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## A Classification Model for the Identification of Prominent Microblogs Users during a Disaster

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### ABSTRACT

Content shared in microblogs during disasters is expressed in various formats and languages. This diversity makes the information retrieval process more complex and computationally infeasible in real time. To address this, we propose a classification model for the identification of prominent users who are sharing relevant and exclusive information during the disaster. Users who have shared at least one tweet about the disaster are modeled using three kinds of time-sensitive features, including topical, social and geographical features. Then, these users are classified into two classes using a linear Support Vector Machine (SVM) to evaluate them over the extracted features and identify the most prominent ones. The first results using the actual dataset, show that our model has a high accuracy by detecting most of the prominent users. Moreover, we demonstrate that all the

proposed features used by our model are indispensable to achieve this high accuracy.

### Keywords

Information retrieval, Microblogs, Disaster management

### INTRODUCTION

The rapid development of communication technologies has offered access to rich information which was not previously accessible using traditional communication techniques. These technologies, such as microblogs, have become indispensable within everyday life and have been significantly implicated in several domains, particularly within the field of disaster management.

With the emergence of microblogs such as Twitter, geographic information became easier to reach by harnessing Ambient Geographic Information (AGI) posted on the field by microblogs' users. Moreover, the message behind this feed of information is not only related to geography, but is indeed very rich, opening unprecedented insights into various research domains, particularly as they relate to human and social dynamics. Controlling and analyzing this rich information eases many disaster management challenges (Bizid et al., 2014).

The need for emergency teams to go on the disaster affected zones, risking their lives, in order to collect information about what is taking place diminishes greatly. People from surrounding areas can provide nearly real-time observations about disaster scenes by interacting in microblogs. Citizens in the affected zones can share on the field information about what they are experiencing; watching and hearing during a disaster. This information is fundamental to have an accurate insight into what is happening on the ground, in order to manage emergency situations in a responsive manner.

However, a huge amount of information is shared in these microblogs during disasters referring mostly to irrelevant, noisy or redundant information which is

not useful for emergency responders. In fact, in order to manage critical situations in real-time, emergency responders need to access and identify the relevant and useful information shared in microblogs. Nevertheless, data shared in these microblogs could be expressed in several languages and in various forms (i.e. image, text, link and videos) that have to be analyzed using various time consuming techniques (e.g. text mining, image analysis...). These techniques make the retrieval task more complex and computationally infeasible in real time.

To address this problem, we propose a classification model which detects the prominent users who are sharing valuable and fresh information in a given disaster. The contribution proposed through this model is based on a set of new time-sensitive features characterizing the topical, social and geographical position of each user regarding the disaster. These features are computed using various metrics extracted from the user's profile and timeline as well as some other metrics describing the disaster. We use a linear SVM to classify each user who has shared at least one tweet related to the disaster as a prominent or non-prominent user.

The rest of this paper is organized as follows, Section 2 reviews related works that addressed the identification of prominent users in online social networks. Section 3 details the proposed features. Section 4 describes the learning step of our classification model. Section 5 outlines the dataset used to learn and test our classification model. Section 6 surveys the experiments and results. Section 7 concludes and outlines future works.

## RELATED WORK

According to recent internet live stats, 90% of information produced daily is provided essentially from social networks. The microblog Twitter is ranked in the second position with around 700 million tweets generated daily. This data has to be explored daily in order to retrieve relevant and exclusive information which was not yet shared in traditional communication channels. To achieve this, many organizations have opted to employ certified persons to continuously follow the information shared about a given topic in real time. However, this practice is tedious and infeasible in real-time, especially when there's a surge of new information in a short period of time, a phenomenon that commonly observed with each new disaster.

To address this problem, some works have proposed to coordinate between human and machine intelligence in order to classify the information shared in microblogs (Imran et al., 2014). Others have opted to analyze tweets contents according to their types by applying text mining techniques if it includes a text, image processing if it contains an image and so on (Imran et al., 2013). However, these techniques cannot be applied for real-time disaster relief as they are computationally unfeasible in real time. Therefore, many researchers have opted to identify key users who tend to share relevant information during the event, in order to follow their activities instead of focusing on the entire host of information shared on microblogs (Ghosh et al., 2012; Hajian and White, 2011; Romero et al., 2011; Wagner et al., 2012). This approach is agnostic of the content type of the shared tweets by the user, it depends on simple measures that can be computed according to the features characterizing users who are classified into three categories

The first category defines key users as the central ones in the network who can be identified using standard centrality measures such as PageRank (Heidemann et al., 2010) and HITS (Cappelletti and Sastry, 2012). As these measures depend only on the structure of the network, many works have proposed to adapt these measures and more precisely PageRank and HITS algorithms to the specificities characterizing microblogs (Shoubin and Ling, 2011; Silva et al., 2013; Tang et al., 2009; Weng et al., 2010). Measures proposed in these two categories are more suitable for the identification of influential users who are more prominent than others in a specific topic. Moreover, they are still time consuming and sensitive to well-connected users (e.g. CNN, BBC...) as they are using mainly the PageRank or Hits algorithms. Other works have identified topical key users according to the features describing their activities shared in microblogs (Pal and Counts, 2011). These approaches are computationally feasible in real time, nevertheless, they are sensitive to old fashioned information as they do not take into account neither the topical user's behavior features over time nor the spatiotemporal features.

