus forms the second set of information that represents the needs of an information system.

The final section presented the set of information that answers the initial problem: What decision-relevant information from social media can be processed automatically? To obtain this set, we took each entity in the information system requirements set and looked at whether it met the information needs of the decision-makers. The result of this filtering led to the model presented in Figure 3.10. This model guides the next two chapters. In the fourth chapter, it is used to define the information that we will try to collect automatically using a semi-supervised algorithm. This offers the opportunity to create instances of the model's classes automatically. However, this requires a method capable of detecting information in the social media data. The next chapter, therefore, proposes a method allowing to automatically extract the required information in the context of crisis management. The fifth chapter is a proposal for an information system architecture based on similar information models fed by machine learning models.

4

Extracting actionable entities for disaster response using semi-supervised learning

Introduction

The previous three chapters have highlighted the importance of information in crisis management. The first chapter introduces the notion of Common Operational Picture (COP). The COP is a cartographic representation used by all response actors to facilitate their organization. This map uses concepts that are common to all actors. The third chapter, proposed concepts to support crisis management (Figure 3.10). The advantage of these concepts is that they can provide a computer representation of the crisis. This allows the information related to these concepts to be manipulated automatically. In particular, the third chapter highlighted two essential information needs for decision-makers: situational awareness and access to actionable information. Having access to the right information at the right time is a critical need of the response actors. Concurrently, social media are recognized as sources of information of interest. However, they are complicated to process due to the volume of data, their heterogeneity, and uncertainties regarding the information they convey. Organizations in charge of the response are therefore looking for tools to reduce the complexity of the processing. This observation brings us to the second research question identified in the first chapter: *How can the actionable information available on social be automatically retrieved during crisis response?* Therefore, this chapter proposes a method to collect automatically actionable information for decision-makers. The presented method is based on artificial intelligence and automatically retrieves the information presented in the previous chapter. Figure 6 repeats the diagram presented in the first chapter (Figure 1) and highlights the scope of the contribution made in this chapter.

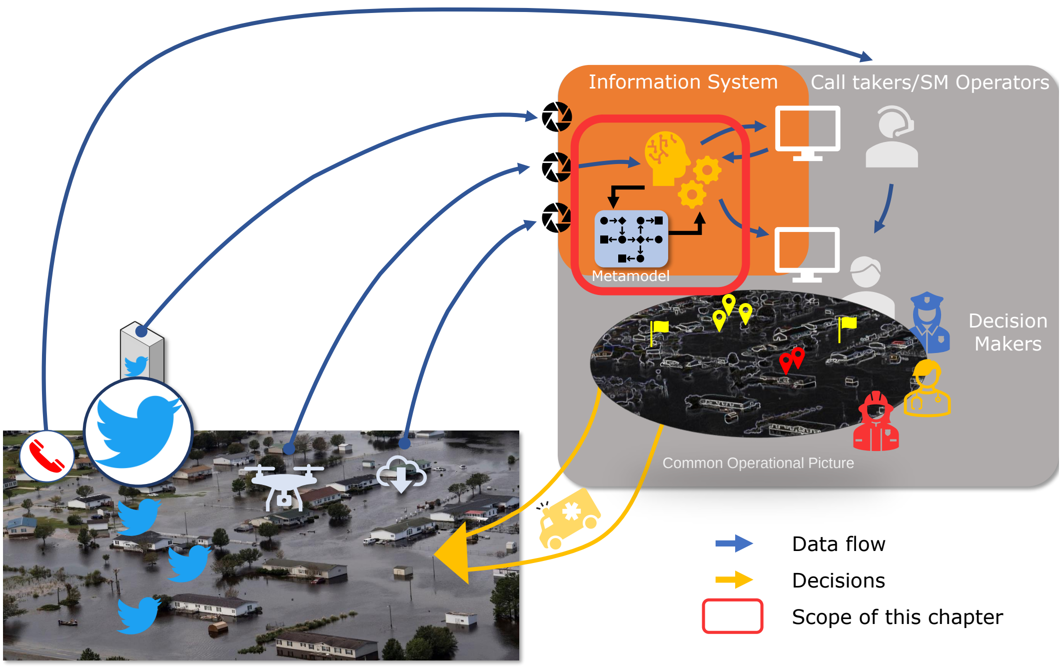

Figure 4.1: Location of this chapter in relation to the body of this manuscript.

The proposed approach aims to collect information present in the information model proposed at the end of chapter 3 (see Figure 3.10). The method relies on machine learning to identify the information expected by decision-makers within the messages posted on social media.

Unlike most of the other approaches that process the social media information in this context, the processing is not performed at the scale of the message itself. Instead, the message is processed at the scale of the different terms that compose the message. The method relies on previous work realized on this topic to take the data further. Figure 4.2 illustrates the positioning of our contribution in the light of previous work.

The chapter is organized into three sections. The first section presents the business and technical constraints that emerge when retrieving this information. The second section details the scientific foundations and the functioning of the proposed method. Finally, the last section presents and discusses the results of the method on a test data set.

4.1 Problem statement

Chapitre 3 shown that most of the information retrieval is currently performed manually. Dedicated operators are charged to identify relevant information coming from different information channels (reports, calls made to the call centers, news, social media, etc.). However, social media raises new challenges due to the high volume of data and the noise/information ratio. The literature review in Chapter 2 highlighted the trend toward automation in crisis informatics. This trend is intended to reduce the monitoring burden that operators must bear to achieve their results. In addition, crisis response is usually not an environment that leaves room for insufficiently effective resources. The call takers have thus developed frameworks that allow them to obtain information aligned with the needs of the decision-makers. The first section of Chapter 2 has already presented the most important systems designed for automatic social media processing. The systems described all seek to simplify the processing of social media by the responders. Automatic detection of information in a message stream is subject to constraints.

This section presents the environment in which the automated processing takes place. In particular, two components are highlighted in dedicated sub-sections. A technical component related to the use of machine learning is presented first. Then a second part presents a business component that emphasizes the needs and constraints of recovering the actionable information in social media texts.

4.1.1 Machine learning for disaster response

Machine learning approaches rely on data to provide information to people who consume the results. These approaches are generally composed of two phases. The first phase refers to the step where data are used to train the machine learning model. During this phase, the model learns the latent patterns in the data to produce its results. To do so, the data provided are annotated, meaning that each data point is associated with a label. Hence, the model learns to associate the data with the appropriate label. Once the model is trained, it enters the inference or prediction phase. In this phase, new, unseen data are provided to the model. The machine learning then infers the label associated with the data provided. There are then two types of data: labeled and unlabeled. Different methods are used depending on the proportion of labeled data used in the training phase. When the training set is entirely composed of labeled data, the approach is said supervised. This approach is the one most often chosen when training a model. However, it comes at the cost of having a set of data annotated. Data annotation can be time-consuming, expensive (if trained professionals annotate them), or challenging when the labels used are too ambiguous. The opposite is said unsupervised or self-supervised when the entire training set is unlabeled. Nowadays, more and more tasks are handled using this approach, particularly in the case of large models. The chosen approach trains the model by providing the label directly in a sentence. For example, a model trained to translate text from English to French following this method would use sentences expressing the translation. Thus, instead of providing the model with the couple ("potato," "patate"), the model receives the sentence "The word 'potato' is translated as 'patate' in french." The last way to train a model is to use a semi-supervised approach where the training set is composed of two sets. The first set comprises labeled data and the second one of unlabeled data. This approach relies on the labeled data to identify the required information to learn. Then, the unlabeled data are used to generalize the patterns learned to more data points.

The crisis informatic domain takes on the challenge to provide valuable tools to help process social media data. To reduce the load on the operators, many approaches have been taken. The first approach consists in increasing the processing capacity through the help of volunteers. Crowdsourcing tools allow the former to help in the classification of the messages that can then be forwarded to decision-makers (Imran et al., 2014). A second approach is to lower the incoming flow of data that the operators are facing. Some explored ways to reduce the noise part of the flow by filtering messages according to their relevance (linked or not to the ongoing event) (Caragea et al., 2011; Imran et al., 2014). Others attempted to shrink the incoming flow as a whole by summarizing the information from the incoming data (Rudra et al., 2016). Zahra et al. (2020) proposed to identify direct eyewitnesses of events using a machine learning model trained in a supervised way. The model, a Random Forest, uses features that the authors extracted manually to increase the performances of the model. A common solution to most NLP problems nowadays is to fine-tune a pre-trained language model. This approach associates a good ratio of performance/data labeled and can be performed on a reasonable amount of hardware to run. However, this approach still requires a significant amount of labeled data, representative of the data that the model will process in the future. This approach has already been used to classify the relevance of messages posted on social media (Kozlowski et al., 2020). The architecture of these models is synthesized in Figure 4.2

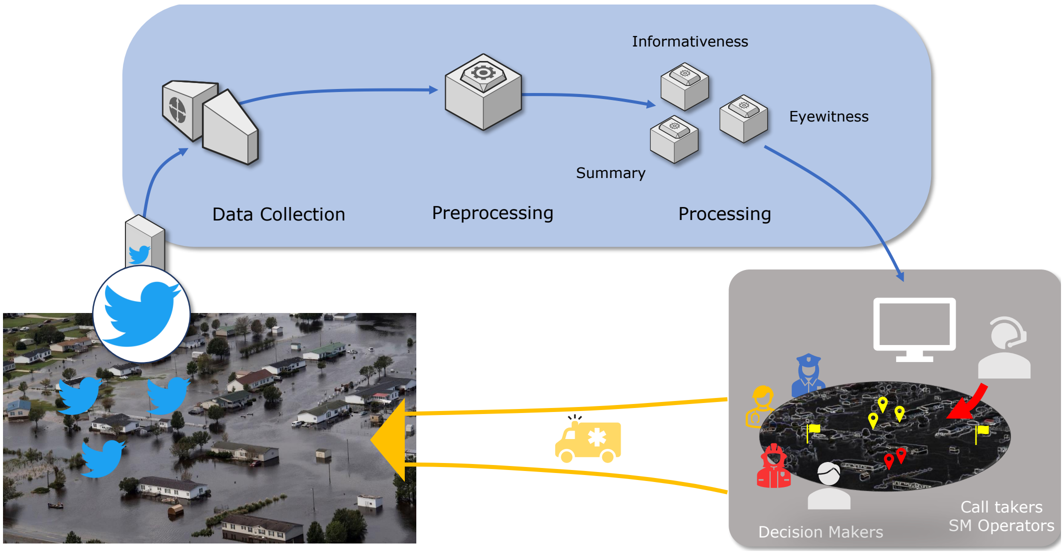

Figure 4.2: Data processing pipeline used in most of social media processing tools.

Most of the approaches used to deal with social media in crisis management are now based on supervised machine learning models. These models are trained using publicly available data sets. Most of the models are trained using sets such as the *CrisisLexT26* (Olteanu et al., 2014; Olteanu et al., 2015). However, these sets only offer labels associated with messages (composed of tweets posted on Twitter). This means that they do not specify the content of each message, nor if there could be more than one piece of information contained in the message. Thus, obtaining actionable information seems complex in the case of supervised learning for several reasons:

1. The model is trained on past data, and there is no guarantee that the new data will be similar (especially in crisis management). However, disasters are, by nature, unpredictable. The model's performances can become uncertain in this context.

2. Models are not explicable/interpretable, which can have consequences. It is essential to consider the user-machine relationship, especially in complex and/or stressful situations. The worst-case scenario would be that the system provides erroneous results and that the decision-makers still take into account, unaware of the errors. To avoid this scenario, Endsley (2016) recommends including the operators in the functioning of the algorithm by allowing them to influence the results of the algorithm in the most intuitive way possible.

3. If one wishes to retrain the model at the time of the crisis, it will require labeled data, which cannot necessarily be done.

This observation, therefore, motivates the choice of a training method that is not supervised. A self-supervised approach is not feasible in the case of named entity recognition. Hence the choice of a semi-supervised model to recover actionable information.

4.1.2 Issues raised by the context of disaster response

Social media make a significant volume of data available through text, photos, or videos. Processing social media content is tedious and more challenging when compared directly with phone calls. Part of this challenge comes from the fact that most of the data are unrelated to the current event operators are interested in. The challenges faced by potential social media operators are hence twofold. First, they need to process the volume of incoming data. Secondly, they need to screen each remaining message to identify the relevant information. Therefore, the emergency staff is looking for tools to help them in their task. The solution proposed hence need to solve two challenges:

- It has to reduce the time spent processing incoming messages by reducing the number of unrelated messages and screening.
- It has to deliver value to the decision-makers by providing the information required by the different actors.

As shown previously, the first challenge has already been discussed significantly in the scientific literature. Hence, the contribution made in this chapter builds on previous work and focuses on addressing the second part of the challenge. Therefore, the goal is to highlight the information valuable information for decision-makers. Here, valuable information refers to the concepts presented at the end of Chapter 3. This objective is close to an NLP task, the Named Entities Recognition (NER). NER is a classification problem that seeks to (i) locate and (ii) label the named entities (brand, person, organization, location, etc.) contained in a sentence. The term "entity" is used rather than "word" to reflect that social media messages can be composed of other elements such as URLs, for example. However, instead of looking for named entities, our approach aims to identify predefined entities, which are the different concepts of the information model. This model is trained to perform this task using a semi-supervised learning approach to overcome the challenges presented in the previous section. This approach taken is summarized in Figure 4.3

To summarize, the aim is to facilitate the processing of social media data. This is achieved by highlighting the information decision-makers need, i.e., information in the information model presented at the end of Chapter 2. The following part details the proposed solution, a machine learning model trained to recognize entities within a sentence.

4.2 Scientific foundations of the approach

The proposal is to train a machine learning model in a semi-supervised way to recognize the entities that belong to the different classes. The approach relies on two properties of the most recent language models. First, they allow encoding textual data into vectors. In our case, each word, labeled or not, is associated with a vector. Secondly, the word vectors are obtained to create a vector space. This vector space has the property that the distance between the different vectors represents the semantic similarity between the words associated to the vectors. The vector space thus contains clusters of vectors composed of semantically similar entities. These vectors are obtained by processing the vector space data with a clustering algorithm. It is from this step that the labeled data intervene in the method. The terms labeled by the operators are included with the other terms. Therefore, they appear in some of the clusters identified previously. The labeled terms are used to associate the

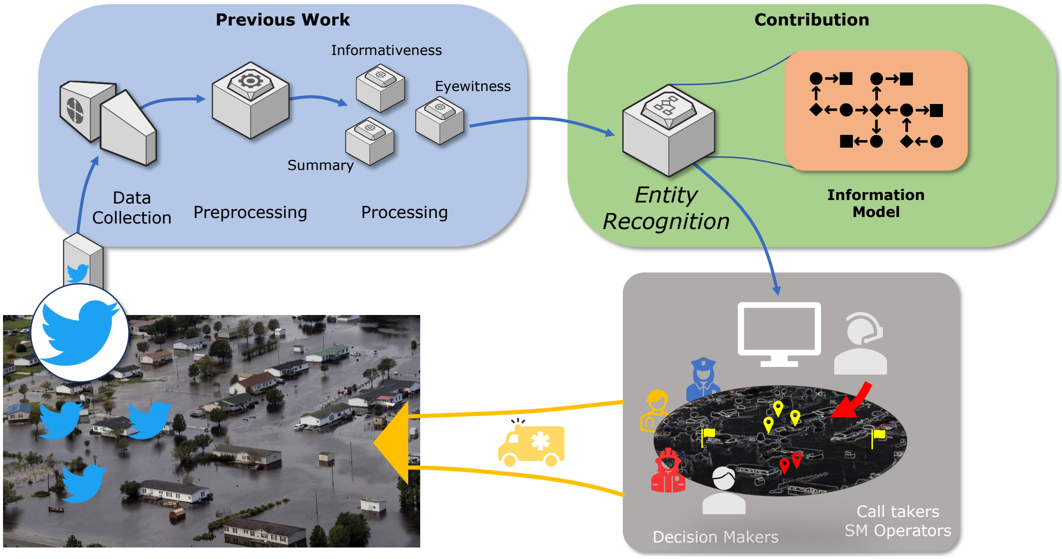

Figure 4.3: Positioning of our contribution with respect to other social media processing tools.

non-labeled content of the clusters with the labels. The labels are then propagated from the labeled terms present in a cluster to the non-labeled terms. In this way, the non-labeled terms semantically close to the labeled terms are associated with the different concepts we identify. The different steps of the algorithm are outlined in Figure 4.4. The method is composed of four main steps after data normalization. These are:

1. Generation of the word vectors associated with each token.
2. Dimension reduction of the vector space obtained previously to facilitate the following clustering.
3. Identification of semantic clusters present in the vector space using a clustering algorithm.
4. Label propagation within the different semantic clusters.

The semi-supervised approach implies that the training is made using two distinct datasets. One dataset contains labeled data, and the other has unlabeled data. The former, in our approach, contains text messages obtained from previous disaster events. These messages are sliced to obtain a list composed of the entities that make up the message. This process of breaking down sentences is called text *tokenization*. Unlabeled sentences are thus broken down into lists of corresponding tokens. Once all messages are split, a vocabulary is created. This vocabulary is composed of all the unique entities used in the original text messages. The labeled dataset is composed of words/tokens paired with one of the information labels. The two sets of tokens are then merged to create a set of unique tokens, where some are labeled. The next section presents how language models convert these tokens to vectors that embed the semantic of each token.

4.2.1 Language models and semantic representation of textual data

Texts can be seen as data with two components: a syntactic one and a semantic one. The syntax composes the form of the text, the *graph* of the words, and how they are combined to

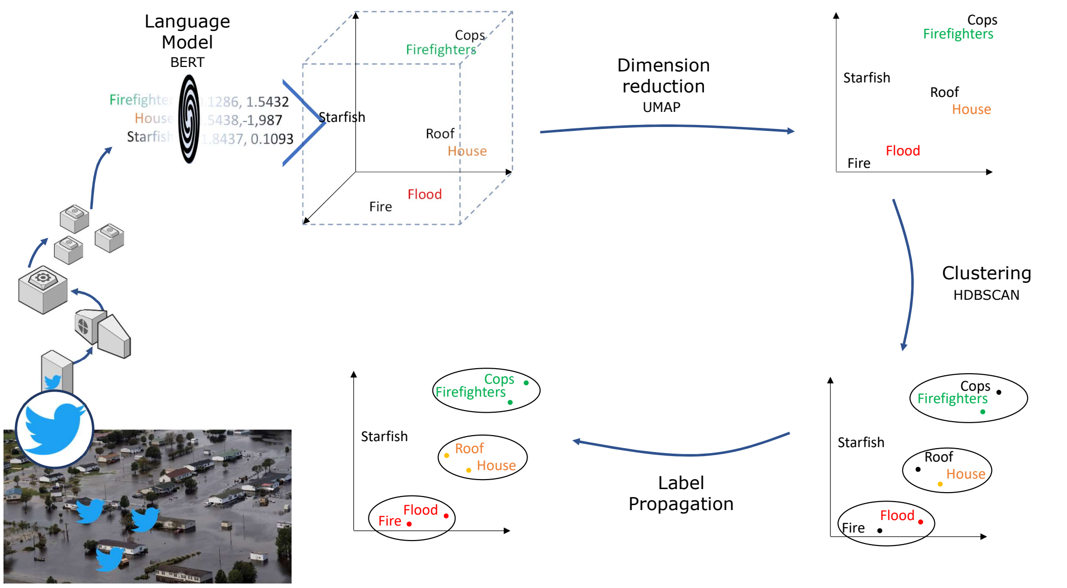

Figure 4.4: Overview of the approach developped in this chapter. The colors associated with the dots and words correspond to the different information proposed in Figure 3.10

create sentences. The semantic compose the meaning of the text, the ideas that the text has to convey through a statement. Computers have many means to process the syntactic part of textual data, but these same tools do not allow meaning processing. The NLP domain developed different approaches and tools to represent the semantic part of data. Language models are one of these tools. They associate the components that form the meaning of a language with mathematical vectors. They are statistic models representing the probability distribution over sequences of the symbols used to create sentences. These symbols can be words, letters, or phonemes. Hence, a language's sequence of symbols is associated with a vector. The vectors that compose the probability distribution are built assuming that languages have a distributional structure (Harris, 1954). This assumption states that the meaning of a word in a given sentence is provided by the words surrounding it. This reasoning is applied with the sequences of symbols. Most recent languages models rely on neural networks to construct the vectors. The neural network is trained to predict the probability distribution of the sequences of symbols found in the different sentences of the training set. Once the training is over, the distributed representation encoded in the networks' "hidden" layers is used to represent each word. Each word is then mapped onto an n-dimensional vector of reals called a *word embedding*. Here, n is the size of the last hidden layer and corresponds to the dimension of the vectors. The representations obtained have the distinct characteristic of modeling semantic relations between words as linear combinations.

This approach was popularized with the Word2Vec model proposed by Mikolov et al. (2013). Improvements to this method were gained with models such as GloVe and FastText (Bojanowski et al., 2016; Pennington et al., 2014). In a following, attention-based models Consecutively, attention-based models appeared to embed the semantic in longer sentences. This new generation of self-trained models is led by architectures such as ELMo, BERT, or GPT (Devlin et al., 2018; Peters et al., 2018). Following a similar trend as with Word2Vec, improvements were conducted on this model to increase its performance. The main differences with this new generation of models are their size. Models such as FastText or GloVe are composed of a few hidden layers that have hundreds of thousands of parameters. Newer models are now composed of up to hundreds of billions of parameters. As explained in the RoBERTa article (Y. Liu et al., 2019), their size makes the training process challenging. Indeed, these models require significantly more training data with a wider variety. Languages models have also been trained using data specific to a problem, using previously mentioned architectures. The crisis informatic domain attempted to create crisis-specific BERT models (J. Liu et al., 2021). However, training these models is challenging as they are usually limited due to the limited domain-specific data available. Also, all these models are not necessarily made available to the research community. As they are very costly in time and resources to train, they can only be retrained by a handful of institutions. This approach produces more compact representations than previous methods, whose dimension grows proportionally to the number of unique words in the training dataset. Embedding layers create an arbitrary-sized vector of each word that incorporates semantic relationships.

The proposed method relies on the word embedding of a language model. The word embeddings are used to produce vectors associated with each token of the set previously created. These vectors then create a vector space, where the distance between two vectors is equivalent to the semantic similarity between the two vectors. This property creates a vector space where some vectors, representing semantically close tokens, are spatially close too (see step 1 in Figure 4.4). The next step is to identify these "semantic clusters" in the vector space. This will allow linking the unlabeled tokens of a cluster to the labeled tokens that are part of the same cluster. This is achieved by using a label propagation approach within the clusters. However, while the resulting vector spaces are called "low-dimensional," their dimensions are still too crucial for clustering algorithms to identify relevant clusters. Consequently, their dimension is first reduced. The next section presents the motivation and the algorithm used to perform the dimension reduction.

