Narratives and Needs: Analyzing Experiences of Cyclone Amphan Using Twitter Discourse

Ancil Crayton¹, João Fonseca², Kanav Mehra⁵, Michelle Ng², Jared Ross¹, Marcelo Sandoval-Castañeda¹ and Rachel von Gnechten²

¹Booz Allen Hamilton, ²International Water Management Institute, ³NOVA Information Management School (NOVA IMS), ⁴New York University Abu Dhabi, ⁵Independent Researcher
ancil.crayton@ucdconnect.ie, jpfonseca@novaims.unl.pt, {jaredrossj, kanav.mehra6} @gmail.com, {m.ng, r.vongnechten} @cgiar.org, marcelo.sc@nyu.edu

Abstract
People often turn to social media to comment upon and share information about major global events. Accordingly, social media is receiving increasing attention as a rich data source for understanding people’s social, political and economic experiences of extreme weather events. In this paper, we contribute two novel methodologies that leverage Twitter discourse to characterize narratives and identify unmet needs in response to Cyclone Amphan, which affected 18 million people in May 2020.

1 Introduction
With wind speeds gusting up to 200 kilometres per hour, Cyclone Amphan was the first super cyclone to form in the Bay of Bengal since 1999 [Hansen, 2020]. It made landfall in West Bengal, India on May 20, 2020 before tracing a destructive path northward to Bangladesh [Beer, 2020]. Along the way, Cyclone Amphan damaged nearly 3 million houses, 18,000 square kilometres of agricultural lands and 449,000 electric poles, leaving 18 million affected people in its wake. Cyclone Amphan, which hit several of Red Cross and Societies, 2020. On-the-ground response efforts by governments, disaster relief organizations and civil society are no doubt crucial and life-saving following extreme weather events. Could online data serve as an additional tool to supplement on-the-ground efforts, particularly when they are hindered? Although online data cannot paint a complete or representative picture of offline realities, it could help fill knowledge gaps when there are challenges reaching affected people, such as those caused by COVID-19.

We took Cyclone Amphan as our use case in exploring the potential for Twitter content to target relief efforts in response to extreme weather events. We first aimed to characterize how collective knowledge about Cyclone Amphan was produced on Twitter. Twitter is a decentralized microblogging platform, meaning that anyone from anywhere in the world can add their commentary to an issue — thus influencing its narrative and adding layers of interpretation to on-the-ground realities. After exploring who and what is shaping the narratives around Cyclone Amphan, we aimed to answer: Can Twitter content help identify unmet needs of people affected by Cyclone Amphan? If so, how?

2 Natural Disasters and Social Media
Social media platforms serve as massive repositories of real-time situational and actionable data during man-made or natural emergencies, such as extreme weather events. For instance, people can use social media to organize volunteer or donation campaigns in support of on-the-ground relief efforts or directly contact relevant organizations via their official social media accounts [Imran et al., 2015]. Thus social media posts regarding extreme weather events vary broadly from people sharing personal experiences and opinions to emergency response agencies posting updates, warnings and information about relief efforts.

Furthermore, social media content can be used to characterize people’s experiences of extreme weather events and trace how narratives took shape through collective knowledge production. Several existing studies focus on developing efficient and scalable methods for extracting important, actionable information from social media content using a range of techniques based on natural language processing (NLP), text mining and network analysis [Imran et al., 2013b;...
3 Approach

3.1 Dataset

We extracted around 470,000 tweets using the Twitter API. We targeted tweets from May 1st, 2020 to June 15th, 2020, which cover the build-up through the aftermath of Cyclone Amphan. The main languages targeted in our query were English, Odia, Hindi and Bengali, but some tweets in other languages were extracted as well. We also filtered out terms related to other catastrophes happening in the area during the same time period, such as Cyclone Nisarga, which hit the Indian subcontinent at the beginning of June.

3.2 Preprocessing data

Given the multi-language approach of our query, the first step in the preprocessing pipeline is to translate non-English tweets into English using the Google Translate API. The Twitter API identifies and tags the language of each Tweet. We take advantage of this attribute such that only non-English tweets are translated, thus reducing computational costs.

The next step is to remove URLs and reserved words from the content of the tweets. This includes hashtags, emojis and words like ‘RT’ or ‘FAV’. Then we remove all remaining punctuation and change any uppercase letters to lowercase. As a final step, we remove all stop words found in the text of the tweets, following NLTK’s stop words list for English [Loper and Bird, 2002], and lemmatize the remaining words using NLTK’s WordNetLemmatizer.

