Crisis Mapping During Natural Disasters via Text Analysis of Social Media Messages

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Abstract. Recent disasters demonstrated the central role of social media during emergencies thus motivating the exploitation of such data for crisis mapping. We propose a crisis mapping system that addresses limitations of current state-of-the-art approaches by analyzing the textual content of disaster reports from a twofold perspective. A damage detection component employs a SVM classifier to detect mentions of damage among emergency reports. A novel geoparsing technique is proposed and used to perform message geolocation. We report on a case study to show how the information extracted through damage detection and message geolocation can be combined to produce accurate crisis maps. Our crisis maps clearly detect both highly and lightly damaged areas, thus opening up the possibility to prioritize rescue efforts where they are most needed.

Keywords: Twitter · Social media mining · Emergency management · Crisis mapping · Geoparsing

1 Introduction

Nowadays, a large number of people turns to social media in the aftermath of disasters to seek and publish critical and up to date information [13]. This emerging role of social media as a privileged channel for live information is favored by the pervasive diffusion of mobile devices, often equipped with advanced sensing and communication capabilities [20]. Recently, decision makers and emergency responders have envisioned innovative approaches to exploit the information shared on social media during disasters such as earthquakes and floods [16]. However, such information is often unstructured, heterogeneous and fragmented over a large number of messages in such a way that it cannot be directly used. It is therefore mandatory to turn that messy data into a number of clear and concise messages for emergency responders. Academia showed great interest for such an issue [14], setting up studies and developing experimental solutions along

J. Wang et al. (Eds.): WISE 2015, Part II, LNCS 9419, pp. 250–258, 2015.
DOI: 10.1007/978-3-319-26187-4_21

several research directions, such as emergency event detection [2,19], situational awareness [6] and crisis mapping [5,18]. Among these, the task of crisis mapping is of the utmost importance [12], as demonstrated during recent disasters such as the Tōhoku earthquake and tsunami (Japan – 2011), the Emilia earthquake (Italy – 2012) and the Hurricane Sandy (US – 2012).

In order to produce crisis maps, traditional systems only rely on geotag metadata of social media messages [18]. However, statistics report that only 1 % to 4 % of all social media messages natively carry geotag metadata [7]. This limitation drastically reduces the number of useful messages and results in very sparse maps. Recent work have instead demonstrated that emergency reports frequently carry textual references to locations and places [3,4], as shown in Fig. 1. Therefore, a fundamental challenge of novel crisis mapping systems is that of *geoparsing* the textual content of emergency reports to extract mentions to places/locations thus increasing the number of messages to exploit. Geoparsing involves binding a textual document to a likely geographic location which is mentioned in the document itself. State-of-the-art systems, such as [18], perform the geoparsing task by resorting to a number of preloaded geographic resources containing all the possible matches between a set of place names (toponyms) and their geographic coordinates. This approach requires an offline phase where the system is specifically set to work in a geographically-limited region. Indeed, it would be practically infeasible to load associations between toponyms and coordinates for a wide region or for a whole country. Moreover, all crisis mapping systems detect the most stricken areas by considering the number of messages shared and by following the assumption that more emergency reports equals to more damage [18]. Although this relation exists when considering densely and uniformly populated areas [15], it becomes gradually weaker when considering wider regions or rural areas.

Fig. 1. Tweets shared in the aftermath of the 6.0 magnitude earthquake occurred in the South Napa region, California, US – August 24, 2014. These messages convey both situation assessments (green and red colored) and position information (blue colored) (Color figure online).

Contributions. Our proposed system exploits both situation assessments and position information contained in Twitter emergency reports. Figure 1 shows an example of Twitter emergency reports, highlighting the pieces of information we aim to extract. Overall, the main contributions of this work are summarized as in the following:

– We train and validate a machine learning classifier to detect messages conveying information about damage to infrastructures or communities. The classifier exploits a wide set of linguistic features qualifying the lexical and grammatical structure of a text. To our knowledge this is the first work employing a damage detection component in a crisis mapping task.
– We propose a novel geoparsing technique which exploits semantic annotation tools. By resorting to the Wikipedia and DBpedia collaborative knowledge-bases, it potentially allows to geocode messages from all over the world, thus overcoming the restriction of working on a specific geographic area. The semantic annotation process also alleviates the problem of toponymic polysemy (the word "Washington" may refer to the first US president, to the US capital, to the US state, etc.) by disambiguating the textual content of emergency reports. We propose and validate 2 implementations of this technique which respectively exploit TagMe [10] and DBpedia Spotlight [17].
– We leverage information visualization techniques and combine message geolocation and damage detection to produce crisis maps. We exploit D3.js[1] to build interactive, Web-based visualizations where geographic regions are colored according to the likelihood of damage. Our crisis maps can be easily embedded into Web emergency management systems, such as [3].
– We investigate a real case study to demonstrate the effectiveness of our system in detecting both highly and lightly damaged areas.

