Abstract

Quantifying the characteristics of public attention is an essential prerequisite for appropriate crisis management during severe events such as pandemics. For this purpose, we propose language-agnostic tweet representations to perform large-scale Twitter discourse classification with machine learning. Our analysis on more than 26 million COVID-19 tweets show that large-scale surveillance of public discourse is feasible with computationally lightweight classifiers by out-of-the-box utilization of these representations.

Keywords: text classification, sentence embeddings, Twitter, natural language processing, deep learning

1. Introduction

Coronavirus disease 2019 (COVID-19) was declared a pandemic by the World Health Organization on 11 March 2020 [1]. Since first recorded case in Wuhan, China in late December 2019, 17.1 million people have been infected by COVID-19 and consequently, 670,000 people have lost their lives globally as of 30 July 2020 [2]. This constitutes 400 times more deaths than SARS and MERS combined [3]. During such large-scale adverse events, monitoring information seeking behaviour of citizens, understanding general overall concerns, and identifying recurring discussion themes is crucial for risk communication and public policy making [4, 5]. This need is further amplified in a global pandemic such as...
COVID-19 as the primary responsibility of risk management is not centralized to a single institution, but distributed across society. For instance, a recent study by Zhong et al. shows that people's adherence to COVID-19 control measures is affected by their knowledge and attitudes towards it [6]. Previous national and global adverse health events show that social media surveillance can be utilized successfully for systematic monitoring of public discussion due to its instantaneous global coverage [7, 8, 9, 10, 11, 12].

Twitter, due to its large user-base, has been the primary social media platform for seeking, acquiring, and sharing information during global adverse events, including the COVID-19 pandemic [13]. Especially during the early stages of the global spread, millions of posts have been tweeted in a span of a couple of weeks [14, 15, 16, 17, 18]. Consequently, several studies proposed and utilized Twitter as a data source for extracting insights on public health as well as insights on public attention during the COVID-19 pandemic. Focus of these studies include nowcasting or forecasting of the disease, sentiment analysis, topic modeling, and quantifying misinformation/disinformation. Due to the novelty and unknown epidemiological characteristics of COVID-19, accurate quantification of public discussions on social media becomes especially relevant for disaster management (e.g. devising timely interventions or clarifying common misconceptions).

So far, manual or automatic topical analyses of discussions on Twitter during COVID-19 pandemic have been performed in an exploratory or descriptive manner [19, 20, 21]. Characterizing public discourse in these studies rely predominantly on manual inspection, aggregate statistics of keyword counts, or unsupervised topic modeling by utilizing joint distributions of word co-occurrences followed by qualitative assessment of discovered topics. Main reasons for previous studies to avoid supervised approaches can be lack of annotated (labeled) datasets of public discourse on COVID-19. Furthermore, previous studies either restrict their scopes to a single language (typically English tweets) or examine tweets from different languages in separate analyses. This is mainly due to limitations of traditional topic modeling algorithms as they do not operate in a
multilingual or cross-lingual fashion.

In this study, we propose large-scale characterization of public discourse themes by categorizing more than 26 million tweets in a supervised manner, i.e., classifying text into semantic categories with machine learning. For this purpose, we utilize two different annotated datasets of COVID-19 related questions and comments for training our algorithms. To be able to capture themes from 109 languages in a single model, we employ state-of-the-art multilingual sentence embeddings for representing the tweets, i.e., Language-agnostic BERT Sentence Embeddings (LaBSE) [22]. Our results show that large-scale surveillance of COVID-19 related public discourse themes and topics is feasible with computationally lightweight classifiers by out-of-the-box utilization of these representations. We release the full source code of our study and the trained models along with the instructions to access the experiment datasets. We believe our work contributes to the pursuit of expanding social media research for disaster informatics regarding health response activities.

