



Tweet Scrutiny For Fast Communication Reporting

K.V Subbaiah¹, K.BalaManikanta²

Department of CSE, PBR Visvodaya Institute Of Technology & Science, Kavali.

Abstract:

The major target of the system is develop a new earthquake detection algorithm it is used for To speed-up the detection process and reduce false detections. But here having one problem is "Absence of evidence is not evidence of absence" Why? Because traditional phase associators do not know If the missing station is broken. If not, when the pick for that station will be made available. That is used for Detection bases ONLY on the presence of picks in a certain time-window. Assumption: If the network is reliable, all the operating stations in the surrounding of the epicenter will detect ground motion change and the picker will produce a P-wave detections with a priori known delay. If the network is reliable, we can look only at close stations. The number of words in a tweet message and the position of the query within a tweet. We can apply methods for sensory data detection to tweets processing .

Keywords: Tweets, social sensors, earthquake, confirmed.

I Introduction:

We investigated the real-time nature of Twitter for event detection Semantic analyses were applied to tweets classification We consider each Twitter user as a sensor and set a problem to detect an event based on sensory observations Location estimation methods such as Kaman filters and particle filters are used to estimate locations of events We developed an earthquake reporting system, which is a novel approach to notify people promptly of an earthquake event. An important common characteristic among micro blogging We plan to expand our system to detect events of various kinds such as rainbows, traffic jam etc. services is its real-time nature. Although blog userstypically update their blogs once every several days, Twitter users write tweets several times in a single day. **Japan-March , 2011, M9, Tokyo-stopped trains; cell phone notification; 8-10 minutes tsunami Kobe-fault under city give a real-time and punctual information for the detection delay of the forthcoming earthquake (a crucial**

input for EEW systems. Initial smaller earthquake during the first 4 seconds have higher frequency waves than larger earthquake.

II Related Work:

Subsequently, we make a probabilistic spatiotemporal model of an event. We make a crucial assumption: each Twitter user is regarded as a *sensor* and each tweet as *sensory information*.

These virtual sensors, which we call *social sensors*, are of a huge variety and have various characteristics: some sensors are very active; others are not. A sensor could be inoperable or malfunctioning sometimes (e.g., a user is sleeping, or busy doing something). Consequently, social sensors are very noisy compared to ordinal physical sensors. Regarding a Twitter user as a sensor, the event detection problem can be reduced into the object detection and location estimation

problem in a ubiquitous/pervasive computing environment in which we have numerous location sensors: a user has a mobile device or an active badge in an environment where sensors are placed. Through infrared communication or a WiFi signal, the user location is estimated as providing location-based services such as navigation and museum guides [9, 25]. We apply Kalman filters and particle filters, which are widely used for location estimation in ubiquitous/pervasive computing.

As an application, we develop an earthquake reporting system using Japanese tweets. Because of the numerous earthquakes in Japan and the numerous and geographically dispersed Twitter users throughout the country, it is sometimes possible to detect an earthquake by monitoring tweets. In other words, many earthquake events occur in Japan. Many sensors are allocated throughout the country. Figure 1 portrays a map of Twitter users worldwide (obtained from UMBC eBiquity Research Group); Fig. 2 depicts a map of earthquake occurrences worldwide (using data from Japan Meteorological Agency (JMA)). It is apparent that the only intersection of the two maps,

which means regions with many earthquakes and large Twitter users, is Japan. (Other regions such as Indonesia, Turkey, Iran, Italy, and Pacific US cities such as Los Angeles and San Francisco also roughly intersect, although the density is much lower than in Japan.) Our system detects an earthquake occurrence and sends an e-mail, possibly before an earthquake actually arrives at a certain location: An earthquake propagates at about 3–7 km/s. For that reason, a person who is 100 km distant from an earthquake has about 20 s before the arrival of an earthquake wave. We present a brief overview of Twitter in Japan: The Japanese version of Twitter was launched on April 2008. In February 2008, Japan was the No. 2 country with respect to Twitter traffic⁵. At the time of this writing, Japan has the 11th largest number of users (more than half a million users) in the world. Although event detection (particularly the earthquake detection) is currently possible because of the high density of Twitter users and earthquakes in Japan, our study is useful to detect events of various types throughout the world. The contributions of the paper are summarized as follows: •The paper provides an example of integration of semantic analysis and real-time nature of Twitter, and presents potential uses for Twitter data. For earthquake prediction and early warning, many studies have been made in the seismology field. This paper presents an innovative social approach, which has not been reported before in the literature. This paper is organized as follows: In the next section, we explain semantic analysis and sensory information, followed by the spatiotemporal model in Section 3. In Section 4, we describe the experiments and evaluation of event detection. The earthquake reporting system is introduced into Section 5. Section 6 is devoted to related works and discussion. Finally, we conclude the paper.

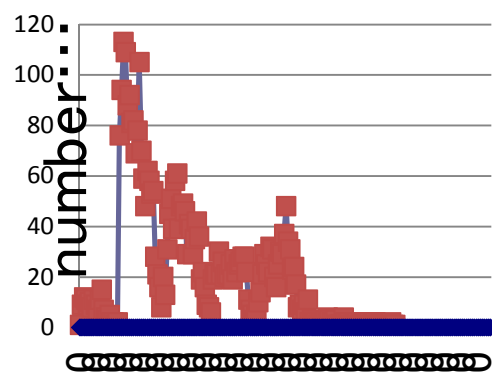
III Our Scheme Development:

A syndrome is a collection of symptoms (specific and non-specific) that are indicative of a class of diseases; Six syndrome categories were chosen: constitutional, respiratory, gastrointestinal, hemorrhagic, rash syndromes and symptoms were based on those in the BioCaster ontology, developed by experts in computational linguistics, public health, genetics and anthropology. Symptom lists were expanded to include informal synonyms found in Twitter data, e.g. ‘stomach ache’, ‘belly ache’, ‘belly pain’, ‘stomach hurt’. Case descriptions for each syndrome were then

developed with positive and negative examples. Sensor values are noisy and sometimes sensors work incorrectly. We cannot judge whether a target event occurred or not from one tweets. We have to calculate the probability of an event occurrence e from a series of data. We propose probabilistic models for event detection from time-series data. Location estimation from a series of spatial information. Proposed spatiotemporal models need to meet one condition that sensors are assumed to be independent

We check if information diffusions about target events happen because if an information diffusion happened among users, Twitter user sensors are not independent. They affect each other “earthquake” query

Features	Recall	Precision	F-Value
Statistical	87.50%	63.64%	73.69%
Keywords	87.50%	38.89%	53.85%
Context	50.00%	66.67%	57.14%
All	87.50%	63.64%	73.69%



IV conclusion:

Investigated the use of a previously untapped data source, namely, messages posted on Twitter to track and predict influenza epidemic situation in the real world. Results show that the number of flu related tweets are highly correlated with ILI activity in CDC data with a Pearson correlation coefficient of 0.9846. Build auto-regression models to predict number of ILI cases in a population as percentage of visits to physicians in successive

weeks. Tested our regressive models with the historic CDC data and verified that Twitter data substantially improves our model's accuracy in predicting ILI cases. In view of the lag inherent in CDC's ILI reports, Twitter data provides near real time assessment of influenza activity and can be used to effectively predict current ILI activity levels. Opportunity to significantly enhance public health preparedness among the masses for influenza epidemic and other large scale pandemic.

V References:

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