# Spatial cognition and local knowledge in open space: ontologies in risk situations

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## Abstract

Recently, the diffusion of social networks is opening new research scenarios in risk assessment. In an emergency, during critical events, massive flows of information (text messages) posted on social networks could contribute to save lives or to help people in danger – provided they were tapped into and correctly interpreted by emergency agencies. These potential sources of information, in most cases, consist in unstructured social contents reflecting people's intentions, perceptions and needs and they often have elements of complexity and uncertainty, hindering interpretation and thus thwarting response management.

The text messages are in natural language; they frequently contain locational information which, if properly extracted and processed, could make a key contribution to disaster management, and search and rescue in particular.

This research aims to contribute to understanding, in the context of social streaming analysis in a risk situation, how locational information and other implicit spatial knowledge may be organized to be effectively shared between all actors

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involved in disaster management. To that aim, an integrated approach involving machine learning and ontological models has been tested to help discover spatial knowledge.

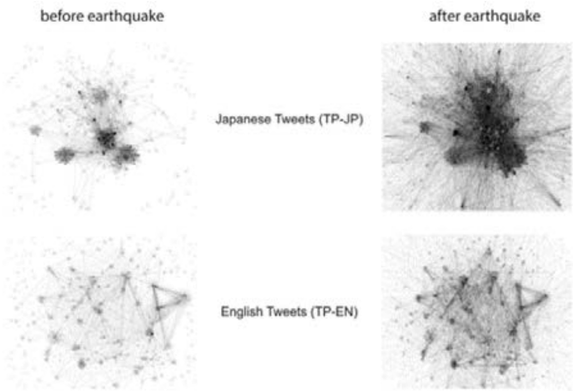
**Keywords**

Local Knowledge, Ontology, Social Sensing, Text Mining, Spatial Analysis

## Social Sensing and disaster management

Over the last decades, natural disaster events (such as flooding, earthquakes, tsunamis and hurricanes) have caused extensive damage (to housing and infrastructure) and severe loss of lives in vast regions worldwide.
When these events occur, the role played by international organizations and cooperation to ease the management of emergencies and available resources are key aspects, which are widely debated in the literature (Quarantelli, 2006; Reddy et al., 2008). Similarly, since the 1950s, scholars have highlighted the valuable contribution of citizens as active participants to handle emergency events. Lately, this contribution has been closely linked to the diffusion of new *Information and Communication Technology* (ICT) (Simon et al., 2015; Whittaker et al., 2015), which has enabled a wider public participation in the decision-making process.
The large increase in the use of Social Networks in risk dynamics is a relatively recent aspect. The international literature considers several studies on the Haiti Earthquake of 2010, Tōhoku (Japan) earthquake and tsunami of 2011, Christchurch (New Zeland) earthquake of 2011, Queensland

(Australia) flooding of 2012 and/or Haiyan (The Filippines) hurricane of 2013 to cite a few (Hughes and Palen, 2009; Vieweg, et al., 2010). These studies have in common the analysis of *messages* posted on different social media during and after the occurring of a disaster event. Also, text messages are analysed to shed light on their dynamics during rescue operations (Qu, et al., 2011).
Figure 1 shows the findings of a study by Lu and Brelsford (2014): the authors emphasize a communication stream across thousands of people on Twitter[2] soon after the 2010 earthquake in Japan.




| LANGUAGE | PERIOD | USER | TWEETS |
|---|---|---|---|
| Twitter Post-JP | Before | 36893 | 42678 |
| | after | 36893 | 114247 |
| Twitter Post-EN | before | 36234 | 49095 |
| | after | 36234 | 64507 |

Figure 1 - Network structure and community evolution on Twitter: Before and after the earthquake in Japan 2010. Adapted from Lu and Brelsford (2014).

[2] Twitter is a social networking service where users post and read short messages called 'Tweets'. Registered users can post and read tweets, but those who are unregistered can only read them.