2 The Text Analysis System

The dataset exploited for this work is an improvement of the dataset originally used in [8], which is freely available for research purposes[2]. It is composed of Italian tweets, collected in the aftermath of 3 natural disasters. Tweets have been manually annotated for mentions of damage according to 3 classes: (i) tweets related to the disaster and carrying information about damage to infrastructures/communities (*damage*); (ii) tweets related to the disaster but not carrying relevant information for the assessment of damage (*no damage*); (iii) tweets not related to the disaster (*not relevant*). The inclusion of a class for tweets that are not related to a disaster (*not relevant*) is necessary because the automatic data collection strategy we adopted does not guarantee that all the tweets collected are actually related to the disaster under investigation.

Damage Detection. The goal of this component is that of automatically detecting mentions of damage in tweets. To perform this task we trained a machine learning classifier operating on morpho-syntactically tagged and dependency parsed

[1] http://d3js.org/.
[2] http://socialsensing.eu/datasets.

Table 1. Results of the damage detection task.

		damage			*no damage*			*not relevant*		
Dataset	Accuracy	Prec.	Rec.	F-M.	Prec.	Rec.	F-M.	Prec.	Rec.	F-M.
L'Aquila	0.83	0.92	0.87	0.89	0.81	0.87	0.84	0.77	0.71	0.74
Emilia	0.82	0.91	0.88	0.90	0.85	0.89	0.87	0.54	0.46	0.50
Sardegna	0.78	0.86	0.93	0.89	0.50	0.46	0.48	0.31	0.14	0.19

texts. Given a set of features and a learning corpus (i.e. the annotated dataset), the classifier trains a statistical model using the feature statistics extracted from the corpus. This trained model is then employed in the classification of unseen tweets and, for each tweet, it assigns the probability of belonging to a class: *damage*, *no damage*, *not relevant*. Our classifier exploits linear Support Vector Machines (SVM) using LIBSVM as the machine learning algorithm. Since our approach relies on multi-level linguistic analysis, both training and test data were automatically morpho-syntactically tagged by the POS tagger described in [9] and dependency-parsed by the DeSR parser using Multi-Layer Perceptron as the learning algorithm [1].

We focused on a wide set of features ranging across different levels of linguistic description [8]. The whole set of features is organized into 5 categories: *raw and lexical text features*, *morpho-syntactic features*, *syntactic features*, *lexical expansion features* and *sentiment analysis features*. This partition closely follows the different levels of linguistic analysis automatically carried out on the text being evaluated, (i.e. tokenization, lemmatization, morpho-syntactic tagging and dependency parsing) and the use of external lexical resources.

As shown in Table 1, we devised 3 experiments to test the performance of the damage detection component, one for each disaster covered by our dataset. Table 1 shows that the system achieved a good global accuracy for damage detection, ranging from 0.78 (Sardegna) to 0.83 (L'Aquila). Particularly interesting for this work are the scores obtained in the classification of the *damage* class. The F-Measure score for this class is always higher than 0.89 thus showing that the damage detection component is accurate enough to be integrated in a crisis mapping system.

Message Geolocation. Our proposed geoparsing technique builds on readily available semantic annotation tools and collaborative knowledge-bases. Semantic annotation is a process aimed at augmenting a plain-text with pertinent references to resources contained in knowledge-bases such as Wikipedia and DBpedia. The result of this process is an enriched (annotated) text where mentions of knowledge-bases entities have been linked to the corresponding Wikipedia/DBpedia resource. Here, we aim to exploit semantic annotations for our geoparsing task by checking whether knowledge-bases entities, which have been linked to our tweet disaster reports, are actually places or locations.