## USERS' MODELING

In order to learn and apply our classification model, we have to represent each user who has shared at least one tweet related to the disaster according to a set of time-sensitive features reflecting his social, geographical and topical positions during the event. The three categories of features are described in depth in the

next subsections.

### Topical user's position features

The features proposed in this category estimate the extent to which a user is connected to the disaster according to his tweeting behavior. These features rely on the frequency of on-topic and off-topic tweets shared by each user during the disaster. A tweet is recorded as on-topic if it meets two criteria. It must contain at least one keyword or hashtag identifying the disaster and it should not include any words reflecting non-serious or non-valuable contents (i.e. advertising or joke words and symbols such as sale, rent, pub, lol and so on). We use the following notations in the sequel:  $OnT$ ,  $OfT$  represent respectively the number of on-topic and off-topic tweets shared by the user from  $t_0$ , time of the occurrence of the disaster, to  $t_{OnT+1}$ , extraction time of the user's tweets.  $t$  is the time of share of the on-topic tweet  $i$ .  $OfT_i$  is the number of off-topic tweets shared between  $t_i$  and  $t_{i+1}$ .

*On-topic attachment*: the more the user is sharing consecutive on-topic tweets over time the more he is interested in the disaster.

$$S_{on}(u) = OnT + \sum_{i=0}^{OnT} \frac{1}{t_{i+1} - t_i}$$

*Off-topic attachment*: the more the on-topic shared tweets are interrupted by off-topic ones the more the user is potentially detached from the disaster. Many news channels like CNN and BBC would fall into this category, as they are interested in many topics at once and do not particularly exclusive information.

$$S_{off}(u) = OfT + \sum_{i=0}^{OnT} \frac{OfT_i}{t_{i+1} - t_i}$$

### Social user's position features

This category of features evaluates users according to their position in the microblogs' social graph. They promote users having a high number of on-topic followers  $OnF$  and on-topic followees  $OnFe$  who have shared their first on-topic tweet  $t_i$  after a while from the occurrence of the disaster. These features are adjusted by the number of the user's followers  $F$  and followees  $Fe$ .

*User's Followers Implication*: indicates how much the user's followers are implicated in the disaster.

$$UFIF(u) = \frac{\sum_{i=1}^{OnF} \frac{1}{t_i - t_{event}}}{OnF + 1} + \frac{OnF}{F}$$

*User's Followees Implication Feature*: estimates how much the user's followees are interested in the disaster.

$$UFIF_{ee}(u) = \frac{\sum_{i=1}^{OnFe} \frac{1}{t_i - t_{event}}}{OnFe + 1} + \frac{OnFe}{Fe}$$

### Geographical user's position features

These features evaluate each user according to his geographic position regarding the disaster. Users who are geolocated in the disaster area may share relevant information not only about what they are hearing but also about what they are seeing and experiencing.

#### *Spatial Co-location Feature (SCF)*

SCF indicates the matching rate between the set of unique locations  $Lu$  specified by each user and the set of unique locations included in the disaster zone  $Ld$ . The extracted locations are drawn from the user's profile location.

$$SCF(u) = \frac{Lu \cap Ld}{Lu \cup Ld}$$

#### *Spatial Global Co-geolocation Feature (SGCF)*

SGCF indicates the inclusion rate of the geolocation specified by the user in the territory threatened or affected by the disaster. The disaster area is represented by a polygon or a set of polygons  $P_g$  that may include many distant zones. This feature takes into account only specific geographic coordinates  $C_u$ .

$$SGCF(u) = \frac{C_u \cap P_g}{C_u \cup P_g}$$

#### Spatiotemporal Local Co-geolocation Feature (STLCF)

STLCF is motivated by the fact that in one disaster many sub-disasters may occur in a shorter period and a more specific location. Considering only the geographic coordinates shared by each user, we extract the geolocation list  $C_u$  for each user according to the period of time  $T_i$  corresponding to the duration of each defined sub-disaster  $i$ . Each user  $u$  is represented by a sub-disasters vector  $SGCF(U) = [SGCF_1(u, T_1), SGCF_2(u, T_2) \dots SGCF_n(u, T_n)]$  and each sub-disaster can be weighted according to its importance during the disaster.

$$STLCF(u) = \frac{\sum_{i=1}^n w_i * SGCF(u, T_i)}{n}$$

#### USERS' CLASSIFICATION

After computing the different features scores, we have to assign the vector of features  $V$  representing each user.

$$V(u) = (S_{on}(u), S_{off}(u), UFIF(u), UFIF_{ee}(u), SCF(u), SGCF(u), STLCF(u))$$

Then, these features are used to classify all the users interacting about the disaster into two classes:

*Class 1 (C1)* includes prominent users who are sharing valuable and exclusive information indispensable for disaster management

*Class 2 (C2)* represents users who are sharing non-valuable or/and not exclusive information

Since we generate only 7 features at this stage of work, we decided to keep things

as simple as possible by using a linear Support Vector Machine (SVM) to learn the classification model. The two types of SVMs; linear and non-linear have been tested in order to decide which SVM classifier is more suited to identify prominent users (C1). As proved in the next sections, the linear SVM is the most suited for our case.

