Twitter Under Crisis: Can we trust what we RT?

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ABSTRACT

In this article we explore the behavior of Twitter users under an emergency situation. In particular, we analyze the activity related to the 2010 earthquake in Chile and characterize Twitter in the hours and days following this disaster. Furthermore, we perform a preliminary study of certain social phenomenons, such as the dissemination of false rumors and confirmed news. We analyze how this information propagated through the Twitter network, with the purpose of assessing the reliability of Twitter as an information source under extreme circumstances. Our analysis shows that the propagation of tweets that correspond to rumors differs from tweets that spread news because rumors tend to be questioned more than news by the Twitter community. This result shows that it is posible to detect rumors by using aggregate analysis on tweets.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval

General Terms

Experimentation, Measurement

Keywords

Rumor Identification, Social Media Analytics, Twitter

1. INTRODUCTION

Twitter is a micro-blogging service that brings together millions of users. Allowing its users to publish and exchange short messages, also known as *tweets*, through a wide variety of clients. Users can post their tweets by sending e-mails, SMS text-messages, directly from their smartphones and a wide array of Web-based services. Also, Twitter enables real-time propagation of information to a large group of users. This makes it an ideal environment for the dissemination of breaking-news directly from the news source and/or geographical point of interest. Twitter has been found to be useful for emergency response and recovery e.g. [12]. Nevertheless, as we observe in this study, Twitter not only enables the effective broadcasting of valid news, but also of baseless rumors.

In this paper we examine how Twitter is used during a particular emergency situation. Our main focus is to characterize Twitter as an information source during this crisis. First, we present general characteristics of the post-quake Chilean Twitter community, which confirms some results observed in related work and extends existing research. Second, we focus on the issue of *veracity*. Based on anecdotal evidence, we observed that false rumors spread quickly contributing to general chaos in the absence of first-hand information from traditional sources. Motivated by this finding, our work seeks to contribute towards a deeper understanding of *valid news and baseless rumors* during a disaster. Additionally, we believe that some of our findings can be applied to some extent to other types of phenomenons, such as non-critical situations in which no a priori reliable information source is available.

The Chilean earthquake of 2010. The earthquake occurred off the coast of the Maule region of Chile, on Saturday, February 27, 2010 at 06:34:14 UTC (03:34:14 local time). It reached a magnitude of 8.8 on the Richter scale and lasted for 90 seconds; it is considered the seventh stronger earthquake ever recorded in history[1]. A few minutes after the earthquake, a tsunami hit the Chilean shores. Nearly 500 people were reported dead after the disaster and more than 2 million people were affected in some way.

In the hours and days after this earthquake, Twitter was used to *tweet* time-critical information about tsunami alerts, missing people, deceased people, available services, interrupted services, road conditions, functioning gas stations, among other emerging topics related to the catastrophe. The earthquake reached the level of *trending-topic* in Twitter a few hours after the event. Figure 1 shows Twitter activity related to the *hash-tag* `#terremotochile` (*chileearthquake*) during a period of 10 days after the event [2]. Nevertheless, it should be noted that due to infrastructure issues, telecommunications (including Internet) were intermittent in Chile for the first 48 hours after the quake. [3] The first tweets from Chile with information of the event were only observed around 3:56 AM (local time). This meant that tweet frequency originated from Chile was much lower than expected due to the circumstances.Therefore, during times when bursts of activity would have been expected (right after the quake), the number of tweets dropped considerably and did not recover completely in the next 48 hours.

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[1] `http://en.wikipedia.org/wiki/List_of_earthquakes#Largest_earthquakes_by_magnitude`
[2] `http://trendistic.com`
[3] `http://www.nic.cl/anuncios/2010-03-01.html`

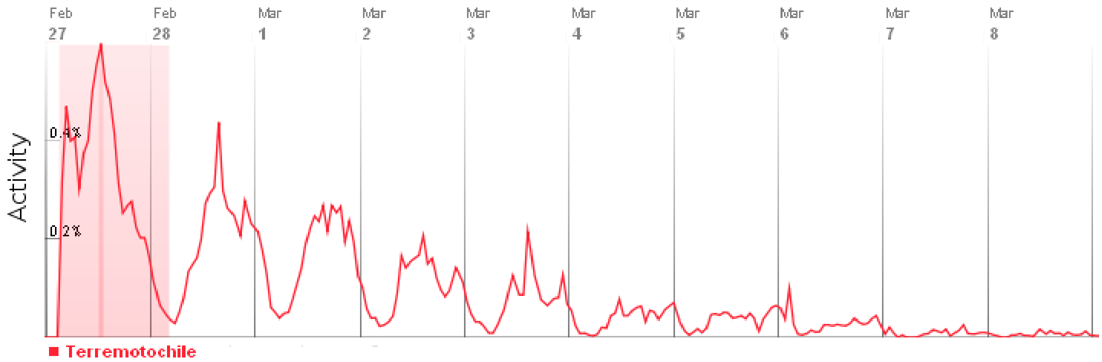


Figure 1: `#terremotochile` **trend activity during Feb. 27 and Mar. 8, 2010**

Research questions. To analyze the impact of Twitter on the propagation of information during the Chilean earthquake, we perform two types of studies over post-quake tweet data: (i) We characterize the usage and social networks of the days immediately after the event. The goal of this task is to observe how rumors and news are propagated and the dynamics of the followers/followees relationship. Also, we look at how the most authoritative users influence topics discussed in the network and how terms in tweets are correlated, among other things. (ii) We investigate the ability of the social network to discriminate between false rumors and confirmed news. To do this we examine tweets related to confirmed news and to rumors, classifying manually each tweet. The aim of this task is to measure if and how the network filters false information from accurate news.

