

Disaster Analysis using User-Generated Weather Report

Yasunobu Asakura
Tokyo Metropolitan University
asakura-yasunobu@ed.tmu.ac.jp

Masatsugu Hangyo
Weathernews Inc.
hangyo@wni.com

Mamoru Komachi
Tokyo Metropolitan University
komachi@tmu.ac.jp

Abstract

Information extraction from user-generated text has gained much attention with the growth of the Web. Disaster analysis using information from social media provides valuable, real-time, geolocated information for helping people caught up these in disasters. However, it is challenging to analyze texts posted on social media because disaster keywords match any texts that contain words. For collecting posts about a disaster from social media, we need to develop a classifier to filter posts irrelevant to disasters. Moreover, because of the nature of social media, we can take advantage of posts that come with GPS information. However, a post does not always refer to an event occurring at the place where it has been posted.

Therefore, we propose a new task of classifying whether a flood disaster occurred, in addition to predicting the geolocation of events from user-generated text. We report the annotation of the flood disaster corpus and develop a classifier to demonstrate the use of this corpus for disaster analysis.

1 Introduction

With the recent spread of the Web, disaster information is now being posted to the social media in real time. In the case of the 2011 Great East Japan Earthquake, Twitter was used to share information regarding damage states, tsunami warnings, and safety confirmations. As increasing amounts of information have been produced by users, information extraction from social media has attracted attention in the field of natural language processing. Flood disaster analysis using information from social media is heavily awaited because precise information such as time and location of a flood is crucial for supporting (potential) victims of the disaster. However, information extraction from social media faces several problems. Here, we address two important problems.

First, collecting posts including keywords about a disaster is not sufficient to judge whether the disaster actually occurred. The following posts concerning disasters illustrate this problem.

- (1) The street in front of my house is flooded.
- (2) There are several flood disasters around here.
- (3) Last year's flood was terrible.
- (4) Please be aware of flood hazards.

We desire to extract posts such as post (1) refer to a disaster but there are posts that do not refer to any specific disaster, (2) refer to a generic event rather than a specific event, (3) refer to a past accident instead of a current situation, and (4) does not refer to any disaster but alerts a reader regarding the possibility of future catastrophe.

Second, another important problem in disaster analysis is temporal and/or geographical uncertainty. Although 0.77% posts on Twitter¹ contain GPS information (Hecht et al., 2011), not all posts include exact geolocation. In addition, a post that contains GPS information need not refer to the location of a disaster event described in the post. The following post concerning a disaster illustrates this problem.

- (5) I heard that it was flooded in Okinawa.

In the case of (5), the disaster occurs not in the place that GPS information indicates but in Okinawa prefecture.

Therefore, we propose new tasks (1) that classify whether a disaster occurred and (2) that predict the geolocation of events from social media. The task of geolocation prediction from Twitter has also been recently addressed (Han

This work is licenced under a Creative Commons Attribution 4.0 International Licence. Licence details: <http://creativecommons.org/licenses/by/4.0/>

