Predictive analysis of social streams for natural disasters risk assessment

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Abstract

The aim of the present paper is to manage the capacity of social systems to cope with natural disaster events. Based on the Sendai Framework for Disaster Risk Reduction 2015-2030, the latest developments of Information and Communications Technology (ICT) and the tools for Public Participation Geographic Information Systems (PPGIS), we emphasise the role of community participation with the use of social networks.

We argue about Content Management System (CMS) to create open-source Web platforms, contribute to the construction of knowledge and diffusion of information and enhance a sense of participation across the public in view of disaster management initiatives.

Keywords

Social sensing; Machine learning; Natural disasters; Spatial data infrastructure; Social streaming.

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Introduction

In the last decades there has been an increase in the public awareness of natural disasters events. The latest contributions of the international community to monitor and assess natural disasters and the increasing role of the media attention at a global scale have shaped the scientific research to analyse, study and model catastrophic events in response to climate change. Climate change is currently altering the frequency, magnitude, spatial coverage and the duration of many natural disasters (Van Aalst, 2006; World Bank, 2010; IPCC, 2014).

The impacts of natural disasters on social and ecological systems are recognised at various geographical scales and offer significant challenges to develop knowledge-based governance for resilient societies through increased worldwide interdependency between people, places and natural systems (Hung et al., 2016).

The above global transformations and interdependencies also concern the use and management of portals which offer opportunities for the development of networking across communities. These opportunities also arise from rethinking the perceptions of the needs in an emergency context and the creation of new values (Watson et al. 2011). Often, it is difficult for researchers and practitioners to gain an overview about the needs of a community in disaster risk management. Classical economic models (Varian, 2009) generally consider need(s) as embedded into socio-economic processes. Alternatives to these models are the use of ontologies: a powerful approach to share knowledge across society. In the context of natural climatic events ontologies provide '*the essential characteristics of the event*' (Borgo and Guarino, 2015, p. 6) and can contribute to uncover latent community needs in emergency situations.

The disclosure of new community needs and information sharing (Kamalahmadi and Parast, 2016) within the global network supports the evolution of the adaptive capacity to natural disasters. This favours the effectiveness of a continuous knowledge construction to help society with the establishment of new practices to enhance community adaptive responses to extreme climatic events.

What roles can international bodies and national governments play to accelerate the degree to which a community cope with natural disasters? What if these roles are coordinated but not harmonised? (Shaw and Nerlich, 2015).

In the last twenty years under the lens of the sustainable development concept and numerous international accords (Agenda 21, Millennium Development Goals, Aarhus Convention) we witnessed the growth of various initiatives to involve public participation in the decision making process. Recently, the increase in mobile phones and smartphones and the realization of Public Participation Geographic Information Systems (PPGIS) application (Floreddu, 2012; Hilburn et al, 2020) have progressively favoured geo-database collection in a more structured and systematic way (crowdsourcing) enriching the existing Spatial Data Infrastructure (SDI) (Mansourian et al, 2006) often used as support platforms in risk assessment. Consequently, new specific Content Management System (CMS) platforms are helpful to create open-source Web platforms that use "crowd-sourced" information. The Ushahidi (www.ushaidi.org) project is an example of CMS that turns citizens into potential sensors (Zeile et al. 2012) in favour of a 'social sensing' mission (Ali et al. 2011; Aggarwal and Abdelzaher, 2013; Shao et al., 2020).

The aim of this study is to manage the capacity of social systems to cope with natural disaster events. Based on the insights of the Sendai Framework for Disaster Risk Reduction 2015-2030 (United Nations, 2015) which sets, among its goals, '*the strengthening of resilience of people and assets to withstand residual risk*' (United Nations, 2015, p. 11), the latest developments of Information and Communications Technology (ICT) and the tools for PPGIS, we reach the above aim by emphasizing the role of community participation through social sensing technology. This technology integrates dedicated tools to gather structured knowledge on catastrophic events and to engage the crowd with structured on-line forms (To et al. 2014). In addition, the above technology uses social networks (e.g. Twitter, Facebook) to collect and classify unstructured knowledge by means of text mining and machine learning techniques.