The work also draws attention to data exchange and availability on the web during the event, and the potential of exploring local knowledge associated to this data.
In particular, the study analyses the communication streams occurred on Twitter before, during and after some above mentioned disaster events. The contents of the text messages are analysed according to the event (e.g. earthquake, flooding) and phase types (*ex ante, in itinere, ex post*).
The text messages are written in natural language; they frequently contain locational information which can be explicit (i.e. coordinates) or implicit (i.e. place names or toponyms). These descriptions are characterized by different people's spatial perception and specific place knowledge. Hence, to be used by an emergency system, they must be transformed into structured information (quickly usable in computer processing).
The specific objective of this research is to contribute to understand, in the context of social streaming analysis in a risk situation, how locational information and other implicit spatial knowledge may be organized to be effectively shared between all actors involved in disaster management.
To that aim, different data mining methods have been tested to single out every element that is necessary to identify and locate the place described in the text messages, while an ontological approach is introduced to bridge the communication gap between different communities of practice (Oltramari et al. 2003; Gaio et al., 2010).

## Ontologies to improve emergency domain

Formal ontologies can be a bridge between different communities (Oltramari et al. 2003; Gaio et al., 2010). They identify, within a specific domain, entities and their respective properties and relations based on a logical system. Ontologies pursue one or more among the following three goals (Gaio et al., 2010: 108): "the representation of information; the description of a certain domain; the development of a systematic theory for a specific entity".

Over the last decades, several types of ontologies have been established. These differ in terms of the level of abstraction of the real world and the formalization and representation. One of the key differences within the field of formal (or computational) ontologies is the one drawn between foundational (upper) and lightweight ontologies.

In recent years, the development of methodologies to implement these ontologies has generated a debate around the heterogeneity issue. It should be remembered that one of the principal objectives of an ontology is to facilitate knowledge sharing. The scientific community should aim to create a shared integration mechanism whereby ontologies that describe the same domain or have overlapping areas adopt unambiguously the same concept.

Noy (2004) identifies two methods for tackling this issue. The first one, which has met wide consensus in the literature, turns to foundational or upper-level ontologies to identify the classes that serve as a link between specific ontologies. The second approach includes heuristics-based techniques or machine learning that take advantage of the distinct features of ontologies (structure, definitions of concepts, instances of classes) to work towards a shared mapping.

The information sharing can be treated at different levels, and this operation involves the use of both foundational – such as the Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE[3]) (Masolo et al., 2002), shown in Figure 2 – and lightweight ontologies realized to draw the different forms of Social Media Geographic Information(Campagna, 2016).

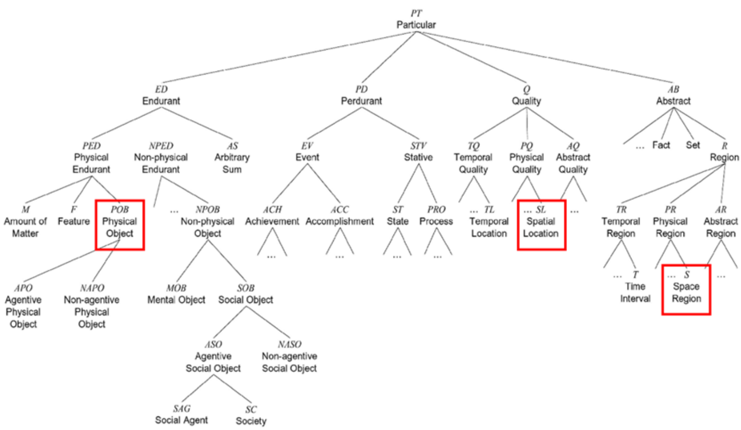



Figure 2 - DOLCE’s taxonomy of entities. Adapted from Masolo *et al.* (2003).

DOLCE is also a Multiplicative ontology since it has a general view of the real world and admits distinct entities that can share the same Spatio-temporal area (i.e. entities can be co-localised) (Masolo et al., 2003).

[3] DOLCE is based on the OntoClean methodology developed by LOA-CNR as a validation tool aimed at assessing the robustness and adequacy of the taxonomy’s relations (Guarino and Welty, 2009).

