To alert or not to alert? That is the question

Maude Arru
Paris-Dauphine University
PSL Research Universities
CNRS, LAMSADE
75016 Paris, France
maude.arru@dauphine.fr

Elsa Negre
Paris-Dauphine University
PSL Research Universities
CNRS, LAMSADE
75016 Paris, France
elsa.negre@dauphine.fr

Camille Rosenthal-Sabroux
Paris-Dauphine University
PSL Research Universities
CNRS, LAMSADE
75016 Paris, France
camille.rosenthal-sabroux@dauphine.fr

Abstract

Most of crises, environmental, humanitarian, economic or even social, occur after different presaging signals that permit to trigger warnings. These warnings can help to prevent damages and harm if they are issued timely and provide information that helps responders and population to adequately prepare for the disaster to come. Today, there are many systems based on Information and Communication Technologies that are designed to recognize foreboding signals of crises to limit their consequences. Warning system are part of them, they have proved to be effective, but as for all systems including human beings, a part of unpredictable remains. In this article, we provide a method of data analysis that allows decision makers in crisis cells to have answer elements to the question of alerting or not populations in a given geographical area. This method is based on a selection of factors that influence population behaviors, for which we establish a list of relevant indicators that can be informed in the preliminary phase of a crisis into warning systems. From these indicators, we propose a tool for decision support (based on a decision tree as a possible representation).

1. Introduction

The insertion in computer systems of cognitive elements and simulation of realistic human behaviors to reproduce or predict events or actions is a challenge for developers. Understanding human behavior so that it can be integrated into computerized systems is still a challenge, requiring the interconnection of heterogeneous elements that can be physiological, psychological, social or environmental. Today, thanks to advances in data management, it is faster and more efficient to manage real time data, make maps from geolocalized data or make assessments based on scenarios that integrate data from different sources. These evolutions enabled to improve crisis management systems, developed to support those who respond to disasters. Indeed, a lot of important decisions have to be taken before and during crises. They are based on objective data and information but are also determined by subjective elements such as cognitive biases that can limit the effectiveness of the response. A manner to limit the effect of cognitive biases is to improve the completeness of information in crisis management systems. Crisis management systems help in particular to predict as precisely and as soon as possible the consequences of a crisis and its evolution in a given territory. They allow to take into account more and more complex information. Indeed, crisis management systems integrate data from different sources and natures to predict as finely as possible and in advance the emergence, the flow of a crisis and its consequences on a given territory. Despite knowledge and technologies developed in order to minimize or avoid disastrous consequences that a crisis can produce, crises remain, partly, determined by uncertain phenomena, which are not always considered in these crisis management systems. The vulnerability of territories, the need for coordination among services, and the probable behaviors of populations-in-danger, for example, are sometimes neglected [1].

Before and after a crisis, people act according to their own knowledge and interpretation schemes. These schemes do not always allow people to react in an appropriate way to risky situations and can lead to dangerous reactions [2]. ICTs are a key element in these warning systems, they help to guide the behavior of individuals when a crisis is announced by

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providing them knowledge before the crisis, and by guiding them in the interpretation of the signals perceived during the crisis. Several actors gravitate around these warning systems with different roles. The main actors are the crisis management specialists and experts who build models and help fueling the warning system, the decision-makers who act for the resolution of crisis, the actors of the field who apply the decisions taken in the crisis cell and finally the populations. This article will only focus on the last category of actors, the populations, by offering an analysis based on their behavior during a crisis. Taking into account the laws and phenomena governing behavior in crisis situation seems to us an important axis of research and reflection on the improvement of the alert/warning diffusion, the crisis communication and on the development of policies of education and targeted outreach. Indeed, many recommendations advocate referring warning systems to more human-centered aspects, mainly through the participation of populations in decision-making processes [3]. It seems to us complementary to this approach to integrate these human-centered aspects in the knowledge of the risk and in the sensitization made through the knowledge of its behaviors.