4.2.2 Dimension reduction: UMAP

The main objective of reducing the dimensionality of a vector space is to avoid facing the so-called "curse of dimensionality" (Bellman, 1966). This "curse" refers to counterintuitive phenomena that appear in high-dimensional spaces. For instance, as the dimensionality increases, the volume space increases exponentially. Thus, data become too sparse, and the notion of distance becomes obsolete. Dimension reduction is then often used to provide visualizations of high-dimensional spaces. It consists in transforming data from their original space, to a space of lower dimension. As this projection results in information loss, the goal is to find the transformation that will keep most of the meaningful information. There are two means (that are often combined) of achieving the projection: (1) the extraction of the meaningful components and (2) the projection of the data to a lower-dimensional space. In practice, most of the algorithms are developed using both approaches. They first identify or extract meaningful components or representations of the data and then project these to a lower-dimensional space in a way that will preserve most of the original structure of the data. Among all the available methods and algorithms, the Principal Components Analysis (PCA) is very prominent (Hotelling, 1933). This linear method creates a mapping between the original high-dimensional space and the low-dimensional destination space to ensure minimal loss of information. The algorithm's output consists of the vectors used for the linear mapping. This result is explainable, hence explaining the wide adoption of this method partially. However, this method shows limitations as the number of dimensions increase. Indeed, the assumption of the linear distribution of the data becomes less and less correct as the number of dimensions increases. As a result, non-linear alternatives have been developed. Most of these approaches rely on kernels or intermediate representations. Recently, new approaches based on optimization methods gained significant traction thanks to their ability to provide visualizations that capture the original vector space's global and/or local properties. For instance, t-distributed Stochastic Neighbor Embedding (t-SNE) uses a low-dimensional map using probability distributions of data points (Maaten et al., 2008). However, t-SNE is only currently capable of reducing to a two or three-dimensional space. Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP) uses a fuzzy topological structure to represent the data structure (McInnes et al., 2020).

UMAP can be simplified as a two-step process. The first one consists of building a weighted topological graph representing the latent structure formed by the vectors in the space of the initial dimension. The particularity of this graph is that edge weights are not fixed values, but probabilities that represent the distance instead. The second step is to transpose the fuzzy weighted graph into the lower-dimensional space. For this, UMAP builds a new graph in the arrival space in the same way as in the first step. Creating the best graph in the target space corresponds to an optimization problem where the objective is to find the low dimensional representation with the closest fuzzy topological structure. Given the problem's setup, where edges of both graphs are represented using probability distributions, the goal is to minimize the cross-entropy between both probability distributions. The cross entropy formula takes in two probabilities distributions $p(x)$ and $q(x)$, defined over the discrete variable x, with $p \in \{y, 1-y\}$ and $q \in \{\hat{y}, 1-\hat{y}\}$ where y is the set of input probabilities and $\hat{y}$ the set of output probabilities. The formula is given by

$$H(p,q) = -\sum_{\forall x} p\left(x\right) log\left(q\left(x\right)\right) \ = -ylog\left(\hat{y}\right) - \left(1-y\right) log\left(1-\hat{y}\right)$$

Cross entropy allows scoring the difference between the original graph constructed from the high dimensional data and the constructed arrival graph. $p(x)$ is referred to as the true distribution and is represented by the edges obtained from the original graph. $q(x)$ is the distribution of the edges of the arrival graph. The probabilities of the edges of the arrival graphs are optimized using a Stochastic Gradient Descent process, which uses the cross-entropy as loss function.

Four main parameters then drive the algorithm:

- Number of neighbors: intervenes in the construction of the weighted topological graph and balances the role of the local versus the global structure of the data in the end result.
- Minimum distance: represents the minimum distance the algorithm can use between several points (assists in forming dense clusters if needed).
- Number of components: the dimensionality of the reduced dimension space in which the data will be embedded.
- Distance metric: the distance metric used by the algorithm.

The dimension reduction is associated with a compromise left to the user of the algorithm. Indeed, reducing the dimension of the vectors too much can lead to a significant loss of information. This compromise also depends on how the reduced dimension space is used. In our case, it is the grouping of the data into clusters supposed to represent sets of words with similar semantics. In the same way as for UMAP, the following section presents the algorithm chosen for clustering.

4.2.3 Clustering: HDBSCAN

Clustering consists of grouping sets of data that share similar properties. This similarity is then represented as the distance between data points. The representation of data in the form of vectors determines the similarity between data more obvious. This similarity, or distance, can then be computed as the vector product (or L2 distance) or the cosine between these two vectors. Many algorithms create clusters of data using different distances. These algorithms are grouped according to their approach to creating the clusters. They can be grouped as below:

- the hierarchy (decision tree)
- the centroid (K-Means)
- the distribution of the data (Gaussian mixtures)
- the density of the data (DBSCAN/OPTICS)

Each approach has its strengths and weaknesses. We will choose one approach depending on the problem and the objective we want to reach. For example, algorithms based on the centers of gravity often require the number of clusters to be identified. This assumption is restrictive, primarily when the number of clusters searched is not known a priori. Thus, other approaches have been developed to discover clusters without a priori knowledge of the number of clusters. These approaches focus more on the density or distribution of the data to declare the presence of clusters. Another advantage of this approach is identifying data points that do not belong to any cluster. In the context of this chapter, clustering is used to identify clusters of tokens that are close semantically in the vector space created during the previous steps. The algorithm chosen to perform the clustering on the vector space is Hierarchical DBSCAN (HDBSCAN). This algorithm is a variant of the DBSCAN algorithm. The choice of HDBSCAN is made because it is a fast and not greedy clustering algorithm that allows predicting clusters for new points.

HDBSCAN extends DBSCAN with a hierarchical clustering approach where the flat clustering is extracted based on the stability of the clusters.

HDBSCAN works through 5 consecutive steps. First, it transforms the vector space according to the density of data points. The core is based on single linkage clustering, which is very sensitive to noise. The noise impact is reduced by making sure that noise data points are more distant than those belonging to a cluster. This is achieved by using the *mutual reachablity distance* between different points that is given by

$$d_m reach - k(a, b) = \max\left\{core_k(a), core_k(b), d(a, b)\right\}$$

where $core_k(a)$ is the distance between a point a and its farthest neighbor among its k neighbors.

The mutual reachability distance between the data points is used to generate a graph that connects all the vertices together and with the minimum possible total edge weight. This graph can be obtained by computing the graph's minimum spanning tree. Each data point represents a vertex, and the mutual reachability distance weighs the relationships between the different points.

The minimum spanning tree is used to compute the hierarchy between the clusters. The edges of the tree are sorted by distance and iterate through each vertex to merge them to a cluster. These three steps compose the DBSCAN algorithm. However, the resulting clusters can only be obtained at that stage by setting a threshold at which clusters are defined. This threshold is a parameter set by the user in DBSCAN that has to define where to "cut" the hierarchy. This parameter is hard to set in the current situation, as the mutual reachability distance is linked to the density of the cluster. A better approach is to cut the hierarchy tree at various places to reflect the density difference between the clusters.

The hierarchy tree is then condensed. Instead of aggregating the data points to form clusters, the problem is turned upside down: we start with a single set that is "losing points" at each split. To define is points are "lost", the user set a *minimum cluster size*. If a cluster has fewer points at a split than the minimum cluster size set, then the part with fewer points is dropped off the group, and the part with more points than the minimum is aggregated with the original cluster. Conversely, if both parts have more points than the minimum cluster size at a split, then two independent clusters are created. Using this approach, the cluster tree is much smaller than previously. Using this condensed representation, it is now easier to extract clusters as fewer nodes and splits are in the hierarchy tree.

Just as UMAP, HDBSCAN has a lot of parameters to tune the different parts of the algorithm. As mentioned earlier, the minimum cluster size is the main and mandatory parameter of the method. Another parameter of interest is the number of minimum samples. This parameter intervenes in the creation of the first hierarchy tree and influences the conservativeness of the clustering. Large values of this parameter lead to more points labeled as noise. It is tied with the minimum cluster size parameter and takes its value as default. Other parameters specific to our use case are described in the experimental sections.

HDBSCAN allows identifying clusters formed by semantically close words. The advantage of this algorithm is that it is very efficient in terms of computation and allows to distinguish efficiently points that are part of a cluster or belong to noise. Among all the clusters thus formed, some contain some of the words initially labeled by the operator. The next step is to propagate the labels within these clusters in an ordered way to discover new terms associated with the concepts of the information model.

4.2.4 Label propagation algorithm

The clustering algorithm has identified clusters within the data, which represent semantic clusters whose words have a joint semantic base. However, there is no way to know to which type of information,i.e., to which label, the different clusters refer. For this purpose, the words labeled by the operator are used. As some of these words are located within clusters, they will be used as tags within the cluster, and their associated labels will be propagated to the rest of the cluster. In this way, it is possible to capture many words that refer to the same concept from a few labeled terms. Hence, a label propagation approach is used. This method composes the core of the semi-supervision aspect of our approach.

Label propagation is a method initially designed for graphs (Zhu et al., 2002). For a given graph, the idea is to provide a label to some nodes of the graph and propagate the labels of these nodes until the graph is fully labeled. While following the same logic, the label propagation used here is different. The original method is overly aggressive in labeling the data in our setup, where the data are very similar. To remedy this problem, some improvements have been made.

Propagation takes place within clusters that have at least one label. Thus, there are two cases:

1. There is only one label in the cluster: in this case, the label is simply propagated to all the other tokens in the cluster
2. Several labels coexist within the cluster.

In the former case, it needs to be controlled. Indeed, a label should not be propagated on tokens belonging to other labels. In the same way that we split our starting space into semantic clusters, these same semantic clusters can be split again to identify sub-clusters (referred to as "domains") of different labels. Once the domains within a semantic cluster are identified, the label propagation is performed similarly to the case where the cluster contains a single label. This step returns to the case where the cluster is composed of a single label. This approach mirrors the operation of a K-Means algorithm, which slices a data space into k zones to identify clusters. The most important parameter of this algorithm is k, the number of clusters present in the data space. However, the number of domains in a given semantic cluster is unknown at that point. Therefore, HDBSCAN is reapplied to identify the number of domains in the semantic cluster. The value of the parameter k used for the K-Means depends on the number of clusters identified. Again, there are two cases here: i) there are more labels than domains identified, or ii) there are more (or the same number of) domains identified than labels present in the cluster. In the former case, the number of domains is passed to the number as k. The K-Means will then split the space into k partitions which will become our domains. For each domain that contains a labeled token, the label is propagated to all tokens that are part of this domain. In the case where the number of labels is equal to or less than the number of identified domains, k takes as value the number of labeled tokens in the semantic cluster. Each of the labeled tokens is passed as an origin to the K-Means, which then creates the domains around these tokens. In this sense, each labeled token becomes the epicenter of the propagation of its label within its assigned domain.

In overview, the propagation algorithm is relatively straightforward (see Algorithm 1). The inputs to Algorithm 1 is the set of clusters from the vector spaces that contain at least a labeled word.

Algorithm 1: LabelPropagation

Data: A set of *Clusters* that possess at least a labeled word.
Result: The set of original *Clusters* with their inner labels propagated.

```
begin
    for Cluster ∈ Clusters do
        NbLabels ⟵ GetNbLabels(Cluster)
        if NbLabels > 1 then
            NbDomains ⟵ GetNbDomains(Cluster)
            if NbLabels > NbDomains then
                Domains ⟵ KMeans(NbLabels)
            else
                Domains ⟵ KMeans(NbDomains)
            end
            for Domain ∈ Domains do
                PropagateLabel(Domain)
            end
        else
            PropagateLabel(Cluster)
        end
    end
end
```

The propagation of the labels within the clusters completes the training phase of the proposed method. The obtained vector space is now composed of different areas of the space that are labeled. Overall, the most computational passes are dimension reduction and the first clustering. Regarding computation time, the label propagation is relatively inexpensive, as the propagation algorithm runs only on the semantic clusters containing labeled tokens. The next and final section explains how new incoming data are labeled using the vector space created.

4.2.5 Runtime algorithm

The trained model is used at response time to highlight relevant entities in messages coming from social media. Incoming tokens that are already present in the vector space are directly given the associated label. However, the case of new tokens needs to be handled.

Algorithm 2 details the different steps followed. At first, the incoming message is tokenized, reusing the exact same tokenizer used during the training phase. Then, the word vector of the token is generated using the language model, and its dimension is reduced using the UMAP model previously trained to map the high dimensional space to the lower-dimensional space. Similarly, the same HDBSCAN instance is reused to predict a cluster to the incoming token by looking at where the new point would belong in the condensed tree. Once the cluster has been identified, it remains to assign the corresponding label to the new token. If the incoming token does not belong to a cluster, it takes its nearest neighbor's label. If the new token is assigned to a cluster, the situation depends on the number of labels in the cluster. If there is only one label, the token receives the label of the cluster. Conversely, if the cluster has several labels, the new token is assigned the label of the nearest word labeled. When all the tokens of the message are labeled, the message is sent back to the operator with the labels corresponding to each of the tokens of the sentence.

Algorithm 2: Runtime

```
Data: Incoming Message.
Result: The Tokens of the initial Message labeled.
begin
    Tokens ⟵ Tokenize(Message)
    for Token ∈ Tokens do
        TokenVector ⟵ GenerateVector(Token)
        TokenVectorLow ⟵ DimensionReduction(TokenVector)
        TokenClusterID ⟵ PredictCluster(TokenVectorLow)
        if TokenClusterID = −1 then
            TokenLabel ⟵ NearestNeighborLabel(Token)
        else
            NbLabelsCluster ⟵ NbLabelsCluster(TokenClusterID)
            if NbLabelsCluster > 1 then
                TokenLabel ⟵ NearestNeighborLabel(Token, TokenClusterID)
            else
                ClusterLabel ⟵ GetClusterLabel(TokenClusterID)
                TokenLabel ⟵ ClusterLabel
            end
        end
    end
end
```

Incoming unknown tokens are then added to the previous ones. These tokens will also be used when updating the model. The fast training of the model allows regular updates. The method greatly benefits from caching, making many of the computations reusable for predictions. Also, as the number of tokens grows, the number of semantic clusters does not grow linearly. For example, once the "medical" cluster is discovered, new tokens would just be added to it without necessarily creating a new cluster.

This section presented our method for labeling tokens in social media posts. It consists of five consecutive steps:

1. Normalization of the initial data and extraction of the tokens that compose the vocabulary.

2. Generation of the word vectors associated with each token.

3. Dimension reduction of the vector space obtained previously to facilitate the following clustering.

4. ClusteringIdentification of semantic clusters present in the vector space using a clustering algorithm.

5. Label propagation within the different semantic clusters.

The proposed approach has the advantage that it uses little labeled data and allows the operator to adjust the predictions of the algorithm in quasi-real-time. The following section details the performance of our approach in both qualitative and quantitative terms.

4.3 Experimental results

The proposed approach is evaluated using data coming from datasets used as benchmarks by the crisis informatics community. This section presents the testing environment created and the results obtained. As a reminder, the problem of interest is to label the relevant entities for a crisis operator in a stream of messages from social media. Therefore, for the evaluation of our method, the efficiency is measured over the labeling of similar content. The social media chosen here is Twitter. Twitter[1] allows easy and broad access to messages posted by users during events such as natural disasters. Thus, many datasets related to disasters have been constituted via content posted on this platform.

4.3.1 Context of the evaluation

The experimental setup is designed to create evaluation conditions similar to the ones encountered in the initial problem. In our case, the goal is to identify relevant entities for decision-making during the response to a crisis event. The objective is to assist social media operators in their search for information by highlighting the information they need in the messages related to the event. The support provided consists of filtering the data related/unrelated to the current crisis, then highlighting the information that decision-makers need in the response. The first part of the filter identifies the relevant tweets—i.e., the tweets refer to the ongoing event. As shown in the literature review, this part has already seen many contributions.

This experimental part aims at (i) implementing our approach to demonstrate its interest and (ii) evaluating the performances with the chosen algorithmic approach. Thus, the goal is to identify relevant entities for decision-making in a corpus of tweets already identified as related to the crisis. The relevant entities chosen for the experiment correspond to the information identified in Chapter 3, which presented some of the information expected by decision-makers during disaster response. The actionable information presented were:

- Event
- Effect
- Emerging Risk
- Environment Components (Good, People and Natural Site)
- Actor (Actor on Site)
- Resource (Resource on Site)

Some of the information listed above can be ambiguous. For example, distinguishing whether a resource or actor is on-site or an effect of an event. For this reason, the information is gathered under common labels. Thus, the resulting labels used are composed of:

[1] https://developer.twitter.com/en/docs/twitter-api

- Event — an event that occurs and its effects (a car accident, a fire, an earthquake, a person trapped/injured)
- Environment — the geographical context where the event takes place (description, how many people are present, the dangers present)
- Hazard — an emerging risk or a danger that threatens the actors present on an event (a weakened building, a strong water current, a fallen cable)
- Actors — Individuals present at the scene of the event. They can be crisis responders, civilians, or victims (victims, firefighters, police officers, doctors).
- Equipment — Equipment and resources used in response to the event and can be used to protect oneself from danger. (a fire truck, safety barriers, a rescue boat, etc.)

These five classes correspond to the labels used in data annotation for the experimentation.

4.3.2 Experimental setup

Datasets

The evaluation of the algorithms calls for various datasets. On the one hand, the training phase of the model requires the constitution of an unlabeled set of data that will be used to constitute the vocabulary and a labeled set of words of interest. On the other hand, the evaluation of the model calls for a dataset of labeled tweets at the word level that is as close as possible to real-world application. The next two subsections present the datasets used, the reason behind these choices, and how they are preprocessed in our case.

Training data The initialization (or training) of the model presented in the previous section relies on two separate sets of data. The first set, unlabeled, is composed of a vocabulary of terms that will potentially be used to identify entities in incoming text messages. The second set, labeled, is a set of words of interest for the consumer of the inferences.

The vocabulary is obtained from the CrisisLexT26 (Olteanu et al., 2015). First, all English tweets are aggregated. Then the vocabulary was extracted from all previous tweets, i.e., each word used in the dataset was retrieved. Words that have less than five occurrences are then discarded as they are probably outliers. The tokenization (segmentation of a sentence into tokens) consists of the following steps:

- Usernames are replaced by "@USER"
- Links are replaced by "HTTPURL"
- Emojis are turned into text using the emoji library[2]
- Shorten the length of repeated characters
- Remove spaces when numbers are involved
- Normalization of reduced forms and contractions
- Remove punctuation

[2] https://pypi.org/project/emoji/

As the tokenization is impacting the performances (Farzindar et al., 2017, p. 21). The choice is then made to specify the tokenizer to the format of the data encountered (here tweets). The second dataset, the words of interest associated with the concepts, is taken from Olteanu et al. (2014). In this article, the authors suggest a set of keywords to use when querying the Twitter API. The terms used to constitute the labeled set in the experimentation are derived from this list. The processing consists of extracting the unique words from this list and removing the adjectives. The list was then completed by synonyms (especially for buildings) to reach a set of 76 words associated with a concept of the information model. The constitution of this list, which remains relatively generic, required less than fifteen minutes of labeling work.

Evaluation data Evaluating the algorithm's performance requires data that are representative of those that will be provided to the algorithm in reality. The evaluation, therefore, calls for data that are linked to a crisis, with a certain proportion of noise. The dataset that will be used for this evaluation is Zahra et al. (2020). This dataset is composed of tweets collected during different events (floods, fires, typhoons, earthquakes) and has been labeled to identify reports from direct witnesses of the event. However, this dataset is labeled at the message level and not at the word level as we would like in our case. An annotation phase was therefore conducted to label the words present in the messages.

The annotation was performed using LabelStudio (Tkachenko et al., 2020). It consisted of the annotation of 400 tweets, with 100 tweets taken randomly from each of the listed events. The disasters studied were: a wildfire, a hurricane, a flood, and an earthquake. For each event, the proportion of tweets attributed to direct witnesses of the event is 80%, and 20% of tweets are considered as not related to the event. This distribution of data corresponds to the performance presented by state-of-the-art models developed to classify disaster-related tweets (Xukun et al., 2020). As presented earlier, such a classifier will be used to feed the model with disaster-related messages instead of the raw data flow. The data are then labeled using the labels presented in the previous section. The labeling of the complete dataset took about 4 hours, compared to the 15 minutes to associate the 76 entities to the different concepts. The data, along with annotation instructions, are publicly available [3]. Six hundred words were labeled within the corpus at the end of the labeling process. The distribution is provided in Table 4.1.

Table 4.1: Distribution of labels among the five classes studied in the test dataset.

Category	# of labels associated
Event	434
Hazard	89
Environment	69
Equipements	5
Actors	3

The distribution of labels within the dataset corresponds to the remark made earlier about the information available in social media. Two-thirds of the labels refer to an event, and the remaining labels are mostly found among two classes — Hazard and Environment.

Algorithms parameters and language model used

The language model used to create the vector representations of words is the BERT model [4]. The UMAP algorithm, used to perform dimension reduction, was configured using the following parameters:

[3] https://code-gi.mines-albi.fr/stash/projects/GIND-THESIS-JCOCHE/repos/gind-thesis-jcoche
[4] https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/3

- Number of Neighbors: 15
- Minimum Distance: 0.0
- Repulsion Strength: 1.0
- Number of Components: 50
- Distance Metric: ‘cosine‘
- Number of Epochs: 1000
- Learning rate: 0.1

This setting aims to force UMAP to focus on the local structure of the data and create clusters that are as split as possible to facilitate HDBSCAN work. Thus, the *Number of Neighbors* is set to a low value. Similarly, the *Minimum Distance* is set to 0.0 to pack the data points very tightly. Inversely, setting the *Repulsion Strength* to 1.0 forces the algorithm to split the clusters it may find. The dimension is reduced to 50. This value is a comprise, as a high value will impede HDBSCAN, but a too low value will sacrifice too much information. Cosine is used to compute the distance between the different vectors, as data are not necessarily normalized. The *Number of Epochs* and *Learning rate* are linked to the Stochastic Gradient Descent and respectively define the duration of the training and length of each step.