Generally, the latter is structured as a taxonomy of concepts, often hierarchically structured (Oltramari et al., 2003; Gaio et al., 2010). The former, on the other hand, faces more general and cross-cutting issues between different domains and communities that generate ambiguities across meanings arise.

Using ontologies to improve knowledge organization in the emergency management domain is well established in the scientific literature. Wang et al. (2006; 2009) define an ontological model of events, processes and actions based on sharing a vocabulary to exchange information. Xu et al. (2014) use specific geo-ontology libraries to describe an earthquake event. A geo-ontology is oriented to a geo-spatial hierarchy of information, and it offers a semantic interpretation of concepts.

Murgante et al. (2009) address seismic risk in urban areas through the use of an ontology. The model is developed to share knowledge so that concepts are fully understandable and accessible to the intended stakeholders.

Lee et al. (2013) apply an ontological model to develop a smart-type approach through the use of a context-aware platform and address real-time emergency operations/situations.

Apisakmontri (2013) uses an ontological approach for Refugee Emergencies in Disaster Management, which resonates with the approach adopted in the present work, as it involves the construction of an ontology to define needs or integrating a lightweight ontologies with four foundational ones (namely, DOLCE, SUMO, FOAF, and SWEET).

Recently, specific ontologies have been developed to describe social media concepts of the like of 'Semantically Interlinked Online Communities' (SIOC) ontology - which was originally developed to model websites such as blogs

and online forums (Imran et al. 2015) - while Meaning-Of-A-Tag (MOAT) implements an ontology with semantic tagging of social media data (Passant and Laublet, 2008).
The conceptual aspects of the ontology are inspired to the work by Mele and Sorgente (2011): The Eventory project. This project takes its roots from the journalism field and adopts the model called 'W's and one H'. This model uses six fields to represent an event: 'Who', 'When', 'Where', 'What', 'Why', and 'How'. Regarding the design aspects, the ontology refers to the model proposed by the W3C Incubator Group Report 2009 (Ianella, 2009), which is based on three fields: 'What', 'Where', and 'Who'.
The analysis of the simulation study illustrated in this section and by the recent literature (e.g. the Haiti earthquake[4], the Hurricane Sandy5) justifies the ontological model structured into the following macro-fields: 'What', 'Where', 'Who' and 'When'.
Before illustrating the entities attached to the fields of 'What', 'Where', 'Who' and 'When', it is relevant to briefly introduce the 'Why' field (which is not included in the above taxonomy). Under certain aspects, this field can be present in text messages and justifies the existence of the domain.
The W3C Incubator Group Report (Ianella, 2009) focuses on the major aspects of communication between rescue operators in a post-disaster situation, and uses foundational

[4] Haiti crisis map
https://datahub.io/dataset/ushahidi/resource/81d058a8-173a-49d9-8ce9-4edf5e7cafc9

https://github.com/unthinkingly/haiti.ushahidi.com-twitter-export

[5] Hurricane Sandy http://www.zubiaga.org/datasets/hurricane-sandy-tweets/

and non-foundational ontologies. The ontological model (Figure 3) is built around three sections: i) 'What' deals with needs issues; ii) 'Where' refers to spatial aspects; and iii) 'Who' deals with the actors involved in the post-disaster event. The model W3C does not focus on the time frame ('When') although it is an important aspect (e.g., 'I need food by tomorrow').

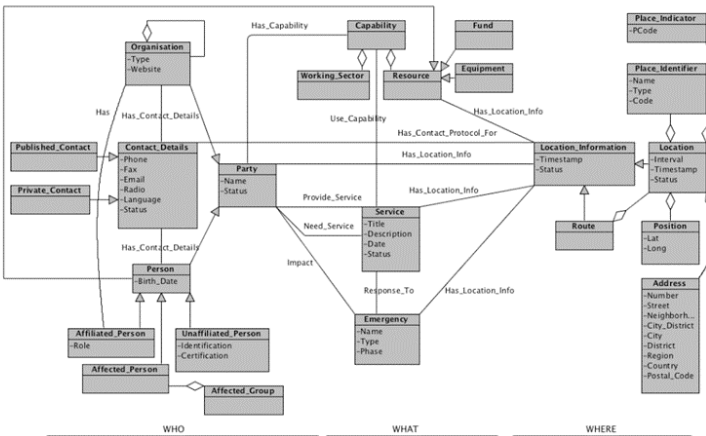



Figure 3 - Who, What, Where information models. Adapted after the W3C Incubator Group Report (Ianella, 2009).