Thus, in order to improve the adaptation of warning systems to the populations concerned, we propose in this article a method to help decision-makers (often in a crisis cell) to determine whether or not they should alert people according to their likely behaviors. Warning populations can help to cope with a crisis by protecting the populations, but it can also constitute a threat and have more harmful effects than those of the crisis. On November 13, 2015, during the attacks in Paris, the President of the Republic decided not to evacuate the *Stade de France* for example, to avoid crowd movements with new dangerous consequences.

At first, we define here the main concepts related to our proposal, via a state of the art. We then propose our decision support process to determine whether populations need to be alerted to their likely behaviors. We then apply our approach to real cases in order to validate its feasibility. Finally we conclude and give some research perspectives.

2. Related works

The reactions of the populations have a major impact on the resolution of a crisis. One of the challenges of early warning systems is to take into account the natural reactions of the people affected by the crisis to make them evolving upstream of the crisis, to anticipate them, and to correct them if necessary during and after the crisis.

2.1. Early warning systems

Natural disasters are a constant cause of human suffering and economic loss around the world. Climate change and rapid urbanization only aggravate the problem. For upstream contingency plans to be as effective as possible, it is vital to have an early warning system. Early-warning is the provision of timely and effective information that allows organizations and individuals to take action to avoid or reduce their risk and prepare for effective response [4]. It should be noted that an early warning system is specific to a type of environment but also to the environment for which it has been set up (geographical area, political decisions, etc.). Therefore, there are no two identical systems.

A complete and effective EWS comprises four elements [3]:

- Risk knowledge: knowledge of the relevant hazard and vulnerability;
- Monitoring and warning service: technical capacities to constantly monitor hazard precursors, prediction of potential risks and warning issue;
- Dissemination and communication: dissemination of understandable warnings with prior preparedness information;
- Response capability: knowledge of risks, warning services plans and appropriate actions for persons at risk.

In this sequential list, each element has two direct links and interactions with each of the other elements. Failure of any part of the system will imply failure of the whole system. Human factor in particular plays a significant and transversal role in all steps [5, 6].

We consider in this paper, according to [7], that an early warning system is a "Chain of information communication systems comprising sensor, detection, decision, and broker-subsystems, in the given order, working in conjunction, forecasting and signaling disturbances adversely acting the stability of the physical world; and giving sufficient time for the response system to prepare resources and response actions to minimize the impact on the stability of the physical world".

Thus, an early warning system is a set of tools for predicting hazards [8, 9]. Understanding and responding adequately to early warning signals before they manifest themselves and turn into acute needs is in many cases more effective than responding only after the disaster has occurred. Ideally, early warning signals should trigger appropriate actions to alert the population of the danger. Alerts and decisions to evacuate the population; deploy disaster relief teams in a city/region; or pre-position goods, are the interface between preparation and response. The sooner an alert is issued, the more time it takes to trigger these actions. However, the information on the danger is often not very precise in the preliminary phase of a crisis, it becomes more and more precise only as the time passes (likewise, the threat becomes more and more concrete). Before deciding on the actions to be taken, the decision-makers seek to obtain the most precise information possible on the event, what are the possible actions and the necessary resources.

In addition to this information, we propose to integrate the characteristics of the population that can have an impact on their reactions to the alert and to the crisis itself.

2.2. Population and Behaviors

The behavior concept needs to be clarified and well defined, since it can be approached very differently in the scientific sphere. Some speak of "nomadic" concept that can take several meanings according to the disciplines [10]. In philosophy, for example, definitions rest on the notions of conscience and experiences [11], although in cognitive sciences it can be approached as a logical suite of actions [12]. The most important works on the subject are provided by human sciences, notably in ethology and in psychology domains [13, 14]. In this paper we take up the definition of [15] for whom the behavior corresponds to the "reactions of a person, considered in a milieu and in a given time unit to an excitation or a set of stimulation". Human behavior is also integrated in artificial intelligence research whose idea is to transport knowledge elements in a virtual reality and to provide reasoning for the treatment of these elements. Applications of artificial intelligence, for example, enable virtual agents to make strategic choices. We find these kinds of research in domains such as automatic production of explanations or solving mathematical problems [16], but it is still difficult today to integrate cognitive dimensions of behaviors to these computer science representations.