¹<https://twitter.com/>

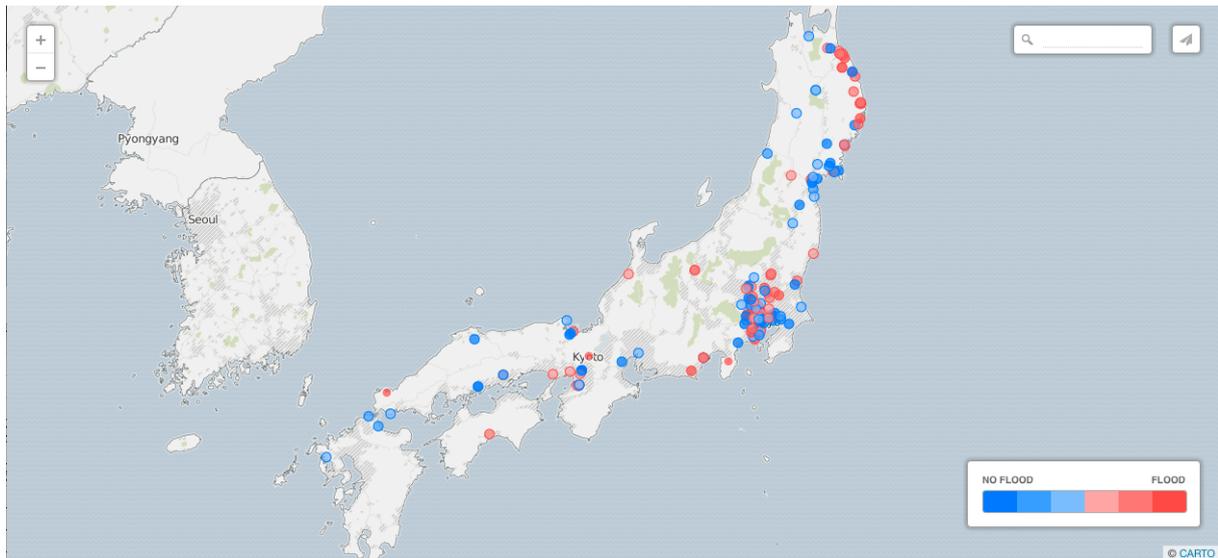


Figure 1: Visualization system of flood disaster for the Typhoon Lionrock crossed northern Japan on August 29, 2016. It caused heavy flood in Iwate prefecture, and its damage is clearly found in this visualization (red circles in the upper right coastline). The flood did not cause severe damage in other parts of northern Japan (shown in blue circles).

et al., 2014). However, in the present study, we attempt to predict the location of an event that a post refers to rather than the location of the post.

Figure 1 is a demonstration of our visualization system² of flood disaster. This visualization system uses the disaster classifier we built in this study. We aim to make a visualization system that can capture the exact location of the disaster in real time.

The main contributions of this study are as follows:

- We proposed a new task of flood disaster analysis and created a flood event dataset.
- We developed a supervised classifier to classify whether a disaster occurs to predict time when a disaster occurs and to predict distance between a reporter and disaster.

2 Related Work

With the development of the information society, studies of disaster information analysis from social media have attracted attention in the NLP literature.

In the case of the Great East Japan Earthquake, Neubig et al. (2011) constructed an information extraction system that visualized the security of the people in the disaster-stricken area using Twitter. They made a corpus by annotating safety information to tweets and trained a classifier to categorize the security of the population. We also perform disaster information analysis; however, we focus on event classification rather than classification of personal information. In addition, Varga et al. (2013) extracted distress and support information concerning disaster from tweets. Their distress recognizer used geographical information as a feature; however, they did not estimate the location of the disaster event. Our work differs in that we try to estimate how far the disaster event is from the person posting in terms of time and location.

Similar to our study, Sakaki et al. (2010) constructed a reporting system that classifies whether an earthquake or typhoon occurs when the text was posted. They predicted the location of disaster events using GPS data from the tweets; however, they did not address the problem of tempo-spatial distance between the person posting and the event. They were not able to tackle this problem because there were very few tweets posted with GPS data (Hecht et al., 2011). In this study, we created a flood event corpus from a blog in which almost all users posted their reports with the geolocation. Moreover, we separated the task of location prediction of posts and location prediction of events.

Regarding information extraction concerning a flood, Herfort et al. (2014) used specific geographical features like hydrological data and digital elevation models to prioritize crisis-relevant Twitter messages. In this study,

²https://wni.carto.com/u/wx/viz/6ac4d3b0-da61-48a1-a7bb-68177f1194db/public_map

label	value	description
disaster	positive negative	From the post, we can judge that a flood disaster is occurring when the text is posted. From the post, we can judge that a flood disaster is not occurring when the text is posted.
time	future	high probability low probability unmentioned
	present	occurring probably occurring not occurring
	past	occurred occurred long before unmentioned
distance	close far misc	From the post, we can judge that a reporter alerts a future flood in advance. From the post, we can judge that a reporter is anxious about a future flood. From the post, we can judge that a reporter does not mention about a future flood. From the post, we can judge that the flood is occurring. From the post, we can presume that the flood is occurring. From the post, we can judge that a flood is not occurring. From the post, we can judge that a flood occurred recently. From the post, we can judge that a flood occurred long before. From the post, we can judge that a reporter does not mention a post flood in the past. We can judge from the post that a reporter reports flood in front of him/her. We can judge from the post that a reporter reports flood but he/she is not at the place where he/she experienced flood. Except close and far.

