Using Tweets During a Natural Disaster to Gauge Public Sentiment on Climate Change

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Abstract— **How people react to natural disasters on social media platforms is an important topic for understanding the social implications of climate change. Using an enormous data set of tweets collected before, during, and after Hurricane Dorian, work is done on analyzing public sentiment toward climate change, and to see how much natural disasters influence it.**

A keyword based classifier was used to analyze whether or not tweets were relevant to climate change and natural disasters, as well as the sentiment of the tweets - whether the user felt positively or negatively toward the idea of climate change. The results of this classifier were then analyzed as a function of time. While sentiment cannot conclusively be proven nor disproven to change with natural disasters, frequency of discussion of climate change in does increase markedly. Future work could involve further research on the sentiment of the tweets.

I. INTRODUCTION

Anthropogenic climate change and it influence on events such as natural disasters is an ongoing field of research. Scientific evidence and discussion has been overwhelmingly supportive of climate change, and some studies have suggested a link to natural disasters such as forest fires.[1] However, policymakers are influenced not only by the testimonies of experts, but also by the voices of the general public. Therefore, it is important to measure public opinion of climate change and natural disasters on social media platforms such as Twitter.

One such institution interested in researching this is the Center for Ultra-Wide-Area Resilient Electric Energy Transmission Networks (CURENT), a National Science Foundation Engineering Research Center. In 2017, CURENT started a project that, using an enormous data set of tweets, began analyzing people's reactions to natural disasters. In addition, machine learning techniques are applied in novel ways to glean information from natural language. The study of this Twitter project is focusing on the social effect and content related to natural disasters. Deep learning models such as convolutional neural networks, recurrent neural networks (LSTM), and the latest language model, BERT, were trained with relevant tweets that were labeled by humans. This project is a branch of the original Twitter project, focusing on public sentiment that related to climate change and how it correlates with natural disasters.

The ongoing Twitter project has already proposed a procedure or a general approach for this type of task. First, data was gathered using selected keywords to filter out most of the irrelevant tweets. Second, a random sample of the data was analyzed to gain a better understanding of the raw data. During this process, a list of keywords that indicate whether the tweets have either positive or negative sentiment was created.

II. METHOD

A. Data Collection

One part of the project mentioned above is sourcing the tweets that will then be analyzed. There are several methods in-place for gathering data: A web crawler to read tweets the same way a web browser would, Twitter's REST API, and Twitter's streaming API. Twitter's REST API is straightforward and yields a significant amount of metadata, but it is prohibitively slow due to rate limits. On the other hand, the web crawler has none of the aforementioned limitations, but it only has access to the data that is visible to users of the website. Therefore, for this project we will be focusing on the tweets obtained from the streaming API.

For this project, we will be using CURENT's collection of tweets obtained via the streaming API that contain climate change keywords. This collection is quite sizeable, having roughly 45 million tweets that were obtained in the time range spanning from about a year ago to today. This set is much larger, with almost 100 million tweets, but it is also much noisier, with previous analyses done with Doc2Vec suggesting that anywhere from 65% to 95% of the tweets may be irrelevant to electric power.

B. Keyword Filtering

When determining whether a tweet was focused on climate change or not, the two most commonly used phrases were "climate change" and "global warming". Other keywords specific to maintaining the environment were considered, such as "trees" and "clean air", but many tweets were advertisements to promote eco-friendly products. Instead, a direct search for climate change and global warming tweets was utilized.

A direct keyword search for earthquakes, tornadoes, hurricanes, and storms was chosen. This is because these are not only the most recognizable keywords for a natural disaster, but also because tweets that directly touch on any of these subjects usually convey a sentiment.

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The keywords for either acceptance or denial of climate change were chosen based on direct synonyms and acronyms of denial. Specific wording was chosen such as "hoax" or "scam" used to make climate change feel like an economic agenda instead of an environmental one, or words of great exaggeration like "extreme", "severe", or "grave" since these words commonly coincide with abnormal weather conditions.

Keywords to illustrate positive sentiment were chosen by using words commonly associated with prayer, as such words are common when offering people sympathy. Tweets expressing negative sentiment commonly sounded like an "angry rant" towards a specific group. These "hate" Tweets frequently used swearing, insulted their target's intelligence, and used terms stating that those believing in climate change were overreacting. “Angry” terms, such as swears, were used as keywords for tweets expressing negative sentiment.