The HDBSCAN algorithm has been parameterized as follows:

- Minimum Cluster Size: 15
- Minimum Samples: 8
- Cluster Selection Method: ‘leaf‘
- Cluster Selection Epsilon: 0.0
- Distance metric used: ‘euclidean‘

Again, the main parameter here is the *Minimum Cluster Size.* Thus, clusters with fewer than 15 points will be considered as noise. *Minimum Samples* is linked to the Minimum Cluster Size and is by default set to its value. It can be seen as the "conservativeness" of the clustering. Setting a lower value will allow points at the "border" of a cluster to be integrated. The *Cluster Selection Method* is set to ‘leaf‘ instead of the default ‘excess of mass.‘ as it provides better results in the case of a high number of clusters that share a similar amount of data points. Finally, the distance used here is ‘euclidean,‘ as data are normalized for this step.

These parameters are set to maximize the outcome for any type of event. There is little interest in "fine-tuning" the model in our context, as every situation, hence incoming messages, will be different. A set of parameters could do exceptionally well on a given dataset but not replicate the performances on another one. The motivation between these choices is to find a good compromise that should work in the most significant number of disaster configurations.

4.3.3 Evaluation of the results

The developed model is studied through a set of metrics that allow evaluating its performances. Two aspects are evaluated:

- The efficiency of the Named Entities Recognition
- The effect of the Dimension Reduction

The following sub-sections present how they are evaluated in the context of this research. It is important to note that the evaluation is done as close as possible to the standards of the NLP community. However, these evaluations ignore the dynamic dimension to which the algorithms may be subjected. With the setup usually proposed, the evaluation is at best evaluated in conditions that reflect the onset of the event. In this configuration, the user set generic terms that are unchanged during the whole duration of the event.

NER performances evaluation

NER is a classification problem, and consequently, can be evaluated using Precision, Recall, and F1-Score metrics. Precision refers to the fraction of elements correctly labeled among the features labeled. The Recall represents the fraction of relevant elements that were retrieved. Figure 4.5, originally proposed on the Wikipedia's page on Precision and Recall[5] illustrates both concepts.

The F1-Score corresponds to the harmonic mean of the Precision and Recall.

$$2 \cdot \frac{precision \cdot recall}{precision + recall}$$

However, NER evaluation also involves predicting the location of the entity in the sentence. Consequently, there are many ways to obtain results partially correct. Hence, conferences such as CoNLL defined a variant of the F1-Score better suited for this task (Tjong Kim Sang et al., 2003). It redefines the three previous metrics as follows:

- Precision is the percentage of predicted entity name tokens that line up exactly with the tokens in the evaluation data. If the whole entity is not retrieved by the method, its Precision is zero.
- Recall the percentage of entities that appear at exactly the same location in the predictions.
- F1 score remains the harmonic mean of the Precision and Recall.

In the context of disaster response, *Recall* is the preferred metric, as missing out reports or relevant information due to excessive filtering might be detrimental to the system.

4.3.4 Results

This section presents the results of the evaluation of the method presented, using the parameters mentioned and the datasets presented. First, the performances of the NER are reported. Then the performances of the semi-supervision. Finally, the last part is dedicated to investigating the interest of dimension reduction in the setup.

The Figure 4.6 provides a visual of the result of the method, where the semantic cluster related to fire is displayed.

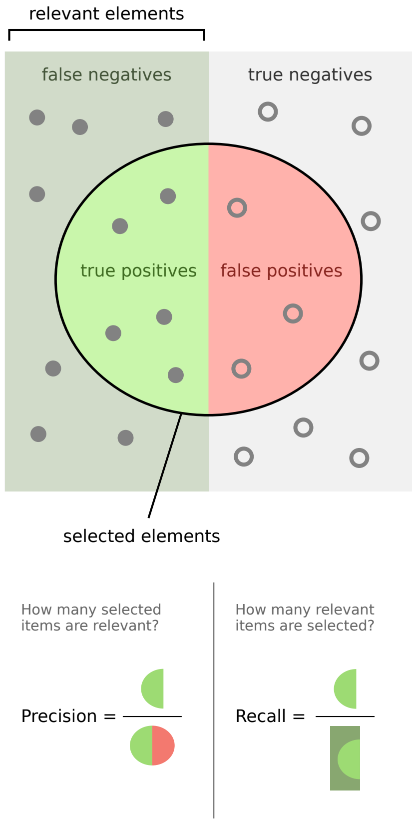

Figure 4.5: Visual representation of the relationship between precision and recall. Illustration originally proposed on the Wikipedia's page on Precision and Recall.

NER performances

The performances of our method over all types of events are reported in Table 4.2

The performances for each type of disaster are reported as well. The method obtains its best results on the Event class (see Table 4.3, Table 4.4,Table 4.6) except for the flooding event (Table 4.5). The method performed poorly on the flood event because the labeled terms were not matching the ones used during the event. However, the same terms applied to the hurricane dataset provided much better performances if one compares both weighted average F1-Score. The Environment class is partially retrieved over all datasets. The three remaining classes — Actors, Hazard and Equipements — are harder to evaluate, as there are very little data to explore. The only significant one is the Hazard class in the fire event, where there are 74 occurrences. The model correctly labeled a significant part of the entities in this case.

As mentioned in the definition of the metrics used, the results are only a static view of the method. However, the method does not aim to remain static and is intended to evolve with the situational awareness of the users. So, while these results provide valuable hints on the model's performance, it does not depict the performances of the model in suitable conditions.

Influence of the dimension reduction

An additional experiment has been conducted to test the influence of the dimension reduction to evaluate how this step influences the performances. All the parameters are kept the same,

[5] https:en.wikipedia.orgwikiPrecision_and_recall

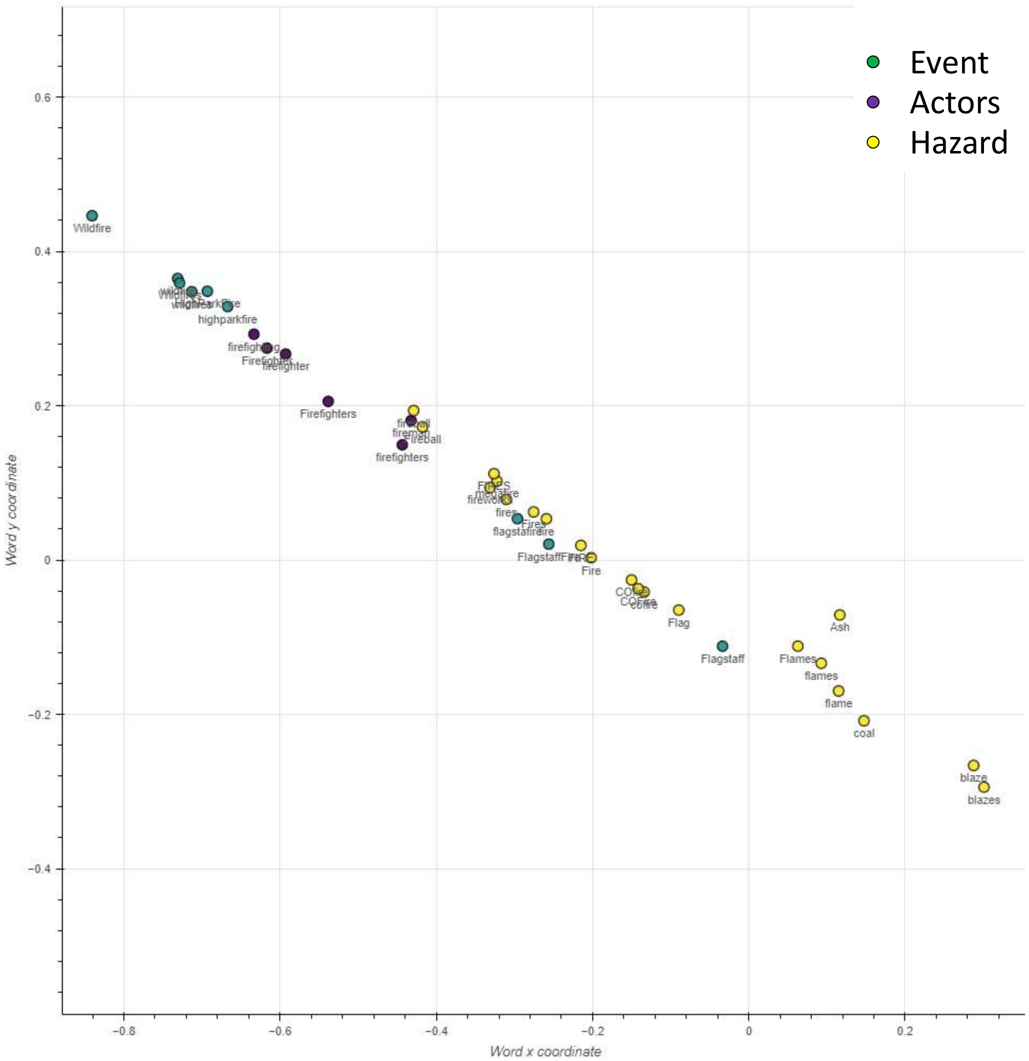

Figure 4.6: 2D projection of the semantic cluster related to *fire* after label propagation. The projection is obtained using UMAP.

except that the dimension is never performed anywhere during training or inference. The results are displayed Table 4.7. The performances slightly increased, from 0.565 to 0.571 weighted average F1-score. This version performs better on the Environment category (0.409 from 0.328 weighted average F1-score) and the Event category (0.721 from 0.645 weighted average F1-score). Notably, there is a trade between the Precision and the Recall in this case. For the Environment category, Precision went from 0.643 to 0.792 while Recall diminished from 0.652 to 0.275. A similar trend is observed for the Event category, where the Precision went from 0.263 to 0.862. However, the loss of Recall is less severe (from 0.647 to 0.620). Maybe most importantly, this change in the model made it unable to identify Hazards (0.0 weighted average F1-score) while its counterpart was able to label some of the tokens.

These results call for more investigations on this aspect, but it hints that different models may perform differently based on the dimensions fed to the clustering algorithm.

Table 4.2: Results on the four types the events.

Category	Precision	Recall	F1Score	Support
Environment	0.220	0.652	0.328	69
Event	0.643	0.647	0.645	434
Actors	0.040	0.333	0.071	3
Hazard	0.263	0.764	0.391	89
Equipements	0.176	0.600	0.273	5
weighted avg	0.531	0.663	0.565	600

Conclusion

This chapter presented a novel approach to process social media, based on machine learning, that aims to be used in disaster response situations to provide the information expected by decision-makers. The first part discussed the context of disaster response and how it influences the processing of social media data. In particular, it discusses the use of supervised machine learning in the context of disaster response. This part highlighted both the advantages and disadvantages of this approach.

The second part of this chapter presents the model itself, details the functioning of its different parts and the motivation behind the choices made. The resulting algorithm is composed of 4 steps:

1. Generation of the word vectors associated with each token.
2. Dimension reduction of the vector space obtained previously to facilitate the following clustering.
3. Identification of semantic clusters present in the vector space using a clustering algorithm.
4. Label propagation within the different semantic clusters.

As of today, there is little evidence that traditional machine learning approaches are suited for such context. Consequently, the model is designed to quickly adapt the results to fit as much as possible to the ongoing event. In a sense, the model aims to fit the context, not the data provided initially. The overall composition of the model is then designed with practicability in mind over raw performances.

The last section of the chapter explored the performances above. The attempt was to explore the different aspects of the approach and quantify their impact on performances.

Table 4.3: Result on the Earthquake event.

Category	Precision	Recall	F1Score	Support
Environment	0.132	0.417	0.200	12
Event	0.920	0.939	0.929	98
Actors	0.000	0.000	0.000	1
Hazard	0.000	0.000	0.000	5
Equipements	0.000	0.000	0.000	0
weighted avg	0.791	0.836	0.806	116

Table 4.4: Result on the Fire event.

Category	Precision	Recall	F1Score	Support
Environment	0.333	0.857	0.480	14
Event	0.651	0.719	0.683	57
Actors	0.071	1.000	0.133	1
Hazard	0.698	0.905	0.788	74
Equipements	0.000	0.000	0.000	0
weighted avg	0.640	0.829	0.713	146

Table 4.5: Result on the Flood event.

Category	Precision	Recall	F1Score	Support
Environment	0.183	0.591	0.280	22
Event	0.291	0.228	0.256	101
Actors	0.000	0.000	0.000	1
Hazard	0.000	0.000	0.000	8
Equipements	0.111	1.000	0.200	1
weighted avg	0.252	0.278	0.242	133

Table 4.6: Result on Hurricane event.

Category	Precision	Recall	F1Score	Support
Environment	0.250	0.714	0.370	21
Event	0.641	0.702	0.670	178
Actors	0.000	0.000	0.000	0
Hazard	0.015	0.500	0.029	2
Equipements	0.400	0.500	0.444	4
weighted avg	0.590	0.698	0.629	205

Table 4.7: Results of our method **without dimension reduction** over the four types the events.

Category	Precision	Recall	F1Score	Support
Environment	0.792	0.275	0.409	69
Event	0.862	0.620	0.721	434
Actors	0.000	0.000	0.000	3
Hazard	0.000	0.000	0.000	89
Equipements	0.500	0.200	0.286	5
weighted avg	0.719	0.482	0.571	600

Improvements can be thought for several aspects of the model. Currently, the approach is limited as it accounts for independent tokens only. However, this issue can be solved by considering the surrounding tokens through a window sliding over the sentence. Another aspect linked to label propagation is that semantic clusters of interest that do not contain a labeled word are currently ignored. This aspect represents an exciting avenue for future work. I want to emphasize that the evaluation of machine learning models, or other related systems, using the standard practices of the NLP domain, can hardly evaluate the true performances of these systems in the context of disaster response. Evaluation on a given, the fixed dataset does not represent the unexpected and evolving nature of the problem they try to address. Halse et al. (2019) proposed a tool to simulate a stream of tweets from a dataset based on message sending information. If this tool was originally designed for training social media operators, an adapted version could be used to test machine learning algorithms dynamically. This area remains open to contributions that will undoubtedly yield important outcomes for crisis management organizations. Finally, the algorithm presented here has only solved a sub-part of the initial problem. The objective of automatically retrieving information from social media cannot answer the initial challenge. Improving disaster indeed asks for better decision-making of the different actors involved. Similarly, improved decision-making requires better access to quality information. However, if decision-makers informational needs might help improve the quality of the information delivered, the accessibility falls out of scope. As described in the previous chapter, information retrieval is rarely performed by decision-makers themselves but more often by dedicated operators. Hence the final research question: *How should be organized social media processing systems in disaster management situations?* The next chapter explores the challenges and possibilities in designing an information system for disaster response.

5

Embbedding machine learning models into an information system for crisis management

Introduction

This chapter takes a step back and looks at the information system as a whole. In particular, it questions the place and stakes of machine learning in an information system for crisis management. It is organized around the third research question identified initially in Chapter 1: *What challenges are faced by an information system dedicated to crisis management that embeds machine learning models?*

The previous chapters aimed to address a specific question: *What kind of information are staff from emergency centers looking for on social media?* It presented a method to automatically identify and retrieve entities within a text related considering decision-makers information expectations. This solution built on previous work realized to filter information coming from social media. Like the other approaches, the proposed solution follows a data processing framework inspired by the Cross-Industry Standard Process for Data Mining (CRIP-DM) (Martínez-Plumed et al., 2021). This generic model for data mining consists of six steps:

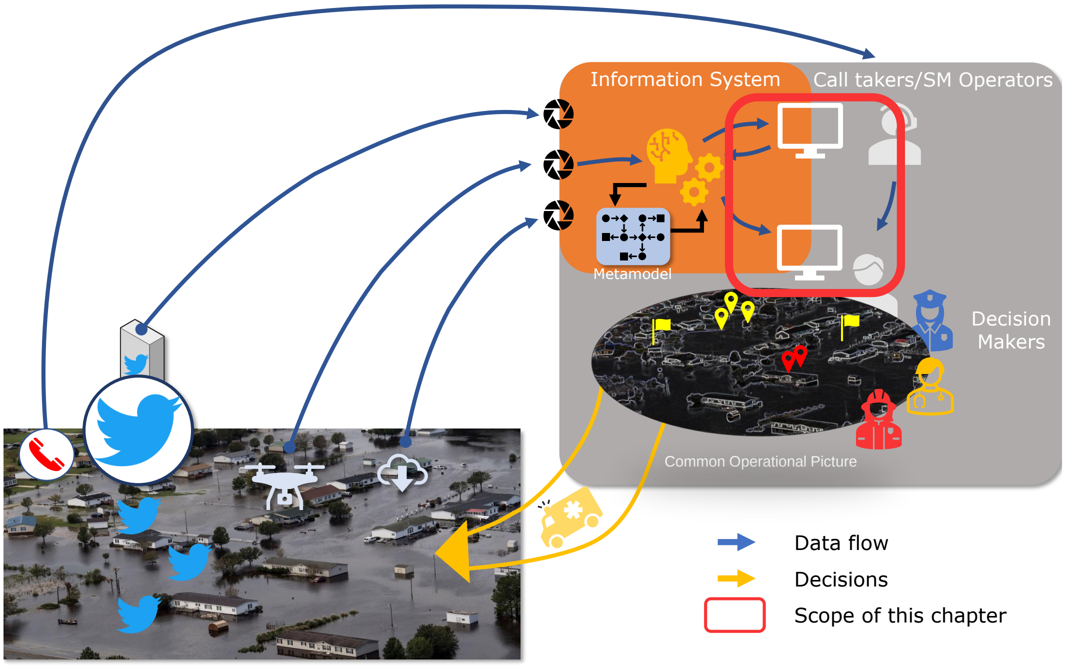

Figure 5.1: Position of this chapter with respect to the body of this manuscript.

1. *Business understanding* that defines the desired outcome of the process in accordance with available data.
2. *Data understanding* identify and map the available data to solve the business issues identified.
3. *Data preparation* preprocessing of the data to fit with the modeling proposed.
4. *Modeling* creation of actionable representations that match the business practices.
5. *Evaluation* of the performances of the process according to the metrics defined in the first steps.
6. *Deployment* If the evaluation matches the outcomes defined at the first step, the solution is deployed to process the new incoming data automatically.

This data processing model is found in most systems reviewed in Chapter 2. It can be summarized with the following components illustrated Figure 5.2.

- The **data collection** is a connector to the Application Programming Interface (API) of a social media platform, such as Twitter. This connector queries data in real-time from the platform according to a set of topics of interest.
- The **preprocessing** is in charge of normalizing the incoming data and preparing it for the processing aspect.
- The **processing** component provides information addressed to decision-makers, and that supports them in their operations, usually by enhancing their situational awareness of the ongoing event.

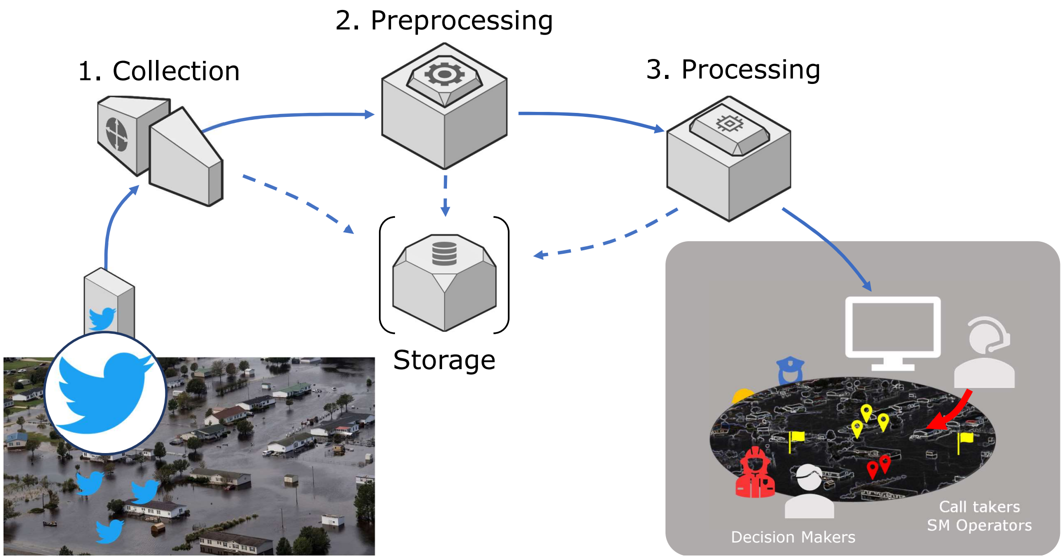

Figure 5.2: Main pattern of steps in processing social media data used in previous attempts.

Some variants integrate other components. Some systems may provide to visualize the results through a dashboard or a geographical representation. Others may propose an interface for crowdsources annotation of data used to train event-specific machine learning models.

The steps that compose this model are also found in systems that process images taken from citizens (Alam et al., 2017) or drones (Fan et al., 2021). To improve performances or solve new challenges, systems built over time are different. While they generally follow the previous model, they propose tweaks and differences to accommodate the added constraints. There are, however, some elements that can be factorized:

- The preprocessing of the data is a pipeline composed of sequential steps. For instance, model A may need lowered text as input, whereas model B needs the original text. Also, tokenizers, while often being different, are always present when one processes textual data.
- Processing and preprocessing are not uniquely paired. A processing component requires an appropriate preprocessor. However, a preprocessor, or several ones, can be common to multiple processors. Hence, it is possible to scope them to match different processing components.
- A processor can be appended to the processing pipeline. The same data can then be processed for different purposes or reused the results from the previous components to support the next one.

Hence, the data pipeline used to train and feed machine learning models with new data is a complex component of an information system. However, previous works are often designed as data processing systems associated with visualization tools. Few take into account the information system on which crisis management organizations rely. From there, two organizations are possible. The first is to make the information system coexist with the machine learning models and associated visualization tools. The second is to integrate the machine learning models within the information system. While the first option is easier to implement, the second one allows greater agility in the processing. Additionally, several studies have shown the importance of better integration of the different sources of data and information in crisis management (Comes et al., 2015; A. H. Tapia et al., 2016). This chapter explores the second path envisioned. It details the challenges and opportunities of an information system that integrates machine learning models to process social media data. The first section presents the different challenges encountered by this architecture. A second section presents a general framework that exposes two systems: the data system and the information system. These systems are built according to the previous challenges identified. A consecutive section describes the implementation of the social media module for the R-IO Suite software, using the previous framework. The fourth and last section opens on the purpose of such systems: to provide information to decision-makers

5.1 Information System, Operator and Machine Learning: challenges of the ecosystem

Machine learning methods have many applications for crisis response. AI facilitates the processing of data and information by speeding the processing, allowing to consider large volumes of data, etc. In disaster response, this ease of processing saves valuable time. Nevertheless, some machine learning methods trade this additional efficiency at the price of the explainability of the results. This section investigates the potential effects of a lack of transparency of information system components. The first sub-section presents the problems encountered when designing an information system to improve situational awareness (SA). The second sub-section extends this reflection by looking specifically at the impact of machine learning.