Table 1: Labels for the flood disaster events.

we focus on the prediction of an event using linguistic features to discuss potential issues in text-based event classification. Vieweg et al. (2010) analyzed tweets generated during a flood event. They found that 6% of the tweets contained location information. In this study, we focus on annotating the locational relation of a reporter and disaster. Bruns et al. (2012) compiled a dataset of tweets that relates to the crisis event by using hashtags. We made a flood disaster dataset by collecting report containing keywords related to floods because the social media used in this paper does not support hashtags. However, almost all of our data already has the exact GPS information.

3 Annotation of Flood Event

3.1 Data

We collected 567 posts including Japanese keywords for a flood event such as “inundation” and “flood” from a weather report sharing site known as “weathernews³.” Approximately, 500,000 reports on weather are posted on this site every month by users, and these reports contain posting time and GPS information. Each reports comprises picture and text about weather, and some exclusive label of weather (e.g., onomatopoeia such as ポツポツ, ザーザー etc.) and temperature (e.g., hot or cold) by users’ subjective judgment. In this study, we used only the text of weather reports.

We used posts of 17 days that included July, which is during the typhoon season, and February, which is the snowy season in Japan, and 4 days during the 2011 Great East Japan Earthquake. The average number of sentences in one post is 5, while the average number of phrases and words in one sentence are 5 and 17, respectively.

We labeled the posts according to whether a disaster occurred when the text was posted. We call this binary label *disaster label*. In addition, we annotated the time and distance of the disaster event from the post because flood disaster analysis should predict the time and place where a disaster occurred or is still occurring from a post. We call these labels *time label* and *disaster label*. In disaster labels, we annotated only one label for each post including at least one keyword. If there were more than one disaster event, we annotated the event that was closer to the keyword. In time and distance labels, we annotated each keyword in a post.

3.2 Labels

Table 1 summarizes the labels of this task. With regard to the time label, it is necessary to recognize not only whether a flood occurs but also whether a disaster persists. Therefore we divided the time label into following labels: future, present, and past instead of using generic time specification such as TimeML (Pustejovsky et al., 2003). Unlike TimeML, we assigned the time label to only the disaster keyword based on a relationship between the posting time and time of the reported disaster by considering the tense expression in the report. In addition, we assigned values of all three tenses (future, present, past) to the disaster keyword because we supposed to construct applications that estimate the ordering of flood disaster at the posting time, future and past. We prepared three values for each time label. We will describe details of the labels below.

Disaster label. We prepared *positive* and *negative* to estimate the presence of flood disaster at the time of posting.

³<http://weathernews.jp>

Future label. We prepared *high probability*, *low probability* and *unmentioned* because there are three patterns of reports that mentioned alerts, anxiety, and nothing about a flood event. We labeled the report such as an alert future catastrophe like “It seems to be flood!,” to *high probability* and labeled the report that mentioned only an anxiety about the occurrence of a flood, e.g., “I am anxious about a disaster,” to *low probability*.

Present label. We prepared *occurring*, *probably occurring* and *not occurring*. The value of probably occurring is created to reflect the temporal uncertainty of a flood. There is ambiguity in terms of tense in the representation such as “浸水していました (had flooded),” which refers to a disaster that occurred or is occurring. For such a representation, we labeled the posts as “probably occurring.” We did not prepare *unmentioned* because we label the post as *not occurring* if a disaster is not mentioned in the case of present.

Past label. We prepared *occurred*, *occurred long before* and *unmentioned*. The value of occurred long before is necessary to distinguish a report that refers to a recent accident and an accident that occurred long time before.

Distance label. We just annotated whether a reporter is in front of the place (*close*) or has already left the place (*far*) because we use the flood event corpus constructed from a social media where almost all users post their reports with location information. We assigned a *misc* label in case where it is difficult to estimate the distance only from the post. For example, we labeled the report that did not mention about disaster that reporter experienced but disaster that reporter heard in the news to *misc*.

Examples of annotated posts are as follows.

(6) Tokyo Station was flooded, but this street is safe.

[disaster]: positive

[time]: future = unmentioned, present = probably occurring, past = occurred

[distance]: far

(7) My balcony is flooded.