Individual behaviors in crisis situations do not correspond to everyday life behaviors. It is difficult to represent these behaviors from the information that has been obtained after a crisis, as this information is always static, punctual and contextual. This causes difficulties to integrate the great diversity of human reactions that can appear in crisis situations. We can however work to establish tendencies, or correlations on factors that orient particular behaviors.

This information nevertheless makes it possible to cite some types of behavior frequently observed in crisis situations [17]: evacuation, flight; panic escape; stupidity, stupefaction; immobility; confinement, sheltering; fight against the effects of the disaster; search for relatives; assistance, emergency relief; so-called "antisocial" behavior; curiosity; return to the place of residence, of work.

There are three types of behaviors: (i) reflex or instinctive behaviors that allow rapid action through struggle, stun or flight, (ii) panic behaviors, emerging crowd phenomena via imitation mechanisms or contagion and (iii) controlled behaviors that are reasoned reactions [18].

It is important to take into account a maximum of elements to study the behaviors in crisis situation; two events which seem similar can bring very different reactions. Between the tsunami that occurred in Fukushima on March 11, 2011 and the one that occurred five years later, on November 22, 2016, the reactions of the authorities and the inhabitants evolved in a very significant way. In 2016, the Prime Minister ordered the government to warn the public with accurate and reliable information on evacuation procedures and calls to evacuate were much more numerous. Reactions in general were greatly influenced by the lived experience five years ago. Emotions such as fear or surprise can also have a strong influence on crowd movements, as it was the case after the football match on June 3, 2017 in Turin following a bomb attack rumor.

2.3. Decision support in crisis management

In France, protection against accidents and disasters is a function of the State. This role is provided by the civil safety teams, which rests on different specialist services who act for civil safety, firefighters, military units of training and intervention, pilots of aircraft and helicopters as well as mine-clearing experts. Their roles are directed by the Direction Générale de la Sécurité Civile et de la Gestion des Crises (General Direction of the Civil Safety and of the Crisis Management) under the direction of the Ministry of the Interior. They define particularly the missions of evaluation, preparation, coordination and application of protection, the information and warning systems for populations, the prevention of civil risks of all types, and the planning of civil security measures. This organization rests on the 101 prefectures present on the French territory.

2.3.1. The decision in a crisis cell

The urgency of a crisis situation requires that decisions leading to its resolution be quick and effective [19]. In a crisis cell, decisions are conditioned by high uncertainties, a high number of stakeholders, extremely short or relatively long durations, communication problems, and important issues far beyond the immediate operational aspects [20]. Whether or not they are part of safeguarding plans, many decisions need to be made. These decisions are generally made collectively and focus on the choice of the actions to be carried out and the resources allocated to these actions. Decisions are made by a multiplicity of stakeholders, which can create difficulties in finding common ground for all stakeholders. Decisions do not always make consensus. Thus, tools to help making decisions are needed.

2.3.2. Tools available to decision-makers

The simplest tools are often the most used in crisis management. They are used for different purposes during the prodromal phase of a crisis, for prospective analysis activities by analyzing the multi-domain consequences following different assumptions, situation analysis and planning activities.

Decision-makers have at their disposal descriptive models (Tables, Geographical Information Systems, Ontologies …) and models of decision support.

There are many specific models dedicated to decision support for a type of crisis in a given territory, but few generic models have been proposed in the literature, but we should mention: Avoidance model [21], Generic model of Nioche [22], Sayech Model [23], and Meta-ontology of the ISyCri project [24]. On the other hand, there are decision support models that are not specific to crisis management, such as (multicriteria) decision support models, recommender systems or predictive models derived from Machine Learning. The latter two require large volumes of data to learn the model and verify its applicability. In crisis management, such a volume of data relating to many "similar" crises is currently non-existent. We have therefore turned to decision support models that have the ability to work with small datasets and, in addition, allow for some explanations of the proposed decisions.