The contribution of our work to the current literature is to build a conceptual model which emphasizes the role of community participation to natural disasters with the use of CMS and current PPGIS tools. The conceptual model is then applied to the case of 2010 Haiti earthquake. The conceptual model serves as a good practice to strengthen communication and collaboration among stakeholders and decision makers and among citizens to take action and foster community resilience to natural disasters.

The paper is structured as follows. In the next section, we briefly review and contextualize ICT platforms to natural disasters. The subsequent sections illustrate the conceptual model its application to the case of the 2010 Haiti earthquake, respectively; finally, the last section discusses the obtained results and concludes the work.

Literature background

In this paper we consider the use of CMS and PPGIS as tools to increase the resilience of societies to natural disaster events. Since the mainstream of ecological engineering and economics in early 1970s, the concept of resilience, defined as '*the measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables*' (Holling, 1973, p. 14), has taken various shapes and extensions over time. It has gradually interested social sciences, natural disaster risk and land use management researches (Adger, 2000; Perrings, 2001; Folke, 2006; Norris et al, 2008). The UNISDR (2005) argues that resilience lies in the capacity of societies to learn from past events and reduce future risks.

The study by Folke (2006), in particular, considers resilience in terms of innovative responses through social behaviours. We agree with the author that resilience is a '*way of thinking*' (Folke, 2006, p. 260) where society plays an important role. According to Folke, the social dimension is able to empower the adaptation of ecosystems to new equilibria through collaboration among various stakeholders operating at different social and ecosystem levels and provide in favour of a knowledge-based organization of the society.

In 2009, again the UNISDR (2009) establishes a glossary of terms under the umbrella of disaster risk reduction strategies in order to increase public participation to the issue of, among other things, resilience. Later in time, the IPCC (2012, 2014) reports emphasise that community participation favours the increase of resilience to reduce the risks of natural disasters and climate change. The Sendai Framework for Disaster Risk Reduction 2015-2030 (UNISDR, 2015) also sets, among its goals, '*the strengthening of resilience of people and assets to withstand residual risk*' (UNISDR, 2015, p. 11). The key priority actions of the UNISDR document is to ensure that disaster risk management has a strong institutional base at local level in order to identify a knowledge-based administration at all levels of governance.

The multi-level governance system would then be able to enhance early warning, strengthen natural disasters preparedness and supply an adequate response to reduce risks to socio-ecological systems. Bruneau et al (2006), assess the four dimensions of community resilience such as technical, organizational, social and economics – before and after seismic events. In particular these dimensions respond to the four 'R' of 'Robustness', 'Redundancy', 'Resourcefulness', and 'Rapidity' of a resilient system. In similar studies, Cutter et al (2008, 2014), emphasizes that '*resilience [...] includes pre-event measures to prevent hazard-related damage and losses (preparedness) and post-event strategies to help cope with and minimize disaster impacts*' (Cutter et al, 2008, pp 600). In this work we do not investigate a comprehensive review of the concept of resilience. We attempt to extend this concept in the light of the latest developments of ICT as described below.

The beginning of 1990s witnesses the first attempts of active citizens participation to various decision making initiatives born after numerous international accords such as the Agenda 21, the Millennium Development Goals, the Aarhus Convention and various EU funding programmes as Leader, Urban, Interreg and Equal. These initiatives and under the lens of sustainability, environmental protection and support to disadvantaged populations provide communities to set up and/or enhance democratic mechanisms through the direct participation of citizens to the decision-making process (Harwood, 2015).

With the introduction and diffusion of web technology in 2004, the public participation to the decision making process evolves to the digital paradigms such as e-Democracy, e-Participation, and Gov 2.0 (Floreddu, 2012; Latre, 2013; Graziano, 2017).

The growing exchange of information on the world wide web and in particular on the social media plays a key role to the development of ICT for the management of a natural disaster event (Palen and Liu, 2007; Simon, 2015; Orimoloye et al, 2020). This latter is a complex mechanism to manage. It involves the spatial and international coordination of thousands of people who volunteer to help with the local community. To assess resilience, these people can either act as independent agents or as 'citizens as sensors for crisis events' (Schade et al. 2013). As a consequence, interaction evolves across local and /or international institutions and organizations, through knowledge and participation sharing using social media tools such as Twitter and Facebook (Mostashari et al., Sprake and Rogers, 2014; Hung et al. 2016,). The above media tools provide the building of real time knowledge frameworks during rescue operations in emergency situations (Teodorescu, 2015). As a result, the resilience of urban systems and communities to natural disasters significantly improves (Asadzadeh et al., 2015).

