Asian Journal of Multidisciplinary Studies
Vol. 1, No. 3 Special Issue (2018)
ISSN 2651-6691 (Print)
ISSN 2651-6705 (Online)

Georeference Social Sensing for Disaster Response Assessment using Support Vector Machine

Ricardo A. Catanghal Jr
University of Antique
Sibalom, Antique, Philippines
catanghal.ric@gmail.com

Abstract - *Social sensing is based on the idea that communities or group of people can provide a set of information analogous to those what we can achieve from a sensor network. Classifying this considerable information, produced during and after the disaster could significantly help the government in making an informed situational assessment for relief operation. Support Vector Machine (SVM) was used to classify tweets from typhoon Melor using a tf-idf as an implementation of a bag of words model for data representation. The cleansed data were used to train the SVM following a five-fold cross-validation technique, geolocation referencing from the tweets were used to obtain location. The resulting corpus was plotted on the map as an assessment tool, that would be a valuable tool for disaster management.*

Keywords: *Support Vector Machine, Data Mining, Disaster Management, NLP.*

1. Introduction

Research efforts in the natural language processing social media analysis have focused on exciting applications of tweets as they are more popularly known or Twitter messages, and other short socially communicated messages, such as SMS and micro-blogging messages or comments. One interesting problem in tweet analysis is the automatic detection of topics being discussed in tweets [1].

The social sensing is derived on the idea that communities or group of people can supply an array of information similar to those obtainable from the social network [2]. In social sensing, it is assumed that 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 considerable variety and have various characteristics: some sensors are very active; others are not [3]. Harnessing a billion users of the social media as a sensor through data mining for the assessment in a post-disaster event will be of great help for the concerned government agencies and other organization to have a quick and informed decision. This information could help in addressing the appropriate response to the localities in need.

There are thousands of microblogs (commonly called 'tweets') posted during a disaster event, only a small fraction contribute to disaster response assessment, while the majority of the tweets merely reflect the opinion of the masses (e.g., sympathizing with the victims affected by the disaster). It is humans are the best judges of what information contributes to situation assessment [4][5], tweets are posted so rapidly during large-scale disasters that it is infeasible for humans even to leave alone identifying tweets which contribute to situation assessment.

The objective of this study is to develop a social sensing classifier algorithm that can distinguish and extract disaster situation assessment tweets from tweet streams posted during a disaster. Categorizing the tweets for situational assessment based on the geolocation- reference mentioned in the tweet.

2. Materials and Methods

The initial study and methodology were discussed in the previous work [6], the tweets were gathered from Twitter users about the typhoon via Twitter Search API provided by Twitter in order to get public tweets that correlate to the given parameters being search. Specifically tweets regarding the Typhoon Melor (locally known Nona), from December 14 to 15, 2015 were gathered and used as a corpus of the study. In the process of collecting of the said tweets, first, they were filtered to include messages that contain the following hashtags or keywords: Melor, nonaph, Nona, Typhoon Nona, Typhoon Melor, and TyphoonPH with the use of a web scrapper. The parameters include both the local and international name of the typhoon, common hashtag words for the typhoon, and official hashtags used by the Philippine government over Twitter. The gathering and collection of data were conducted in compliance with the terms and conditions stipulated by the site. The fields included Twitter usernames alone which are publicly viewable and dates of the post, data collected did not include any identifying information or geolocation tags. In total, we collected 43, 648 tweets using the process.

Data Processing

In the cleaning of data, the proponent first transformed the string tweets into lower case for easier correlation and comparison then discard the stop-words, URL, hash symbol (#), emoticons, RTs, mentions (@mention), expressions and other unique/miscellaneous characters that are present in each tweet. This process was performed in order to produce a more compact "dictionary" which will help decrease the dimension of the data set that is going to be used [6].