2. Relevant Work

2.1. COVID-19 Twitter

Content analysis of Twitter data has been performed by various studies during the COVID-19 pandemic. Some studies approach their research problem by manual or descriptive (e.g. n-gram statistics) content analysis of Twitter chatter for gaining relevant insights [21, 23, 24, 25, 26, 27, 28, 29], while other studies utilize computational approaches such as topic modeling [19, 20, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49]. A high percentage of studies performing topic modeling and topic discovery on Twitter utilize the well-established Latent Dirichlet Allocation (LDA) algorithm [20, 30, 33, 34, 36, 37, 40, 41, 42, 43, 44, 45, 46, 49]. Similar unsupervised approaches of

[https://github.com/ogencoglu/Language-agnostic_BERT_COVID19_Twitter](https://github.com/ogencoglu/Language-agnostic_BERT_COVID19_Twitter)
word/n-gram clustering [38, 39, 47] or clustering of character/word embeddings [35, 48] have been proposed as well.

Tweet data utilized for most of these studies are restricted to a single language. Majority of the studies restrict their analysis only to English tweets [19, 24, 29, 33, 37, 39, 41, 43, 44, 45, 46, 48], possibly exacerbating the already existing selection bias. Other studies have restricted their datasets to Japanese [47], Korean [21], Persian/Farsi [36], and Polish [31] tweets. While studies that collect multilingual tweets exist, they typically conduct their analyses (e.g. topic modeling) separately for each language [23, 25, 40].

2.2. Representing Tweets

As effective representation learning of generic textual data has been studied extensively in natural language processing research, tasks involving social media text benefit from recent advancements as well. While traditional feature extraction methods relying on word occurrence counts (e.g. bag-of-words or term frequency-inverse document frequency) have been extensively utilized in previous studies involving Twitter [50, 51, 52], they have been replaced by distributed representations of words in a vector space (e.g. word2vec [53] or GloVe [54] embeddings). Distributed word representations are learned from large corpora by a neural network, resulting in words with similar meanings being mapped to closer vector representations with a feature number that is much smaller than the vocabulary size. Consequently, sentences, documents, or tweets can be represented, e.g. as an average-pooling of its word embeddings. Such representations have also been learned specifically from Twitter corpora as tweet2vec [55, 56] or hashtag2vec [57].

While distributed word/sentence embeddings provide effective capturing of semantics, they operate as a static mapping from the textual space to the latent space. Serving essentially as a dictionary look-up, they often fail to capture the context of the textual inputs (e.g. polysemy). This drawback has been circumvented by contextual word/token embeddings such as ELMo [58] or BERT [59]. Contextual word embeddings enable the possibility of same word being repre-
sent as different vectors if it appears in different contexts. Several studies involving tweets utilized these deep neural network techniques or their variants either as a pre-training for further downstream tasks (e.g. classification, clustering, entity recognition) or for learning tweet representations from scratch [60, 61, 62, 63, 64, 65, 66, 67]. Even though BERT word embeddings are powerful as pre-trained language models for task-specific fine-tuning, Reimers et al. show that out-of-the-box sentence embeddings of BERT and its variants (also known as transformers) can not capture semantic similarities between sentences, requiring further training for that purpose [68]. They propose a mechanism for learning contextual sentence embeddings using BERT neural architecture, i.e. sentence-BERT, enabling large-scale semantic similarity comparison, clustering, and information retrieval with out-of-the-box vector representations [68]. Studies involving Twitter data have been utilizing these contextual sentence embeddings successfully as well [69, 70, 71, 72].

3. Methods

3.1. Data

For Twitter data, we utilize the publicly available dataset of 152,920,832 tweets (including retweets) related to COVID-19 between the dates 4 Janu-
uary 2020 - 5 April 2020. Tweets have been collected using the Twitter streaming API with the following keywords: COVID19, CoronavirusPandemic, COVID-19, 2019nCoV, CoronaOutbreak, coronavirus, WuhanVirus, covid19, coronaviruspandemic, covid-19, 2019ncov, coronaoutbreak, wuhanvirus. As Twitter Terms of Service does not allow redistribution of tweet contents, only tweet IDs are publicly available. Extraction of textual content of tweets, timestamps, and other meta-data was performed with the use of open-source software Hydrator with a Twitter developer account. For our study, we discard the retweets and at the time of extraction 26,759,164 unique tweets were available which is the final number of observations used in this study. Daily distribution of these tweets (7-day rolling average) can be observed from Figure 1.