Alongside the diffusion of social media tools, new techniques and methodologies arise for the development of open source platforms to comply with international regulations for the sharing of real time geospatial information, mitigate the side effects of natural disasters and facilitate rescuing operations. The 2007 EU Inspire directive establishes an infrastructure for spatial information and contributes to close the gap of semantic aspects and harmonisation of data sharing and formats across member states (European Commission, 2007). Similarly, in the US, the National Spatial Data Infrastructure (NSDI) promotes the implementation of geospatial data across various levels of government, sectors of the economy, organizations and academia (Federal Register, 2003). At the international level, the United Nations advocate the necessity to set an agenda for geospatial data information and management (https://www.fgdc.gov/nsdi/nsdi.html). One of the key areas of work is disaster risk management and emergency response. Crowdsourcing platforms for disaster management play an important role in response to natural and environmental disasters (Yang et al., 2014). Some platforms deal with citizen participation and engagement, such as the Austrian Ministry of Environment (www.partizipation.at), the think tank INVOLVE (www.involve.org.uk) or the geospatial website GeoPlatform (www.geoplatform.gov), Pan European eParticipation Network (www.pep-net.eu), and many others. The aim of these platforms is to disseminate knowledge about public participation and share trusted data to organizations, government, and citizens. Few platforms purpose specifically the assessment of participation programs. Examples suggest Ushahidi and Participedia (www.participedia.net), which focus on sharing large amounts of data on public participation based on real world cases. In particular, the Ushahidi platform was used to collect geo-referenced reports from citizens during the Haiti earthquake on the 12th January 2010 and Fukushima nuclear disaster on the 11th March 2011.

However, scholars sound unconvinced about the degree of diffusion and utilization of these new digital tools among citizens for the effective assessment design of risk mitigation (Becerril-Chavez et al., 2012). There already exists particular tools such as PPGIS that are used to create bottom up digital knowledge maps for risk assessment (Ai et al., 2016) and the Volunteered Geographic Information (VGI), which is conceived the same way as the PPGIS but is independent by any institutional aspect. Nonetheless, these tools exhibit some drawbacks. First, they are difficult to interpret; and second, it seems not easy to contextualize the type of knowledge they offer. Therefore, it is urgent a clear-cut idea of the participatory tools that web designers intend to realise including knowledge-based methodologies (Leighninger, 2011).

In the last decades, technological progress has grown fast and found solutions to allow the sharing of transformations within the society. Contrarily, international research on cognitive aspects has moved slowly to deepen the study of human behaviours (Lindell, 2013) and the satisfaction of real needs in emergency situations from natural disasters (Cherry, 2009). This aspect affects the efficacy of crowdsourcing platforms and their application to disaster risk management (To et al.2014; Horita et al. 2018).

The complexity of community resilience to natural disasters other than being intrinsically unpredictable also depends by several spatio-temporal and socio-economic factors which require specific knowledge and studies.

We investigate, from a cognitive point of view, the role of various agents and needs in disaster risk management. In particular, we analyse unstructured information in social networks and attempt to make them functional to the rescuing operations where the semantic components appear decomposed in single elements as the 'who'(i.e. agents), 'what'(i.e. needs) and 'where' (i.e. spatio-temporal needs) to realise SDI (Latre et al., 2013).

Methods

We propose the following conceptual model (Figure 1).

The construction of common knowledge on disaster risk is based on a combination of social sensing and machine learning approaches.