3.3 Feature Extraction

The next goal is to extract information from the Twitter data. This process is divided into 4 independent tasks:

Sentiment analysis

The extraction of data information regarding the writer’s sentiment is a common, well-studied NLP task. In this work, the sentiment of each tweet is not known beforehand. Therefore, we leverage the Valence Aware Dictionary and Sentiment Reasoner (VADER) model [Hutto and Gilbert, 2014] to capture the sentiment of each tweet. VADER determines the sentiment of a document through a rule-based approach using a sentiment lexicon (i.e., a list of lexical features labelled according to their semantic orientation) to determine how positive/negative a specific tweet is [Hutto and Gilbert, 2014]. It is advantageous in the context of this paper as it was developed for social media text.

Point-of-view extraction

We use point-of-view extraction to classify tweets as first person, second person or third person, with the goal of determining whether the user experienced Cyclone Amphan personally. It is done by iterating over all tokens in the tweet’s text and identifying any word matching a list of pronouns mapped to first, second or third person speech. Examples of first person speech could be tokens such as ‘I’, ‘my’ and ‘our’; for second person, this may include ‘you’ or ‘your’; and, finally, for third person, it may include ‘them’, ‘they’ or ‘it’.

Our classification strategy is to assign a tweet to be first, second or third person based on the order of precedence, respectively. Therefore, if the tweet contains any first person pronouns, it is designated to be first person point of view. If the tweet contains second person pronouns, but does not contain any first person pronouns, it is assigned to be second person. Finally, if the tweet contains third person pronouns, but does not contain second or first person pronouns, it is classified as third person.
Zero-shot text classification

In order to extract critical information and derive actionable insights from large volumes of social media content generated during extreme weather events, it is imperative to effectively categorise the microblogs into distinct classes.

Due to the unavailability of large annotated training sets, we present a novel application of zero-shot text classification for a multi-label classification of tweets that is not only scalable but also generalizable across different crisis events. Researchers have proposed an approach of using a pre-trained NLI (Natural Language Inference) sequence-pair classifier as a zero-shot text classifier [Yin et al., 2019]. The model considers a sequence input (tweet) as the premise and each candidate topic label as a hypothesis. For our purpose, we use the zero-shot classification pipeline implementation available in the Transformers package that uses a large BART model [Lewis et al., 2019] pre-trained on the MNLI dataset [Williams et al., 2018]. This pipeline is shown in Figure 1.

After experimenting with different combinations, we settle on a comprehensive set of N specific labels that cover a wide variety of information: {‘sympathy’, ‘criticism’, ‘hope’, ‘job’, ‘relief measures’, ‘compensation’, ‘evacuation’, ‘ecosystem’, ‘government’, ‘corruption’, ‘news updates’, ‘volunteers’, ‘donation’, ‘cellular network’, ‘housing’, ‘farm’, ‘utilities’, ‘water supply’, ‘power supply’, ‘food supply’, ‘medical assistance’, ‘coronavirus’, ‘petition’, ‘poverty’, ‘assistance required’}.

The entire set of unique tweets is fed to the zero-shot classifier after basic preprocessing steps outlined in section 3.2. However, to preserve more text and conform the data closer to the training data of the BART model, we omit the case folding, stopword removal and lemmatization steps for this task. The classifier yields a confidence score ranging between 0 and 1 for every tweet-label pair. To ensure minimum overlap and maintain exclusivity, each tweet is assigned to a topic label if the confidence score associated with the pair is above a certain threshold, say $\alpha$. We experiment with a set of values for $\alpha$ and observe the best results with $\alpha = 0.7$.

User and Tweet embeddings

Embeddings are vector representations of either words, documents (tweets) or a set of documents (the user). They allow the conversion of non-numerical data (text) into an $n$-dimensional space, where the relationships among words, tweets and/or users is preserved. There are many methods directed toward vector representation of words. Amongst the most popular methods is one-hot encoded representations, distributed representations, Singular Value Decomposition, continuous bag of words and skip-gram model.

Tweet vectorization is done using a skip-gram model otherwise known as the Doc2Vec algorithm [Le and Mikolov, 2014]. This choice was motivated by not only its popularity and computational efficiency, but also its capacity to maintain a logical spatial structure among tweets, both regarding the tweets’ corpus and their underlying topic and sentiment. The Doc2Vec model is trained using unique tweets and replies in order to avoid the bias toward highly retweeted tweets that would come from keeping duplicate text. This results in a model trained on approximately 113,000 documents over 50 epochs. Tweets containing rare words in the dataset’s corpus (i.e., words appearing twice or less) are rejected for training. The output are 200-dimensional embeddings for each tweet in our dataset.