[disaster]: negative

[time]: future = unmentioned, present = occurring, past = unmentioned

[distance]: close

(8) Although there are several past flood hazards around here, at present, there has not been any such hazard.

[disaster]: negative

[time]: future = unmentioned, present = not occurring, past = occurred long before

[distance]: misc

In the case of (6), a flood has not occurred near the reporter; however, the flood likely occurred somewhere nearby. In the case of (7), a flood occurs in the balcony of the poster; however, it is not considered to be a disaster. In the case of (8), a flood does not occur when the text is posted.

3.3 Analysis

The annotation was conducted using two annotators. The κ coefficient is 0.870 for the disaster label, 0.796 for the future label, 0.691 for the present label, 0.672 for the past label and 0.637 for the distance label.

Table 2 shows the number of labels. There are some labels in which the number is small like *occurred long before*. However, for disaster reports, it is necessary to distinguish between a past report that mentions an ancient disaster and an up-to-date report that mentions a recent disaster. Moreover, we would like to distinguish between reports that alert future catastrophe and reports that mention only anxiety to help evacuation. Therefore, we define and annotate those labels although their numbers are small. If we focus on developing a practical system, infrequent labels can be merged to alleviate data sparseness. In addition, these fine labels can be used not only in this task that estimates the presence of flood disaster at the time of posting but also in other tasks (e.g., the task of predicting that a disaster occurs in the future).

4 Classification of Flood Event

In this study, we conducted three experiments using disaster corpus that we developed. We formulated the flood information analysis as a classification problem and proposed a supervised approach to classify flood event. Table 3 shows the description of features used in these experiments.

label	number	
disaster	positive:329 / negative:238	
time	future	high probability:83 / low probability:48 / unmentioned:498
	present	occurring:272 / probably occurring:100 / not occurring:257
	past	occurred:121 / occurred long before:13 / unmentioned:495
distance	close:322 / far:59 / misc:248	

Table 2: Number of labels.

example	今日は大雨が降るので 浸水 する 予定。(Today there is going to be flooding because of heavy rain.)
BoN	Bag of n -grams of word from the sentences including the keywords of flooding. ($n = 1, 2, 3, 4$) We use either the entire sentence or a window around the keywords (window size = 5).
	example: 今日 [uni] は [uni] 大雨 [uni] が [uni] 降る [uni] ので [uni] 浸水 [uni] する [uni] 予定 [uni] 。 [uni] ($n = 1$)
Dep	Bag of n -grams of words from the chunks of words including a keyword and chunks that depend on or are dependent on chunks that include a keyword.
	example : 大雨 [dep] が [dep] 降る [dep] ので [dep] 浸水 [dep] する [dep] 予定 [dep] 。 [dep] 大雨 [dep] が [dep] 降る [dep] 降る [dep] ので [dep] ので [dep] 浸水 [dep] 浸水 [dep] する [dep] する [dep] 予定 [dep] 予定 [dep] 。 [dep] ($n=1,2$)

Table 3: Features used for the experiments.

First, we built a supervised classifier to estimate the presence of a flood disaster at the time of posting using disaster labels of disaster corpus (single model). We used the BoN (bag-of-ngram) and Dep (dependency) features extracted from the sentence including in the keywords.

Second, we built a time analyzer that predicts the occurrence time of a disaster using time labels of disaster corpus and a distance analyzer that predicts the positional relationship between a reporter and the disaster that has occurred using distance labels from the disaster corpus. In the time analyzer and distance analyzer, we used the BoN around keywords and the Dep features.

Finally, we proposed an improved disaster analysis model based on time analysis. In time analysis, the present labels are almost equivalent to the disaster label. A big difference between the present label and the disaster labels is that the present labels are labeled for each disaster keyword whereas the disaster labels are labeled for each report. Therefore, we compared two classifiers. Baseline classifier is a single model. The other classifier aggregates time labels for all the keywords in the report to judge whether a disaster occurred or not (aggregate model). In order to identify a disaster label from present labels, we considered that the disaster label of a report is positive if at least one *occurring* label or one *probably occurring* label is included in the report.

5 Experiment

5.1 Setting

In this task, we used MeCab⁴ (ver.0.996) with IPADic (ver.2.7.0) for word segmentation and CaboCha⁵ (ver.0.68) for dependency parsing.