Our contributions. First, we characterized at a local level Twitter data related to a recent natural disaster. Second, we study Twitter as an environment for the quick propagation of real and fictional news and finally we discuss how users behave in when faced with these types of information.

Roadmap. The remaining of the work is organized as follows: Section 2 presents an exploratory analysis of the data, focused on the presentation of the dataset and the description of the social interactions and keywords used during the quake. Section 4 presents an analysis of confirmed news and false rumors obtained from a human-assessment process. In Section 5 we discuss related work and finally in Section 6 we show conclusions and future work.

2. THE TWITTER NETWORK DURING AN EMERGENCY

2.1 Experimental Framework

To study how Twitter was used during the earthquake in Chile, we collected user activity data (tweets, plus other user-related information) during the time window between February 27, 2010 and March 2, 2010. To determine the set of tweets that were more or less local, or closely related to the Chilean Twitter community, we used a filter-based heuristic approach. This was necessary because the data at our disposal from Twitter did not provide geographical information about its users (there are no IP addresses or reliable location information in general). Therefore, we focused on the community that *surrounded* the topic of the earthquake. For this we selected all tweets using the *Santiago* timezone, plus tweets which included a set of keywords (using background knowledge from the authors) which characterized the event. These keywords included

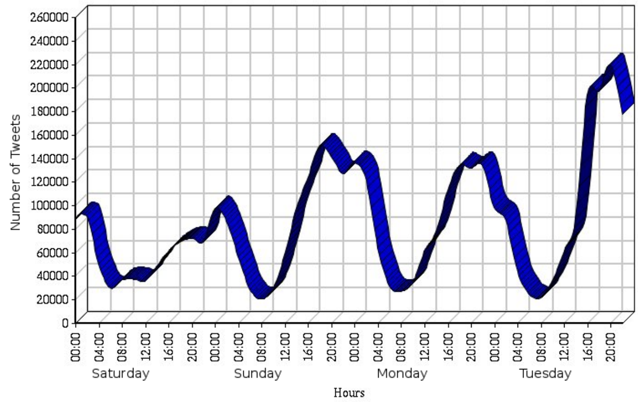


Figure 2: Twitter activity (local time)

hash-tags such as `#terremotochile` and the names of the affected geographic locations (all of them in Spanish). This preliminary selection indexed 4,727,524 tweets and 19.8% of these tweets corresponded to *replies* to other tweets.

The activity for the entire collection is shown in Figure 2 and shows the highest volume on the last day (when communications were restored in most of the country).

2.2 The Social Network

The indexed tweets are related to 716,344 different users, which registered an average of 1,018 followers (number of people following that person) and 227 followees (number of people a person follows). A scatter plot of number of followers versus number of followees is shown in Figure 3.

The plot shown in Figure 3 is in a logarithmic format in both axes. The plot shows a great fraction of users registering less than 2,000 followees (friends). This phenomenon is due to the fact that there is an upper limit on the number of people a user could follow. However, Twitter does not consider this constraint for users who register more than 2,000 followers, being posible to follow the same number of tweeters that registers as followers.

In the case of the followers count, this variable exhibits a considerable variance. It is common to observe that the number of followees is less than the number of followers. In fact, 355,343 users registers more followers than followees (49.6%), 331,546 users registers more followees than followers (46.2%) and only 29,455 users registers the same number of followers and followees (4.2%). The number of authority users with more than 100,000 followers

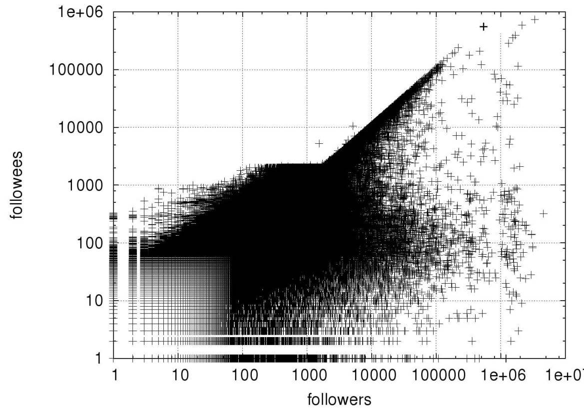


Figure 3: Followers/followees scatter plot.

