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# Detecting Help Seeking Tweets in Natural Crises

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## 1. INTRODUCTION

Social media has become a popular channel for sharing crisis related information in recent years. Affected people reflect on damages, road situations, desired resources, and what they can provide. First responders benefit help seeking posts to distribute resources more efficiently and locate injured ones. However, requests for help are difficult to obtain among millions of other posts. To detect help seeking posts, researchers have mostly focused on textual features such as n-grams and sentence structures. Dependence on textual features has led to missing help seeking posts that do not have specific words and also false positives. What has been overlooked in the previous research is usefulness of context. In Twitter, each tweet comes with a set of fields such as location, source, mentions, and URLs. In this poster we propose a method based on these fields, *context*, for detecting help seeking tweets. We show the effectiveness of the proposed method with our experimental results on a Hurricane Sandy dataset.

## 2. BACKGROUND AND RELATED WORK

Disaster relief [Abbasi et al. 2011], situational awareness [MacEachren et al. 2011], crisis management [Kumar et al. 2011; Starbird and Palen 2013], and crisis coordination [Gao et al. 2011-1] using social media have attracted many researchers. Several systems have been implemented for disaster relief such as Ushahidi [Okolloh 2009] and Twitris [Sheth et al. 2010]. Specifically, detecting help seeking posts, which is our goal in this poster, is both related to information seeking after disasters [Qu et al. 2011] and finding questions that seek information in social media [Zhao and Mei 2013].

Help seeking tweets can be found using content, n-grams and regular expressions [Purohit et al. 2014]. However, the importance of context has been overlooked. Context is features that provide information in addition to text. In this work we use context to detect help seeking tweets.

## 3. APPROACH AND UNIQUENESS

There is a wide range of context fields associated with each tweet[1]. We study six context fields and later

[1] https://dev.twitter.com/overview/api/tweets

use them in our detection approach: method of publishing (source), geolocation, frequency of entities (mentions, URLs, and hashtags), and length.

We first study differences between help seeking and other tweets in terms of context fields[2] which have not studied before, to the best of our knowledge. Afterwards, we use these fields to train classifiers that detect requests for help. To find the best classification method, we test four different classifiers. Moreover, we show the robustness of our approach to imbalanced classes and training size.

# 4. RESULTS AND CONTRIBUTIONS

Our experiments are on a Hurricane Sandy dataset which was collected in October 27 for 11 days using relevant hashtags such as #sandy. By manual annotation, 3261 help seeking tweets have been extracted [Purohit et al. 2013]. 6500 Negative examples are randomly sampled from the remaining tweets.

**Table 1: Comparison of Help Seeking and other tweets**

| Feature | Help Seeking | Other |
|---|---|---|
| Tweets with at least a mention | 38% | 61% |
| Tweets with at least one URL | 66% | 44% |
| Average word count per tweet | 19.8 | 15.7 |

Three most distinctive features of help seeking tweets are listed in Table 1. They are longer and have more URLs to convey as much information as possible. Moreover, usage of mentions is low because requests are not necessarily conversations.

[2] We will use context fields, fields, and features interchangeably in this poster.

Four different classifiers, Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and AdaBoost have been trained and compare using Precision, Recall, and F-Measure. Based on the results in Table 2 DT has the highest F-Measure.

**Table 2: Performance of different classifiers**

| Classifier | Precision | Recall | F-Measure |
|---|---|---|---|
| SVM | 0.40 | 0.78 | 0.53 |
| DT | 0.90 | 0.90 | **0.90** |
| RF | 0.90 | 0.83 | 0.86 |
| AdaBoost | 0.91 | 0.87 | 0.89 |

Manual labeling is expensive and time consuming but classifiers need sufficiently large training sets. To show resilience of our method to size of the training set, we have changed the percentage of our dataset to be used for training phase from 90% to 30% and F-Measure only drops by two percent.

Help seeking tweets are quite rare [Purohit et al. 2014] so the classifier faces the challenge of imbalanced classes. To show the effect of this issue on our method, we have changed the ratio of help seeking to other tweets from 50% to 20% and the lowest performance is 0.86 which is comparable to our original settings.

**Table 3: Effect of Train to Test Ratio on Performance**

| Help Seeking Ratio | Precision | Recall | F-Measure |
|---|---|---|---|
| 50% | 0.95 | 0.95 | 0.95 |
| 33% | 0.90 | 0.90 | 0.90 |
| 20% | 0.86 | 0.86 | 0.86 |

# 5. REFERENCES

[1] Abbasi, M.A., Kumar, S., Andrade Filho, J.A. and Liu, H., 2012. Lessons learned in using social media for disaster relief-ASU crisis response game. InSocial Computing, Behavioral-Cultural Modeling and Prediction (pp. 282-289). Springer Berlin Heidelberg.

[2] Gao, H., Barbier, G., Goolsby, R. and Zeng, D., 2011. Harnessing the crowdsourcing power of social media for disaster relief. Arizona State Univ Tempe.

[3] Gao, H., Wang, X., Barbier, G. and Liu, H., 2011. Promoting coordination for disaster relief–from crowdsourcing to coordination. In Social computing, behavioral-cultural modeling and prediction (pp. 197-204). Springer Berlin Heidelberg.

[4] Kumar, S., Barbier, G., Abbasi, M.A. and Liu, H., 2011, July. TweetTracker: An Analysis Tool for Humanitarian and Disaster Relief. In ICWSM.

[5] MacEachren, A.M., Jaiswal, A., Robinson, A.C., Pezanowski, S., Savelyev, A., Mitra, P., Zhang, X. and Blanford, J., 2011, October. Senseplace2: Geotwitter analytics support for situational awareness. In Visual Analytics Science and Technology (VAST), 2011 IEEE Conference on (pp. 181-190). IEEE.

[6] Okolloh, O., 2009. Ushahidi, or 'testimony': Web 2.0 tools for crowdsourcing crisis information. Participatory learning and action, 59(1), pp.65-70.

Purohit, H., Castillo, C., Diaz, F., Sheth, A. and Meier, P., 2013. Emergency-relief coordination on social media: Automatically matching resource requests and offers. First Monday, 19(1).

[7] Purohit, H., Hampton, A., Bhatt, S., Shalin, V.L., Sheth, A.P. and Flach, J.M., 2014. Identifying seekers and suppliers in social media communities to support crisis coordination. Computer Supported Cooperative Work (CSCW), 23(4-6), pp.513-545.

[8] Qu, Y., Huang, C., Zhang, P. and Zhang, J., 2011, March. Microblogging after a major disaster in China: a case study of the 2010 Yushu earthquake. InProceedings of the ACM 2011 conference on Computer supported cooperative work (pp. 25-34). ACM.

[9] Sheth, A.P., Purohit, H., Jadhav, A.S., Kapanipathi, P. and Chen, L., 2010. Understanding events through analysis of social media.

[10] Starbird, K. and Palen, L., 2013, February. Working and sustaining the virtual Disaster Desk. In Proceedings of the 2013 conference on Computer supported cooperative work (pp. 491-502). ACM.

[11] Zhao, Z. and Mei, Q., 2013, May. Questions about questions: An empirical analysis of information needs on twitter. In Proceedings of the 22nd international conference on World Wide Web (pp. 1545-1556). 9