## Knowledge Discovery in Text

Text messages, albeit heterogeneous, tend to show common characteristics that are suitable for clustering and classification analysis. Two steps and two methods are taken into account, in order to illustrate the process:

- Step 1: Identification of two types of methods that allow to reorganize the information in emergency situations,

through supervised algorithms instructed by a training set.
- Step 2. Processing of Information Extraction aiming at limiting the text, it's extracting only conceptual principal entities (needs, geo-location, people) (needs, geo-location, people) (Liu et al., 2011; Ritter et al. 2011, Imran, 2015). The extracted concepts will first be structured by an ontological analysis, and then by a shared spatial data infrastructure.

Message extraction including a conceptual approach is carried out with different textual analysis such as lexical, syntactic and semantic analysis.

The present paper identifies four conceptual domains included in a message shared during disaster response events: needs, spatial location, actors, timing.

Each of these concepts requires an in-depth analysis for the construction of linguistic patterns that take into account knowledge and common sense related to the places where the event takes place. The use of natural language regarding the spatial location is of particular concern to understand local knowledge. Natural languages use terms and combinations of terms that are often unknown outside certain local/spatial contexts.

The existence of a natural language which creates information and supports local knowledge in text analysis is one of the focal points of this work. The sharing and understanding of local knowledge is the primary requirement of an information system at a global level (e.g. when responding to humanitarian crises). Based on these assumptions, local knowledge should require and deal with ontological models.

Knowledge Discovery in Text (KDT) aims at detecting and dismissing data (noise) which is not useful to the purposes of the platform. It provides 'extraction' of latent knowledge (Swanson,1991).

## Methodologies and Results

Figure 4 shows the methodological framework of the present work.

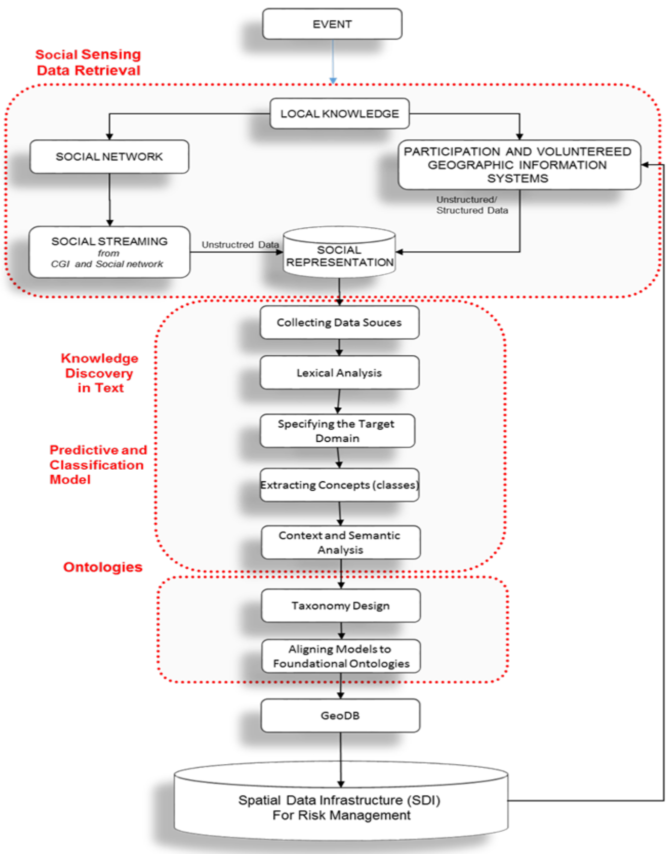



Figure 4 - Methodological framework

In the framework, 3 sections may be highlighted. Each section comprises a definition of risk and its declinations and of a non-structured dataset. The latter serves to study local knowledge, which provides for decision support systems in risk domains.