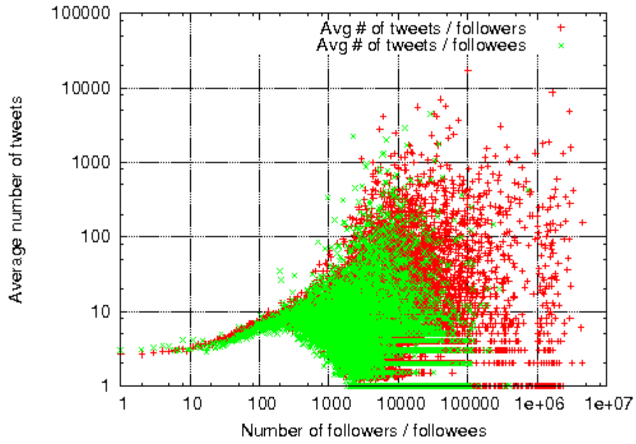


Figure 4: Average number of tweets against number of followers/followees.

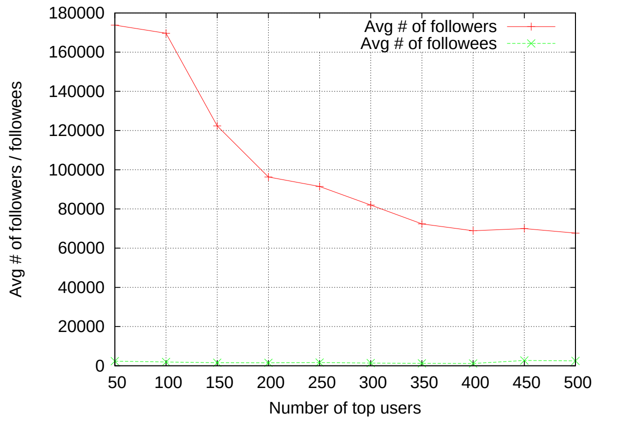


Figure 5: Average number of followers/followees for the top users.

is only 633 and in general they are mostly politicians/celebrities or mass media (e.g. CNN, The New York Times, Breaking News).

We count the number of tweets each user contributed around the event in Table 1. Over 50% of the users contributed only 1 tweet. On the other hand, only 11.47% of users tweet 10 or more tweets during this period. The average number of tweets per user (6.59) is above the median, indicating that there are outliers who tweet far more than expected.

Table 1: Number of tweets per user.

# of tweets	# of users	Percentage
1	377,112	52.64
2	110,887	15.48
3	51,649	7.21
4	30,478	4.25
5	20,677	2.89
6	15,006	2.09
7	11,406	1.59
8	9,342	1.30
9	7,642	1.07
10	82,145	11.47

We analyze the relation between the number of followers / followees and the number of tweets each user posts. In Figure 4 we plot the average number of tweets against the number of followers/followees.

As we can see in Figure 4, the average number of tweets per number of followers/followees exhibits a wide variance in the range $[1, 10^4]$ which is also where the majority of the tweets are concentrated. The average number of tweets per number of followees is greater than the average number of tweets per number of followers in the range $[1, 10]$, as opposed to the relation that exhibits the range $[10, 10^4]$. We can also see that the number of tweets increases when the number of followers and followees increases. In fact, when the number of followers/followees is greater than 2,000 we can observe that the number of tweets increases by one order of magnitude.

To investigate how the authority of a user influences the number of tweets that it produces, we retrieve users which register most tweets. We calculate the average number of followers/followees for the top-k users who register more activity during the event. We plot the k variable in the range [50,500]. The results are shown in Figure 5.

As Figure 5 shows, for the top users the number of followers is by two orders of magnitude higher than the number of followees. In fact, the number of followees reaches an average close to 1,800, while the average number of followers is more than 100,000. We can observe also that when the number of tweets decreases, the number of followers decreases. In fact, the top-50 most active users register a significant fraction of the followers in the network.

In Table 2 we show the top-10 most active users during the earthquake, ordered by the number of tweets they post. Eight out of these ten users are associated to mass media outlets (either journalists of these organizations, or *institutional* accounts such as "CNNBreakingNews"). As we can see their number of followers is three or four orders of magnitude larger than their number of followees.

We also investigated how these most active users relate to each other. In Figure 6 (left) we show the followees graph for the top 20 most active users during the event. Each node represents a Twitter user and each edge represents a relation *is a follower of* (friend). The area of each node is proportional to the number of followers each user registers. Figure 6 (left) shows that the social graph has a strong connected component among these users. However, the most authoritative user (CNNBreakingNews, that appears on the