We conducted a 5-fold cross-validation and evaluated the performance of the analysis by its accuracy, precision, recall and F1 score.

In this study, we used linear and polynomial kernels for the SVM as the linear and non-linear classifiers in the disaster label classification and linear kernel SVM in the time and distance label classification, respectively. We used libSVM (ver.1.04) to train the model. We tuned the cost parameter C and coefficient of the kernel function during preliminary experiments. We set the degree of the polynomial kernel to 3. When comparing the single model and the aggregate model, both models are trained on linear kernel SVM, while the single model uses the Dep feature and the aggregated model uses the BoN feature.

5.2 Result

Table 4 shows the results of the flood disaster classification using the linear and polynomial kernel SVMs. In this experiment, there are no notable differences between the linear and polynomial kernel SVMs. Therefore, I will discuss only the result of linear SVM in the next section.

⁴<http://taku910.github.io/mecab/>

⁵<http://taku910.github.io/cabochoa/>

Feature	Linear			Polynomial		
	Precision	Recall	F1	Precision	Recall	F1
BoN	75.9	85.9	80.4	75.6	85.0	79.8
Dep	79.2	84.7	81.6	79.2	83.7	81.1
BoN+Dep	76.7	85.9	80.8	78.0	85.6	81.3

Table 4: Accuracy of the disaster label classification of SVMs.

Feature	Accuracy			
	Past	Present	Future	Distance
BoN	85.9	74.7	85.1	71.4
Dep	87.9	73.3	84.6	70.0
BoN+Dep	86.0	73.8	85.7	70.0

Table 5: Accuracy of time and distance label classification.

label	value	Precision	Recall	F1
future	high probability	71.4	42.2	53.0
	low probability	80.0	16.7	27.6
	unmentioned	86.5	98.8	92.2
present	occurring	75.0	82.7	78.7
	probably occurring	66.1	41.0	50.6
	not occurring	76.4	79.4	77.9
past	occurred	78.7	48.8	60.2
	occurred long before	100.0	13.3	23.5
	unmentioned	86.8	97.2	91.7
distance	close	70.7	83.2	76.4
	far	77.8	11.9	20.6
	misc	72.2	70.2	71.2

Table 6: Precision, Recall and F1-score of time and distance label classification.

classifier	Precision	Recall	F1
aggregated model	84.3	88.4	86.4
single model	79.2	84.7	81.6

Table 7: Accuracy of disaster label classification.

Table 5 shows the accuracy of the time and distance label classification and Table 6 shows the precision, recall and F1-score of time and distance label classification using linear kernel SVM with the BoN feature.

Table 7 shows the result of model comparison of the classifier using the document level disaster label (single model) and the classifier using the keyword level time labels (aggregated model). Aggregated model achieved better performance over single model in all the evaluation measures.

6 Discussion

Table 4 shows that we can obtain the highest precision using the Dep feature. Comparing the Dep feature and the BoN feature, it appears that the Dep feature is strongly related to the flood keywords because it considers only the chunks near a keyword. On the other hand, the BoN feature gave a strong positive bias to the classifier. Therefore, the BoN results in low precision compared with the result of the Dep feature. It is thought that the Dep feature enhances the precision because it filters the noise of the BoN feature by removing phrases that are not related to the keyword. We examined the Dep features from the linear kernel SVM. Table 8 shows features and corresponding weights. There are many negative features related to an advance alert, such as “注意 (attention)”, “心配 (worry).”

Table 9 shows examples of the primary classification errors. There are multiple classification errors, such as the first example, that are caused by complex modality. In this study, we used the polynomial kernel SVM in addition to the linear kernel SVM; however, the polynomial kernel SVM was ineffective because the amount of data used in this study was so small that it made the combinatorial features sparse. The second example demonstrates that

Positive feature	weight	Negative feature	weight
津波 (tsunami)	0.32826	冠水_する (to be flood)	-0.43767
冠水_と (flooding and)	0.31268	dative case marker	-0.37203
、_冠水 (, flood)	0.25815	accusative case marker	-0.34530
冠水_して (is flooded)	0.25528	注意 (attention)	-0.34294
の_冠水 (flooding of)	0.23073	心配 (worry)	-0.34058
冠水_状態 (flood state)	0.22084	道路_の (of road)	-0.31980
道 (road)	0.20543	冠水_や (flood or)	-0.30046
して_いる (ing)	0.20365	し_そう (be about to)	-0.29838
あちこち (here and there)	0.20088	そう (likely)	-0.28952
bias term	0.41139		

Table 8: Feature and weight of the linear classifier using Dep features.