## *Social Sensing Data Retrieval*

The understanding of local knowledge in disaster risk is based on a combination of social sensing and machine learning approaches. The former includes both structured information from public participation (participation and volunteered geographic information system) and unstructured data from social networks (Facebook, Twitter and others). These form the social representation containing useful information from people's perception about type, extent, intensity, impacts and emergencies in disaster response. The latter includes a machine learning approach which is based on information extraction to obtain the final dataset and compute the predictive model. The results obtained by the predictive model feed back into the social sensing context to form the spatial data infrastructure and enrich both the knowledge of the public and that of the expert. Next, a detailed description of the conceptual model is offered.
Information retrieved form social media can be stored in a database. However, some limitations exist because information is stored as text with no input constraints. A further limitation of the social representation is that users should be aware of the application and be willing to install it on their mobile devices. To solve this problem, several platforms add new modules and link these to social network, to capture further information and data. This process is

attainable through application programming interface (API)[6] which are dedicated libraries between the platform and the social media (e.g. Twitter, Facebook). The social streaming captures, saves and stores text messages containing keywords, such as 'earthquake', with the corresponding indication of location.

The present work assumes that the user is accustomed to at least one of the most common social media to exchange information, including requests for, and offers of, help in disaster response. However, ethical issues arising from social network streaming processing should not be overlooked: Users may not want, or may not be aware, that their messages can undergo a streaming process and be stored in databases. In disaster events, users are willing to share their text messages with as many people as possible.

Social streaming can be considered the latest development to data and information retrieval. Should this be suitably contextualized, it would open new research opportunities to public participation.

How to treat data with no input constraints from social streaming? The next section will deal with specific methodologies to retrieve structured knowledge from unstructured data.

To understand latent knowledge it is useful to shed light on Text Mining (TM), Text Data Mining (TDM) and KDT.

KDT o TM is applied to any corpus of documents and is mainly designed to:

- Identify thematic groups
- Extract concepts for taxonomies and ontologies
- perform classifications

[6] In Computer Science, an API is a set of available procedures and tools to execute a function or a set of functions.

- Discover hidden associations
- Extract specific information (i.e. addresses)

Usually, it implies four main phases like shown in Figure 5:

1. Information Retrieval (IR),
2. Information Extraction (IE),
3. Information Mining (IM),
4. Interpretation (I).

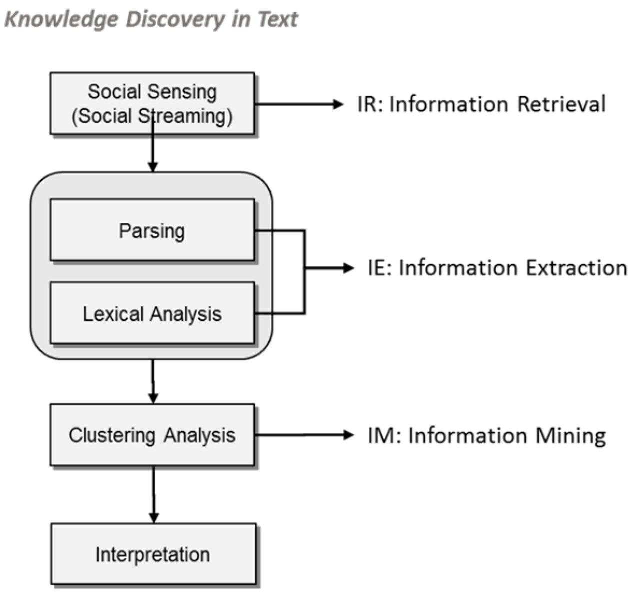



Figure 5 - Text mining phases

Information Retrieval is the first phase those texts are identified which it is possible to extract information from.
During Information Extraction, information is extracted from a text and encoded into vectors or matrices to be processed for further analysis.
Several different methods are employed in Information Mining to extract knowledge from texts.