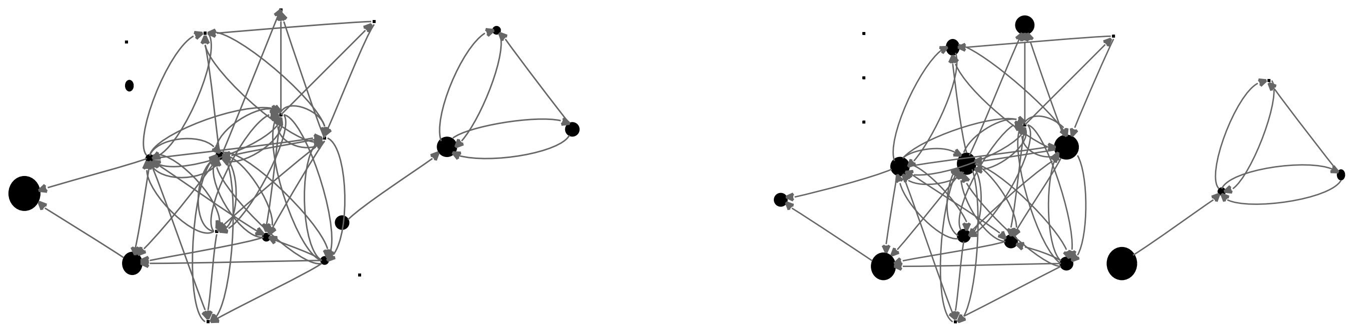


Figure 6: Followee relationships for top-20 most active users, node size represents the # of followers each user has (left), or # of tweets posted by the user (right).

Table 2: Top-10 most active users during the quake. Users related to mass media sources (mostly news) are in boldface.

User	tweets	followers	friends
BreakingNews	8584	1665399	203
CruzRojaChilena	7940	6101	978
NicolasCopano	7004	41324	0
MauricioBustamante	5579	47846	323
Cooperativa.cl	5526	19199	0
24HUltimaHora	4877	9132	50
CNNBreakingNews	4767	2930769	28
Tele13	4438	32778	29061
SocialNetworksCafe	4385	2977	0
FernandoPaulsen	4112	35733	107

Table 3: Top-10 trends registered in our dataset (ordered by number of tweets).

hash-tag	# of tweets	# of users
#terremotochile	9,810	4,122
#chile	4,246	2,562
#tsunami	1,393	1,010
#fuerzachile	944	641
#hitsunami	800	613
#terremotochile:	791	212
#prayforchile	680	595
#terremoto	670	387
#terremotoenchile	523	346
#prayersforchile	465	446

far left side of the graph) is followed by only two top users, and it does not register any *is a follower of* relationship in the top-20. In the social graph of our entire collection this authority follows 28 users but it is followed by 2,930,769. 11 of the 20 most active users correspond to mass media organizations or celebrities related to mass media. The rest of the top-20 belong to other types of organizations, such as non-profits, and the also register few friends (users that they follow or followees).

We also illustrate the activity of each of the top-20 users during the quake. In Figure 6 (right) shows the same relationship as Figure 6 (left) but in this case the size of each node represents the number of tweets of the user. As Figure 6 (right) shows, followees relationships are closely related to the number of tweets each user posted during the event. Users with most activity are more connected among each other. In particular, the most connected component of the followees graph represents the Chilean news media that is strongly influenced by the event. It is not the case of the most authoritative users, like CNN, which are located on the border of the graph because they register activity also in other topics. Thus, observing only activity related to the earthquake, the connected component of news media concentrates a significant fraction of the tweets during the event.

The most active trending-topics related to the earthquake are shown in Table 3. This table also shows the number of tweets each trend registers and the number of users who contributed at least one tweet to the trend. As Table 3 shows, the most popular trending-topic is identified with the #terremotochile hash-tag. It registers close to 10,000 tweets during the event, posted by more than 4,000 users. All topics are about the Chilean earthquake. However, the fraction of users who contributed to a trending-topic is not very significant compared to the total number of users who posted tweets during the event. In fact, the total number of tweets registered for the top-10 trending-topics is only 20,322, which represents 35.52% of the tweets posted by the top-10 most active users.

The analysis of the Twitter network during this crisis exhibits similar results as prior work (see for example Kwak et al. [5], where Twitter is not analyzed under emergencies/atypical situations). Therefore the characteristics of the network maintain their properties in atypical situations. This is a *static* observations because in this first approach, we did not measure how the network evolved during the days of the earthquake.

3. TWITTER ACTIVITY DURING AN EMERGENCY: THE EARTHQUAKE

In this section, we first analyze Twitter activity in our post-quake dataset. Then, we examine the nature of the information disseminated through Twitter during this critical event.

We analyze the variations in activity during the first day after the earthquake. Figure 7 shows the number of tweets registered for this day which contained the word "earthquake" ("terremoto" in Spanish). The impact of the event was very high the first day, measured in the number of tweets shown in Figure 7. Tweets containing the term "earthquake" register two peaks in activity, the first one a few moments after the quake, and the second one at 1:00 p.m. (local time). It should be noted that a large portion of tweets were affected by Internet interruptions during this day.