Filtering was done in order to remove repeated tweets or retweets, and filtering by the length of 3. This will give us the unique tweets. After the process, 5780 unique values were returned. For data representation, the proponents created string vectors by computing the tf-idf of each word in each tweet as an implementation of the bag-of-words model. Term Frequency (TF) of a word in a tweet was computed by counting the number of occurrences of a word in a tweet and dividing it by the total number of words in the tweet. On the other hand, Inverse Document Frequency (IDF) of a word was computed by counting the total number of tweets collected, dividing it the by the number of tweets where the word appears and computing the logarithm of the quotient in base 10. Consequently, TF-IDF of a word was then computed by multiplying the TF and IDF values of a word in a tweet.

$$tf = \frac{frequency\ of\ a\ word\ in\ a\ tweet}{total\ number\ of\ words\ in\ a\ tweet}$$

$$idf = log(\frac{total\ number\ of\ tweets}{frequency\ of\ a\ word\ in\ the\ collection\ of\ tweets})$$

When a word has a high TF-IDF value, it means that the word is relatively relevant to the collection of tweets. On the other hand, when a word has a low TF-IDF value, the word is possibly just a noise or a stop-word. Below a sample of string vectors created from tweets, with ":" as a separator of the word's index in the "dictionary" and of its TF-IDF value.

101:0.3085431 446:0.3636406
814:0.34153634

815:0.45472562 1:0.139794
162:0.33064252

For the training and testing set, +1 or -1 was inserted as a prefix in each string vector to signify that it belongs to the positive class (disaster-related tweet) or negative class (disaster-unrelated tweet). The figure shows the summary of the methodology employed in the study.

Fig. 1. Methodology Summary

Georeference

Asian Journal of Multidisciplinary Studies
Vol. 1, No. 3 Special Issue (2018)
ISSN 2651-6691 (Print)
ISSN 2651-6705 (Online)

Geo-location information is a clear identifiable information that includes street addresses and intersections, city names, county names, highways and place-names (schools, landmarks, etc.) Whether very precise or more general, tweets that include information about the location of people, fires, evacuation sites (among others) can help those who receive such information in assessing their personal situations, as well as achieving an extensive understanding of the situation as a whole. This type of information not only aids those who receive such tweets but also accommodates the automatic retrieval of relevant information regarding the situation in the area.

We also noted location-referencing in some tweets. Location-referencing refers to information that uses one place as a reference for another or the mention of location via a landmark, i.e. "x miles from y," where the reference point is ambiguous without knowledge of situational context. For example, regarding power supply tweet sample we read:

No electricity Virac turned into a Ghost Town again.

Alternatively, from an evacuation tweet:

143,223 individuals (29,015 families) evacuated in Sorsogon

These tweets do not contain easily extractable geo-location information. They do, however, contain information that can give an idea about the location of both the Twitterer and the disaster-affected area if we further uncover the reference points to which the user is referring. The abbreviation "i.e." means "that is," and the abbreviation "e.g." means "for example."

Support Vector Machine (SVM)

Support Vector Machines (SVM) is a large-margin classifier which means it is a method of machine learning based on a vector where the goal is to find a decision boundary between two classes that is maximally far from any point in the training [7]. Its classification is based on which side of the boundary an instance falls on, given that that instance is mapped into that same vector space. In other words, when applied to this study, the distance of the contents of a tweet from the decision boundary determines whether that tweet is disaster-related or not.

3. Results and Discussions

The proponents in this experimental setup gathered the tweets as sensor values. The cleaning and filtering showed that out of 43, 648 tweets that were scrap using the Twitter Search API 86.76% of it were noise or duplicates and only 13.24% or 5780 are unique values.

The proponents then performed 5-fold cross-validation to validate the performance of the SVM classifier and to produce the best model (training set) for the disaster situation assessment tweets. In which 80% of both disaster assessment and disaster assessment unrelated tweets were chosen randomly for cross-validation set and another 20% were chosen randomly for the final testing set.

Table 1. Model and Accuracy

Model #	Accuracy	Precision	Recall
1	91.78%	85.60%	100%
2	73.15%	65.30%	100%
3	88.20%	81.25%	99.15%
4	95.35%	92.45%	99.50%
5	93.52%	88.65%	99.85%

The table 1 shows that it is the model/training set #4 that yielded the highest accuracy. Therefore, it is the best model for classifying disaster situation assessment tweets. The proponents then used this model in classifying the 20% final testing set generated earlier and were able to obtain an accuracy of 95.35%, precision of 92.45% and recall of 99.50%. The value for accuracy means that the model can correctly classify a disaster situation assessment or disaster situation assessment unrelated tweet with an accuracy of 95.35 which is very high. Moreover, the value for precision means that out of the final testing set, 92.45% of the classifications made were correct and the value for recall means that 99.50% of the final testing set were correctly classified.