We implemented our geoparsing technique with 2 state-of-the-art semantic annotation systems, namely TagMe [10] and DBpedia Spotlight [17]. However, it is worth noting that our proposed geoparsing technique does not depend on the annotators exploited in our prototypical implementations. Indeed it can be implemented with any annotator currently available, or with a combination of them. Thus, for each tweet we query the semantic annotators and we analyze the returned annotated texts. Such annotated texts come with the ID/name of the linked Wikipedia/DBpedia pages. Semantic annotation systems also provide a confidence score for every annotation. Higher confidence values mean annotations which are more likely to be correct. Thus, after annotating a tweet, we resort to Wikipedia/DBpedia crawlers in order to fetch information about all the entities associated to the annotated tweet. In our implementation we sort all the annotations on a tweet in descending order according to their confidence value, so that annotations which are more likely to be correct are processed first. We then fetch information from Wikipedia/DBpedia for every annotation and check whether it is a place or location. The check for places/locations can be simply achieved by checking for *coordinates* fields among entity metadata. We stop processing annotations when we find the first Wikipedia/DBpedia entity which is related to a place or location and we geolocate the tweet with the coordinates of that entity.

Table 2. Results of the message geolocation task.

	Precision	Recall	Accuracy	F-Measure	MCC
TagMe [10]	0.88	0.80	0.86	0.84	0.72
DBpedia Spotlight [17]	0.85	0.51	0.74	0.64	0.49

Then, following the approach used in [11,18], we manually annotated a random subsample of tweets to validate the geoparsing operation. Table 2 shows the results of the validation phase in terms of well-known metrics of information retrieval. Noticeably, the TagMe implementation achieves results comparable to those of the best-of-breed geoparsers with an F-Measure = 0.84, whether the systems described in [11,18] scored in the region of 0.80. Although exhibiting encouraging Precision, the DBpedia Spotlight implementation has a much lower Recall value (0.51 vs 0.80 of TagMe) which results in degraded performances in terms of Accuracy, F-Measure and Mathews Correlation Coefficient (MCC).

3 Case Study

In this section we validate our crisis mapping system on a real case study by combining information extracted by the damage detection and the message geolocation components. The 5.9 magnitude earthquake that struck Northern Italy on May the 20th 2012, is among the strongest in recent Italian history[3]. The shaking was clearly perceived in all Central and Northern Italy and caused 7 deaths and severe damage to the villages of the epicentral area[4]. The epicenter was located near the village of Finale Emilia in a rural and sparsely populated area. This represents an added challenge for the crisis mapping task since most of the tweets came from the big urban centers in Northern Italy, such as Milan, Venice and Genoa.

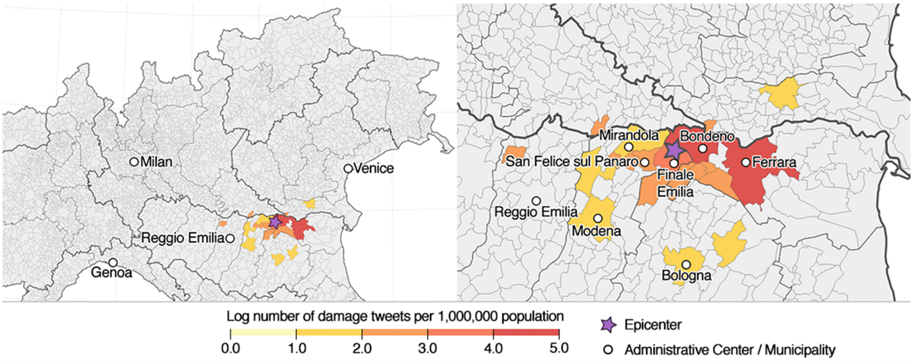

Fig. 2. Choropleth map for the Emilia 2012 earthquake showing the distribution of damage tweets among the municipalities of Northern Italy (Color figure online).

Figure 2 shows a choropleth map of Northern Italy where municipalities are colored so as to represent mentions of damage among tweet reports. Specifically, a color is assigned to a municipality according to the log number of tweets of the *damage* class geolocated in that municipality, normalized by its population. Data about the population of municipalities has been automatically fetched from Wikipedia and DBpedia during the crawling and query operations described in Sect. 2. The normalization allows to highlight the risk of damage also for rural and sparsely populated municipalities, where the number of available tweets is very low. Areas in which our system did not geolocate any *damage* tweet are grey colored in Fig. 2. As shown, despite geolocating tweets in all Northern Italy, our system only highlighted municipalities around the epicenter, clearly pointing to the damaged area. In figure, reddish colors are assigned to the municipalities of Bondeno, Ferrara, Finale Emilia and San Felice sul Panaro, thus accurately matching the most damaged locations.