As mentioned before, the impact of the quake also affects trending-topics. Figure 8 shows Twitter activity for two trending-topics. The first one, identified with the "Viña del Mar Festival" label corres-

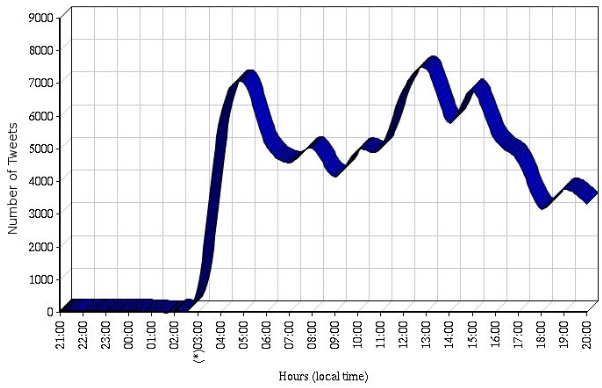


Figure 7: Frequency of tweets containing the term "earthquake" (Feb. 27, local time).

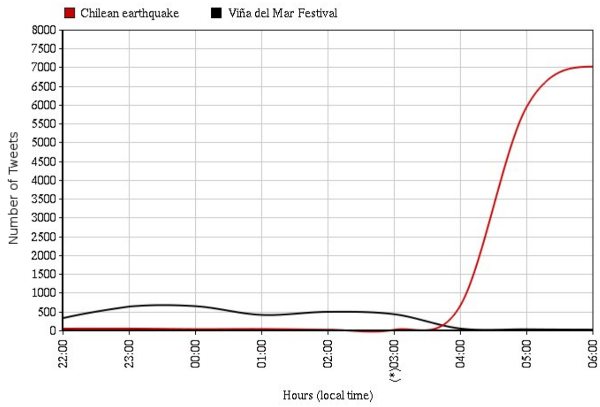


Figure 8: Two trending-topics with different fates during the earthquake.

ponds to a local music festival that normally gathers the attention of most local media during the studied time window. The second trending-topic, identified with the "Chilean earthquake" label, corresponds to the emerging earthquake trend hash-tag.

As Figure 8 shows, the "Viña del Mar Festival" trend decays quickly just a few moments after the quake. Moreover, the activity of this topic is reduced to zero just twenty minutes after the quake. On the other hand, the "Chilean earthquake" trend increases significantly in the first two hours after the quake. These results suggest, as we can expect, that the Twitter activity is proportional to the significance of the event.

We illustrate the impact of the quake by measuring the re-tweet activity during the first hours. A re-tweet (RT) is a quote of another tweet, which may or may not include a comment or reply. However, most re-tweets posted by a user are of tweets originally posted by one of its followees (which can also be re-tweets). Therefore, re-tweet activity reflects how the social network helps in the propagation of the information. An *active* social network facilitates the quick dissemination of relevant tweets. In certain way, when a user reads a tweet and re-tweets this to other users, it determines the importance of the original tweet. As a collective phenomenon, how deep re-tweets cover the social graph indicates the relevance of the tweet for the community.

In Figure 9 we show the re-tweet graphs that emerge in the first hour post-quake. In order to illustrate how the propagation process works over the Twitter social network we plot the graphs considering intervals of 15 minutes.

Figure 9 shows that tweets with the term "earthquake" are quickly propagated through the social network. In fact, we observe that only thirty minutes after the quake some re-tweet graphs exhibit interesting patterns. In some cases tweet propagation takes the form of a tree. This is the case of direct quoting of information. And in other cases the propagation graph presents cycles, which indicates that the information is being commented and replied, as it is passed on. This last case involves reciprocity in the information dissemination process. The biggest subgraph is shown in Figure 9(d) and it displays 6 degrees of separation. The remaining subgraphs have less than 6 degrees of separation. Finally we can observe that a significant fraction of the subgraphs has only one or two edges.

Tweet vocabulary. We analyze the vocabulary of tweets in this crisis situation. Intuitively, we expect a significant amount of tweets to contain terms related to the earthquake. Therefore, we also expect a high correlation of terms used in the collection.

To illustrate the properties of the Twitter vocabulary during the Chilean earthquake, we retrieve the top-50 most used terms each day. Then we count the number of occurrences of these terms in tweets. In this analysis, the vocabulary of terms has been processed to eliminate accents, digits and punctuation. Moreover, stopwords found in the collection have also been eliminated.