C. *Classifier*

In terms of model selection, considering the complexity of this task and the size of the dataset, a simpler keyword-based classifier was used in order to prevent overfitting. The classifier was used to predict the entire dataset, then a random sample of the predicted data was checked in order to evaluate the performance of the model. By manually checking, the performance of the classifier is accurate enough so that the predicted data can be used to draw a conclusion.

Once these keywords were collected, a simple classification algorithm was constructed with them. For each set of keywords associated with a class, the set of stemmed words in a given tweet was compared to the set of stemmed keywords for that class. If there was any intersection between the two sets, the tweet was associated with that class. To refine the keywords, a subset of the tweets from our dataset was classified and manually validated. Any common words among misclassified tweets were considered for addition/removal.

After refining the keyword sets, the method was applied to the entire data set. Tweets in the dataset that were labelled as both relevant to climate change and natural disasters were placed in a subset. The number of tweets in a given day was plotted as a function of time with two different time resolutions: one day (i.e. the number of tweets that were sent on a given day) and ten days (i.e. the number of tweets that were sent within a 10-day time window). Using two different time resolutions enables interpretation of the tweets in both the short-term and the long-term.

From this subset of tweets relevant to both climate change and natural disasters, the same process was applied on tweets in this set that were labeled as negative. These tweets were plotted in a similar manner. Additionally, the tweets were considered as a binomially-distributed random variable with the following parameters:

$$n = (\text{\# of Tweets})$$

$$p = \frac{(\text{\# of Negative Tweets})}{(\text{\# of Tweets})}$$

From this, we plotted the percentage of tweets in a given time resolution that were negative, as well as the binomial proportion confidence interval (with a target error of $\alpha = 0.95$) for each time resolution:

$$p \pm \operatorname{erf}^{-1}(\alpha)\sqrt{\frac{2p(1-p)}{n}}$$

III. RESULTS

Of the 1,000 random tweets selected from the sample of tweets discussing climate change and natural disasters, there were 376 climate change tweets. These 376 could be categorized as follows: Natural Disaster Tweets (9), climate change acceptance tweets (46), climate change denial tweets (16), tweets with sentiment (48), and tweets without sentiment (45).

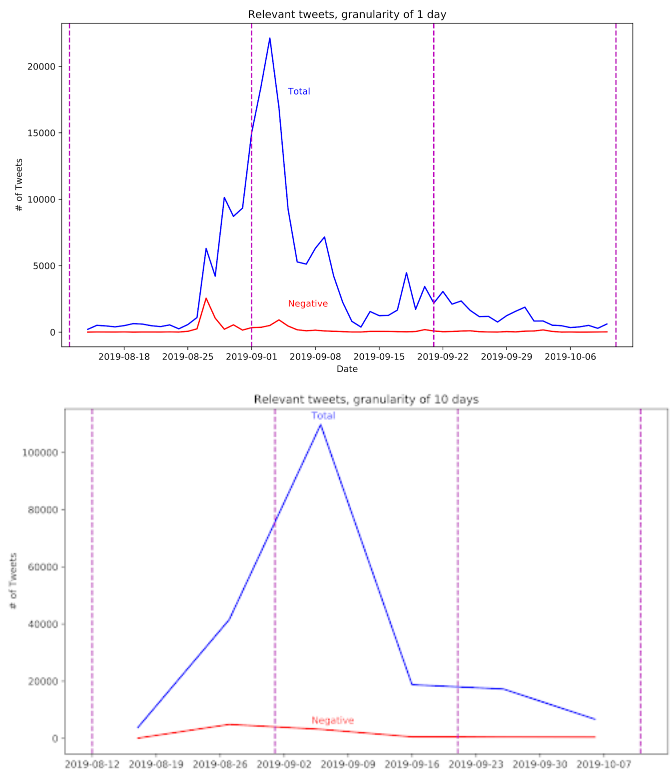

Fig. 1. Plot of relevant tweets over time

Figure 1 shows how the number of tweets discussing both climate change and natural disasters changed in response to Hurricane Dorian, as well as the subset of those tweets which were classified as negative. The purple dotted lines demarcate the regions of time that were considered to happen before, during, and after the hurricane, in that order. The second line also denotes when the hurricane made landfall in the Bahamas.

The total number of relevant tweets starts low and suddenly rises near the end of the "before" section. The number peaks at around a day after Hurricane Dorian made landfall. The value then declines rapidly, but remains above its initial value for several weeks afterward, until around halfway in the "after" section.