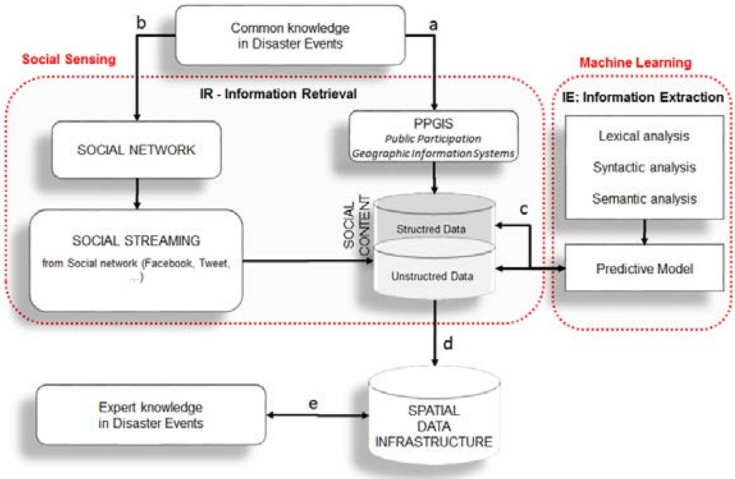

Figure 1 - Knowledge based conceptual model for a resilient community to natural disasters

The former includes both structured information from public participation retrieved from platforms such as PPGIS, Ushahidi, or VGI to cite a few, and unstructured data from social networks such as Facebook, Twitter and many others. These form the social content containing useful information from people's perception about type, extent, intensity, impacts and emergencies in the event of a natural disaster. The latter includes a machine learning approach which is based on information extraction to obtain the final dataset to compute the predictive model. The results obtained by the predictive model feed back onto the social sensing context to form the SDI to enrich both the knowledge of the public and that of the expert. Next, we describe the steps of our conceptual model summarised above.

Social Sensing Section: Social sensing gathers ex-ante, present, and ex-post common knowledge in emergency situations in the event of a natural disaster and is arranged as follows:
a) *Structured knowledge:* It uses a specific app to collect information which is saved in a database. The app is designed through a dedicated web interface where the user inputs his/her message such that it is possible, in real time, to geo-localize the thread on an interactive map and classify it in a given category. As for data analysis and machine learning, our study makes use of a dataset created during the aftermath of the Haiti earthquake on January 12 and July 5th, 2010. Figure 2 shows the web interface realised with the Ushahidi platform used by the Haitian community during the dramatic events of the earthquake. The information collected are organised according to: *Incident Title, Incident Date, Location, Description*, *Category*, *Latitude,* and *Longitude*.
Our analysis is based on the archived data available in the fields *Description* and *Category*. The former contains the description of the message, the latter its classification. Figure 2 illustrates the various categories used to classify the messages such as 'emergency', 'treaths', 'response', 'person news' and many more. b) *Unstructured:* This type of knowledge uses information retrieval based on social network streaming, Ushahidi platform and / or other crowdpulse websites which, through specific application programming interface (api) functions, gather messages from Facebook and/or Twitter filtering data using special hashtags. However, the posts retrieved in such a way present some drawbacks. These should be validated and classified at a later stage by appointed experts. Therefore, the timing of these operations can last several days and suggest the presence of inefficiencies, should the community proceed with the elaboration of the posts in natural disaster events.

Figure 2 - Ushahidi platform used to submit emergency requests from the Haitian community

Our study attempts to overcome this limitation. The assessment of the particular stream of information available on the social networks could save human and animal lives and the ecological system, should these assessed information be promptly read and /or observed by the rescue team.

Machine Learning Section. The main aim of machine learning is to observe, learn and classify through proper algorithms the common knowledge (Bishop, 2006) as described earlier and make it available on an SDI as well as an expert knowledge system.

We argue that a simple operation that can save lives is to extract as rapidly as possible high priority posts compared to other messages containing the request for minor emergencies. To do so, we apply a predictive model to our structured and unstructured knowledge base retrieved from social networks and the Ushahidi platform. We employ RapidMiner Studio v. 9.0. RapidMiner is an open-source software for data mining enabling data analysis and reporting simultaneously. It has several advantages that inspire us to use it for: i) an immediate graphical user interface for input and output processes; ii) the handling of data from several formats; iii) a comprehensive text mining; iv) the ability to apply several methods for model predictions (http://docs.rapidminer.com/).

However, it is necessary to perform pre-processing activities with the use of text-mining techniques to obtain an unbiased data entry matrix to run the predictive model. We proceed with the text-mining analysis as follows: i) *tokenize* allows to isolate every single word (token) from the others; ii) *stopwords* allow to drop all irrelevant words listed in the stopwords dictionaries (English, French and Haitian); iii) *replace token* replaces compound words with single words; and iv) *stemming* reduces the number of the words collected and that have in common the same root in a single token (Verma, 2014).