#### DATA AND METHODOLOGY

In order to learn the classification model, we collected most of the tweets shared during the floods that have occurred from 29<sup>th</sup> to 30<sup>th</sup> September 2014 in the Hérault area, situated in the south of France. The flooded area witnessed record-shattering 252 mm of rainfall in just three hours, causing important damages estimated between 500 and 600 million Euros.

Data collection was processed using our multi-agent System called MASIR. At the lowest level, the system detects the different users who have shared at least one on-topic tweet (i.e. talking about the floods) during the analyzed period. On topic-tweets are detected using the hashtags and keywords “#Hérault, Hérault, #Hérault, #interpériés, #crues, #flooding, #Montpellier, #Alert, #Inondations, #RedAlert” which were employed by Twitter users to share information about the disaster. The system then crawls all the on-topic and off-topic tweets shared by the detected users from 29<sup>th</sup> September at 00 am ( $t_0$ ) to 1<sup>st</sup> October at 00 am ( $t_{0nt+1}$ ). We collected 63 195 tweets composed of on and off-topic tweets shared by 3 163 users during the 2 days of the disaster. 18% of these tweets are geolocated with exact GPS coordinates and 95% of the crawled profiles contain the location name of the user. The set of polygons representing “Montpellier”, “Pinet” and “Sète” cities placed in red alert were assigned in order to compute the STLCF score of each user by fixing the same weight for each city (0.33).

We asked 45 volunteers from our laboratory to evaluate these users anonymously according to the relevance and recency of their tweets regarding the event (66 users/volunteer). These volunteers have to study the tweets of each user (from 1 to 82 tweets/ user) and attribute them to one of the 2 classes. According to this study, 88 and 3075 were classified respectively in *C1* and *C2*.

To train our model, we divided the set of users into two sets: a training set  $Tr$ ; test set  $Ts$ .  $Tr$  contains 45 and 1602 attributed respectively to *C1* and *C2*.  $Ts$  includes 43 and 1473 assigned respectively to *C1* and *C2*. Then, we used the linear Support

Vector Machine (SVM) to model our classification problem using  $Tr$  and we tested the efficiency of the resulted model using  $Ts$ .

## EVALUATION AND RESULTS

We compared our model with 2 baseline models learned by non-linear SVM classifiers as described below:

Baseline1: The model has been learned using the kernel *radial basis function* in SVM.

Baseline2: The model has been learned using a quadratic SVM.

Our model: We used a linear SVM to learn our classification model.

The classification results obtained by these baselines are detailed in *Table 1*. According to these results, the linear SVM outperforms the other baselines as it detects 39 prominent users among 43 users confirmed by the ground truth. Overall, the classification results obtained by our model achieved a high accuracy (96%).

	<b>Our model</b>	Baseline1	Baseline2
True Positives	<b>39</b>	34	38
False Positives	<b>49</b>	40	53
True Negatives	<b>1424</b>	1433	1423
False Negatives	<b>4</b>	9	5

*Table 1: Classification results using different models*

In order to test the performance of the three categories of features proposed in this paper, we train the linear SVM classifier using firstly only Topical Features (TF), then, using TF and Spatiotemporal Features (SpF) and finally using TF and Social Features (ScF). The results returned by the learned model using each set of features are reported in *Table 2*. These results show that TF are necessary to detect the most prominent users. The resulted model using only TF and SpF has yielded promising results as 41 prominent users have been retrieved among 43. However, using only these two features makes the model sensitive to false positives. Hence, according to the reported results, all the categories of features are valuable to

achieve the best result in terms of the classification model accuracy.

	True Retrieved Prominent Users	False Retrieved Prominent Users
TF	39	51
TF+SpF	41	440
TF+ScF	39	52
<b>All features</b>	<b>39</b>	<b>49</b>

*Table 2: Classification results using different categories of features*

## CONCLUSION AND FUTURE WORK

In this paper, we proposed a new classification model based on new topical, social and spatiotemporal features. This model could be used in order to detect the prominent users who are sharing valuable and exclusive information during a disaster. According to the first experimental results, our learned classification model gives a very high accuracy by using the three categories of features to represent users interacting during the disaster. Moreover, we showed that topical and spatiotemporal features are necessary to detect most of the prominent users.

For future work, we aim to enrich our classification model with further features by taking into account the nature of tweets. Furthermore, as the results obtained by our model are not precise enough, we wish to propose a ranking model in order to be able to identify the top N prominent users. Moreover, we aim to test our final model with other natural disasters in order to evaluate it in real time and in other contexts.

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