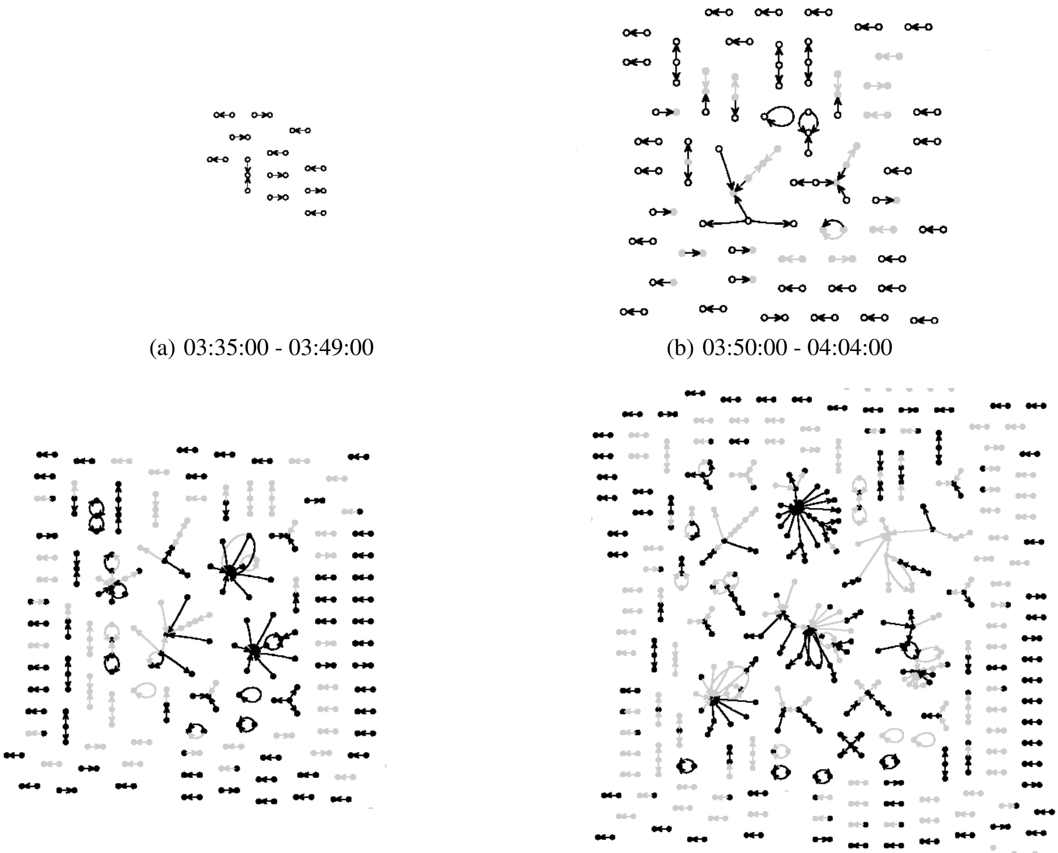
We plot term collections as term clouds. The size of each term is proportional to the number of occurrences each term registers in our dataset. The terms have been translated from Spanish to English. Term clouds are plotted in Figure 10.

Figure 10(a) shows the term cloud for the first day of the event. As the term cloud shows, the most significant terms are "tsunami" and "deceased". Thus, these terms illustrate the focus of tweets for the first day: the tsunami which hit the shores of Chile minutes after the quake, and the death toll count. In Figure 10(b) we show the term cloud for the second day of the catastrophe. In this day topics are focused on "missing people", as a consequence of the earthquake and the tsunami of the previous day. Terms as "list" or "favor" indicate that tweets are focused on asking for help to locate missing people. In Figure 10(c) we show the term cloud for the third day of the event. As in the previous day, people are looking for help to locate missing people. Popular terms are "help", "people", "favor" and "people finder". Another term used this day was "Concepcion", the name of a city located very close to the epicenter of the quake. Finally, Figure 10(d) shows the term cloud for the fourth day of the event. Some terms are related to the need of finding people, such as "help". But another trending-topic emerges this day. A NASA report released this day claims that in addition to causing widespread death and destruction, the earthquake may have shifted the Earth's axis permanently and created shorter days[4]. Thus, tweets where terms as "Earth" and "axis" became very popular after the fourth day.

4. FALSE RUMOR PROPAGATION

In this section we conduct a case study to test the veracity of information on Twitter and how this information is spread through the social network. To achieve this task, we manually selected some relevant cases of valid news items, which were confirmed at some point by reliable sources. We refer to these cases as *confirmed truths*. Additionally, we manually selected important cases

[4]Based on calculations thus far, every day should be 1.26 microseconds shorter



(a) 03:35:00 - 03:49:00

(b) 03:50:00 - 04:04:00

(c) 04:05:00 - 04:19:00

(d) 04:20:00 - 04:34:00

Figure 9: Trend propagation: tweets and re-tweets that include the term "earthquake" in the first hour post-quake. Gray edges indicate past re-tweets.

of baseless rumors which emerged during the crisis (confirmed to be false at some point). We refer to these cases as *false rumors*. Our goal is to observe if users interact in a different manner when faced with these types of information. Each case studied was selected according to the following criteria:

1. A significant volume of tweets is related to the case (close to $1,000$ or more).

2. Reliable sources (external to Twitter) allow to asses if the claim is true or false.

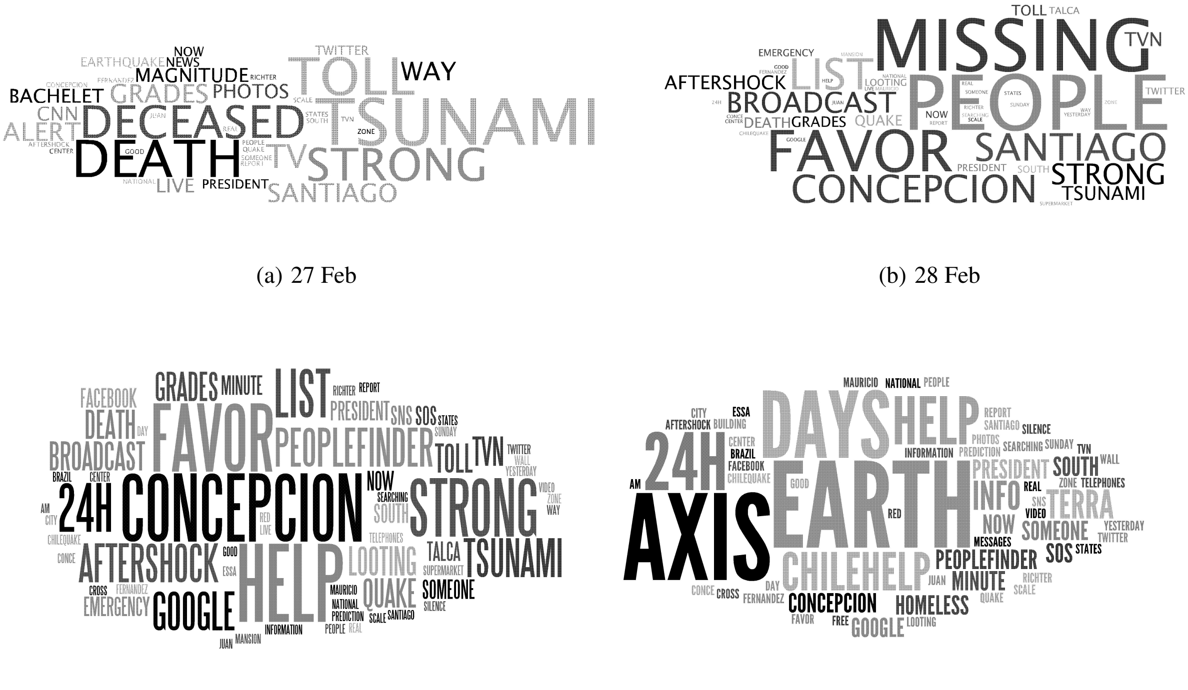
The following step was to create a list of 7 confirmed truths and 7 false rumors. This list was obtained by manually analyzing samples of tweets and also using first-hand background knowledge of the crisis. For example, a true news item (confirmed truth) was the occurrence of a tsunami in the locations of Iloca and Duao. In fact this information was quickly informed through Twitter sources while government authorities ignored its existence. On the other hand, a baseless rumor was the death of locally famous artist Ricardo Arjona. In each case we collected between 42 and 700 *unique* tweets for classification (identical re-tweets were discarded for classification purposes). These tweets were retrieved by querying the collection using keywords related to each true or false case. The next step was to classify tweets into the following categories: *affirms* (propagates information confirming the item), *denies* (refutes the information item), *questions* (asks about the information item), and *unrelated or unknown*. We automatically propagated labels in such a way that all identical re-tweets of a tweet get the same label. The results of the classification are shown in Table 4.

The classification results (see Table 4) shows that a large percentage (95.5% approx.) of tweets related to confirmed truths validate the information ("affirms" category label). The percentage of tweets that deny these true cases is very low, only 0.3%. On the other hand, we observe that the number of tweets that deny information becomes much larger when the information corresponds to a false rumor. In fact, this category concentrates around 50% of tweets. There are also more tweets in the "questions" category in the case of false rumors. This information is shown in Figure 11.

These results show that the propagation of tweets that correspond to rumors differs from tweets that spread news because rumors tend to be questioned more than news by the Twitter community. Notice that this fact suggests that the Twitter community works like a collaborative filter of information. This result suggests also a very promising research line: it could posible to detect rumors by using aggregate analysis on tweets.

5. RELATED WORK

Twitter has attracted a considerable amount of research in recent years. For the interested reader, reference [8] presents a general overview of some key Twitter characteristics including the distribution of different types of tweets. A more recent and in-depth



(a) 27 Feb

(b) 28 Feb

(c) 01 Mar

(d) 02 Mar

Figure 10: Term clouds for the first days after the Chilean earthquake.

Table 4: Classification results for cases studied of *confirmed truths* and *false rumors*.

Case	# of unique tweets	% of re-tweets	# of unique "affirms"	# of unique "denies"	# of unique "questions"
Confirmed truths					
The international airport of Santiago is closed	301	81	291	0	7
The *Viña del Mar International Song Festival* is canceled	261	57	256	0	3
Fire in the Chemistry Faculty at the University of Concepción	42	49	38	0	4
Navy acknowledges mistake informing about tsunami warning	135	30	124	4	6
Small aircraft with six people crashes near Concepción	129	82	125	0	4
Looting of supermarket in Concepción	160	44	149	0	2
Tsunami in Iloca and Duao towns	153	32	140	0	4
TOTAL	1181		1123	4	30
AVERAGE	168,71		160,43	0,57	4,29
False rumors					
Death of artist Ricardo Arjona	50	37	24	12	8
Tsunami warning in Valparaiso	700	4	45	605	27
Large water tower broken in Rancagua	126	43	62	38	20
Cousin of football player Gary Medel is a victim	94	4	44	34	2
Looting in some districts in Santiago	250	37	218	2	20
"Huascar" vessel missing in Talcahuano	234	36	54	66	63
Villarrica volcano has become active	228	21	55	79	76
TOTAL	1682		502	836	216
AVERAGE	240,29		71,71	119,43	30,86

analysis is due to Kwak et al. [5]. An application of twitter to detect news events is due to Sankaranarayanan et al. [10].