At the end of the text-mining phase, we obtain the data matrix to run the predictive model in which the words are classified as *primary* if they contain the following primary needs, in the three languages English, French and Haitian, as defined by the Maslow's (1943) hierarchy of needs: 'Food', 'Water', 'Home', 'Maison', 'Need', 'Kay dlo manje', 'San', 'Blood'; and *not-primary* otherwise and the absolute and relative frequencies of each word in each document. The total number of the messages in our matrix is 3,593.

Among the available algorithms in RapidMiner, we use Näive Bayes and K-Nearest Neighbors (K-NN) predictive models which produce the best performance. The Näive Bayes model is based on assessing to an event a posterior probability which is obtained by a normalised 'a priori' conditional probability that the feature of that event occurs (Mitchell, 2015). The k-NN model is a non-parametric model typically used in machine learning to classify an object (the word in our case) to a class according to its nearest neighbour (Duda et al., 2000). Both Näive Bayes and K-NN models are popular in machine learning due to the ease of application in natural language classification (Valsamidis, 2013; Khan, 2014).

Both models use a training set obtained over 1,000 posts randomly chosen. The remaining part of the dataset is used for the model prediction analysis.

Results

Figure 3 illustrates the training and predictive processes in RapidMiner.

4018	not primary	Eliante Valentin	May 3, 2010 8...	18,539167	-72,335	664 Blv. Jean...
4020	not primary	Shelters needed for school in Dikini	Feb 15, 2010 ...	18,539838	-72,406425	Carrefour, zo...
4030	not primary	Help needed in 1ere section, Leogane	Apr 26, 2010 ...	18,499145	-72,651215	"corail l...
4033	not primary	Help needed in Brochette	Mar 17, 2010 ...	18,52519	-72,458954	Brochette 99, ...
4035	not primary	Clogged toilet in canape vert	Mar 19, 2010 ...	18,539513	-72,327118	Canape Vert
4050	not primary	how haiti is right now and how it was during the earthquake	Jun 24, 2010 ...	22,278381	114,174287	centre
48	primary	Border road down, Looting stared in P-au-P	Jan 13, 2010 ...	18,521283	-72,372437	border crossi...
76	primary	Looking for Hemst Marcelin (age 5) and Nalexia Marcelin (20 m...	Jan 13, 2010 ...	18,633333	-72,266667	Bon-repos, h...
194	primary	URGENT - College Canape Vert, PaP	Jan 14, 2010 ...	18,539269	-72,336408	Conape Vert
209	primary	Person Trapped - 66 Rue St. Gerard	Jan 14, 2010 ...	18,527235	-72,338513	66 Rue St. G...
212	primary	Need Help with Crowd Control	Jan 14, 2010 ...	18,54085	-72,316313	christ-roi rue ...

Figure 3. An example of the classified social post

To validate the robustness of our results, we proceed with a cross-validation approach. Generally, cross-validation procedures distinguish *n*-fold and leave-one-out cross-validation (Suh, 2010). The former is carried out with a nested approach and is the algorithm included in Rapidminer. Data are split into *n*-folds of equal size and trained and tested *n*-times. Of these *n*-subsets, a single subset is hold as input of the testing sub-procedure, and the rest of the *n*-1 subsets are then applied as training data in the subsequent reiteration (i.e. as input of the training sub-procedure) (http://docs.rapidminer.com/). The cross-validation is repeated *n*-times treating the *n*-subsets as holdout sets each time. The cross-validation procedure predicts how sensitive is the model (i.e. how well performs the model) to a hypothetical holdout dataset. The results of the cross-validation are illustrated in Table 1.

Performance Vector (Näive Bayes)
Accuracy: 55.33% +/- 13.94% (mikro: 55.38%)

Confusion Matrix:

True:		Actual: not-primary	Actual: primary
Predicted	not-primary:	346	243
	primary:	201	205

Performance Vector (K-NN)
Accuracy: 55.94% +/- 16.38% (mikro: 55.88%)

Confusion Matrix:

True:		Actual: not-primary	Actual: primary
Predicted	not-primary:	326	218
	primary:	221	230

Table 1. Cross-validation results for the Näive Bayes and K-NN models.