Finally, to make information accessible to decision-makers who are not computer scientists but who make decisions with major issues, a possibility is to use decision trees [25] that have the specificity of representing a set of choices, in the graphic form of a tree. The different possible decisions are located at the ends of the branches (the "leaves" of the tree), and are reached according to decisions made at each stage. The decision tree is a tool used in various fields such as security, data mining, medicine, etc. It has the advantage of being easy to read and quick to execute [25].

3. Our decision support process

Many factors can influence the decision to alert people about the threat of a future crisis. We can cite the level of risk, the warning devices or the material and human resources that can be deployed in the area, but also factors that are more difficult to anticipate, such as the behaviors of the populations: the way the populations respond to the alert can have a positive or negative impact on the consequences of the crisis. The decision to alert, itself, can have an influence on major issues, particularly the economic stake with the shutdown of the activity at the time of the alert, and the political stake: alert may have impacts on people's perception of their level of security or of the authorities' ability to protect them.

The decision to alert or not the populations is generally taken by a group of decision-makers present in the crisis cell; it is based on information elements which were collected on the nature of the crisis (potential or certain), on its potential impacts, and the human appreciation based on the experience of those present. It is therefore based on both objective and subjective elements, but it has been shown that the decisions made by the decision-makers, whether in the pre-crisis phase (latency phase), during the response period or during the post-crisis phase are subject to cognitive biases that may influence them in a way that is contrary to rationality and effectiveness of the response to the various issues of these three phases [26]. It is therefore important to offer decision-makers assistance in their analysis of the situation. We propose our process of decision support to alert or not the populations, according to the behaviors that may be observed in response to the alert.

We present our contribution through the creation of a process for the construction of a decision support tool. This approach aims to help decision-makers in the prodromal phase of a crisis to identify the

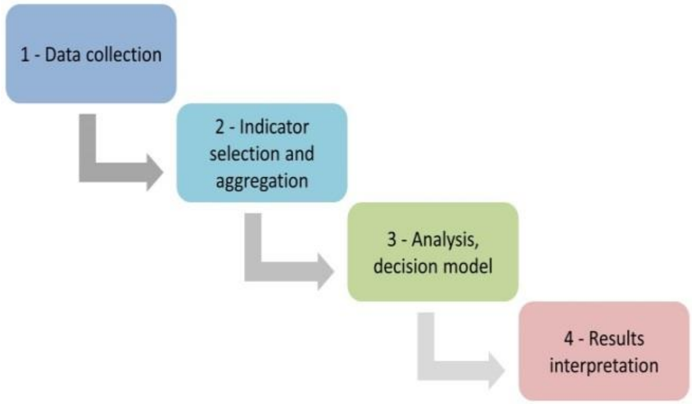

Figure 1: Our decision support process

warning zones and the means to implement, as well as the information to be disseminated. It is based on explicit knowledge, relating to the behavior of populations in case of alert or crisis. We therefore propose an approach for the design of a structured decision support tool in four steps: (1) Data collection from heterogeneous sources, (2) indicators selection and aggregation, (3) analysis based on a decision-making model and (4) results interpretation (Figure 1).

The aim is to provide a systemic view of the behavior of populations in crisis, to provide an indication of the likely behavior of a population in response to an alert for a crisis announced in a given city.

The first step in the process is to build a knowledge base on past crises. This database will be a collection of data from heterogeneous sources obtained from research on social networks, field surveys based on questionnaires, vulnerability studies, weak signal sensors or individual and collective motion sensors, and search on the web. The data collected correspond, among others, to the behavioral factors as well as to the actual behavior of the populations during the crisis.

From the data collected in the first step, we determine a second step of indicator selection and aggregation to obtain a new set of indicators that are as independent as possible from each other. The selection is obtained from interviews with experts and decision-makers or from algorithms.

The third step is to use this new set of indicators to analyze data on population behavior factors to determine actual behaviors for a given crisis. We choose to use algorithms to generate decision rules to perform this analysis, as this type of model allows an easily understandable reading of the results for the decision-maker. One possible representation, among others, would be a decision tree.

Finally, the last step is for the decision-maker to interpret the results to make a decision, identify any inconsistencies or erroneous rules based on examples of situations.