5.1.1 The SA daemons looming over the Information System

Endsley, who originated the definition of situational awareness, identified various factors that prevented systems from providing maximum value to their users (Endsley, 2016). The authors identify 8 "daemons" (factors) in the design of the system that harms the Situational Awareness of the operators:

- Attentional tunneling: fixating on one information set and excluding the others.
- Requisite memory trap: over-reliance of the system on the operator's short memory.
- Workload, anxiety, fatigue, and other stressors
- Data overload
- Misplaced salience: misplaced warnings or signs that incorrectly catch the user attention
- Complexity creep: complex systems, cluttered of features, prevent the user from creating an accurate mental model
- Errant mental models: users have not learned the proper mental framework for understanding the situation and projecting the system's future state.
- Out-of-the-loop syndrome: automated systems sometimes do not entirely inform the user

Additionally, they provide thoughts on the automation of resolving problems that involve a certain degree of Situation Awareness. Automation can be responsible for three issues: (i) the operator feels outside the system, (ii) inaccurate understanding of the system by the operator, and (iii) diminishing return of decision support systems. To prevent these caveats, the authors advise adaptive automation considering the user. They organize their recommendations through eleven principles (Endsley, 2016):

- Components of the system should be automated only if necessary, as poorly realized automation can lead to lack of understanding, difficulty with onboarding, and out-of-the-loop syndrome.
- Use automation for assistance in carrying out routine actions rather than higher-level cognitive tasks
- Provide SA support rather than decision-support, similarly to a route guidance system.
- Keep the operator in control and in-the-loop to avoid automatic behavior and loss of mental engagement.
- Avoid the proliferation of automation modes where users have to deal with the complexity of the surrounding black boxes.
- Make modes and system states salient to engage and inform the user of the system's state.
- Enforce automation consistency, through common vocabulary across the systems and interfaces.
- Avoid advanced queuing of tasks where the users can set up different tasks for the automation to perform in advance.
- Avoid the use of information cueing in cluttered displays and, instead, declutter the display.
- Use methods of decision support that create human/system symbiosis.
- Provide automation transparency by providing information on the current mode of the system or uncertainty indications with the propositions.

These insights are valuable in designing an effective social media processing system for crisis response. Yet, these principles will only be valuable to provide a better SA to the user of such a system.

5.1.2 Is machine learning really coming to the rescue?

The use of machine learning in high-stakes systems is not without risk. Many proposals have failed despite the best efforts of the teams to make the system successful. Google proposed, for example, a service (Google Flu Trend) to follow the evolution of the flu in different countries. The system relied on the searches performed by its users to predict future flu epidemics. This system was discontinued in 2015 due to the large gap between predictions and reality, among other factors Kandula et al. (2019) and D. Lazer et al. (2015). Another example is IBM's Watson Health AI system (Strickland, 2019). When this AI system launched in 2011, it promised to revolutionize medical diagnostics by replacing doctors. A few years later, faced with the task's difficulty, IBM scaled back its medical ambitions for its AI. IBM Watson Health is now developed as an AI librarian and provides valuable literature resources on certain pathologies. However, it remains far away from its original promises. As the article concludes: "The Watson Health story is a cautionary tale of hubris and hype.". Unfortunately, these two examples are not the only ones, and many other projects have failed. The available post mortems mostly point to a common problem: understanding the data used to train the machine learning models was simply insufficient. Based on this conclusion, Sambasivan et al. (2021) conducted a qualitative study on the reasons for these failures. Their main conclusion is that teams do not dedicate enough time to acquiring data of sufficient quality for the problem that the machine model is supposed to address. Complex problems require datasets that reflect the complexity of the problem, allowing the machine learning model to identify the correct latent patterns. Since the development of a machine learning model is sequential, each error or shortcoming in one of the steps affects the final result. Based on this study and other concurrent projects, the same team summarized their findings in a guidebook of recommendations for products or systems that embed machine learning models (PAIR, 2021). This guidebook has also been informed by the testimonials of hundreds of AI practitioners. It is articulated around six axes that system or product designers should be mindful of:

- User needs & defining success—the AI needs to solve a problem. Automate unpleasant tasks, where there's a need for scale, and where people can define what the correct way to do it is. Augment high stake tasks or where people disagree on the "correct way" to do it.
- Data collection & Evaluation—Data and its quality are of the utmost importance when building a machine learning model. Make sure that the users need to translate through the data.
- Mental Models—Build a system whose interface and functioning are familiar to the users. The differences should be highlighted at the onboarding stage (e.g., with a tutorial). Communicate the limitations of your system.
- Explainability & Trust–Users can easily rely blindly on the system, especially in stressful situations. Thus, the system should provide as much as possible an indicator of the relevance of the prediction.
- Feedback & Control—People like to remain in control, especially when the stakes are high. Therefore, the system must provide feedback to users so that they feel included in the decision-making process. Particularly the type of information that the AI should consider.
- Errors & Graceful failure—Define failure and success according to your user's expectations (e.g., 60% accuracy can be a success or a failure). The user should not be locked with a faulty AI, and the system should provide a path forward from failure.

Of the six recommendations made, many overlap with the previous recommendations formulated in Endsley (2016). Both authors agree on certain aspects, such as keeping the user in the loop, highlighting the moments when the system is faulty, or creating a symbiosis between the human and the machine. However, systems that rely on machine learning models do not seem to eliminate the previous daemons. On the contrary, this approach brings new difficulties, which must be considered; otherwise, the whole system could be rendered unusable. These insights will be used in the next sections.

5.2 Information systems for disaster response: place and role of data and information

As presented in Chapter 1, information systems (IS) are responsible for managing information in an organization. They are organized around four functions:

- Collect: they provide a gateway to users to ingest information;
- Process: information internal to the system can be processed to obtain newly derived information;
- Store: the IS is in charge of preserving the information it contains;

- Distribute: reverse function of the collection - the system proposes a way to exploit the ingested data.

These functions and the definition of the information system originated from the beginnings of computer science as a discipline. If the different functions remain unchanged, achieving them has changed through technological innovations. Decision support systems, for instance, rely on different types of artificial intelligence to deliver results to the users. The first iterations of decision support systems used fixed rules to deliver value. The rules embedded expert knowledge to deliver insights automatically. In recent years, the machine learning branch of artificial intelligence boomed. First, the rules embedded in the information are now automatically learned from data without the intervention of an expert using machine learning models. Secondly, and as a direct consequence of the first outcome, data management now occupies a larger role in the system. The information system is then split into two: one system responsible for the data and another one responsible for the information delivered to the users. The role and importance of data in a machine learning system have already been presented in Chapter 4 and below. Hence, the following subsections focus on a systematic solution to the data management issue.

5.2.1 Machine learning models lifecycle: lessons from MLOps

Machine learning models undergo two phases in their existence within a system. The first phase corresponds to the training of the model. For this, the model takes the data previously collected and processed as input. Once the training is complete, the model's performance is then assessed to determine if it meets the expectations of the users. The second phase exploits the trained model by providing it with new data from which we want to obtain a prediction.

During the second phase, the system is deployed to make predictions on incoming data. Treveil et al. (2020, Chapter 1) highlight that this approach causes several issues. First, contrary to the deployed model, the environment is constantly changing. This phenomenon is called drifting and corresponds to a degradation of the performances, similar to wear. This wear is not internal to the model (as we could conceive it for a machine in a factory) but to the environment in which the model evolves. Thus, because of drifting, the models must be regularly updated. In the case of crisis management, depending on the type of event and problem that one wants to solve, the model can be updated more frequently. A flooding event, for instance, is a relatively well-known event. It benefits from an extensive collection of data, so a model can be trained to recognize messages related to this event. However, this model will not identify more subtle sub-events resulting from an event cascade. Another issue that Treveil et al. highlights are the difficulty for a team to maintain machine learning models by hand. Due to the above-mentioned environmental conditions, models have to be constantly monitored and adjusted in case of drifting.

This life cycle of machine learning models and their computing environment is at the heart of the Machine Learning Operations approach (MLOps). This approach shares its acronym and philosophy with the DevOps methodology as well as the CRISP-DM model presented in the Introduction. DevOps is the contraction of Development and Operations and aims to reduce the software development life cycle while maintaining high quality. Inspired by this approach, Machine Learning Engineers developed a dedicated methodology for machine learning models. However, the objective remains unchanged: reduce the time and complexity of machine learning models deployment. The MLOps methodology is centered around the machine learning life cycle, illustrated Figure 5.3 (Burkov, 2020; Treveil et al., 2020).

As in the CRIPS-DM model, the first steps, the objective definition, and the data collection are crucial to the success of the project as a whole. Once quality data are retrieved and the value offered is clear, features used by the machine learning model are extracted. The

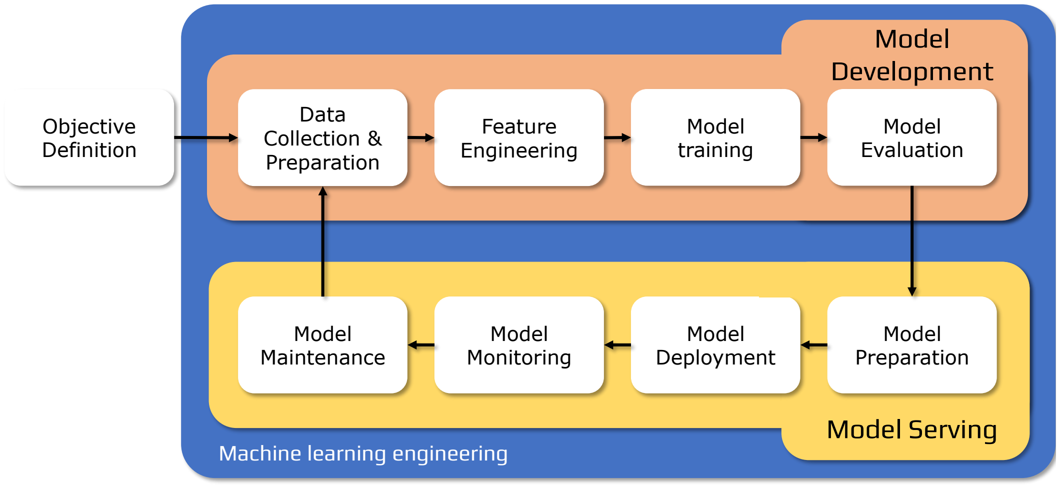

Figure 5.3: Life cycle of a machine learning project.

model is then trained on the data and associated features. This model is then evaluated to determine if it performs sufficiently to solve the users' problems. These steps mark the end of the model development phase. Onward, the model is deployed to serve its predictions. The model preparation step sees quality testing and risk evaluation performed. Once this step is clear, the model is packaged and deployed. During its deployment, the model is monitored. Ideally, its inputs and outputs are logged to capture the aforementioned environment changes. The last step is model maintenance, where the model is updated according to the changes previously recorded. One of the underlying motivations of the MLOps methodology is to perform as much as these steps automatically. In the crisis management configuration, all steps up to the deployment of the model must be performed during the crisis preparation phase. This way, the model is ready to be used during an event. Suppose the model needs to be updated because it cannot provide the operator's help. In that case, the system must be designed to 1) notify the user of this fact 2) take into account the new entries recorded in order to update itself automatically. This behavior must be transparent to the users of the system.

5.2.2 Position and purpose of data and information in the system

An information model that integrates machine learning models sees its information coexist with data. *Data* and *Information* were first defined by Ackoff (1989) in its DIKW framework. Rainer et al. (2021) define *data* as "an elementary description of things, events, activities, and transactions that are recorded, classified, and stored, but are not organized to convey any specific meaning." As for *information*, the definition proposed is "[information] refers to data that have been organized so that they have meaning and value to the recipient". In the context of crisis management, Benaben et al. (2017) propose to interpret the conversion of data into information through the use of a metamodel. The latter is designed to act as a "reference framework" between the data sources and the information required to perform the response. Although many systems have been developed by mixing the two concepts, the separation and organization allow for an overall vision conducive to discovering new opportunities.

The following research question guides the rest of this subsection: *how do data and information management coexist within an information system based on machine learning models*? The previous sections highlighted the importance of data within a system that contains machine learning models. Consequently, the information system is no longer the only system present and paired with a Data System (DS). Figure 5.4 provides an overview of the different components of both systems and how they organize to the machine learning life cycle. The two following sub-sections discuss the place of data and information, respectively.

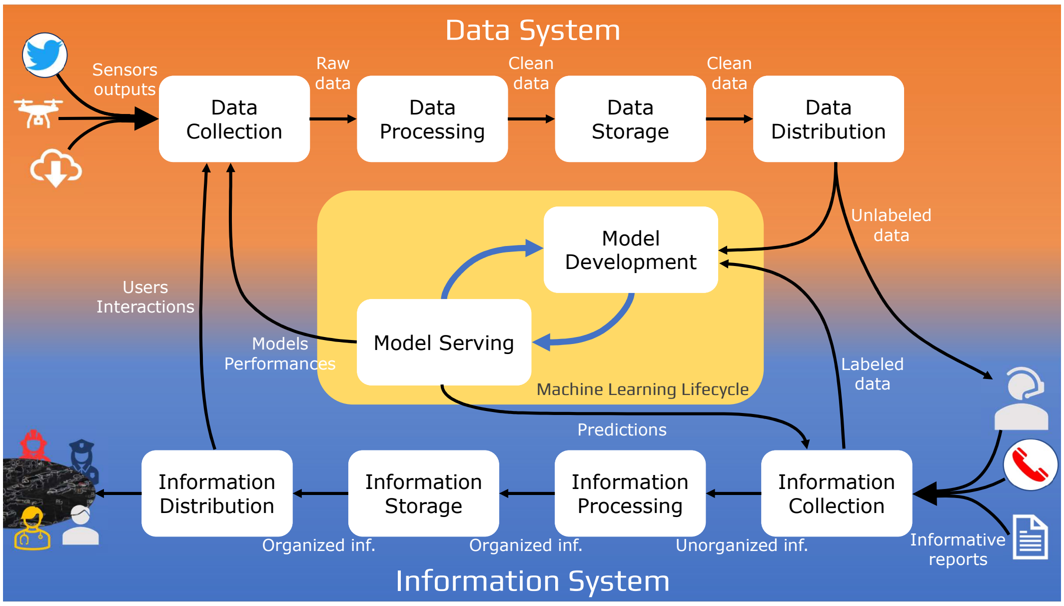

Figure 5.4: Representation of the data system and the information system that compose a decision support system which uses machine learning models. The models are managed according to the machine learning life cycle.

5.2.3 The Data system

The management of data by a system is often considered through several characteristics. First, Laney (2001) proposed three characterictis throuh 3 V: *Volume*, *Variety* and *Velocity*. Later, (Kalyvas et al., 2014) suggested to add another V for the *Veracity* of the data. These 4Vs (Volume, Veracity, Variety, and Velocity) correspond to different characteristics that describe a data flow. Given the context in which the system will be deployed, it is assumed that each V will correspond to the following:

- Variety: the system is potentially expected to process a wide variety of data. The data expected are text messages from social media but can also be images associated with the messages, sensor readings, or drone footage.
- Volume: the volume of data is correlated with the data sources. If the Data System only processes text messages and sensor data, the load can be expected to be standard and not require further actions.
- Velocity: Data are produced in real-time by the sources, and the resulting information is expected in near real-time. Hence, the latency induced by the processing should be kept as low as possible.
- Veracity: The veracity is highly variable in this context and is directly related to the data source.

The data system manages the machine learning models' data to provide information and display metrics to the end-users. In the former case, its role is twofold. First, it manages the data used to train the models to adapt to an ongoing event. Secondly, it provides the models with live data. Therefore, the data system is composed of four components, similar to the information system: (i) Data collection, (ii) Data processing, (iii) Data storage, and (iv) Data distribution. Each component is presented individually in the following subsection.

Data Collection

This component is responsible for the connection with the different data sources. Data are collected from a variety of data sources. These sources can be social media messages, sensor records from IoT devices, drone images, etc. It consists of a data broker that handles the different data sources. In the case of data collection through social media, it is done through public APIs made available by the platforms. The platforms provide the data according to a list of terms or topics designated by the users. Messages that contain the keywords or the topic are then returned or streamed back to the user.

This component listens to the different data sources and acts as a gateway to them. The main issue of this component echoes the previous sections on data quality. It may be tempting to connect to automated data sources because of their ease of access. However, a prior study must be conducted to understand the quality of the data provided by the source. This study allows evaluating the relevance of the data provided and handling it with appropriate processing specific to the source.

Data Process

Once collected, data are available as "raw data." This component is responsible for "cleaning" the data. It also corresponds to the preprocessing step presented in Chapter 4. The data must be processed to match the format expected by the rest of the system. This component corresponds to the preprocessing step mentioned in the machine learning life cycle (Figure 5.3). Again, this processing is typically done in two steps to ensure that the machine learning part fulfills its objectives. First, during the preparation phase of the crisis management, the preprocessing to be performed is decided according to the data source. Once this part is completed, the automated processing can be used during a crisis situation. This processing is specific to the source of the data. For instance, drone images and images posted on social media might require different processing. The same is true with different types of sensors, different social media platforms, etc. Twitter, for example, introduces special features in the messages (RT, URLs, user mentions, etc.) that need to be processed. The preprocessing of images and text is also different. As mentioned in the Introduction, this preprocessing is often done sequentially on the data. Thus, using the example of Twitter and Facebook, parts of the processing pipeline can be pooled. Therefore, this component corresponds to a catalog of preprocessing methods associated with data sources and models. This data can then be stored or used as input for the machine learning models through the distribution component.

Data Storage

Once the data are "cleaned" or preprocessed in the previous step, they are stored in databases. Data storage is performed following the data policy of the organization. Some data may not be stored for privacy reasons. The purpose of this component is to store the data in two types of databases, depending on the usage. A "hot" database is used to store data that will be used during the event. These data are then used to provide indicators to the decision-makers or consumed to train machine learning with event-specific data. A second "cold" database accumulates the data that will be used during the post mortem of the event. These data will allow the system to be adjusted for future events.

Data Distribution

This component is a data gateway oriented towards the consumption of the data. The data are distributed similarly to the data sources from which they come. The different information system components or the machine learning life cycle can request data according to their needs. Unlike information, the previous steps do not prepare the data for direct consumption by decision-makers. The data can be aggregated to provide indicators such as the volume of data flow handled by the system. It can also feed the next component, the information collection, with unlabeled data, which external agents then label. However, this data is primarily used to feed the machine learning models. It can be used to make predictions and provide information to the decision-maker. They can also be used for supervised or unsupervised training of models.

5.2.4 The Information system

Information systems are already used by crisis management organizations. They make use of the data collected to provide information to decision-makers. As mentioned earlier, it is composed of four parts: Collection, Processing, Storage, and Distribution. Similarly to the Data system, each part is described.

Information collection

Information acquisition is, by design, one of the roles of IS. One of the system's interfaces allows users to enter information. Many information can be logged in the system during disaster response. Phone calls, handled by call takers, are one instance of such information. Using systems such as the CAD system in the US, call takers can enter the answers to the Six W's they obtain. The calls illustrate the definition of information provided previously. They correspond to data that, associated with other pieces of data to create a context, possess a meaning and a value to the recipient. Another example of information that can be entered in the Information System is the reports from emergency teams dispatched on the different hotspots of the event. Other similar reports (weather forecast, specialized services, etc.) also fit in this category.

In an Information System that uses machine learning models, other sources of information appear. First, the data is annotated to train the machine learning models. The training datasets are data collected by various types of sensors, which appropriate professionals then label. The former create information that the machine learning model will use by organizing or contextualizing the data points with associated labels. Finally, the predictions of the machine learning models are also a source of information. This information is then processed in the next step.

Information processing

The information can be processed in different ways. First of all, they can be enriched using metadata associated with the documents entered. This metadata can then be used to organize the different information present in the system. This organization can be hierarchical, i.e., some documents can have a higher value or priority than other documents. The information entered can also be associated with other information already present in the system.

Information storage

This component stores the organized information coming from the information processing one and stores it. It faces similar to the data store. Historically, information systems stored data organized in databases. However, additional value can be obtained by creating semantic relations between the different pieces of information. Relational databases are not expressive enough to allow such storage. Hence, graph databases can be used in addition to relational ones to express semantic relationships. It is the organization of this data by these databases that brings information. However, here again, machine learning brings specificity. Indeed, the predictions made by a model can be perceived either as data or as information. The latter case is allowed if the prediction is linked to the data initially provided to the model. This last information is often sought in practice by the users of such systems for reasons of traceability or transparency. In the first case, the predictions made can then be investigated after the event to improve the knowledge of the event.

Information distribution

Providing valuable information is the purpose of an information system. Information distribution can take several forms, such as a dashboard proposed to the decision-makers or as a Common Operational Picture. The dashboard can, for instance, provide metrics or summarises directly from data sources. It is also fed by the outputs from the embedded AI components. This step is crucial as this component delivers all the value, and therefore, can be seen as the "value bottleneck" of the information system. Ultimately, the goal is to deliver adequate information to the right person at the right time. Missing one of these conditions hinders the efforts realized in the previous steps. The last section of this chapter elaborates on how the users interpret information. As a closing thought, one can close the loop of the systems by taking into account the user's interaction with the system. These interactions can be logged in the system, collected as events, and used to perform analyses or post mortem of the disaster. Thus, the information distribution component is looping back to the data collection component.

Previously designed information systems for decision support systems usually do not consider the importance of data. With the current development of machine learning methods, more and more systems are adding machine learning models or complex analysis tools to their toolbox to always provide more insights into the situation. This section has argued that future systems should consider two systems: one dedicated to the organization of data and another dedicated to the organization of information. At the interface of these two systems lie the machine learning models. Similar to data and information, these models have their proper life cycle, presented previously. This framework for organizing data and information around machine learning models is used in the proposal presented in the following section.

5.3 Case study: social media integration in the R-IO Suite software

R-IO Suite is introduced Section 1.4.

The R-IO Suite software is an information system that combines a variety of tools. It is designed to support collaboration between actors from different organizations. The software itself is organized around an information model that describes the collaboration between the actors. The previous section presented a framework for designing information systems based on machine learning methods. This questions past developments and to think about new development opportunities for future information systems for crisis response. This section presents how this framework was applied in developing the social media module of the R-IO Suite software. The following subsection presents how the previously proposed framework fits into the crisis management framework. In a second step, the software architecture of R-IO is briefly explained to explain how our proposal fits into this system concretely.

5.3.1 Information system processes in crisis management

The framework presented previously aims to support the response to a disaster. However, it takes place as a major component in the crisis management organization. This section presents its life cycle during the different phases of crisis management to better understand the stakes of its operation. The following three phases are considered: i) Preparation, ii) Response, and iii) Recovery. The system presents functionalities mainly for the Preparation and Response phases.