The number of negative tweets remains roughly constant, with the sole exception of the 27th of August, where the number of negative tweets increases drastically. This seems odd at first, but an analysis of the tweets from that day suggests that the increase was not directly related to Hurricane Dorian. Just a few days prior, news website Axios had published an article with the headline "Scoop: Trump suggested nuking hurricanes to stop them from hitting U.S." [2]. Indeed, of the negative tweets gathered on that day, 58.6% of them mentioned at least one of the words "president", "Trump", "nuke", or "bomb". Therefore, this sudden increase is more closely linked to the aforementioned news article than to the then-upcoming hurricane.

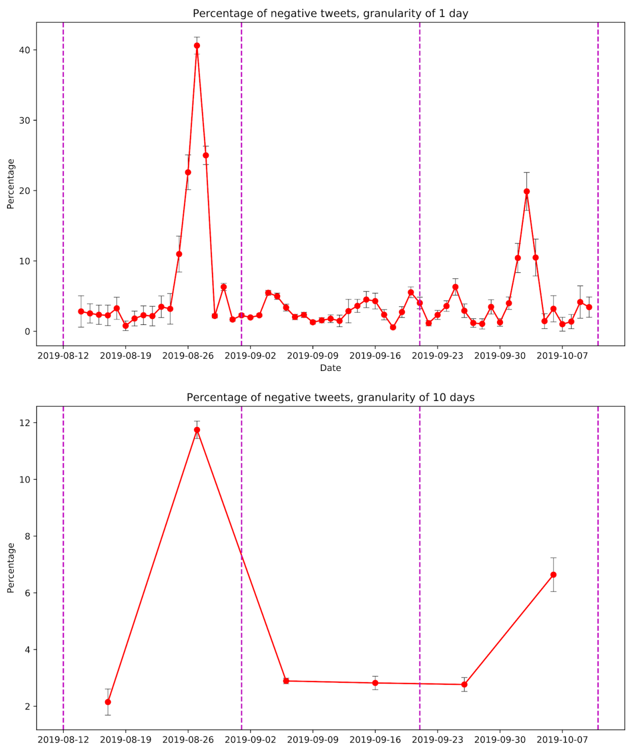

Fig. 2. Plot of negative tweets over time

Figure 2 shows how the number of negative tweets as a percentage of total tweets changes over time, as well as the confidence interval at each time. The confidence interval is rather high in most places, but is markedly low immediately after the hurricane makes landfall. Of course, this is because the total relevant tweets at that time vastly outnumber the negative tweets.

IV. LIMITATIONS

One limitation to this research is the limited time window of the dataset used in this paper. A truly long-term analysis of public sentiment on Twitter would require several months or even years worth of tweets. However, data gathered by CURENT prior to August is less continuous, due to a bug in the collection program. This has since been fixed, but any additional research using this data would need to use data collected during or after the presented times for the most accurate results.

An additional limitation would likely be the keyword-based model in use. Such a model is prone to ignoring factors such as two or more words that frequently co-occur or the ordering of the words in the sentence. A much better approach would be to vectorize the tweets with a word vectorization algorithm, such as TF/IDF or Doc2Vec, and then train a machine learning model, such as RandomForest or a neural network, on the vectorized tweets. However, such a method would require a large set of manually-labeled tweets. Creating such a data set was well outside the time bounds of this paper.

V. CONCLUSION

As can be seen from the figures above, the number of tweets that discuss a connection between climate change and natural disasters do increase, but so does the overall number of tweets, reaching a maximum when the natural disaster takes place. Conversely, there does not seem to be a significant correlation between the occurrence of a natural disaster and the overall negativity of tweets. Rather, the negativity of tweets is more closely connected to other factors such as political discourse.

Further research could involve using the methods discussed above to better analyze the sentiment of tweets with regard to climate change. Additionally, other natural disasters, such as the 2019 California wildfire season, could be examined instead of Hurricane Dorian.

REFERENCES

[1] A. Kilpeläinen, S. Kellomäki, H. Strandman, and A. Venäläinen, “Climate change impacts on forest fire potential in boreal conditions in Finland,” Climatic Change, vol. 103, no. 3–4, pp. 383–398, Jan. 2010.

[2] J. Swan and M. Talev, "Trump suggested dropping nuclear bombs into hurricanes to stop them from hitting the U.S.," Axios, 25 August 2019. [Online]. Available: https://www.axios.com/trump-nuclear-bombs-hurricanes-97231f38-2394-4120-a3fa-8c9cf0e3f51c.html. [Accessed 03 December 2019].