Error example 1	浸水しているそうなので注意です。 (Please be attention because it seems to be flooded.)	False negative
Error example 2	昔ね。我が家も床下浸水した。 (It is all history. My house was flooded.)	False positive

Table 9: Examples of classification errors.

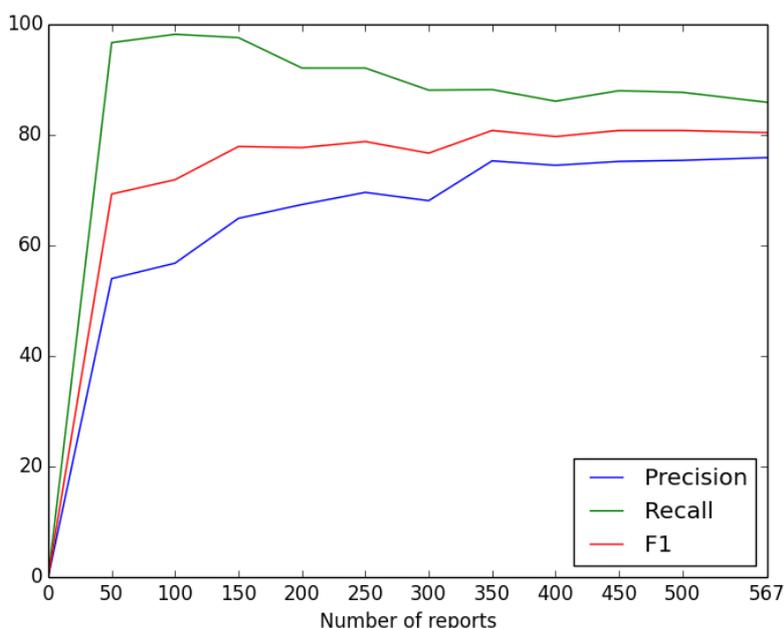


Figure 2: The learning curve of the flood disaster classification.

the classifier cannot classify a post that requires the consideration of inter-sentential context. Features used in this study considered only the words in a sentence, including the flood keyword. We need to employ discourse-level information to appropriately classify these examples.

Figure 2 shows the learning curve for disaster label classification. The classifier converges after the amount of data exceeds 350. It was thought that most surface keywords in posts concerning flood disasters could be learned with a small amount of data because we used only two keywords that directly indicated a flood disaster. However, it will be necessary to learn generic words that do not necessarily refer to flood disasters to boost the recall in flood disaster analysis.

Regarding time and distance classification, Table 6 shows that recall of *low probability*, *occurred long before* and *far* is very low. It is inferred that the number of the label is small. We examined the number of errors of the time analyzer and distance analyzer that use the BoN feature. Table 10 shows the number of errors. In time and distance analysis, there are errors that predict rare labels. As shown in Table 10, minor labels tend to be predicted as major labels. Therefore, it is necessary to search an effective feature for rare labels, especially for present labels

future			
	high probability	low probability	unmentioned
high probability	35	2	46
low probability	8	8	32
unmentioned	6	0	498
present			
	occurring	probably occurring	not occurring
occurring	225	7	40
probably occurring	36	41	23
not occurring	39	14	204
past			
	occurred	occurred long before	unmentioned
occurred	59	0	62
occurred long before	2	2	11
unmentioned	14	0	481
distance			
	close	far	misc
close	268	1	53
far	38	7	14
misc	73	1	174

Table 10: The confusion matrix of time and distance label classification error. Row shows gold label and column shows predicted label.

that contribute to disaster analysis.