4. Applications to real cases

In this section, we apply our decision support process to real cases.

Step 1: (Heterogeneous) data collection

The case studies were selected from the accidents listed in the ARIA database (analysis, research and information on accidents) which lists more than 46000 accidents occurred mainly in France but also abroad. The accidents involved are the result of industrial activities, the transport of hazardous materials, the distribution and use of gas, pressure equipment, underground mines and storage facilities, and dikes and dams. This database is developed by the Ministry of Ecological and Solidarity Transition. It is available free of charge on the website www.aria.developpement-durable.gouv.fr. The 9 case studies that we selected stem from events that occurred in France between 1981 and 2013 and had human and social consequences of 5 or 6 on the European scale of accidents, ranging from 0 to 6. This scale created in 1994 for the application of the SEVESO directive (on the control of major-accident hazards involving dangerous substances) is based on 18 technical parameters intended to characterize the

Table 1: Population behavior factors and indicators

KNOWLEDGE	INFORMATION		DATA							
Behaviors	Factors linked to individual	Civil status	F1a	F1b	F1c	F1d	F1e	F1f		
		Personality	F2a	F2b	F2c	F2d	F2e	F2f		
		Motivation to escape/defend	F3							
		Responsibility	F4							
		Emotions	F5a	F5b	F5c	F5d	F5e	F5f	F5g	
		Experience	F6a	F6b	F6c					
		Explicit knowledge	F7a	F7b	F7c	F7d				
		Risk assessment	F8a	F8b						
		Perception of the alert system	F9							
		Current action	F10a	F10b	F10c					
		Physiological signals	F11a	F11b	F11c	F11d				
	Factors linked to the environment	Geographic zone characteristics	F12a	F12b	F12c	F12d	F12e	F12f	F12g	F12h
		Interaction capacity	F13a	F13b	F13c					
		Perceptible signals of the crisis	F14a	F14b	F14c					
		Period characteristics	F15a	F15b						
		Temporal phase of the crisis	F16a	F16b	F16c	F16d	F16e			
		Alerts / Transmitted information	F17a	F17b	F17c					
		Entourage characteristics	F18a	F18b	F18c	F18d				
		Behaviors of the closer people	F19a	F19b	F19c					
		Entourage global behavior	F20							

effects or consequences of accidents. Each of these parameters has 6 levels. In France, the European scale is represented according to 4 indices including human and social consequences which take for example the total number of deaths, wounded with hospitalization superior to 24h, residents evacuated or confined to their homes, deprived of potable water…

We have collected some data in the ARIA database. The rest of the data has been obtained from various databases made available on institutional sites and from newspaper archives:

- www.georisques.gouv.fr for the existence of risk prevention plans;
- carto.observatoire-des-territoires.gouv.fr for demographic indicators ;
- www.insee.fr for nationality data;
- www.meteofrance.com for meteorological data;
- Local and national newspapers: www.nouvelobs.com, www.ladepeche.fr, www.lemonde.fr...

Step 2: Indicator selection and aggregation

In [27] we proposed different factors and indicators that allow us to integrate knowledge about the behavior of populations into warning systems.

These 20 factors and 74 indicators are intended, through their analysis, to shed light on decisions that may affect populations.

These different factors are presented separately from one to another, in Table 1, but it is important to note the strong dependency between some indicators that compose them and between the factors themselves.

In the remainder of this study, we limit ourselves to the indicators that were readily available in the data sources at our disposal, namely, age, sex, population density, and time of day. Due to the low number of accessible indicators, we do not aggregate them.

Step 3: Analysis and Decision model

With the aim of providing a systemic view of the behavior of populations in crisis situations (which can be useful for improving risk knowledge, the selection of relevant indicators to be monitored during the prodromal phase of a crisis, the issuance of alerts and awareness of populations), we propose a (static) process, based on decision tree. Indeed, as indicated in section 2.3.2, a decision tree has the advantage of being easy to read and quick to execute.