The most relevant data are used to train the machine learning models during the preparation phase—model training & model evaluation. They are then tested by the operators, who can then familiarize themselves with the model preparation tool. Their feedback is taken into account to improve the interface and the predictions.

When an event occurs, the system enters a more active phase. The system then records the data and information related to the event to quickly better understand the situation—data collection. The data system then receives the data from the different recorded sources (social media, sensors, drones, etc.). This data is then processed—data processing—before being stored in a database—data storage. The data in the database is then provided—data distribution—to the different actors who need it, namely:

- The entry of machine learning—model deployment in the ML lifecycle.
- The actors who will label the data, such as specialized call center operators or citizen—information collectors.
- Semi-supervised or unsupervised machine learning models, if they are re-trained during crisis—model training in the ML lifecycle.
- Decision-makers, in the case of aggregated indicators or video data—information distribution.

This data feed different parts of the information system. The latter is in charge of collecting the different information during the disaster. They can come from two sources: humans or computers. In the first case, it is the information entered by the system's users. This can be information obtained from phone calls, reports from the teams deployed in the field, decisions made, or data tagged by volunteers. In the case of that system, the second source of information is the pool of machine learning models that make predictions on input data. The information thus obtained is then organized and stored in a database—information storage. Finally, the information is provided to the decision-makers through a dedicated interface. This interface highlights the information coming from the machine learning algorithms and, if possible, accompanies it with a relevance indicator.

A model may provide insufficient predictions during the event compared to initial expectations—model monitoring. The model in question can be put into maintenance—model maintenance—and re-trained using freshly collected data to reduce the difference between its predictions and reality. If the model is supervised and does not have sufficient labeled data for re-training, the system warns the user, who can then confirm or not the re-training. The following section presents the software architecture of R-IO to describe better how the activities described in this section take place computationally.

5.3.2 R-IO Suite Architecture

R-IO is based on an event-driven architecture (Benaben et al., 2017). The different components are shown in Figure 5.5 and presented in the rest of this section. R-IO suite is composed of a client part and a server part. The client part is in charge of providing the

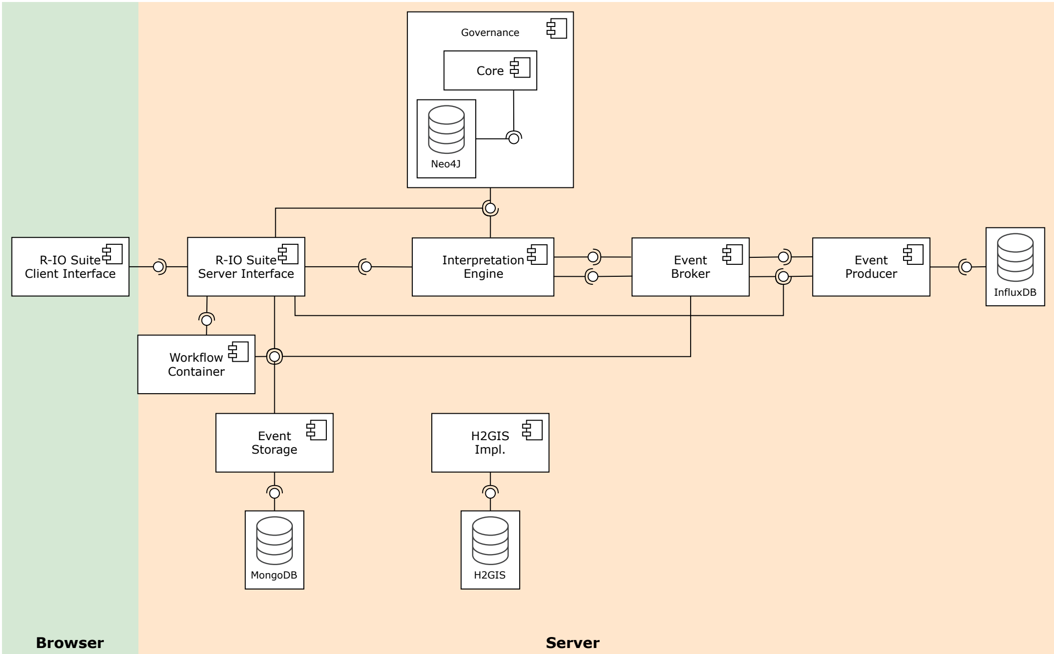

Figure 5.5: Representation of the different components of the RIO Suite software architecture.

interface to the users through a Web browser. It gets the data and information it needs from the server. The client ensures the distribution via the display and the collection of the information provided by the users. The server takes care of the processing and storage of the data/information and the collection of the data provided by automated sources.

The client consists of a single component R-IO Suite Client Interface that links directly to its server-side counterpart, the R-IO Suite Server Interface. Both components are used to transmit data and information between the server and the client. The server components are structured around the Event Broker.

Event Broker The Pub/Sub pattern inspires this component. It offers an interface for the services that produce data (Pub) and an interface for the services that consume data (Sub). For this purpose, the Event Broker creates subject threads in which the Pub services add their data. The services that consume data then subscribe to the topics that interest them and consume them in these threads. In R-IO, the Event Broker creates different threads that correspond to various events. This component is at the heart of the event-driven architecture principle. It is in charge of collecting data from automated sources, such as social media or sensors. These sources then publish their data in dedicated threads consumed, mainly by the Interpretation Engine.

Event Storage The Event Storage records the various events processed by the Event Broker. It consists of a connector to a document database (*MongoDB*) that stores the events.

Interpretation Engine The Interpretation Engine processes the events that need to be processed. It is in charge of processing information and data within the R-IO Suite software. It comprises a Complex Event Processing (CEP) engine that contains rules applied to the different events provided. When the Interpretation Engine receives data (events), the CEP processes this data and sends it back to the Governance or Event Broker. If the CEP determines that the data allows the creation or modification of an MM instance, it passes the result to the Governance and notifies the Event Broker of an event. If the CEP only transforms the data for another use, the result is sent back to the CEP.

Governance The Governance component is in charge of the MM life cycle used by R-IO. It has an implementation of the class model that describes the metamodel presented in Section 3.2. The classes are then implemented through different rules to orchestrate the creation, update, and deduction of instances of the MM. The different instances then live in a graph database, *Neo4J* here. The data received by the Event Broker that is not considered events (the raw data from the data sources) are stored in a database adapted to temporal data *InfluxDB*.

Event Producer This data is stored through the Event Producer, which, like the Event Storage, is an interface to the *InfluxDB* database. This component also allows to "replay" an event and its associated data by retrieving the data and calling the Event Storage. These events are then provided to the Event Broker as a data source, allowing them to perform a simulation in a training context.

Workflow Container These training scenarios are orchestrated by the Workflow Container, which takes care of the underlying processes.

H2GIS Implementation The last component is the H2GIS Implementation, which is an interface to an *H2GIS* database. This database contains different geographical data made available for the cartographic representation provided to the user. The next subsection describes how the elements of the architecture can be adapted to support the components of the previous framework.

5.3.3 Adapting R-IO to embed machine learning models for its processing

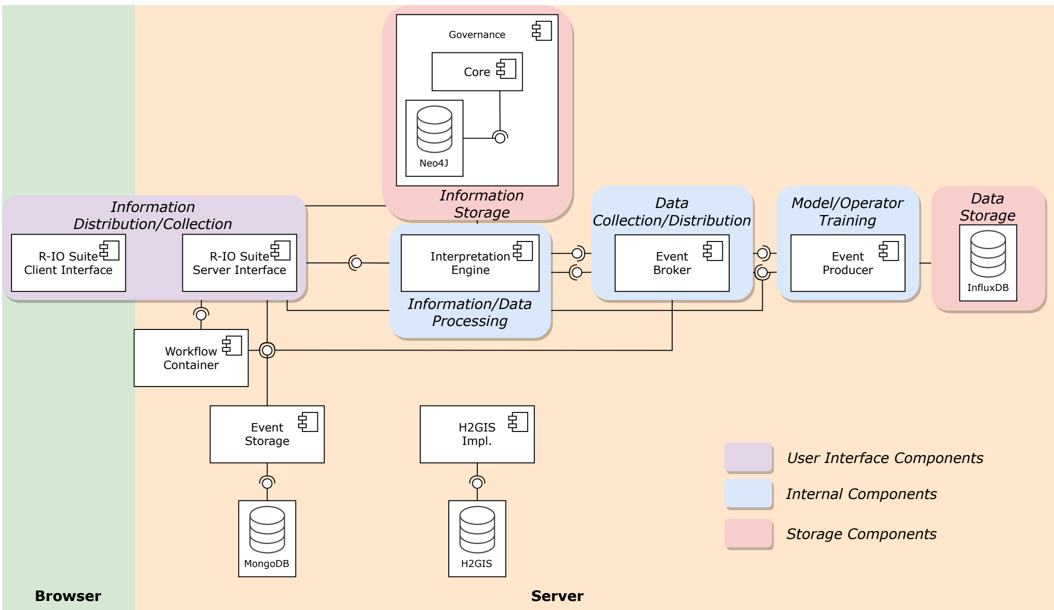

Figure 5.6: Representation of the role played by each components of the RIO Suite software according to the data system/information system framework.

Initially, the information contained in R-IO is processed through a Complex Event Processing engine. The addition of the social media data processing capability leads to new needs. First, the system now requires managing the data collected and processed. Secondly, to process this new data, mainly using machine learning methods and models. Integrating machine models into the operation of R-IO requires taking into account its event-driven architecture.

This section describes to what extent which component is impacted by this input. Indeed, each function of the proposed framework Figure 5.4 has to be integrated. In addition, a way to automatically manage the life cycle of the machine learning models used is also integrated. The contribution of each software component in the data system/information system framework is represented in Figure 5.6. This section presents first the components related to the data system, then the components involved in the information system, and finally, the management of the life cycle of the machine learning models.

Data System Integration

Data Collection The collection of data from automated sources relies on the Event Broker. The first step is to add the ability to connect to the various social media APIs chosen. The data provided by the social media is then populated with threads dedicated to each source. This data must then be processed to be cleaned.

Data Processing The Interpretation Engine is the component in charge of processing in the architecture. Therefore, this component, which acts as a data consumer, must be equipped with various data processing methods, particularly textual ones. Thus, various processing methods can be used depending on the thread consumed by the Interpretation Engine. In this way, it is possible to compose different ways of preprocessing the data depending on the original source. This allows to mutualize this part of the architecture and to simplify the processing, as described in the Introduction of this chapter. The Interpretation Engine then sends the cleaned data to the Event Broker in a new thread, distinct according to the original data.

Data Storage This data can then be consumed by the Event Producer, which stores it in the InfluxDB database.

Data Distribution The advantage of the Event Broker is that it allows the data to be equally distributed to the various services that subscribe to the feed consumed by the Event Producer. The data can be consumed in at least four different ways. First, it can be served to users. This data is then consumed by the R-IO Suite Server Interface, which passes it on to the R-IO Suite Client Interface. They will then be consumed as metrics by decision-makers or labeled by volunteers. This latter case is further developed in the Information Collection paragraph.

The other two ways concern machine learning models, which use the data to train or make predictions. In the latter case, the data can be consumed by one or more machine learning models to provide predictions. The data ready to be stored is then provided as input to the machine learning models. These models live in the Interpretation Engine, which is the component in charge of processing. Therefore, part of the Interpretation Engine must be dedicated to data processing by machine learning models (Model Serving). The role of this module is to provide predictions from the data supplied to it. The machine learning module comprises several models that each correspond to a different task. For instance, this module can be composed of a model that identifies if:

- a text message is related to a disaster event;
- the message is posted by a direct eyewitness of the event;
- geographical information is mentioned in the text;
- relevant information to the decision-makers are contained.

Its predictions will be provided to the CEP, in charge of determining the creation or not of new instances of the metamodel in the Neo4J database. The predictions are then reported to the InfluxDB database, together with the original data. The models' training and life cycles are described in the last part of this section.

Information System Integration

Information Collection As R-IO is an information system, users can input information through its Client Interface. One type of information of interest is labeled data. Interaction with the models is of the utmost importance to keep the users engaged with the model's output. One way is to make the users decide what kind of information they want to obtain. Of course, extensive data labeling by social media operators is not permitted in the context of disaster response. Models, such as the one presented in chapter 4, require labeling a small set of data and should be preferred. Currently, R-IO lacks a dedicated interface in the Client Interface to interact with machine learning models and data labeling. Thus, it is a feature that should be integrated. Also, as mentioned extensively in the previous sections, this part is crucial and should require extra care. Ideally, it should be tested and iterated through the feedback of practitioners. Once the data are transferred to the Server Interface, data are transferred to the Event Broker in a thread dedicated to labeled data. Two components then consume this thread, the Event Producer, which updates the corresponding data in the database, with the labels attributed. Information collected through this interface is then

Information Processing The Interpretation Engine can be seen as composed of two components. A "low" one, which processes data and serves machine learning models, and a "higher" one, in charge of processing the information contained in the system. The "high" level Interpretation Engine is composed of the Complex Event Processing engine that receives the information collected by the system as input. This component analyzes predictions from machine learning models, aggregation of sensor data, and operator entries inputs. The Complex Event Processing engine needs to be adapted to fit with the Incoming information is then used to instantiate the different concepts of the R-IO information model.

Information Storage The Complex Event Processing Engine outputs correspond to different "instructions" sent to the Governance component. This component then creates, updates, or deletes the corresponding instances of the information model classes that live in the Neo4j database. The data attached to the information is published to the Event Broker, who makes it available to the Event Producer for storage.

Information Distribution Finally, the resulting information is provided to the decision-makers through the Client Interface. Currently, a component of the Client Interface, called R-IOPLAY, is in charge of the main interface: a Common Operational Picture. R-IOPLAY displays the different concepts of the information model geographically (see Figure 1.3). This component is powered by the information models present in Neo4J, the data within the InfluxDB database. The geographical information is provided by the H2GIS database, which is populated regularly with information available on Open Street Map. However, R-IOPLAY does not provide other information, such as summaries of critical text messages identified or pictures identified on social media. This part needs to be refined to be adapted to reflect the various formats of data and information that R-IO Suite handles. The final component that requires attention is the management of the lifecycle of the machine learning models.

Machine learning models lifecycle management

The previous section described how the Interpretation Engine would be adapted to serve the models and make predictions from incoming data. However, this component must also be adapted to maintain the deployed machine learning models. This component will consist of a new module within the Interpretation Engine—the maintenance module. Model maintenance consists essentially of a few steps. First, identify if the model needs to go into maintenance. Then, re-train the model with new, labeled data. Put the model back into production so that it can make predictions again. These different steps are orchestrated using the Event Broker. Figure 5.7 illustrates the process of model maintenance using the Broker. When either the user or the module containing the model indicates to put the model in maintenance mode, an event is provided to the Event Broker. The Event Broker then

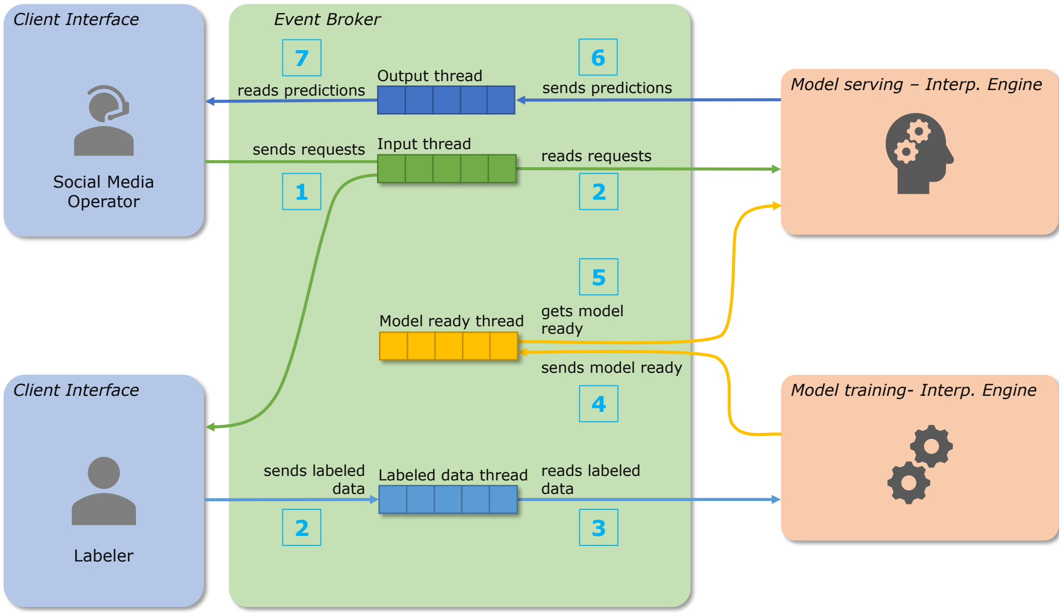

Figure 5.7: Illustration of model maintenance within R-IO using the Event Broker. Illustration adapted from Burkov (2020)

triggers the maintenance module within the Interpretation Engine, which takes care of the re-training. The Event Broker asks the Event Producer for the labeled data it has. The maintenance module consumes the data available to re-train the model. Once the training is completed, the model is added to the Event Broker. If the re-training of the model does not influence other models, the model can then be redeployed directly. If other models depend on the re-trained model, they are re-trained in turn using the same procedure. When all the required models are ready, they are redeployed. This section presented a framework to organize the processing of social media data by machine learning models in an information system dedicated to crisis management. To illustrate its functioning, the last part presented its implementation in the R-IO Suite information system. However, although information systems for crisis management are regularly progressing, they remain the only tools within the crisis management organization. The final section of this chapter discusses issues beyond the information system, including how its results are interpreted.

5.4 Beyond the system

An efficient information system increases the potential of an organization tenfold. However, as stated in Section 5.2.4.4, the added value of the information system depends on its ability to generate better suggestions to the decision-makers. These suggestions must, in turn, enable better decisions, and ultimately, improve the response. All the effort put into providing the best possible information can be wasted if users do not read or understand that information. The first section of this chapter warned of some problems caused by not taking cognitive mechanisms into account. These eight issues identified are essentially related to the perception induced by the system on the user. Other challenges linked to the use of machine learning models in the systems have to be considered during the interface design and data collection. However, more challenges arise beyond the system. As a result, the context of crisis response is far from optimal for the decision-maker. Comes (2016) studied the consequences of this environment on decision-makers. Their main finding is that the crisis conditions reinforce decision-makers' biases. Biases such as conjunction fallacy or confirmation bias steer the decisions made away from the ideal set of decisions. Users can be overly confident in the system if they are not sufficiently solicited or included in the output. Conversely, they may not pay enough attention to the alerts it issues or the indications it provides This last point is partly based on the trust that users have in the decision support system. In this case, we are in a chicken and egg situation. For the system to be adopted, it must show that it is effective, but it cannot be effective if it is not adopted. So the initial step must be as easy as possible to climb, bringing the interface as close as possible to what users expect to use. This also means that they should be able to explore the system's limits through training exercises. Consequently, providing the correct information to the right person at the right time should not be sufficient. The way information is received and understood should also be considered if one wants to build an adequate system. Many scholars have already explored the process of extracting sense from the information. This process is referred to as sensemaking. Several definitions of this process have been proposed. For Weick (1995), sensemaking is the process by which individuals give meaning to their experience. This process is retrospective—the analysis is carried out only at the end of the action. Consequently, action is of prime importance for individuals to make sense of their environment. The role play conducted by Grace et al. (2019) emphasizes this statement. During their study, the authors report the importance of protocols, such as the Six W's presented in Section 3.1.3. Protocols such as the Six W's are designed to help the sensemaking of the 911 operators. These familiar "patterns" reinforce the importance of creating a standard mental model at the level of the system's interface and through the usage habits themselves. Creating such unified representation can be achieved through standard training. Training is, of course, time and resource-consuming and is rarely done in sufficient quantity. More recently, initiatives such as Congès et al. (2020) present an alternative through virtual reality. Virtual environments allow the opportunity to reduce the cost of exercises and regularly train a large workforce to perform complex or dangerous tasks. Such exercises can be performed in crisis management to train operators and operators to deal with complex and unexpected events. But more importantly, it helps the different actors to create a shared framework of action and a common mental model of crisis management.

Conclusion

This chapter considered the crisis management information system as a whole. In particular, it was interested in the stakes of the contribution of machine learning models within an information system dedicated to crisis management. The question initially asked was *What are the challenges faced by an information system dedicated to crisis management that uses machine learning models?* This question was explored in three parts. First, a review of the main feedback was carried out to understand the issues at stake for such a system. The insights provided focused on the information system and machine learning models specifically. In a second step, considering the previous information, I proposed a framework to integrate machine learning models into the information system directly. In this way, the predictions made by the models are associated with the rest of the information present in the system. This framework is then applied to the R-IO Suite software to integrate social media as a data source for this software. Finally, the last section opens on the importance of considering users and their feedback in designing and improving such systems. This approach helps to prevent inappropriate use of the system's indications.

These observations and remarks must be considered at all levels of information system design. From collection to distribution, the system must be thought with the context in which the user will use it. But this remark also applies upstream when designing or choosing the algorithms embedded in the system. Chapter 4 has already highlighted the problems posed by machine learning models in the context of disaster response. In light of the evidence presented in those sections, algorithms over which the end-user can have influence (with proper training) appear as the option that should be preferred. This approach can reduce the threat posed by the eight daemons identified by Endsley. However, the benefit provided by an algorithm or a model might be deemed sufficient to be exploited. In this scenario, extra attention is required in the design and interactions with the end-user to avoid the harmful consequences of opacity. If a weakly explainable algorithm is deployed, as the benefit provided is deemed sufficient, it becomes crucial to reduce the friction with the user. Taking into account these multiple observations is, however, a significant challenge. The multitude of elements to consider implies additional cost during the design because of new constraints.

Conclusion and Perspectives

The response to a crisis is strongly influenced by the ability to make the right decision at the right time. However, the reality of the crisis makes this objective more remote and often forces compromises. In the hope of reducing the gap between reality and the objective, many actors have sought to improve information feedback to decision-makers. This work is part of that effort, seeking to serve content posted on social media to the people who need it. However, many challenges are emerging. Social media is not the only source of data to feed decision-makers situational awareness. Faced with this influx of data and information, it is essential to limit as much as possible the extra and limit the mental load attributed to this task. This observation only increases the status of the information system (IS) in crisis management. The IS becomes responsible for taming the torrent of data, extracting information that it must then organize and provide appropriately. This vision has guided all of the previous work, the main contributions of which are summarized in the following.