A simple operation in the disaster response domain that can save lives is extracting high priority posts while deferring, to a second stage, other messages concerning minor emergencies. To do so, structured and unstructured knowledge is retrieved from social networks and the Ushahidi platform.

### *Ontological Analysis and Spatial Location*

Within the disaster response domain, the contents related to the 'Why' field answer the question of 'Why did the event happen?'. The present work does not consider the reasons why an event happened or why a message is exchanged, as it exclusively deals with post disasters texts.
The lexical and syntactic forms obtained from dataset text processing underline the existence of recurrent forms. These forms establish the rules of belonging to the fields of 'What', 'Where', 'Who', 'When' and 'How'.
Therefore, Figure 6 shows only the elements attributable to this fields, above all the instances of type "where" which represents the main element of study.

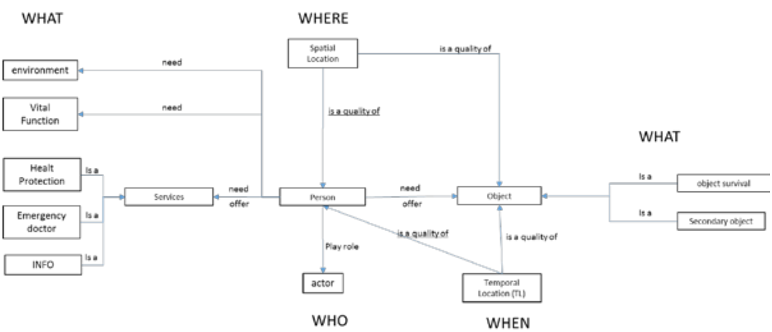



Figure 6 - Taxonomy of the Disaster Response Model

## *Taxonomies and Spatial locations*

By examining the many messages sent in risk situations collected in some datasets during some events (Earthquakes in Haiti and in Italy), we have identified the different ways used by which everyone can communicate, using natural language, their geographical position in an urban space.
Figure 7 shows an ontological model that describes all the possible ways identified. Spatial locations are defined according to a dual approach: the first one identifies the elements of a location with respect to a reference system; the second one, shows a location (e.g. adress, landmark, meeting places), both based on natural language. The above-mentioned details will be addressed in the sub-sequent sections.

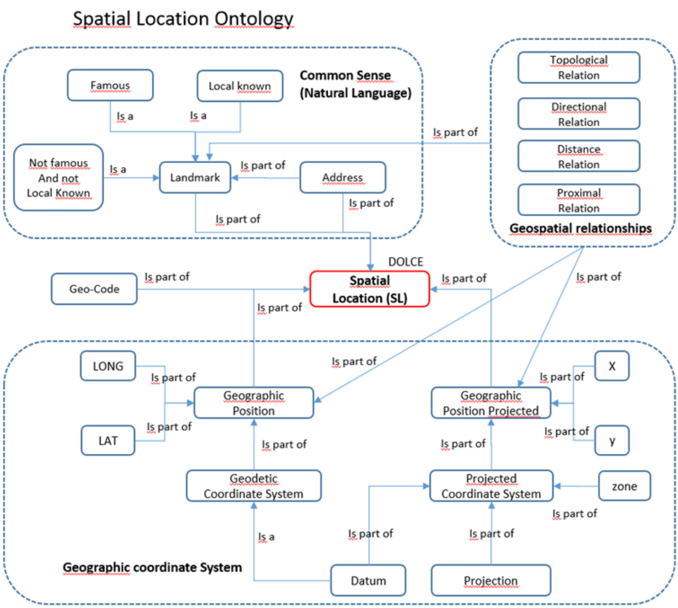



Figure 7 - Spatial Location taxonomy

*Spatial Location* represents the location of an object, an event, or an agent.

Figure 7 shows two ways, labeled with "Common Sense" and "Geographic Coordinate System" in which an agent uses a message to communicate his / her own location

1 *Geographic Coordinate System* includes two scenarios:

A spatial location can be obtained through absolute and relative coordinate systems. These can use different reference systems.