The user embeddings are based on the tweet embeddings, with a process that involves averaging the tweets/retweets belonging to a given user [Hallac et al., 2019]. This allows the analysis of the type of discourse and opinion shared among users in a 200-dimensional space.

3.4 Analysis

The extracted information is then combined to address our research questions as follows.

Identifying narratives and influential users

The pipeline for identifying narratives and influential users in the dataset is shown in Figure 2. We address this question through the usage of user vectors as described in subsection 3.3 as a means of positioning users in a two dimensional space. The projection of the 200-dimensional embeddings was done using t-SNE [Van Der Maaten and Hinton, 2008], resulting into 2-dimensional coordinates used to position each user (i.e., nodes) in the network graph. The network’s edges are assigned based on the number of retweets and/or replies among users, which are then weighted by dividing this number with the users’ euclidean distance (using the original 200-dimensional embeddings). These users can now be grouped into different communities using two different methods: 1) discourse-based, where the clustering is done on the embedding features and 2) community-based, done through network clustering methods. For both clustering methods, the most popular users within each cluster are identified based on centrality measures and the number of followers the user has.
Identifying negative experiences and unmet needs

The pipeline for identifying negative experiences and unmet needs is outlined in Figure 4. The first step is to identify the topics discussed in each tweet by assigning labels via zero-shot text classification. In order to only analyze tweets from users who were personally affected by Cyclone Amphan, the data is then filtered to include only first-person tweets using point-of-view analysis. At this point, we determine to which topic each affected individual is most sensitive. The sentiment analysis results enable understanding of whether the individual’s view is either positive or negative. We narrow down our focus to the labels that have a median negative sentiment score. We set $K = 50$. We present a slight modification by choosing representative tweets returned from the resulting connected components based on a (maximum) score, which takes into account centrality and tweet significance as follows:

$$Score = C + S,$$  

where $C$ represents the degree centrality and $S$ is the node size that is calculated as $S = \log(tweet\_length)$ where $tweet\_length$ is the number of tokens in the tweet.

We create $K$-length summaries for labels with negative median sentiment scores, where $K$ represents the number of representative tweets resulting from the text summarization method. The exact number to be considered can be adjusted by the researcher, policymaker or relief organization interested in learning about the experiences.

A sample of our initial results are reported in Table 1. These three tweets are selected through the text summarization algorithm on first-person tweets in the ‘housing’ label, which has a negative median sentiment score.

| ID  | Text                                                                 | Location          |
|-----|----------------------------------------------------------------------|-------------------|
| 1   | @PMOIndia @narendramodi Khejuri Block II in East Midnapur District/West Bengal is completely destroyed caused to Amphan Cyclone recently. Almost 250 Houses has been destroyed completely. I request to all Administrators to look into this issue so that Khejuri Block II gets proper help during time of crisis. | Kolkata, India     |
| 2   | Siddha when the lifts will be repaired. Shame on u.                   | Kolkata, India     |
| 3   | Lifts are not working since Amphan cyclone. No update from Siddha.   | Kolkata, India     |
Acknowledgements

This project was completed as part of the Data Science for Social Good (DSSG) Solve for Good program. We would like to thank Andrew Bell and Jessica Toth, members of the DSSG Solve for Good team, for their assistance during this project. We would also like to thank Simon Langan at the International Water Management Institute for his support of and feedback on our work. Finally, we thank the International Water Management Institute for graciously funding data collection from the Twitter API.

Disclaimer

The views expressed in this paper are those of the authors and not of their affiliations.

References

[Hernandez-Suarez et al., 2019] Aldo Hernandez-Suarez, Gabriel Sanchez-Perez, Karina Toscano-Medina, Hector Perez-Meana, Jose Portillo-Portillo, Victor Sanchez, and Luis Javier Garcia Villalba. Using twitter data to monitor natural disaster social dynamics: A recurrent neural network approach with word embeddings and kernel density estimation. Sensors (Switzerland), 2019.

[Hutto and Gilbert, 2014] C. J. Hutto and Eric Gilbert. VADER: A parsimonious rule-based model for sentiment analysis of social media text. In Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM 2014, 2014.

[Imran et al., 2013a] Muhammad Imran, Shady Elbassuoni, Carlos Castillo, Fernando Diaz, and Patrick Meier. Extracting information nuggets from disaster-related messages in social media. In ISCRAM 2013 Conference Proceedings - 10th International Conference on Information Systems for Crisis Response and Management, 2013.

[Imran et al., 2013b] Muhammad Imran, Shady Elbassuoni, Carlos Castillo, Fernando Diaz, and Patrick Meier. Practical extraction of disaster-relevant information from social media. In WWW 2013 Companion - Proceedings of the 22nd International Conference on World Wide Web, 2013.