5.5 Summary

The first chapter of this dissertation presented its scientific background composed of three domains: (i) crisis management, (ii) social media, and (iii) natural language processing. This Ph.D. research works were conducted at the intersection at both of these domains and identified the principal research question that guided the rest of the document: *How to design an information system for crisis response that can automatically manage and deliver actionable information from social media data?*

The second chapter provided an overview of previous works on the different aspects of the research question. It highlights the coexistence of two fields around these issues: information sciences and social sciences. Each field explores the space of the problem and meets at certain intersections. This part also shows the important interest of the scientific community for the automatic processing of social media content and the work to implement it in crisis management.

In this context, the third chapter asks what information decision-makers need from social media. Once this information is identified, it needs to be represented in a computerized way to automate its organization and collection. The information science community has proposed numerous computer representations, or information models, for crisis management. The last part of this chapter presented an information model for the information available on social media for decision-makers. This model is obtained by intersecting the needs identified in the first part with the relevant information models identified in the second part.

The fourth chapter builds on the earlier information model to propose a method for automatically identifying this information. This method builds on previous work that seeks to differentiate between messages related to the event and those that are not. The processing among the resulting messages is similar to the recognition of named entities, with the difference that the entities are not named but correspond to actionable information. This identification is performed using a machine learning method. Training the machine learning model in a supervised fashion raises challenges in the context of crisis management. Hence, a semi-supervised approach is preferred for training the model. The latter is based on the word embeddings created by a language model such as BERT. The dimension of the vectors provided by BERT is then adopted to identify the clusters of terms present in the dataset provided as input to the algorithm. Some of these clusters contain terms that the user has previously labeled according to the actionable information of the model. The labels of these terms are then propagated to all the other unlabeled terms present in the cluster. In this way, the terms labeled by the user and their synonyms are highlighted in the incoming message flow.

Finally, the fifth and last chapter considers the IS as a whole. In particular, it asks about the role and issues of integrating the data processing method into an IS for crisis management. After studying the literature on the associated issues in the first part, it is concluded that such an IS is composed of two parts. One part is dedicated to managing data, which are used in part to feed the AI at the heart of the IS. A second part is responsible for information management and considers user input and output. Another aspect of the proposed dichotomy is the distinction between data and information storage. The first case is carried out with the help of a traditional relational database. Information storage is based on the association of an information model, such as those mentioned above, and a graph-oriented database. The graph database allows defining instances of the information present in the model and semantic relations between the different cases. This approach promises many evolutions in processing information exchanged during a crisis.

5.6 Perspectives

The work presented in this document covers a rather large area of study by trying to mix human and technical around this scientific challenge. However, at the dawn of this document, more questions remain unanswered than answers have been given. This field of research remains rich and challenging, both scientifically and technically. The following parts present potential research directions that I currently foresee.

5.6.1 Short terms

The problem of misinformation and fakes was mentioned in Chapter 1 of this dissertation. Although excluded in this work, this issue is more than ever decisive for the success of social media-based modules. Batard (2021) mainly refer to beneficial citizen initiatives in his work. However, the opposite behavior is also observed. Some citizens may actively use social media to share ideas or ideologies detrimental to crisis management. The results obtained around this issue must now be integrated into systems. Their objectives would be to detect and fight more upstream against potential trends that could harm the response. This problem remains a significant issue for many practitioners who regularly mention it as a deterrent to adopting such systems. This integration would reassure them and thus facilitate adoption and experimentation.

Additionally, it would be interesting to consolidate the proposals made on specific issues on the technical aspects. Topics well discussed should free up space for suggestions concerning new uses of the data and feedback on these technologies. Such a topic could be the classification of messages evoking an event. The most effective suggestions could now be consolidated to allow use by practitioners.

5.6.2 Mid-long terms

A better understanding of the expectations and needs of practitioners, especially when dealing with unique situations, would also be very beneficial. A large volume of publications takes a top-down approach, proposing solutions directly to users. However, many of the observations made by the practitioners reveal and reflect their difficulties and needs. Better integration and collaboration between domains would necessarily lead to better results for crisis management. Practitioners who are among the early adopters are key players. Their feedback and testimonies save precious time searching for appropriate solutions to the issue at hand.

This document also mentioned the numerous data sources that can support crisis management. Messages posted on social media and photos or videos are all information accessible from social media. However, other sources have been mentioned, such as video streams from drones or readings from various sensors. The collection and automatic interpretation of these data is currently the focus of scientific attention. This results in a large amount of information being generated through the interpretation of the data. This heterogeneity is an asset, and many developments are to be expected thanks to it.

A future challenge will be to homogenize the available information to exploit its full potential. Such homogenization is made possible by a standard information model that allows the standardization of information obtained from different sources. Two direct consequences are expected. First, using several sources allows for different incidents or different geographical areas. Thus, someone can report an event in progress in an area not covered by a camera or vice versa. This consequence corresponds to an extension of the information or the *horizontal* scaling of the coverage.

This heterogeneity also allows for vertical scaling. Having different data sources covering the same event can provide additional information than a single source. For example, someone can warn via social media that an event is taking place, and a camera on the spot can better understand the context and type of event concerned. This application thus corresponds to an *enrichment* in information. This enrichment can also take place on the same information. For example, a user indicates an event has taken place and mentions a location. At the same time, a surveillance camera also detects an event at this exact location. The concordance of these two pieces of information reduces the uncertainty of some information. Providing an indicator of certainty in the information proposed by the system would also reduce the mental load on decision-makers.

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Bibliography

(Ackoff, 1989) R. L. Ackoff. “From Data to Wisdom”. In: *Journal of applied systems analysis* 16.1 (1989), pp. 3–9 (cit. on pp. 72, 114).

(Agarwal et al., 2020) M. Agarwal, M. Leekha, R. Sawhney, and R. Shah. “Crisis-DIAS: Towards Multimodal Damage Analysis - Deployment, Challenges and Assessment”. English. In: *AAAI - AAAI Conf. Artif. Intell.* AAAI press, 2020, pp. 346–353 (cit. on pp. 34, 35).

(Alam et al., 2017) F. Alam, M. Imran, and F. Ofli. “Image4Act: Online Social Media Image Processing for Disaster Response”. English. In: *Proc. IEEE/ACM Int. Conf. Adv. Soc. Netw. Anal. Min., ASONAM.* Ed. by Diesner J., Ferrari E., and Xu G. Association for Computing Machinery, Inc, 2017, pp. 601–604 (cit. on pp. 34, 35, 71, 109).

(Alam et al., 2020) F. Alam, F. Ofli, and M. Imran. “Descriptive and Visual Summaries of Disaster Events Using Artificial Intelligence Techniques: Case Studies of Hurricanes Harvey, Irma, and Maria”. English. In: *Behaviour and Information Technology* 39.3 (2020), pp. 288–318 (cit. on p. 35).

(Aloudat et al., 2011) A. Aloudat and K. Michael. “Toward the Regulation of Ubiquitous Mobile Government: A Case Study on Location-Based Emergency Services in Australia”. English. In: *Electronic Commerce Research* 11.1 (2011), pp. 31–74 (cit. on p. 45).

(Ashktorab et al., 2014) Z. Ashktorab, C. Brown, M. Nandi, and A. Culotta. “Tweedr: Mining Twitter to Inform Disaster Response.” English. In: *ISCRAM.* Citeseer. University Park, PA: The Pennsylvania State University, 2014, pp. 354–358 (cit. on p. 70).

(Assmann et al., 2006) U. Assmann, S. Zschaler, and G. R. Wagner. “Ontologies, Meta-Models, and the Model-Driven Paradigm”. In: *Ontologies for Software Engineering and Software Technology.* 2006 (cit. on p. 36).

(Avvenuti et al., 2014) M. Avvenuti, S. Cresci, A. Marchetti, C. Meletti, and M. Tesconi. “EARS (Earthquake Alert and Report System): A Real Time Decision Support System for Earthquake Crisis Management”. English. In: *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.* Association for Computing Machinery, 2014, pp. 1749–1758 (cit. on pp. 34, 35).

(Avvenuti et al., 2016) M. Avvenuti, F. Del Vigna, S. Cresci, A. Marchetti, and M. Tesconi. “Pulling Information from Social Media in the Aftermath of Unpredictable Disasters”. English. In: *Proc. Int. Conf. Inf. Commun. Technol. Disaster Manag., ICT-DM.* Ed. by Hadjadj-Aoul Y. Institute of Electrical and Electronics Engineers Inc., 2016, pp. 258–264 (cit. on pp. 34, 35).

(Babitski et al., 2011) G. Babitski, S. Bergweiler, O. Grebner, D. Oberle, H. Paulheim, and F. Probst. *SoKNOS - Using Semantic Technologies in Disaster Management Software*. English. Vol. 6643 LNCS. 2011, p. 197 (cit. on p. 40).

(Babitski et al., 2009) G. Babitski, S. Bergweiler, J. Hoffmann, D. Schön, C. Stasch, and A. Walkowski. *Ontology-Based Integration of Sensor Web Services in Disaster Management*. English. Vol. 5892 LNCS. 2009, p. 121 (cit. on p. 40).

(Backfried et al., 2012) G. Backfried, C. Schmidt, M. Pfeiffer, G. Quirchmayr, M. Glanzer, and K. Rainer. "Open Source Intelligence in Disaster Management". English. In: *Proc. - Eur. Intell. Secur. Informatics Conf., EISIC*. 2012, pp. 254–258 (cit. on pp. 34, 35).

(Bahk et al., 2016) C. Bahk, M. Cumming, L. Paushter, L. Madoff, A. Thomson, and J. Brownstein. "Publicly Available Online Tool Facilitates Real-Time Monitoring of Vaccine Conversations and Sentiments". English. In: *Health Affairs* 35.2 (2016), pp. 341–347 (cit. on p. 58).

(Bail, 2016) C. Bail. "Combining Natural Language Processing and Network Analysis to Examine How Advocacy Organizations Stimulate Conversation on Social Media". English. In: *Proceedings of the National Academy of Sciences of the United States of America* 113.42 (2016), pp. 11823–11828 (cit. on pp. 52, 58).

(Barabási et al., 1999) A.-L. Barabási and R. Albert. "Emergence of Scaling in Random Networks". en. In: *Science* 286.5439 (Oct. 1999), pp. 509–512 (cit. on pp. 17, 18).

(Barthe-Delanoë et al., 2014) A.-M. Barthe-Delanoë, S. Truptil, F. Bénaben, and H. Pingaud. "Event-Driven Agility of Interoperability during the Run-Time of Collaborative Processes". en. In: *Decision Support Systems* 59 (Mar. 2014), pp. 171–179 (cit. on p. 12).

(Batard, 2021) R. Batard. "Intégrer Les Contributions Citoyennes Aux Dispositifs de Gestion de Crise : L'apport Des Médias Sociaux". These de Doctorat. Institut Polytechnique de Paris, June 2021 (cit. on pp. 12, 20, 24, 64–67, 128).

(Bellman, 1966) R. Bellman. "Dynamic Programming". In: *Science* 153.3731 (July 1966), pp. 34–37 (cit. on p. 90).

(Benaben et al., 2014) F. Benaben, A.-M. Barthe-Delanoë, M. Lauras, and S. Truptil. "Collaborative Systems in Crisis Management: A Proposal for a Conceptual Framework". en. In: *15th Working Conference on Virtual Enterprises (PROVE)*. Vol. AICT-434. Springer, Oct. 2014, p. 396 (cit. on pp. 9, 11).

(Benaben et al., 2021) F. Benaben, L. Faugere, B. Montreuil, M. Lauras, N. Moradkhani, T. Cerabona, J. Gou, and W. Mu. "Instability Is the Norm! A Physics-Based Theory to Navigate among Risks and Opportunities". In: *Enterprise Information Systems* 0.0 (Jan. 2021), pp. 1–28 (cit. on p. 11).

(Benaben et al., 2017) F. Benaben, A. Fertier, A. Montarnal, N. Salatge, S. Truptil, S. R. Pouyade, and M. Lauras. "A Conceptual Framework and a Suite of Tools to Support Crisis Management". In: *HICSS 2017 - 50th Hawaii International Conference on System Sciences*. Ed. by HICSS. HICSS. Hawaii, United States, Jan. 2017, p.237–246 (cit. on pp. 114, 119).

(Benaben et al., 2020) F. Benaben, A. Fertier, A. Montarnal, W. Mu, Z. Jiang, S. Truptil, A.-M. Barthe-Delanoë, M. Lauras, G. Mace-Ramete, T. Wang, et al. "An AI Framework and a Metamodel for Collaborative Situations: Application to Crisis Management Contexts". In: *Journal of Contingencies and Crisis Management* 28.3 (2020), pp. 291–306 (cit. on p. 13).

(Benaben et al., 2015) F. Benaben, S. Truptil, M. Lauras, and N. Salatge. "Management of Collaborative Behavior through a Service-Oriented Mediation System: The Case of Crisis Management". In: *2015 IEEE International Conference on Services Computing*. June 2015, pp. 554–561 (cit. on p. 12).

(Bénaben et al., 2008) F. Bénaben, C. Hanachi, M. Lauras, P. Couget, and V. Chapurlat. "A Metamodel and Its Ontology to Guide Crisis Characterization and Its Collaborative Management". English. In: *Proc. ISCRAM - Int. Conf. Inf. Syst. Crisis Response Manage.* Information Systems for Crisis Response and Management, ISCRAM, 2008, pp. 189–196 (cit. on pp. 40, 70, 75).

(Bénaben et al., 2016) F. Bénaben, M. Lauras, S. Truptil, and N. Salatgé. "A Metamodel for Knowledge Management in Crisis Management". In: *2016 49th Hawaii International Conference on System Sciences (HICSS)*. Koloa, HI, USA: IEEE, 2016, pp. 126–135 (cit. on pp. 72, 75, 77, 78, 80).

(Berlin et al., 2011) J. Berlin and E. Carlström. "Why Is Collaboration Minimised at the Accident Scene?: A Critical Study of a Hidden Phenomenon". English. In: *Disaster Prevention and Management: An International Journal* 20.2 (2011), pp. 159–171 (cit. on pp. 44, 45).

(Bhatt et al., 2014) S. Bhatt, H. Purohit, A. Hampton, V. Shalin, A. Sheth, and J. Flach. "Assisting Coordination during Crisis: A Domain Ontology Based Approach to Infer Resource Needs from Tweets". English. In: *WebSci - Proc. ACM Web Sci. Conf.* Association for Computing Machinery, 2014, pp. 297–298 (cit. on p. 46).

(Blanford et al., 2014) J. I. Blanford, J. Bernhardt, A. Savelyev, Gabrielle Wong-Parodi, A. M. Carleton, D. W. Titley, and A. M. MacEachren. "Tweeting and Tornadoes". English. In: *ISCRAM 2014 Conference Proceedings – 11th International Conference on Information Systems for Crisis Response and Management*. Ed. by M. S. P. S.R. Hiltz. University Park, PA: The Pennsylvania State University, 2014, pp. 319–323 (cit. on p. 19).

(Bojanowski et al., 2016) P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov. "Enriching Word Vectors with Subword Information". In: *arXiv:1607.04606 [cs]* (July 2016). arXiv: `1607.04606 [cs]` (cit. on p. 89).

(Bontcheva et al., 2014) K. Bontcheva and D. Rout. "Making Sense of Social Media Streams through Semantics: A Survey". English. In: *Semantic Web* 5.5 (2014), pp. 373–403 (cit. on pp. 52, 58).

(Bubendorff et al., 2021) S. Bubendorff, C. Rizza, and C. Prieur. "Construction and Dissemination of Information Veracity on French Social Media during Crises: Comparison of Twitter and Wikipedia". In: *Journal of Contingencies and Crisis Management* 29.2 (2021), pp. 204–216 (cit. on p. 20).

(Burkov, 2020) A. Burkov. *Machine Learning Engineering*. True Positive Inc., 2020 (cit. on pp. 113, 124).

(Cabrera Aguilera et al., 2016) M. Cabrera Aguilera, B. Bastos da Fonseca, T. Ferris, M. Vidal, and P. Carvalho. "Modelling Performance Variabilities in Oil Spill Response to Improve System Resilience". English. In: *Journal of Loss Prevention in the Process Industries* 41 (2016), pp. 18–30 (cit. on pp. 44, 45).

(Caragea et al., 2011) C. Caragea, N. McNeese, A. Jaiswal, G. Traylor, H.-W. Kim, P. Mitra, D. Wu, A. H. Tapia, L. Giles, B. J. Jansen, and J. Yen. "Classifying Text Messages for the Haiti Earthquake". en. In: (2011), p. 10 (cit. on pp. 22, 70, 85).

(Castagnino, 2019) F. Castagnino. "What Can We Learn from a Crisis Management Exercise? Trusting Social Media in a French Firefighters' Department." In: *ISCRAM*. 2019 (cit. on p. 68).

(Chamlertwat et al., 2012) W. Chamlertwat, P. Bhattarakosol, T. Rungkasiri, and C. Haruechaiyasak. "Discovering Consumer Insight from Twitter via Sentiment Analysis". English. In: *Journal of Universal Computer Science* 18.8 (2012), pp. 973–992 (cit. on pp. 51, 58).

(Charles et al., 2010) A. Charles, M. Lauras, and L. Van Wassenhove. "A Model to Define and Assess the Agility of Supply Chains: Building on Humanitarian Experience". In: *International Journal of Physical Distribution & Logistics Management* 40.8/9 (Jan. 2010). Ed. by P. Tatham and S. Pettit, pp. 722–741 (cit. on p. 12).

(Chary et al., 2017) M. Chary, N. Genes, C. Giraud-Carrier, C. Hanson, L. Nelson, and A. Manini. "Epidemiology from Tweets: Estimating Misuse of Prescription Opioids in the USA from Social Media". English. In: *Journal of Medical Toxicology* 13.4 (2017), pp. 278–286 (cit. on pp. 52, 58).

(Chaturvedi et al., 2018) I. Chaturvedi, E. Cambria, R. Welsch, and F. Herrera. "Distinguishing between Facts and Opinions for Sentiment Analysis: Survey and Challenges". English. In: *Information Fusion* 44 (2018), pp. 65–77 (cit. on pp. 51, 58).

(Chou et al., 2011) C.-H. Chou, F. Zahedi, and H. Zhao. "Ontology for Developing Web Sites for Natural Disaster Management: Methodology and Implementation". English. In: *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans* 41.1 (2011), pp. 50–62 (cit. on p. 40).

(Cobb et al., 2014) C. Cobb, T. McCarthy, A. Perkins, A. Bharadwaj, J. Comis, B. Do, and K. Starbird. "Designing for the Deluge: Understanding & Supporting the Distributed, Collaborative Work of Crisis Volunteers". English. In: *Proc. ACM Conf. Comput. Support. Coop. Work CSCW*. Association for Computing Machinery, 2014, pp. 888–899 (cit. on pp. 45, 47).

(Coche et al., 2019) J. Coche, A. Montarnal, A. Tapia, and F. Benaben. *Actionable Collaborative Common Operational Picture in Crisis Situation: A Comprehensive Architecture Powered with Social Media Data*. English. Ed. by Camarinha-Matos L.M., Afsarmanesh H., and Antonelli D. Vol. 568. Springer New York LLC, 2019, p. 162 (cit. on p. 46).

(Collier, 2012) N. Collier. "Uncovering Text Mining: A Survey of Current Work on Web-Based Epidemic Intelligence". English. In: *Global Public Health* 7.7 (2012), pp. 731–749 (cit. on pp. 52, 58).

(Comes, 2016) T. Comes. "Cognitive Biases in Humanitarian Sensemaking and Decision-Making Lessons from Field Research". In: *2016 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)* (2016), pp. 56–62 (cit. on p. 124).

(Comes et al., 2015) T. Comes, O. Vybornova, and B. Van de Walle. "Bringing Structure to the Disaster Data Typhoon: An Analysis of Decision-Makers' Information Needs in the Response to Haiyan". In: *2015 AAAI Spring Symposium Series*. 2015 (cit. on pp. 71, 80, 110).

(Comfort, 2007) L. K. Comfort. "Crisis Management in Hindsight: Cognition, Communication, Coordination, and Control". In: *Public Administration Review* 67 (2007), pp. 189–197 (cit. on p. 13).

(Congès et al., 2020) A. Congès, A. Evain, F. Benaben, O. Chabiron, and S. Rebière. "Crisis Management Exercises in Virtual Reality". In: *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 2020, pp. 87–92 (cit. on p. 125).

(Department of the Army, 2021) Department of the Army. *Advanced Situational Awareness*. English. 2021 (cit. on p. 70).

(Devlin et al., 2018) J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. "BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding". In: *arXiv:1810.04805 [cs]* (Oct. 2018). arXiv: `1810.04805 [cs]` (cit. on p. 89).

(Endsley, 1995) M. R. Endsley. "Toward a Theory of Situation Awareness in Dynamic Systems". en. In: *Human Factors* 37.1 (Mar. 1995), pp. 32–64 (cit. on pp. 13, 70, 72).

(Endsley, 2016) M. R. Endsley. *Designing for Situation Awareness: An Approach to User-Centered Design, Second Edition*. en. CRC Press, Apr. 2016 (cit. on pp. 86, 110, 112).

(Erdös et al., 1960) P. Erdös, A. Rényi, et al. "On the Evolution of Random Graphs". In: *Publ. Math. Inst. Hung. Acad. Sci* 5.1 (1960), pp. 17–60 (cit. on p. 17).

(Fan et al., 2021) C. Fan, C.-c. Zhang, A. Yahja, and A. Mostafavi. "Disaster City Digital Twin: A Vision for Integrating Artificial and Human Intelligence for Disaster Management". In: *Int. J. Inf. Manag.* 56 (2021), p. 102049 (cit. on p. 109).

(Farzindar et al., 2017) A. Farzindar and D. Inkpen. "Natural Language Processing for Social Media". In: *Synthesis Lectures on Human Language Technologies* 10.2 (2017), pp. 1–195 (cit. on p. 98).

(Fersini et al., 2017) E. Fersini, E. Messina, and F. Pozzi. "Earthquake Management: A Decision Support System Based on Natural Language Processing". English. In: *Journal of Ambient Intelligence and Humanized Computing* 8.1 (2017), pp. 37–45 (cit. on p. 35).

(Fertier, 2018) A. Fertier. "Interprétation Automatique de Données Hétérogènes Pour La Modélisation de Situations Collaboratives : Application à La Gestion de Crise". These de Doctorat. Ecole nationale des Mines d'Albi-Carmaux, Nov. 2018 (cit. on pp. 7, 8, 12, 15).