- The Geographic Position through a *Geodetic Coordinate System* (identified by a specific *Datum* with Latitude and Longitude)
- The *Geographic Position Projected* through a Projected Coordinate System (identified by a specific type of *Datum* and a Projection with its relative *Zone*) with X (East) and Y(North) coordinates.

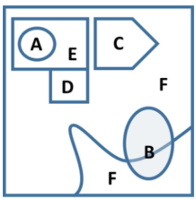
The spatial location can automatically be detected by the system if the application allows to do so, or if the GPS is turned on and records the location of the user.

2 Common Sense. This is achieved by writing a text message in a *Natural Language*. The user supplies as much information as possible about his/her own location as follows:

- *Landmark. The user refers to and describes a generic place* (e.g., ‘red building’). He/she also supplies further elements such as an address (should the location contain one) useful to determine his/her location.
- *Address*. The user shows the address. This alone is an *instance of Spatial Location.*

Another framework for spatial location is the “Geospatial RelationShip”. It contains information of a spatial location according to Geographic Position, Geographic Position Projected, Landmark and Address. Using Geospatial

RelationShip enriches actual information with further spatial elements (Longley et al. 2011, Xu, 2014).
Table 1 shows Geospatial RelationShip such as Topological, Directional, Distance, Proximal.




| Topological | Directional | Distance | Proximal |
|---|---|---|---|
| A inside E | C north of F | C at 100 m from E | C near E |
| D connected To E | A east C | | F far from A |
| C disjoint E | | | |
| B overlaps E | | | |

Table 1 - Geospatial RelationShip example

Topological, Directional, Distance, Proximal express spatial relations between geometric primitives (points, polylines and polygons). A regional space can be modeled by the use of these geometries. A spatial location can be represented by a polygon (e.g. a plaza), by a point (e.g. bus stop) and by a line (e.g. a street). The relationships occurring between these objects identifies useful information on spatial location between two or more objects. Therefore, expressions like 'I am outside the train station' is similar to 'C disjoint E' in Tab. 4.16; 'I am nearby the church' is 'C near E'; 'I am at 500 m from the University' is 'C at 500 m from E' or also 'We moved to North compared to the point 723000, 4523000 – WGS84 UTM 33N'.

## Discussion and Conclusion

The resulting, integrated, modeling approach that has been investigated and put forward in the present paper mixes text mining and ontologies, and seems to be promising in disaster response management.

This research added to the evidence in favor of ontologies as being an adequate approach to disaster response. In such framework, the effective interpretation of text messages was attempted at by building a shared conceptualization of risk. To this purpose, a separate taxonomy was developed (regarding Spatial Location), being linked to a terminal entity in DOLCE foundational ontology (Masolo et al., 2002): "SpatialLocation', for localizations and spatial relationships. Thus, the ontological framework was aligned to that of DOLCE's foundational ontology. This internationally-renowned ontology may represent the coordination apparatus among locally-differentiated knowledge information systems, with a view to enhancing knowledge sharing. Such efforts should however be complemented by the development at international level of shared disaster- and risk-related ontologies – in finer-grained details, so as to refine the linkages between the ontological entities and the concepts embodied in the natural language forms extracted from text messages.

This research work is not without limitations. First, the machine learning and ontological models have only partly been integrated with each other. While machine learning is an application-oriented approach, the ontological framework is a higher-level conceptual construct. Although disaster response interactions have been studied through an integrated approach, the integration was only tested at a conceptual level. The integration of an ontological framework in actual web platforms falls outside the scope of this study.

An important improvement that may be made to the present work in the near future is to consider an empirical integration between the ontological and machine learning approaches in

VGI/PPGIS technologies. In other words, future research could focus on the design and implementation of integrated platforms to collect, retrieve and analyze unstructured data, and communicate structured knowledge to policy makers and citizens.
Based on the above considerations, it may be concluded that the use of natural language should be explored case-by-case, with due consideration of the specific place-based, socio-cultural settings where disaster events occur. On a parallel track, special attention should be paid to sharing advances in the foundational cognitive structures that underpin sense-making and speech acts in disaster response.

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