[Imran et al., 2014] Muhammad Imran, Carlos Castillo, Ji Lucas, Patrick Meier, and Sarah Vieweg. AIDR: Artificial intelligence for disaster response. In WWW 2014 Companion - Proceedings of the 23rd International Conference on World Wide Web, 2014.

[Imran et al., 2015] Muhammad Imran, Carlos Castillo, Fernando Diaz, and Sarah Vieweg. Processing social media messages in Mass Emergency: A survey. ACM Computing Surveys, 2015.

[Internet and of India, 2019] Internet and Mobile Association of India. India internet 2019, 2019.

[Le and Mikolov, 2014] Quoc Le and Tomas Mikolov. Distributed representations of sentences and documents. In 31st International Conference on Machine Learning, ICML 2014, 2014.

[Lewis et al., 2019] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension, 2019.

[Loper and Bird, 2002] Edward Loper and Steven Bird. Nltk: The natural language toolkit. In Proceedings of the ACL Workshop on Effective Tools and Methodologies for Teaching Natural Language Processing and Computational Linguistics. Philadelphia: Association for Computational Linguistics, 2002.

[Mehra and Chandra, 2017] Kanav Mehra and Vibhash Chandra. Summarizing microblogs for emergency relief and preparedness. In CEUR Workshop Proceedings, 2017.

[Mukherji, 2020] Aditi Mukherji. Cyclone amphan and covid-19: the recipe for a cascading disaster. http://www.iwmi.cgiar.org/2020/06/cyclone-amphan-and-covid-19-the-recipe-for-a-cascading-disaster/, June 2020.

[of Red Cross and Societies, 2020] International Federation of Red Cross and Red Crescent Societies. Operation update report india: Cyclone amphan. https://reliefweb.int/report/india/india-cyclone-amphan-operation-update-report-dref-n-mdrin025, July 2020.

[of West Bengal, 2020] State Inter Agency Group of West Bengal. Joint rapid need assessment report on cyclone amphan, June 2020.
[Pourdehrahim et al., 2019] Nastaran Pourdehrahim, Selima Sultana, John Edwards, Amanda Gochanour, and Somya Mohanty. Understanding communication dynamics on Twitter during natural disasters: A case study of Hurricane Sandy. *International Journal of Disaster Risk Reduction*, 37(May):101176, 2019.

[Ragini et al., 2018] J. Rexiline Ragini, P.M.Rubesh Anand, and Vidhyacharan Bhaskar. Big data analytics for disaster response and recovery through sentiment analysis. *International Journal of Information Management*, 2018.

[Rudra et al., 2015] Koustav Rudra, Subham Ghosh, Niloy Ganguly, Pawan Goyal, and Saptarshi Ghosh. Extracting situational information from microblogs during disaster events: A classification-summarization approach. In *International Conference on Information and Knowledge Management, Proceedings*, 2015.

[Rudra et al., 2016] Koustav Rudra, Siddhartha Banerjee, Niloy Ganguly, Pawan Goyal, Muhammad Imran, and Prasenjit Mitra. Summarizing situational tweets in crisis scenario. In *HT 2016 - Proceedings of the 27th ACM Conference on Hypertext and Social Media*, 2016.

[Rudra et al., 2018] Koustav Rudra, Pawan Goyal, Niloy Ganguly, Prasenjit Mitra, and Muhammad Imran. Identifying sub-events and summarizing disaster-related information from microblogs. *41st International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2018*, pages 265–274, 2018.

[To et al., 2017] Hien To, Sumeet Agrawal, Seon Ho Kim, and Cyrus Shahabi. On Identifying Disaster-Related Tweets: Matching-Based or Learning-Based. *Proceedings - 2017 IEEE 3rd International Conference on Multimedia Big Data, BigMM 2017*, pages 330–337, 2017.

[Van Der Maaten and Hinton, 2008] Laurens Van Der Maaten and Geoffrey Hinton. Visualizing data using t-SNE. *Journal of Machine Learning Research*, 2008.

[Williams et al., 2018] Adina Williams, Nikita Nangia, and Samuel Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122. Association for Computational Linguistics, 2018.

[Yin et al., 2019] Wenpeng Yin, Jamaal Hay, and Dan Roth. Benchmarking zero-shot text classification: Datasets, evaluation and entailment approach, 2019.

[Zhang and Vucetic, 2016] Shanshan Zhang and Slobodan Vucetic. Semi-supervised Discovery of Informative Tweets During the Emerging Disasters. 2016.