(Fertier et al., 2020) A. Fertier, A. Montarnal, A.-M. Barthe-Delanoë, S. Truptil, and F. Bénaben. "Real-Time Data Exploitation Supported by Model- and Event-Driven Architecture to Enhance Situation Awareness, Application to Crisis Management". In: *Enterprise Information Systems* 14.6 (2020), pp. 769–796. eprint: `https://doi.org/10.1080/17517575.2019.1691268` (cit. on p. 70).

(Fink, 1986) S. Fink. *Crisis Management: Planning for the Inevitable*. eng. Amacom, 1986 (cit. on p. 7).

(Fuchs, 2021) C. Fuchs. *Social Media: A Critical Introduction*. Sage, 2021 (cit. on p. 17).

(Gao et al., 2011) C.-Y. Gao and D.-H. Peng. "Consolidating SWOT Analysis with Nonhomogeneous Uncertain Preference Information". In: *Knowledge-Based Systems* 24.6 (2011), pp. 796–808 (cit. on p. 63).

(Gaur et al., 2019) M. Gaur, S. Shekarpour, A. Gyrard, and A. Sheth. "Empathi: An Ontology for Emergency Managing and Planning about Hazard Crisis". English. In: *Proc. - IEEE Int. Conf. Semantic Comput., ICSC*. Institute of Electrical and Electronics Engineers Inc., 2019, pp. 396–403 (cit. on p. 46).

(Ghahremanlou et al., 2014) L. Ghahremanlou, W. Sherchan, and J. Thom. "Geotagging Twitter Messages in Crisis Management". English. In: *Computer Journal* 58.9 (2014), pp. 1937–1954 (cit. on pp. 40, 46).

(Gibson et al., 2014) H. Gibson, S. Andrews, K. Domdouzis, L. Hirsch, and B. Akhgar. "Combining Big Social Media Data and FCA for Crisis Response". English. In: *Proc. - IEEE/ACM Int. Conf. Util. Cloud Comput., UCC*. Institute of Electrical and Electronics Engineers Inc., 2014, pp. 690–695 (cit. on pp. 34, 35).

(Glasgow et al., 2014) K. Glasgow, C. Fink, and J. Boyd-Graber. ""Our Grief Is Unspeakable": Automatically Measuring the Community Impact of a Tragedy". English. In: *Proc. Int. Conf. Weblogs Soc. Media, ICWSM*. The AAAI Press, 2014, pp. 161–169 (cit. on p. 35).

(Grace et al., 2018) R. Grace, J. Kropczynski, and A. Tapia. "Community Coordination: Aligning Social Media Use in Community Emergency Management". In: vol. 2018-May. Proceedings of the International ISCRAM Conference. 2018, pp. 609–620 (cit. on p. 47).

(Grace et al., 2020) R. Grace and J. Kropczynski. "Communicating Next-Generation 911 with Local 911 Professionals: Preliminary Recommendations". In: *2020 IEEE International Professional Communication Conference (ProComm)*. IEEE. 2020, pp. 110–114 (cit. on p. 63).

(Grace et al., 2019) R. Grace, J. Kropczynski, A. Tapia, E. Obeysekare, S. Halse, J. Coche, A. Montarnal, M. Beagles, and F. Fonseca. "Role Playing next Generation 9-1-1: Sensemaking with Social Media in Public-Safety Answering Points". In: *Proceedings of the 52nd Hawaii International Conference on System Sciences*. 2019 (cit. on pp. 62, 67, 125).

(Gründer-Fahrer et al., 2018) S. Gründer-Fahrer, A. Schlaf, G. Wiedemann, and G. Heyer. "Topics and Topical Phases in German Social Media Communication during a Disaster". English. In: *Natural Language Engineering* 24.2 (2018), pp. 221–264 (cit. on pp. 34, 35).

(Halse et al., 2019) S. E. Halse, R. Grace, J. Kropczynski, and A. Tapia. "Simulating Real-Time Twitter Data from Historical Datasets". In: *16th International Conference on Information Systems for Crisis Response and Management, ISCRAM 2019*. Information Systems for Crisis Response and Management, ISCRAM. 2019, pp. 780–787 (cit. on p. 105).

(Hariri et al., 2019) R. Hariri, E. Fredericks, and K. Bowers. "Uncertainty in Big Data Analytics: Survey, Opportunities, and Challenges". English. In: *Journal of Big Data* 6.1 (2019) (cit. on pp. 52, 58).

(Harris, 1954) Z. S. Harris. "Distributional Structure". In: WORD 10.2-3 (Aug. 1954), pp. 146–162 (cit. on p. 89).

(Hawkins et al., 2016) J. Hawkins, J. Brownstein, G. Tuli, T. Runels, K. Broecker, E. Nsoesie, D. McIver, R. Rozenblum, A. Wright, F. Bourgeois, and F. Greaves. "Measuring Patient-Perceived Quality of Care in US Hospitals Using Twitter". English. In: *BMJ Quality and Safety* 25.6 (2016), pp. 404–413 (cit. on pp. 51, 58).

(Hemmatian et al., 2019) F. Hemmatian and M. Sohrabi. "A Survey on Classification Techniques for Opinion Mining and Sentiment Analysis". English. In: *Artificial Intelligence Review* 52.3 (2019), pp. 1495–1545 (cit. on pp. 51, 58).

(Hermann, 1972) C. Hermann. "Some Issues in the Study of International Crisis". In: *International crises: Insights from behavioral research* (1972), pp. 3–17 (cit. on p. 6).

(Hirschberg et al., 2015) J. Hirschberg and C. D. Manning. "Advances in Natural Language Processing". In: *Science* 349.6245 (2015), pp. 261–266 (cit. on pp. 20, 21).

(Hotelling, 1933) H. Hotelling. "Analysis of a Complex of Statistical Variables into Principal Components". In: *Journal of Educational Psychology* 24.6 (1933), pp. 417–441 (cit. on p. 90).

(Huang et al., 2015) Q. Huang, G. Cervone, D. Jing, and C. Chang. "DisasterMapper: A CyberGIS Framework for Disaster Management Using Social Media Data". English. In: *Proc. ACM SIGSPATIAL Int. Workshop Anal. Big Geospatial Data, BigSpatial*. Ed. by Chandola V. and Vatsavai R.R. Association for Computing Machinery, Inc, 2015, pp. 1–6 (cit. on pp. 34, 35).

(Imran et al., 2014) M. Imran, C. Castillo, J. Lucas, P. Meier, and S. Vieweg. "AIDR: Artificial Intelligence for Disaster Response". English. In: *WWW Companion - Proc. Int. Conf. World Wide Web*. Association for Computing Machinery, Inc, 2014, pp. 159–162 (cit. on pp. 34, 35, 70, 85).

(Imran et al., 2020) M. Imran, F. Ofli, D. Caragea, and A. Torralba. "Using AI and Social Media Multimodal Content for Disaster Response and Management: Opportunities, Challenges, and Future Directions". en. In: *Information Processing & Management* 57.5 (Sept. 2020), p. 102261 (cit. on p. 22).

(2021). "Information System". en. In: *Wikipedia* (July 2021) (cit. on p. 14).

(Jackson, 2006) B. Jackson. "Information Sharing and Emergency Responder Safety Management, Testimony Presented before the House Government Reform Committee on March 30th, 2006". In: *RAND Corporation Testimoney Series* 30 (2006) (cit. on p. 73).

(H. Jiang et al., 2016) H. Jiang, M. Qiang, and P. Lin. "Assessment of Online Public Opinions on Large Infrastructure Projects: A Case Study of the Three Gorges Project in China". English. In: *Environmental Impact Assessment Review* 61 (2016), pp. 38–51 (cit. on pp. 51, 58).

(Jung et al., 2015) H. Jung and K. Chung. "Ontology-Driven Slope Modeling for Disaster Management Service". English. In: *Cluster Computing* 18.2 (2015), pp. 677–692 (cit. on p. 40).

(Kagashe et al., 2017) I. Kagashe, Z. Yan, and I. Suheryani. "Enhancing Seasonal Influenza Surveillance: Topic Analysis of Widely Used Medicinal Drugs Using Twitter Data". English. In: *Journal of Medical Internet Research* 19.9 (2017) (cit. on pp. 52, 58).

(Kalyvas et al., 2014) J. R. Kalyvas and D. Albertson. *A Big Data Primer for Executives*. First. Auerbach Publications, 2014 (cit. on p. 115).

(Kandula et al., 2019) S. Kandula and J. Shaman. "Reappraising the Utility of Google Flu Trends". In: *PLoS computational biology* 15.8 (2019), e1007258 (cit. on p. 111).

(Kaplan et al., 2010) A. M. Kaplan and M. Haenlein. "Users of the World, Unite! The Challenges and Opportunities of Social Media". en. In: *Business Horizons* 53.1 (Jan. 2010), pp. 59–68 (cit. on p. 16).

(Karmen et al., 2015) C. Karmen, R. Hsiung, and T. Wetter. "Screening Internet Forum Participants for Depression Symptoms by Assembling and Enhancing Multiple NLP Methods". English. In: *Computer Methods and Programs in Biomedicine* 120.1 (2015), pp. 27–36 (cit. on p. 58).

(Kaufhold et al., 2020) M.-A. Kaufhold, N. Rupp, C. Reuter, and M. Habdank. "Mitigating Information Overload in Social Media during Conflicts and Crises: Design and Evaluation of a Cross-Platform Alerting System". In: *Behaviour and Information Technology* 39.3 (2020), pp. 319–342 (cit. on p. 47).

(Kawtrakul et al., 2012) A. Kawtrakul, I. Mulasastra, H. Chanlekha, S. Rajbhandari, K. Prathumchai, M. Nagai, and V. Khunthong. "Improving Disaster Responsiveness Using a Mix of Social Media and E-Government". English. In: *KEOD - Proc. Int. Conf. Knowl. Eng. Ontology Dev.* 2012, pp. 423–426 (cit. on p. 46).

(Kemavuthanon et al., 2020) K. Kemavuthanon and O. Uchida. *Classification of Social Media Messages Posted at the Time of Disaster*. English. Ed. by Murayama Y., Velev D., and Zlateva P. Vol. 575 IFIP. Springer, 2020, p. 226 (cit. on p. 46).

(Khzam et al., 2018) N. Khzam and G. Mussbacher. "Domain-Specific Software Language for Crisis Management Systems". English. In: *Proc. - Int. Model-Driven Requir. Eng. Workshop, MoDRE*. Ed. by Moreira A., Mussbacher G., Sanchez P., and Araujo J. Institute of Electrical and Electronics Engineers Inc., 2018, pp. 36–45 (cit. on p. 52).

(Kozlowski et al., 2020) D. Kozlowski, E. Lannelongue, F. Saudemont, F. Benamara, A. Mari, V. Moriceau, and A. Boumadane. "A Three-Level Classification of French Tweets in Ecological Crises". In: *Information Processing & Management* 57.5 (Sept. 2020), p. 102284 (cit. on p. 86).

(Kropczynski et al., 2018) J. Kropczynski, J. Coche, E. Obeysekare, F. Bénaben, R. Grace, S. Halse, A. Montarnal, and A. Tapia. "Identifying Actionable Information on Social Media for Emergency Dispatch". en. In: *Proceedings of the ISCRAM Asia Pacific* (2018), p. 11 (cit. on pp. 62, 68, 71, 72).

(Kropczynski et al., 2019) J. Kropczynski, S. Halse, R. Grace, N. Elrod, D. Caragea, C. Caragea, and A. Tapia. "Refining a Coding Scheme to Identify Actionable Information on Social Media". English. In: *Proceedings of the 16th International Conference on Information Systems for Crisis Response and Management*. Valencia, Spain: Iscram, 2019 (cit. on p. 72).

(Lagadec, 1994) P. Lagadec. "LA GESTION DES CRISES". fr. In: *La gestion des crises : outils de réflexion à l'usage des décideurs* Ediscience international (1994), p. 300 (cit. on pp. 5–7, 9).

(Laney, 2001) D. Laney. "3D Data Management: Controlling Data Volume, Velocity and Variety". In: *META group research note* 6.70 (2001), p. 1 (cit. on p. 115).

(D. Lazer et al., 2015) D. Lazer and R. Kennedy. "What We Can Learn From the Epic Failure of Google Flu Trends". In: *WIRED* (2015) (cit. on p. 111).

(D. M. Lazer et al., 2018) D. M. Lazer, M. A. Baum, Y. Benkler, A. J. Berinsky, K. M. Greenhill, F. Menczer, M. J. Metzger, B. Nyhan, G. Pennycook, D. Rothschild, et al. "The Science of Fake News". In: *Science* 359.6380 (2018), pp. 1094–1096 (cit. on pp. 19, 20).

(Lee et al., 2013) C.-H. Lee, C.-H. Wu, W.-S. Wen, and H.-C. Yang. "Construction of an Event Ontology Model Using a Stream Mining Approach on Social Media". English. In: *Int. Conf. Comput. Their Appl., CATA*. 2013, pp. 249–254 (cit. on p. 46).

(Li et al., 2010) L. Li, D. Wang, C. Shen, and T. Li. "Ontology-Enriched Multi-Document Summarization in Disaster Management". English. In: *SIGIR - Proc.: Annu. Int. ACM SIGIR Conf. Res. Dev. Inf. Retr.* 2010, pp. 819–820 (cit. on p. 40).

(Lin et al., 2015) Y.-P. Lin, D. Deng, W.-C. Lin, R. Lemmens, N. Crossman, K. Henle, and D. Schmeller. "Uncertainty Analysis of Crowd-Sourced and Professionally Collected Field Data Used in Species Distribution Models of Taiwanese Moths". English. In: *Biological Conservation* 181 (2015), pp. 102–110 (cit. on pp. 52, 58).

(Lindell et al., 2010) M. Lindell and C. Prater. "Tsunami Preparedness on the Oregon and Washington Coast: Recommendations for Research". English. In: *Natural Hazards Review* 11.2 (2010), pp. 69–81 (cit. on pp. 44, 45).

(Linot et al., 2018) B. Linot, F. Charoy, J. Dinet, and V. Shalin. "Une Perspective Computationnelle Sur Un Défi (Probable) CRISORSEC". In: *1ère Biennale de La Sécurité Civile : " L'acceptabilité Des Risques : Approches Pluridisciplinaires "*. Ecole nationale supérieure des officiers de sapeurs-pompiers. Aix-en-Provence, France, June 2018 (cit. on p. 68).

(B. Liu et al., 2012) B. Liu and L. Zhang. "A Survey of Opinion Mining and Sentiment Analysis". English. In: *Min. Text Data*. Vol. 9781461432234. Springer US, 2012, pp. 415–463 (cit. on pp. 51, 58).

(J. Liu et al., 2021) J. Liu, T. Singhal, L. T. Blessing, K. L. Wood, and K. H. Lim. "CrisisBERT: A Robust Transformer for Crisis Classification and Contextual Crisis Embedding". In: *Proceedings of the 32nd ACM Conference on Hypertext and Social Media*. HT '21. New York, NY, USA: Association for Computing Machinery, 2021, pp. 133–141 (cit. on p. 90).

(Y. Liu et al., 2019) Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov. "RoBERTa: A Robustly Optimized BERT Pretraining Approach". In: *arXiv:1907.11692 [cs]* (July 2019). arXiv: `1907.11692 [cs]` (cit. on p. 89).

(Luokkala et al., 2014) P. Luokkala and K. Virrantaus. "Developing Information Systems to Support Situational Awareness and Interaction in Time-Pressuring Crisis Situations". en. In: *Safety Science* 63 (Mar. 2014), pp. 191–203 (cit. on p. 12).

(Maaten et al., 2008) L. van der Maaten and G. Hinton. "Visualizing Data Using T-SNE". In: *Journal of Machine Learning Research* 9.Nov (2008), pp. 2579–2605 (cit. on p. 90).

(Madni et al., 2014) A. Madni and M. Sievers. "Systems Integration: Key Perspectives, Experiences, and Challenges". English. In: *Systems Engineering* 17.1 (2014), pp. 37–51 (cit. on p. 40).

(Martinez et al., 2017) B. Martinez, F. Dailey, C. Almario, M. Keller, M. Desai, T. Dupuy, S. Mosadeghi, C. Whitman, K. Lasch, L. Ursos, and B. Spiegel. "Patient Understanding of the Risks and Benefits of Biologic Therapies in Inflammatory Bowel Disease: Insights from a Large-Scale Analysis of Social Media Platforms". English. In: *Inflammatory Bowel Diseases* 23.7 (2017), pp. 1057–1064 (cit. on pp. 52, 58).

(Martínez-Plumed et al., 2021) F. Martínez-Plumed, L. Contreras-Ochando, C. Ferri, J. Hernández-Orallo, M. Kull, N. Lachiche, M. J. Ramírez-Quintana, and P. Flach. "CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories". In: *IEEE Transactions on Knowledge and Data Engineering* 33.8 (2021), pp. 3048–3061 (cit. on p. 107).

(McInnes et al., 2020) L. McInnes, J. Healy, and J. Melville. "UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction". In: *arXiv:1802.03426 [cs, stat]* (Sept. 2020). arXiv: `1802.03426 [cs, stat]` (cit. on p. 90).

(Mehta et al., 2017) A. Mehta, A. Bruns, and J. Newton. "Trust, but Verify: Social Media Models for Disaster Management". In: *Disasters* 41.3 (2017), pp. 549–565 (cit. on p. 47).

(Meier, 2013) P. Meier. "Strengthening Humanitarian Information: The Role of Technology". In: *Chapter 3 of World Disaster Report 2013, International Federation of Red Cross, Red Crescent Societies (ICRC)* (2013) (cit. on p. 12).

(Middleton et al., 2014) S. Middleton, L. Middleton, and S. Modafferi. "Real-Time Crisis Mapping of Natural Disasters Using Social Media". English. In: *IEEE Intelligent Systems* 29.2 (2014), pp. 9–17 (cit. on pp. 34, 35).

(Mikolov et al., 2013) T. Mikolov, I. Sutskever, K. Chen, G. Corrado, and J. Dean. "Distributed Representations of Words and Phrases and Their Compositionality". In: *arXiv:1310.4546 [cs, stat]* (Oct. 2013). arXiv: `1310.4546 [cs, stat]` (cit. on p. 89).

(Milburn, 1972) T. W. Milburn. "The Management of Crisis". eng. In: *International crises: Insights from behavioral research* (1972), pp. 249–277 (cit. on p. 6).

(Milgram, 1967) S. Milgram. "The Small World Problem". In: *Psychology today* 2.1 (1967), pp. 60–67 (cit. on p. 17).

(Miller, 1995) G. A. Miller. "WordNet: A Lexical Database for English". In: *Communications of the ACM* 38.11 (1995), pp. 39–41 (cit. on p. 21).

(Mitroff et al., 1988) I. I. Mitroff, T. C. Pauchant, and P. Shrivastava. "The Structure of Man-Made Organizational Crises: Conceptual and Empirical Issues in the Development of a General Theory of Crisis Management". en. In: *Technological Forecasting and Social Change* 33.2 (Apr. 1988), pp. 83–107 (cit. on p. 6).

(Moi et al., 2016a) M. Moi, T. Friberg, R. Marterer, C. Reuter, T. Ludwig, D. Markham, M. Hewlett, and A. Muddiman. "Strategy for Processing and Analyzing Social Media Data Streams in Emergencies". In: Proceedings of the 2015 2nd International Conference on Information and Communication Technologies for Disaster Management, ICT-DM 2015. 2016, pp. 42–48 (cit. on p. 47).

(Moi et al., 2016b) M. Moi and N. Rodehutskors. "Design of an Ontology for the Use of Social Media in Emergency Management". English. In: *Proc. Int. Conf. ICT, Soc., Hum. Beings , Web Based Commun. Soc. Media , Big Data Anal., Data Min. Comput. Intell. Theory Pract. Mod. Comput. - Part Multi Conf. Comput. Sci. Inf. Syst.* Ed. by Rodrigues L., Abraham A.P., Roth J., and Kommers P. IADIS, 2016, pp. 129–136 (cit. on p. 46).

(Montarnal et al., 2017) A. Montarnal, S. Halse, A. Tapia, S. Truptil, and F. Benaben. *Automated Emergence of a Crisis Situation Model in Crisis Response Based on Tweets*. English. Ed. by Afsarmanesh H., Fornasiero R., and Camarinha-Matos L.M. Vol. 506. Springer New York LLC, 2017, p. 665 (cit. on p. 46).

(Morel et al., 2010) G. Morel and M. Johanna. *Etude de La Prise de Décision Au CTA-CODIS*. Sept. 2010 (cit. on p. 14).

(Murthy, 2018) D. Murthy. *Twitter*. Polity Press Cambridge, 2018 (cit. on p. 19).

(Narayanasamy et al., 2019) S. Narayanasamy, D. Muruganantham, and A. Elçi. "Crisis and Disaster Situations on Social Media Streams: An Ontology-Based Knowledge Harvesting Approach". English. In: *Interdisciplinary Journal of Information, Knowledge, and Management* 14 (2019), pp. 343–366 (cit. on p. 46).

(Nguyen et al., 2017) D. Nguyen, F. Alam, F. Ofli, and M. Imran. "Automatic Image Filtering on Social Networks Using Deep Learning and Perceptual Hashing during Crises". English. In: *Proc. Int. ISCRAM Conf.* Ed. by Benaben F., Lauras M., Comes T., Montarnal A., and Hanachi C. Vol. 2017-May. Information Systems for Crisis Response and Management, ISCRAM, 2017, pp. 499–511 (cit. on pp. 34, 35).

(Nielsen, 2019) L. Nielsen. "Embracing and Integrating Spontaneous Volunteers in Emergency Response – A Climate Related Incident in Denmark". In: *Safety Science* 120 (2019), pp. 897–905 (cit. on p. 47).

(Norri-Sederholm et al., 2017) T. Norri-Sederholm, M. Joensuu, and A.-M. Huhtinen. "Ensuring Information Flow and the Situation Picture in Public Safety Organisations' Situation Centres". In: European Conference on Information Warfare and Security, ECCWS. 2017, pp. 267–273 (cit. on p. 47).

(O'Hara et al., 1999) M. O'Hara, R. Watson, and C. Kavan. "Managing the Three Levels of Change". In: *IS Management* 16 (June 1999), pp. 63–70 (cit. on p. 14).

(O'Reilly, 2007) T. O'Reilly. "What Is Web 2.0: Design Patterns and Business Models for the next Generation of Software". In: *eBusiness & eCommerce* (2007) (cit. on p. 16).

(Odlum et al., 2015) M. Odlum and S. Yoon. "What Can We Learn about the Ebola Outbreak from Tweets?" English. In: *American Journal of Infection Control* 43.6 (2015), pp. 563–571 (cit. on pp. 52, 58).