There are many algorithms for generating decision trees. The two most known and used [28] are C4.5 and Random Tree. C4.5 builds decision trees from a set of training data using the concept of information entropy [29]. Random Tree is a supervised classifier; it is an ensemble learning algorithm that generates many individual learners. It employs a bagging idea to produce a random set of data for constructing a decision tree. In standard tree each node is split using the best split among all variables [30].

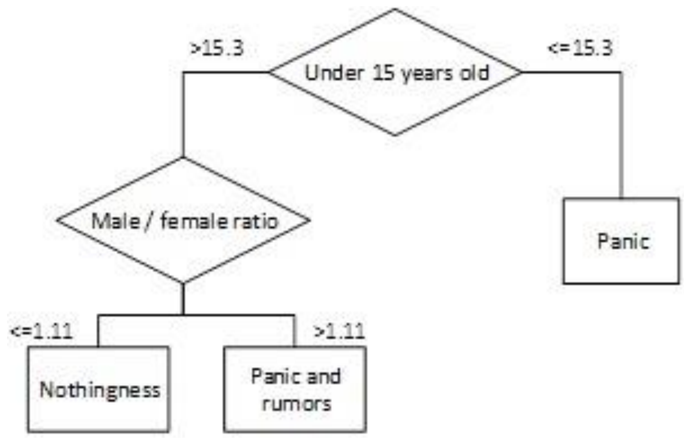

Figure 2: Decision tree obtained with the algorithm J48-C4.5

We therefore used these two algorithms, implemented in the Weka[1] software, to analyze our data (C4.5 is implemented as J48). Finally, it should be noted that these algorithms need possible decisions (classes) as input data and then seek to determine a classification of elements according to the initial classes. From the data sources at our disposal, the possible decisions/classes we have identified are: panic, rumors, panic_and_rumors, nothingness (no reaction of panic or rumor).

Table 2 and Figures 2 and 3 show the obtained results with the 9 instances and 14 attributes we have.

Our 9 instances correspond to accidents/crises that took place in French cities: Lyon (2008), Rouen (2013), Nemours (2005), Villeurbanne (1981), Béziers (2005), Dagneux (2007), Saint-Galmier (2000), Saint-Just-Saint-Rambert (2005), Montoir-de-Bretagne (2002).

The 14 attributes used in our study are:

- Visual signals,
- Sound signals,
- Olfactory signals,
- Population density,
- Type of urbanism,
- Moment of the day,
- Number of foreigners,
- Panic or rumors,
- Part of under 15s (%),
- 75 years and over (%),
- Weather,
- Male/female ratio,
- Number of accidents in the city,
- The city is located within the perimeter of a PPRT (technological risk prevention plan)

Table 2: Summary table of the classification (J48-C4.5 and Random Tree)

	J48 – C4.5	Random Tree
#Instances	9	9
#Attributes	14	14
Correctly Classified Instances	8 (88.89 %)	**9 (100 %)**
Incorrectly Classified Instances	1 (11.11 %)	**0 (0 %)**
Kappa statistic[2]	0.83	**1**
MAE[3]	0.08	**0.03**
RMSE[4]	0.21	**0.08**
RAE[5]	25.06 %	**9.74 %**
RRSE[6]	50.51 %	**20.12 %**
Size of the tree	5	**12**

[1] www.weka.fr

[2] Cohen's kappa coefficient is a statistic which measures inter-rater agreement for qualitative (categorical) items, its value is in [0, 1]. The higher the value, the better the results.
[3] Mean Absolute Error: The smaller the value, the better the results.
[4] Root Mean Squared Error: The smaller the value, the better the results.
[5] Relative Absolute Error: The smaller the value, the better the results
[6] Root Relative Squared Error: The smaller the value, the better the results