Table 7 shows that the classifier using the time label (aggregated model) has better precision, recall, and F1-score than the classifier using the disaster label (single model). It is inferred that fine-grained annotation for each disaster keyword is more effective than coarse-grained annotation for each report in the disaster classification, because there are reports that mention two events in one report such as “It is flooded in Tokyo, but this place is not flooded.” The single model did not perform well in complex tasks such as disaster analysis. Moreover, the aggregated model successfully decomposed a disaster analysis into simpler problems and achieved better performance. Modality analysis is shown to improve the accuracy of factuality analysis (Saurí and Pustejovsky, 2012), and can be applied to this task as well.

7 Conclusion

In this study, we collected posts concerning flood disasters from social media about weather and created a flood disaster corpus. We annotated whether a flood disaster occurred. Furthermore, we annotated the time of disaster and distance between the poster and disaster. In addition, we developed a classifier using linear and polynomial kernel SVMs. In the classification of disaster label, the experimental results show that the use of bag of n -grams from the subtree of a dependency parse is effective for classification of disaster label in terms of F1-score. In addition, we proposed an aggregated model using predicted time labels for disaster label classification. Experimental result showed that the aggregated model is better than the single model. Moreover, it is suggested that modality analysis is necessary for enhancing the performance of a disaster analysis.

In this study, we focus on flood disaster, but this data label creation and the classification can be extended to other natural disasters if the keyword of the disaster is found and has a similar nature to the flood disaster, such as landslides and heavy snowfalls.

In the future, we plan to expand our flood disaster corpus by adding new keywords. It is not straightforward to find appropriate keywords that increase recall without losing too much precision. In addition, we would like to improve the visualization system of flood disaster information using user-generated text to assist relief efforts in future large-scale disasters.

Acknowledgments

This research was (partly) supported by Grant-in-Aid for Research on Priority Areas, Tokyo Metropolitan University, “Research on social big data.” We thank the anonymous reviewers for their constructive comments on the earlier versions of this document. We also thank Yoshiaki Kitagawa for his careful annotation.

References

- Axel Bruns, Jean E Burgess, Kate Crawford, and Frances Shaw. 2012. #qldfloods and @qpsmedia: Crisis communication on Twitter in the 2011 South East Queensland Floods. *Technical report, ARC Centre of Excellence for Creative Industries and Innovation, QUT Z1-515*,.
- Bo Han, Paul Cook, and Timothy Baldwin. 2014. Text-based Twitter user geolocation prediction. *Journal of Artificial Intelligence Research*, 49(1):451–500.
- Brent Hecht, Lichan Hong, Bongwon Suh, and Ed H. Chi. 2011. Tweets from Justin Bieber’s heart: The dynamics of the location field in user profiles. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 237–246.
- Benjamin Herfort, João Porto de Albuquerque, Svend-Jonas Schelhorn, and Alexander Zipf. 2014. Exploring the geographical relations between social media and flood phenomena to improve situational awareness. In *Proceedings of the 17th AGILE Conference on Geographic Information Science*, pages 55–71.
- Graham Neubig, Yuichiroh Matsubayashi, Masato Hagiwara, and Koji Murakami. 2011. Safety information mining — What can NLP do in a disaster—. In *Proceedings of 5th International Joint Conference on Natural Language Processing*, pages 965–973.
- James Pustejovsky, Jose M. Castano, Robert Ingria, Roser Sauri, Robert J. Gaizauskas, Andrea Setzer, Graham Katz, and Dragomir R. Radev. 2003. TimeML: Robust specification of event and temporal expressions in text. In *New Directions in Question Answering*, pages 28–34.
- Takeshi Sakaki, Makoto Okazaki, and Yutaka Matsuo. 2010. Earthquake shakes Twitter users: Real-time event detection by social sensors. In *Proceedings of the 19th International Conference on World Wide Web, WWW ’10*, pages 851–860.
- Roser Sauri and James Pustejovsky. 2012. Are you sure that this happened? Assessing the factuality degree of events in text. *Computational Linguistics*, 38(2):261–299.
- István Varga, Motoki Sano, Kentaro Torisawa, Chikara Hashimoto, Kiyonori Ohtake, Takao Kawai, Jong-Hoon Oh, and Stijn De Saeger. 2013. Aid is out there: Looking for help from tweets during a large scale disaster. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics*, pages 1619–1629.
- Sarah Vieweg, Amanda L Hughes, Kate Starbird, and Leysia Palen. 2010. 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*, pages 1079–1088.