Asian Journal of Multidisciplinary Studies
Vol. 1, No. 3 Special Issue (2018)
ISSN 2651-6691 (Print)
ISSN 2651-6705 (Online)

The following evaluation metrics were used:

- *Precision, ratio of correctly detected events among the total number of detected events:*

$$Precision = \frac{TP}{TP + FP}$$

- *Recall, ratio of correctly detected events among the total number of occurred events:*

$$Recall = \frac{TP}{TP + FN}$$

- *F-Measure, harmonic mean of Precision and Recall:*

$$Fmeasure = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Then using crowdsourcing to identify disaster-related tweets in Twitter and plot them to Google Maps with marker and information as a monitoring and assessment tool.

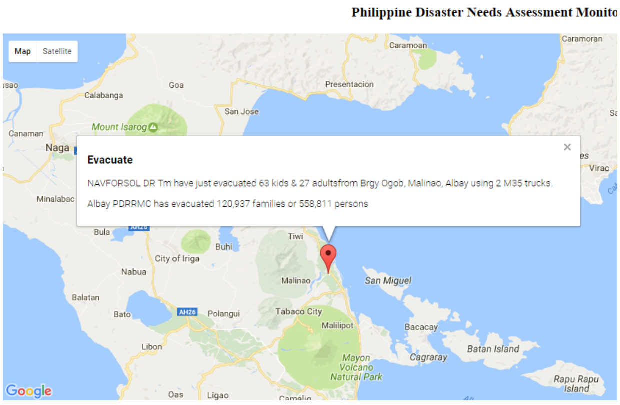

Fig. 4. Sample Generated screen shoots

4. Conclusions and Recommendations

In this study, I have presented a social sensing classifier algorithm that can distinguish and extract disaster situation assessment tweets from tweet streams posted during a disaster. Then categorizing the tweets for situational assessment based on the geolocation- reference mentioned in the tweet using the Support Vector Machine (SVM).

There is still more work needed and room for further research in this area. Some scope for exciting research directions people can take concerning this problem, such as the live scrapping of tweets on detecting different places for an emergency, incorporating features that leverage the graph structure of Twitter to improve classification. Future work of this study includes the completion of several levels of classification in which a tweet is classified into category. Furthermore, future work also includes generating customized marker to suite or differentiate the type of disasters and the type of markers (for disaster or for class suspension).

5. References

[1] Rosa KD, R Shah, B Lin, A Gershman, R Frederking. (2011). Topical Clustering Of Tweets. Retrieved July 14, 2016 from http://www.cs.cmu.edu/~kdelaros/sigir-swsm-2011.pdf

[2] Avvenuti M, S Cresci, A Marchetti, C Meletti, and M Tesconi. (2014). EARS (earthquake alert and report system): a real time decision support system for earthquake crisis management. In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining (KDD '14). ACM, New York, NY, USA, 1749-1758. DOI: http://dx.doi.org/10.1145/2623330.2623358

[3] Sakaki T, M. Okazaki, and Y. Matsuo, "Earthquake shakes twitter users: Real-time event detection by social sensors," Proceedings of International Conference on World Wide Web (WWW)., pp. 851–860 2010.

[4] Vieweg A, L. Hughes, K. Starbird, and L. Palen, "Microblogging During Two Natural Hazards Events: What Twitter May Contribute to Situational Awareness," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI). ACM,2010,pp.1079– 1088.

[5] Qu Y, C. Huang, P. Zhang, and J. Zhang, "Microblogging After a Major Disaster in China: A Case Study of the 2010 Yushu Earthquake," in Proceedings of the ACM Conference on Computer Supported Cooperative Work (CSCW). ACM,2011,pp.25–34.

[6] Catanghal R, T Palaoag, A Malicdem. (2017). Crowdsourcing Approach For

ISSN 2651-6691 (Print)
ISSN 2651-6705 (Online)

Disaster Response Assessment. Matter: International Journal of Science and Technology

[7] Bahmani B, A. Chowdhury, and A. Goel, “Fast incremental and personalized pagerank,” 2010.