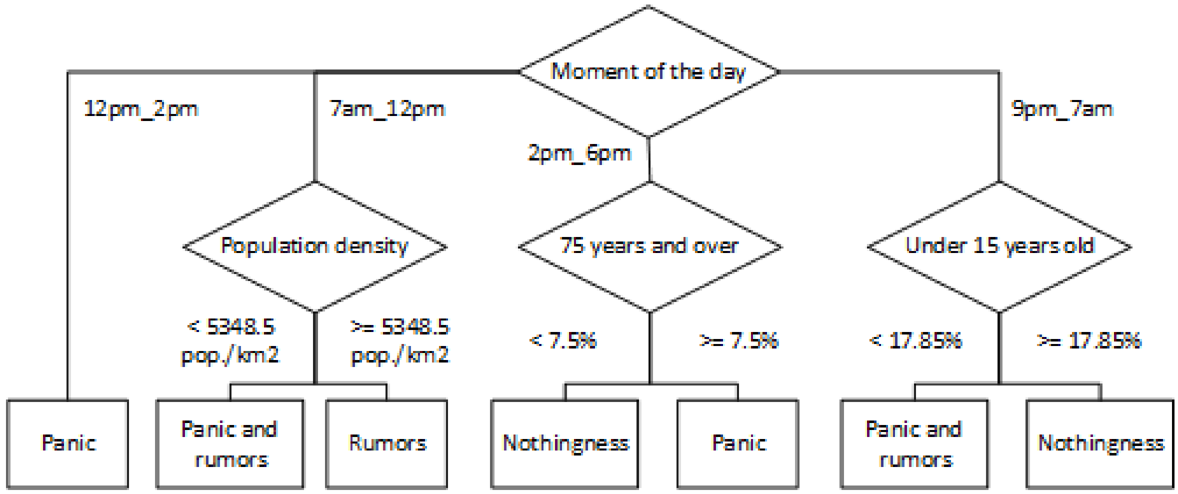

Figure 3: Decision tree obtained with the algorithm Random Tree

Step 4: Results interpretation

The results, presented in the form of decision tables, have the objective to aid decision-makers to evaluate the relevance of alerting the populations by identifying the risks of rumors and panic. They give indications to target the populations thanks to the designation of categories that are more sensible to rumors and panic behaviors.

According to Table 2, we observe that the Random Tree algorithm, based on a random set of indicators selected to represent the decision nodes, offers better performances than the C4.5 algorithm, which uses an entropy function to select the decision nodes. Indeed, with Random Tree, the instances are better ranked (100% against 88.89% for C4.5), the Kappa test has a value of 1 (which is the maximum achievable value), the values of MAE and RMSE are the smallest (> 0.08) and RAE and RRSE are significantly better than C4.5.

The set of rules that emerge from the construction of the decision trees of these two algorithms have the advantage of being easily interpretable by those interested.

According to Figure 2 (C4.5), the decision nodes are identified and make it possible to discriminate between the different categories of the class attribute (here called ratio-man-woman). We can thus classify from this tree (Figure 2) a crisis situation in a city for which the part of the under 15s is greater than 15.3 and the ratio male/female greater than 1.11 as a situation where the risk “panic and rumors” is high.

According to Figure 3 (Random Tree), we observe that more information is accessible (more intermediate classes exist, unlike Figure 2). Thus, the decision-maker has more leeway in his decision. It should be noted that we find close decisions in the two trees, for example, when the part of the under 15s is higher than a certain threshold (rather low), then the risk "Nothingness" is more likely.

Finally, these preliminary results are to be taken with a pinch of salt. Indeed, the data at our disposal are not sufficient for the algorithms to provide realistic decision trees. The purpose of this article and the experiments carried out is to show the feasibility of our approach. It would take hundreds of instances and more indicators to begin to have consistent/realistic results.

5. Conclusion and Future Work

Early warning systems are very strongly linked to the actions of the individuals who constitute them. The reactions of the populations in particular can have a great importance in the effectiveness of the alert and the effects can be felt in the long term. This is why we propose in this article a decision support process to alert or not the populations in a crisis situation.
In order to validate the feasibility of our approach, we applied it to real data by proposing a decision tree for the decision-makers in a crisis cell and thus help them to determine whether to alert the population or not.

As future work, our approach will have to be validated by a cross analysis between risk experts on different domains. It will be necessary to identify the precise characteristics of the alert and the response according to the typology of the crises so that the different factors/indicators and decisions can be appropriately selected. Care must be taken to work on the recovery of data from different sources in a tool that can be integrated into a crisis cell.

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