Both models present the following accuracy rates: 55.33% and 55.94% for the Näive Bayes and the K-NN performance vectors, respectively. Error diagnostic tests are shown in the confusion matrix results in Table 1. A confusion matrix (Kohavi and Provost, 1998) is a contingency table containing information on actual *vs* predicted classification results. It can be interpreted as follows: i) The cells 'not-primary/not-primary' with values 346 and 326 tell us the number of correct predictions that a word is classified as not-primary (TN - true negative rate); ii) The cells 'primary/not-primary' with values 201 and 221, respectively, indicate the number of incorrect predictions that a word is classified as 'not-primary' (FP – false positive rate); iii) The cells 'not-primary/primary' with values 243 and 218 show the number of incorrect predictions that a word is classified as 'primary' (FN – false negative rate); and iv) the cells 'primary/primary' with values 205 and 230 display the number of correct predictions that a word is classified as 'primary' (TP - true positive rate).

The information retrieved by the accuracy rate of the model(s) is(are) not enough to give us an indication of the magnitude of an 'emergency' message during the classification procedure. Generally, the accuracy rate computed above would respond to the question of 'What is the probability that any primary and not-primary word is correctly classified?' What is important to determine in our analysis in terms of community resilience to a disaster event is to respond to the question: 'What is the probability that a primary event is correctly classified?'. To answer this question we compute the precision rate at which the models classify the primary words. This is given by the ratio TP/(TP+FP) and take the values of 50.49% (Näive Bayes) and 50.99% (K-NN), respectively.

Discussion and conclusions

The study of cognitive aspects in emergency situations from natural disasters is not extensively analysed in the literature. The main reason is that, until recently, the study of human behaviors and the satisfaction of real needs during the aftermath of a natural disaster has moved slowly. This aspect is important to strengthen collaboration among the parties involved in emergency situations to take prompt actions and increase resilience in disaster preparedness and survival planning.

While it is evident that international and national governments play a key role to accelerate the degree of community resilience to natural disasters, there emerge some doubts whether collaboration across countries is harmonized to provide an efficient allocation of resources between demand and supply when the states of the world are altered by unforeseen natural events. As Folke (2006) argues, innovative responses through social behaviours are necessary to boost the coping capacity of socio-economic and ecological systems to the challenges posed by the global transformations due to climate change.

The present paper responded to the above doubts and attempted to manage the coping capacity of the social system to improve community resilience to disaster events. The presented conceptual model sheds light on the role of community participation using social sensing technology that integrate structured knowledge (i.e from crowdsourcing) and unstructured knowledge (i.e. from social networks) with the use of text mining and machine learning techniques. By doing so, the information obtained enrich the SDI of both un-expert and expert knowledge bases.

The results obtained from the application of our conceptual model to the 2010 Haiti earthquake indicate that the predictive models, classification and cluster analysis should attain in the near future increasing attention from the international community, as is at present for the case of the Ushahidi platform in disaster risk management. The conceptual model other than being considered as content management system for the collection of geo-localized data opens new scenarios from social media. At present, the effort made by the crowdepulse platform goes into the direction of supervised processes such as the proposed conceptual model. The crowdepulse platform integrates somehow some modules of machine learning which are still of unsupervised type. We argue that integrated platforms are capable of improving community resilience to natural disasters. In addition, these platforms contribute to save human and animal lives, re-stabilize ecological systems and improve the quality of life during the immediate aftermaths of a natural disaster event. Future directions of this research should also consider cognitive models based on a comprehensive view of agents and community needs to manage efficient emergency situations from natural disasters and include the construction of ontologies (Borgo and Guarino, 2015) to further improve the classification mechanism of social sensing data in machine learning approach.

Finally, inspired by the pioneering work of Schön (1984) we argue on the importance of a 'learning by doing' mechanism to set up models which are finalised to a shared knowledge in disaster risk management. The study by Yu et al (2016) also supports this view and extends it to the learning mechanisms for a resilience-based management. The capacity of the society to learn, transform and revise shared targets for an efficient resource allocation including the assessment of consumer behaviour is the key for generating resilient socio-economic and ecological systems.

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