(Olteanu et al., 2014) A. Olteanu, C. Castillo, F. Diaz, and S. Vieweg. "CrisisLex: A Lexicon for Collecting and Filtering Microblogged Communications in Crises". In: *Eighth International AAAI Conference on Weblogs and Social Media*. May 2014 (cit. on pp. 86, 98).

(Olteanu et al., 2015) A. Olteanu, S. Vieweg, and C. Castillo. "What to Expect When the Unexpected Happens: Social Media Communications Across Crises". In: *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing - CSCW '15*. Vancouver, BC, Canada: ACM Press, 2015, pp. 994–1009 (cit. on pp. 86, 97).

(Oneal et al., 2019) A. Oneal, B. Rodgers, J. Segler, D. Murthy, N. Lakuduva, M. Johnson, and K. Stephens. "Training an Emergency-Response Image Classifier on Signal Data". In: Proceedings - 17th IEEE International Conference on Machine Learning and Applications, ICMLA 2018. 2019, pp. 751–756 (cit. on p. 47).

(Opach et al., 2020) T. Opach, J. K. Rød, B. Munkvold, K. Steen-Tveit, J. Radianti, and L. O. Grottenberg. "Map-Based Interfaces for Common Operational Picture WiP Paper -Geospatial Technologies and Geographic Information Science for Crisis Management (GIS) Map-Based Interfaces for Common Operational Picture". In: May 2020 (cit. on p. 15).

(Oshikawa et al., 2018) R. Oshikawa, J. Qian, and W. Y. Wang. "A Survey on Natural Language Processing for Fake News Detection". In: *arXiv preprint arXiv:1811.00770* (2018). arXiv: 1811.00770 (cit. on p. 20).

(Othman et al., 2014) S. Othman, G. Beydoun, and V. Sugumaran. "Development and Validation of a Disaster Management Metamodel (DMM)". English. In: *Information Processing and Management* 50.2 (2014), pp. 235–271 (cit. on pp. 40, 75, 76, 78, 81).

(PAIR, 2021) PAIR. *People + AI Guidebook*. 2021 (cit. on p. 112).

(Palen et al., 2007) L. Palen and S. B. Liu. "Citizen Communications in Crisis: Anticipating a Future of ICT-Supported Public Participation". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2007, pp. 727–736 (cit. on pp. 19, 22).

(Palen et al., 2020) L. Palen et al. "Crisis Informatics: Human-Centered Research on Tech & Crises". June 2020 (cit. on pp. 16, 22).

(Parker et al., 2011) D. Parker, S. Priest, and S. McCarthy. "Surface Water Flood Warnings Requirements and Potential in England and Wales". English. In: *Applied Geography* 31.3 (2011), pp. 891–900 (cit. on pp. 44, 45).

(Paul et al., 2016) M. Paul, A. Sarker, J. Brownstein, A. Nikfarjam, M. Scotch, K. Smith, and G. Gonzalez. "Social Media Mining for Public Health Monitoring and Surveillance". English. In: *Pac Symp Biocomput* (2016), pp. 468–479 (cit. on pp. 52, 58).

(Pennington et al., 2014) J. Pennington, R. Socher, and C. Manning. "Glove: Global Vectors for Word Representation". In: *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Doha, Qatar: Association for Computational Linguistics, 2014, pp. 1532–1543 (cit. on p. 89).

(Peters et al., 2018) M. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer. "Deep Contextualized Word Representations". In: *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*. New Orleans, Louisiana: Association for Computational Linguistics, 2018, pp. 2227–2237 (cit. on p. 89).

(Piccoli et al., 2019) G. Piccoli and F. Pigni. *Information Systems for Managers: With Cases*. Prospect Press, 2019 (cit. on p. 14).

(Poria et al., 2017) S. Poria, E. Cambria, R. Bajpai, and A. Hussain. "A Review of Affective Computing: From Unimodal Analysis to Multimodal Fusion". English. In: *Information Fusion* 37 (2017), pp. 98–125 (cit. on pp. 52, 58).

(Poslad et al., 2015) S. Poslad, S. Middleton, F. Chaves, R. Tao, O. Necmioglu, and U. Bugel. "A Semantic IoT Early Warning System for Natural Environment Crisis Management". English. In: *IEEE Transactions on Emerging Topics in Computing* 3.2 (2015), pp. 246–257 (cit. on p. 40).

(Purohit et al., 2014) H. Purohit, A. Hampton, S. Bhatt, V. Shalin, A. Sheth, and J. Flach. "Identifying Seekers and Suppliers in Social Media Communities to Support Crisis Coordination". In: *Computer Supported Cooperative Work: CSCW: An International Journal* 23.4-6 (2014), pp. 513–545 (cit. on pp. 40, 46).

(Qiu et al., 2017) L. Qiu, Z. Du, Q. Zhu, and Y. Fan. "An Integrated Flood Management System Based on Linking Environmental Models and Disaster-Related Data". English. In: *Environmental Modelling and Software* 91 (2017), pp. 111–126 (cit. on p. 40).

(Ragini et al., 2018) J. Ragini, P. Anand, and V. Bhaskar. "Big Data Analytics for Disaster Response and Recovery through Sentiment Analysis". English. In: *International Journal of Information Management* 42 (2018), pp. 13–24 (cit. on p. 35).

(Rainer et al., 2021) R. K. Rainer and B. Prince. *Introduction to Information Systems*. Ninth. John Wiley & Sons, 2021 (cit. on p. 114).

(Ravi et al., 2015) K. Ravi and V. Ravi. "A Survey on Opinion Mining and Sentiment Analysis: Tasks, Approaches and Applications". English. In: *Knowledge-Based Systems* 89 (2015), pp. 14–46 (cit. on pp. 51, 58).

(Rosenthal, 1986) U. Rosenthal. "Crisis Decision-Making in the Netherlands". In: *Crisis Decision-Making in the Netherlands* 22.2 (1986), pp. 103–129 (cit. on pp. 5–7).

(Rudra et al., 2016) K. Rudra, S. Banerjee, N. Ganguly, P. Goyal, M. Imran, and P. Mitra. "Summarizing Situational Tweets in Crisis Scenario". In: *Proceedings of the 27th ACM Conference on Hypertext and Social Media*. 2016, pp. 137–147 (cit. on p. 85).

(Sailunaz et al., 2018) K. Sailunaz, M. Dhaliwal, J. Rokne, and R. Alhajj. "Emotion Detection from Text and Speech: A Survey". English. In: *Social Network Analysis and Mining* 8.1 (2018) (cit. on pp. 52, 58).

(Salloum et al., 2017) S. Salloum, M. Al-Emran, A. Monem, and K. Shaalan. "A Survey of Text Mining in Social Media: Facebook and Twitter Perspectives". English. In: *Advances in Science, Technology and Engineering Systems* 2.1 (2017), pp. 127–133 (cit. on pp. 52, 58).

(Sambasivan et al., 2021) N. Sambasivan, S. Kapania, H. Highfill, D. Akrong, P. Paritosh, and L. M. Aroyo. ""Everyone Wants to Do the Model Work, Not the Data Work": Data Cascades in High-Stakes AI". In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 2021, pp. 1–15 (cit. on p. 111).

(Santillana et al., 2015) M. Santillana, A. Nguyen, M. Dredze, M. Paul, E. Nsoesie, and J. Brownstein. "Combining Search, Social Media, and Traditional Data Sources to Improve Influenza Surveillance". English. In: *PLoS Computational Biology* 11.10 (2015) (cit. on pp. 52, 58).

(Schulz et al., 2012) A. Schulz, H. Paulheim, and F. Probst. "Crisis Information Management in the Web 3.0 Age". English. In: *ISCRAM Conf. Proc. - Int. Conf. Inf. Syst. Crisis Response Manage.* Simon Fraser University, 2012 (cit. on pp. 34, 35).

(Sell et al., 2020) T. K. Sell, D. Hosangadi, and M. Trotochaud. "Misinformation and the US Ebola Communication Crisis: Analyzing the Veracity and Content of Social Media Messages Related to a Fear-Inducing Infectious Disease Outbreak". English. In: *BMC Public Health* 20.1 (Dec. 2020), pp. 1–10 (cit. on p. 20).

(Senate, 2017) U. Senate. *Extremist Content and Russian Disinformation Online: Working with Tech to Find Solutions*. 2017 (cit. on p. 19).

(Shah et al., 2019) S. Shah, D. Seker, M. Rathore, S. Hameed, S. Ben Yahia, and D. Draheim. "Towards Disaster Resilient Smart Cities: Can Internet of Things and Big Data Analytics Be the Game Changers?" English. In: *IEEE Access* 7 (2019), pp. 91885–91903 (cit. on p. 35).

(Smith et al., 2018) W. Smith, K. Stephens, B. Robertson, J. Li, and D. Murthy. "Social Media in Citizen-Led Disaster Response: Rescuer Roles, Coordination Challenges, and Untapped Potential". In: vol. 2018-May. Proceedings of the International ISCRAM Conference. 2018, pp. 639–648 (cit. on p. 47).

(Starbird, 2017) K. Starbird. "Examining the Alternative Media Ecosystem through the Production of Alternative Narratives of Mass Shooting Events on Twitter". In: *Proceedings of the International AAAI Conference on Web and Social Media.* Vol. 11. 2017 (cit. on p. 20).

(Steen-Tveit et al., 2021) K. Steen-Tveit and B. Munkvold. "From Common Operational Picture to Common Situational Understanding: An Analysis Based on Practitioner Perspectives". In: *Safety Science* 142 (Oct. 2021), p. 105381 (cit. on p. 61).

(Strickland, 2019) E. Strickland. "IBM Watson, Heal Thyself: How IBM Overpromised and Underdelivered on AI Health Care". In: *IEEE Spectrum* 56.4 (2019), pp. 24–31 (cit. on p. 111).

(A. Tapia et al., 2013) A. Tapia, K. Moore, and N. Johnson. "Beyond the Trustworthy Tweet: A Deeper Understanding of Microblogged Data Use by Disaster Response and Humanitarian Relief Organizations". English. In: *ISCRAM Conf. Proc. - Int. Conf. Inf. Syst. Crisis Response Manage.* Karlsruher Institut fur Technologie (KIT), 2013, pp. 770–779 (cit. on pp. 45, 47).

(A. H. Tapia et al., 2011) A. H. Tapia, K. Bajpai, B. J. Jansen, J. Yen, and L. Giles. "Seeking the Trustworthy Tweet: Can Microblogged Data Fit the Information Needs of Disaster Response and Humanitarian Relief Organizations." In: *ISCRAM.* 2011 (cit. on p. 19).

(A. H. Tapia et al., 2016) A. H. Tapia, N. A. Giacobe, P. J. Soule, and N. J. LaLone. "Scaling 911 Texting for Large-Scale Disasters: Developing Practical Technical Innovations for Emergency Management at Public Universities". In: *International Journal of Public Administration in the Digital Age (IJPADA)* 3.3 (2016), pp. 73–85 (cit. on p. 110).

(A. H. Tapia et al., 2014) A. H. Tapia and K. Moore. "Good Enough Is Good Enough: Overcoming Disaster Response Organizations' Slow Social Media Data Adoption". In: *Computer supported cooperative work (CSCW)* 23.4-6 (2014), pp. 483–512 (cit. on pp. 20, 47).

(Tjong Kim Sang et al., 2003) E. F. Tjong Kim Sang and F. De Meulder. "Introduction to the CoNLL-2003 Shared Task: Language-Independent Named Entity Recognition". In: *Proceedings of the Seventh Conference on Natural Language Learning at HLT-NAACL 2003.* 2003, pp. 142–147 (cit. on p. 100).

(Tkachenko et al., 2020) M. Tkachenko, M. Malyuk, N. Shevchenko, A. Holmanyuk, and N. Liubimov. *Label Studio: Data Labeling Software.* 2020 (cit. on p. 98).

(Treveil et al., 2020) M. Treveil, N. Omont, C. Stenac, K. Lefevre, D. Phan, J. Zentici, A. Lavoillotte, M. Miyazaki, and L. Heidmann. *Introducing MLOps.* "O'Reilly Media, Inc.", 2020 (cit. on p. 113).

(U.S. Department of Homeland Security, 2014) U.S. Department of Homeland Security. *National Incident Management System: Communications and Information Management.* 2014 (cit. on p. 15).

(UN Department of Humanitarian Affairs, 1992) UN Department of Humanitarian Affairs. *Internationally Agreed Glossary of Basic Terms Related to Disaster Management.* 1992 (cit. on p. 8).

(Van de Walle et al., 2016) B. Van de Walle, B. Brugghemans, and T. Comes. "Improving Situation Awareness in Crisis Response Teams: An Experimental Analysis of Enriched Information and Centralized Coordination". en. In: *International Journal of Human-Computer Studies* 95 (Nov. 2016), pp. 66–79 (cit. on p. 12).

(Van Gorp et al., 2015) A. Van Gorp, N. Pogrebnyakov, and E. Maldonado. "Just Keep Tweeting: Emergency Responders' Social Media Use before and during Emergencies". In: vol. 2015-May. 23rd European Conference on Information Systems, ECIS 2015. 2015 (cit. on p. 47).

(Vázquez et al., 2014) S. Vázquez, T. Muñoz-García, I. Campanella, M. Poch, B. Fisas, N. Bel, and G. Andreu. "A Classification of User-Generated Content into Consumer Decision Journey Stages". English. In: *Neural Networks* 58 (2014), pp. 68–81 (cit. on pp. 52, 58).

(Verma et al., 2011) S. Verma, S. Vieweg, W. J. Corvey, L. Palen, J. H. Martin, M. Palmer, A. Schram, and K. M. Anderson. "Natural Language Processing to the Rescue? Extracting "Situational Awareness" Tweets During Mass Emergency". en. In: *Fifth International AAAI Conference on Weblogs and Social Media*. July 2011 (cit. on pp. 22, 70).

(S. Vieweg et al., 2010) S. Vieweg, A. L. Hughes, K. Starbird, and L. Palen. "Microblogging during Two Natural Hazards Events: What Twitter May Contribute to Situational Awareness". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2010, pp. 1079–1088 (cit. on p. 22).

(S. E. Vieweg, 2012) S. E. Vieweg. *Situational Awareness in Mass Emergency: A Behavioral and Linguistic Analysis of Microblogged Communications*. en. ProQuest LLC, 2012 (cit. on p. 70).

(Vosoughi et al., 2017) S. Vosoughi, M. 'N. Mohsenvand, and D. Roy. "Rumor Gauge: Predicting the Veracity of Rumors on Twitter". In: *ACM Trans. Knowl. Discov. Data* 11.4 (July 2017) (cit. on p. 19).

(Vosoughi et al., 2018) S. Vosoughi, D. Roy, and S. Aral. "The Spread of True and False News Online". In: *Science* 359.6380 (2018), pp. 1146–1151 (cit. on p. 20).

(S. Wang et al., 2015) S. Wang, M. Paul, and M. Dredze. "Social Media as a Sensor of Air Quality and Public Response in China". English. In: *Journal of Medical Internet Research* 17.3 (2015) (cit. on pp. 52, 58).

(Watts et al., 1998) D. J. Watts and S. H. Strogatz. "Collective Dynamics of 'Small-World' Networks". en. In: *Nature* 393.6684 (June 1998), pp. 440–442 (cit. on pp. 17, 18).

(Weick, 1995) K. E. Weick. *Sensemaking in Organizations*. Vol. 3. Sage, 1995 (cit. on p. 125).

(Wu et al., 2018) Y. Wu, Z. Chen, G. Sun, X. Xie, N. Cao, S. Liu, and W. Cui. "StreamExplorer: A Multi-Stage System for Visually Exploring Events in Social Streams". English. In: *IEEE Transactions on Visualization and Computer Graphics* 24.10 (2018), pp. 2758–2772 (cit. on p. 35).

(Xu et al., 2014) J. Xu, T. Nyerges, and G. Nie. "Modeling and Representation for Earthquake Emergency Response Knowledge: Perspective for Working with Geo-Ontology". English. In: *International Journal of Geographical Information Science* 28.1 (2014), pp. 185–205 (cit. on p. 40).

(Xukun et al., 2020) L. Xukun and D. Caragea. "Improving Disaster-Related Tweet Classification with a Multimodal Approach". In: *ISCRAM 2020 Conference Proceedings–17th International Conference on Information Systems for Crisis Response and Management*. 2020 (cit. on p. 98).

(Yadav et al., 2020) A. Yadav and D. Vishwakarma. "Sentiment Analysis Using Deep Learning Architectures: A Review". English. In: *Artificial Intelligence Review* 53.6 (2020), pp. 4335–4385 (cit. on pp. 51, 58).

(Yang et al., 2012) L. Yang, G. Su, and H. Yuan. "Design Principles of Integrated Information Platform for Emergency Responses: The Case of 2008 Beijing Olympic Games". English. In: *Information Systems Research* 23.3 PART 1 (2012), pp. 761–786 (cit. on pp. 45, 71, 74).

(Yazdavar et al., 2017) A. Yazdavar, H. Al-Olimat, M. Ebrahimi, G. Bajaj, T. Banerjee, K. Thirunarayan, J. Pathak, and A. Sheth. "Semi-Supervised Approach to Monitoring Clinical Depressive Symptoms in Social Media". English. In: *Proc. IEEE/ACM Int. Conf. Adv. Soc. Netw. Anal. Min., ASONAM.* Ed. by Diesner J., Ferrari E., and Xu G. Association for Computing Machinery, Inc, 2017, pp. 1191–1198 (cit. on pp. 52, 58).

(Zade et al., 2018) H. Zade, K. Shah, V. Rangarajan, P. Kshirsagar, M. Imran, and K. Starbird. "From Situational Awareness to Actionability: Towards Improving the Utility of Social Media Data for Crisis Response". In: *Proceedings of the ACM on Human-Computer Interaction* 2.CSCW (Nov. 2018), 195:1–195:18 (cit. on p. 71).

(Zahra et al., 2020) K. Zahra, M. Imran, and F. O. Ostermann. "Automatic Identification of Eyewitness Messages on Twitter during Disasters". In: *Information Processing & Management* 57.1 (Jan. 2020), p. 102107 (cit. on pp. 85, 98).

(Zavarella et al., 2014) V. Zavarella, H. Tanev, R. Steinberger, and E. Vander Goot. "An Ontology-Based Approach to Social Media Mining for Crisis Management". English. In: *CEUR Workshop Proc.* Ed. by Alani H., Nissim M., Lanfranchi V., Gangemi A., Recupero D.R., Kauppinen T., and Cambria E. Vol. 1329. CEUR-WS, 2014, pp. 55–66 (cit. on p. 46).

(Zhu et al., 2002) X. Zhu and Z. Ghahramani. *Learning from Labeled and Unlabeled Data with Label Propagation.* Technical Report CMU-CALD-02-107. Carnegie Mellon University, 2002 (cit. on p. 93).

(Zwass, n.d.) V. Zwass. *Information System | Definition, Examples, & Facts.* en. https://www.britannica.com/topic/in
system (cit. on p. 14).

Contents

Résumé

Conception d'un système de traitement des médias sociaux en réponse de crise : extraction, gestion et distribution des informations pertinentes pour les décideurs.

Nos sociétés ont toujours été ponctuées de situations de crises, mais la complexité croissante de ces événements exige une amélioration constante des méthodologies et des outils employés lors de la réponse. L'établissement d'une conscience de la situation commune à tous les acteurs impliqués est l'une de ces améliorations potentielles. Cependant, cette axe d'amélioration souffre de difficultés liées au manque de ressources à allouer à cette tâche. L'automatisation d'une partie des tâches pour supporter le personnel en charge de cet aspect, est donc une opportunité de recherche. Cette opportunité est également favorisée par le développement des médias sociaux en tant que sources de données massives. Simultanément, le domaine de l'intelligence artificielle a été radicalement modifié par le développement de nouveaux outils et de nouvelles méthodes, permettant la recherche d'informations complexes au sein de données textuelles. À la croisée de ces trois opportunités conjugués, cette thèse explore la question suivante : Comment concevoir un système d'information capable de gérer et de fournir automatiquement des informations pertinentes extraites des données des médias sociaux ?

Une approche en trois temps est proposée. Premièrement, il s'agit de comprendre quelles sont les informations pertinentes lors de la phase de réponse à une crise pour les preneurs de décision. Deuxièmement, une fois les informations pertinentes identifiées, un nouveau module d'intelligence artificielle dédié extrait les éléments pertinents à partir des données disponibles sur les médias sociaux. Ces informations sont alors intégrées dans un modèle de situation de crise, permettant de les organiser automatiquement avec le reste du contexte. La troisième et dernière partie discute de l'organisation des données et des informations au sein d'un système d'aide à la décision pour la gestion de crise. Cette discussion s'intèresse particulièrement à la question de la bonne gestion et de la distribution de ces informations auprès des décideurs. Cette recherche a été menée dans un contexte international : le projet français ANR MACIV, une collaboration entre IMT Mines Albi et Penn State University et en relation étroite avec des praticiens français et américains.

Mots-clés : Gestion de crise, Apprentissage Machine, Traitement Automatique du Langage, Connaissance de la Situation, Système d'information

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Abstract

Design of a social media processing system for crisis response: extraction, management and delivery of relevant information for decision makers

Our societies have always been punctuated by crises, but the increasing complexity of these events requires a constant improvement of the methodologies and tools used in the response. Establishing a common situational awareness among all actors involved is one of these potential improvements. However, challenges arise due to the lack of available resources to allocate to this task during crisis response. The automation of certain tasks to support teams' dedicated actionable information collection, therefore, represents a research opportunity. This opportunity is also enabled by the expansion of social media as big data sources. At the same time, the field of artificial intelligence has been radically changed by the development of new tools and methods, allowing the retrieval of complex information within textual data. At the crossroads of these three opportunities, this dissertation explores the following question: How to design an information system capable of managing and automatically providing relevant information extracted from social media data?

A threefold approach is proposed. The first part aims at understanding what information is relevant in the crisis response phase for decision-makers Second, once the relevant information is identified, a new, dedicated artificial intelligence module extracts the relevant elements from the data available on social media. This information is then integrated into a crisis model, allowing to automatically pair it with associated information available in the context. The third and last part discusses the organization of data and information within a decision support system for crisis management. This discussion is particularly interested in designing a system that can achieve proper management and distribution of information to decision-makers. This research was conducted in an interdisciplinary context: the French ANR MACIV project, a collaboration between IMT Mines Albi and Penn State University and in close relationship with French and American practitioners.

Keywords: Crisis Management, Machine Learning, Natural Language Processing, Situation Awareness, Information System