Figure 3 shows 2 polar (radar) plots in which tweets of both the *damage* and *no damage* classes are considered. The plots are centered on the epicenter and present dotted concentric circles marking distances from the epicenter with a

[3] http://en.wikipedia.org/wiki/2012_Northern_Italy_earthquakes.

[4] http://www.reuters.com/article/2012/05/20/us-quake-italy-idUSBRE84J01K20120520.

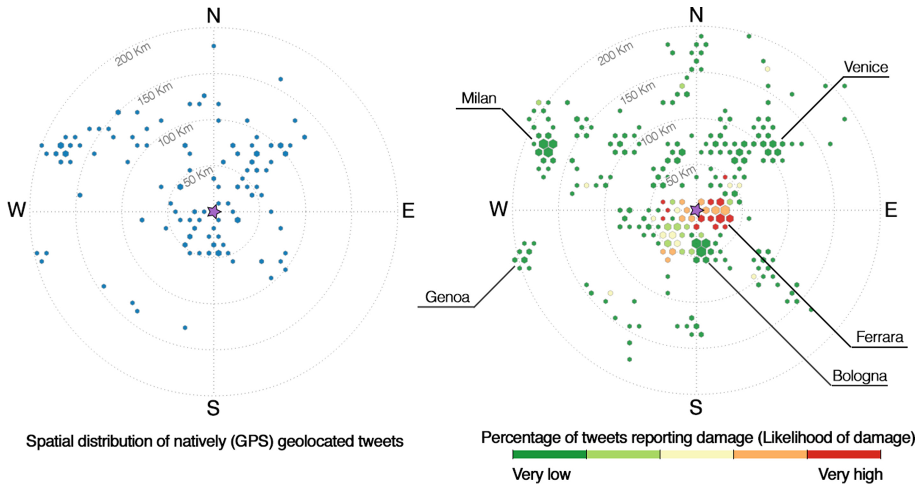

Fig. 3. Polar plots showing the hexbinned spatial distribution of tweets in Northern Italy for the Emilia 2012 earthquake (Color figure online).

step of 50 km. To avoid overplotting, we used an hexagonal binning (hexbinning) technique: the plot's surface is divided into hexagons whose area is proportional to the number of tweets geolocated in that space. Thus, areas with more tweets have bigger hexagons (e.g.: Milan, Bologna). On the left-hand side of Fig. 3 is a polar plot showing the spatial distribution of natively (GPS) geolocated tweets. The low number of natively geolocated tweets is represented by both the sparsity and the small size of the hexagons. This was the starting situation for our work, with a small number of geolocated messages and no damage label. Instead, on the right-hand side of Fig. 3 is the polar plot produced by our system in which hexagons are colored according the ratio of $\frac{\text{damage}}{\text{damage+no damage}}$ tweets. Big urban centers, such as Milan, Venice and Genoa, are represented by clusters of big sized hexagons reflecting the high number of tweets geolocated in those areas. However, despite the number of tweets, only the areas that actually suffered damage are yellow- and red-colored.

4 Conclusions and Future Work

In this work we proposed a novel crisis mapping system that overcomes the main limitations of current state-of-the-art solutions while still producing accurate maps. By introducing damage detection and by proposing a novel geoparsing technique, we are confident that our system represents a seminal work in the research field of crisis mapping. As such, possible directions for future work are manifold. The linguistic analysis carried out as part of the damage detection task could be brought to a deeper level. In fact, the damage detection classifier could be trained to detect the *object* that suffered the damage and such information could be used to enrich the maps. Results for the message geolocation task are already promising, but the validation process showed that there is still space for considerable improvements, especially regarding the Recall metric. Recent developments of semantic annotation tools open up the possibility to provide more implementations of our proposed geoparsing technique. Therefore we envision the possibility to simultaneously exploit multiple semantic annotators in a voting system. Finally, we are currently working to embed the hereby discussed system into the Web emergency management system described in [3].

Acknowledgements. The authors would like to thank Matteo Abrate and Salvatore Rinzivillo, for their insightful suggestions about data visualization. This research was supported by the .it domain registration authority (Registro .it) funded project SoS - Social Sensing (http://socialsensing.it/en).

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