Twitter in emergency events According to the widely used taxonomy of Powell and Rayner [9] (cited e.g. in [6, 7]) there are several stages in a disaster: 1) warning, 2) threat, 3) impact, 4) inventory, 5) rescue, 6) remedy, and 7) recovery. Most studies of microblogging during emergencies, including this one, focus on the stages 3 to 5 according to this taxonomy. These are the stages at which more tra-

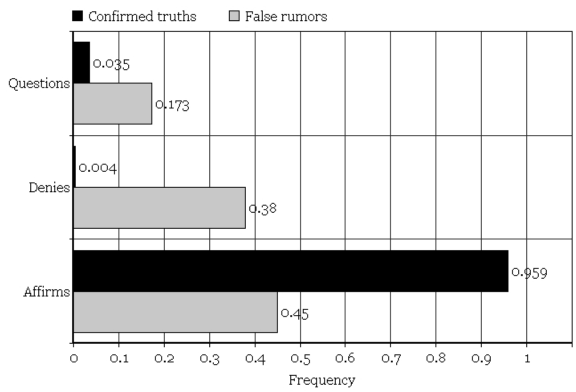


Figure 11: Classification of tweets belonging to "confirmed truths" and "false rumors".

ditional communication channels are less effective than emerging ones.

Some of the first accounts of the use of Twitter during emergency events appeared in *Wired* on October 2007[5] in relation to the wildfires in Southern California. Journalists hailed the immediacy of the service which allowed *to report breaking news quickly – in many cases, more frequently than most mainstream media outlets*.

Kireyev et al. [4] studied Twitter during two earthquakes in American Samoa and Sumatra that overlapped in time (both on September 30th 2009), with an emphasis on studying how to use topic modeling on the content of the tweets. Earle et al.[2] from the US Geological Survey reported they started to correlate tweets with seismic data to improve emergency response in late 2009[6]. In early 2010 researcher Markus Strohmaier coined the term "Twicalli scale" as a description of Twitter's response to recent earthquakes in California and Haiti[7].

Hughes and Palen have described the use of Twitter during emergencies such as hurricanes and mass convergence events such as political-party conventions [3]. Among other findings, they observe that the fraction of reply –prefixed by "@"– tweets is lower during these events (6-8% vs. 22% normally); that the percentage of tweets that include a URL is higher (40-50% vs. 25% normally); and that users that start using twitter during an event tend to adopt twitter afterwards.

Longueville et al. [1] describe the use of Twitter during a forest fire close to Marseille in mid-2009, they identified different types of twitter users: those related to mass media outlets, those acting as aggregators of information, and normal citizens. Sarah Vieweg and collaborators have studied extensively the use of Twitter for situational awareness during emergency situations such as floods and grassfires; see [12, 13, 11] and references therein.

[5] http://www.wired.com/threatlevel/2007/10/firsthand-repor/ http://www.wired.com/threatlevel/2007/10/in-disasters-ev/

[6] http://www.wired.com/wiredscience/2009/12/twitter-earthquake-alerts/

[7] http://mstrohm.wordpress.com/2010/01/15/measuring-earthquakes-on-twitter-the-twicalli-scale/

In the specific case of the Chilean earthquake of 2010 discussed in this study, bloggers have published first-hand accounts on how they used twitter during the emergency[8].

6. CONCLUSIONS

In this paper we presented a study of Twitter during an emergency situation: the recent 2010 earthquake in Chile. First, we analyzed and characterized the social network of the community surrounding the topic. This analysis confirmed that network topology characteristics remained unchanged regarding studies performed under normal circumstances (see for example the recent paper of Kwak et al. [5]). On the other hand we show new interesting insights on how trending-topics behave in this situation and how they propagate. Therefore, our findings on a more or less *local* network present no loss of generality for larger communities. Another interesting insight is that the vocabulary used in crisis situations exhibits a low variance. This fact indicates that tweets tend to describe a common/global topic, diminishing the network entropy.

Second, we focused on the propagation of confirmed truths and false rumors on Twitter. Our results, on a small set of cases, indicate that false rumors tend to be questioned much more than confirmed truths, which we consider a very positive result. As an application, given that detecting when a tweet is asking for information should be possible to do with state-of-the-art text classifiers, microblogging platforms could for instance warn people that many other users are *questioning* the information item they are reading. This would provide signals for users to determine how much to trust a certain piece of information.

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