For training machine learning classifiers, we utilize the following two recently-curated datasets: COVID-19 Intent and COVID-19 Questions. Intent dataset consists of 4,938 COVID-19 specific utterances (typically a question or a request) categorized into 16 categories to describe the author’s intent. For instance, the sample "is coughing a sign of the virus" has an intent related to Symptoms. The dataset consists of English, French, and Spanish utterances and has been synthetically created by native-speaker annotators based on an ontology. We discard the uninformative categories of Hi and Okay/Thanks to end up with 4,325 samples from this dataset. We combine Can_i_get_from_feces_animal_pets, Can_i_get_from_packages_surfaces, and How_does_corona_spread categories into a single category of Transmission. Similarly, we merge What_if_i_visited_high_risk_area category into Travel category to end up with 11 categories (classes).

Questions dataset consists of 1,244 questions categorized into 16 categories collected from 13 sources. 7 of the sources are frequently asked questions (FAQ) websites of recognized organizations such as the Center for Disease Control (CDC) and 6 of them are crowd-based sources such as Google Search. We use 594 samples from this dataset belonging to Prevention, Reporting.
Speculation, Symptoms, Transmission, and Treatment categories. In the end, the dataset for our experiments, i.e., training and validating text classification algorithms, consists of 4,919 textual samples collected from the abovementioned two datasets. 11 category labels of the final dataset are Donate, News & Press, Prevention, Reporting, Share, Speculation, Symptoms, Transmission, Travel, Treatment, What Is Corona?. Sample distribution of languages and categories among the dataset can be examined from Table 1 and Table 2 respectively.

3.2. Tweet Embeddings

As the daily volume of COVID-19 related discussions on Twitter is enormous, computational public attention surveillance would benefit from lightweight approaches that can still maintain a high predictive power. Preferably, numerical representations should encode the semantics of tweets in such a way that simple vector arithmetic should suffice for large-scale retrieval or even classification. Moreover, developed machine learning systems should be able to accommo-
date tweets in several languages to be able to capture the public discourse in an unbiased manner. Multilingual BERT-like contextual word/token embeddings [59] have been shown to be effective as pre-trained models if followed by a task-specific fine-tuning. However, they do not intrinsically produce effective sentence-level representations [68]. In order to be able to take advantage of multilingual BERT encoders for extracting out-of-the-box sentence embeddings, we employ Language-agnostic BERT Sentence Embeddings [22].

LaBSE embeddings combine BERT-based dual-encoder framework with masked language modeling (an unsupervised fill-in-the-blank task where a model tries to predict a masked word) to reach state-of-the-art performance in embedding sentences across 109 languages [22]. Trained on a corpus of 6 billion translation pairs, LaBSE embeddings provide out-of-the-box comparison ability of sentences even by a simple dot product (essentially corresponding to cosine similarity as embeddings are $l_2$ normalized). We encode both the training data and 26.8 million tweets using this deep learning approach, ending up with vectors of length 768 for each observation. Embeddings are extracted with Tensor-Flow (version 2.2) framework in Python 3.7 on a 64 bit Linux machine with an NVIDIA Titan Xp GPU.

3.3. Intent Classification

As our choice of embeddings provide effective, out-of-the-box latent space representations of the textual data, simpler classifiers can be directly employed for identifying semantically similar texts. In fact, LaBSE embeddings provide representations that are suitable to be compared with simple cosine similarity [22]. We train 3 classifiers, namely k-nearest neighbour (kNN), logistic regression (LR), and support vector machine (SVM) to classify the observations into 11 categories. We employ a 10-fold stratified cross-validation scheme to evaluate the performance of the three models. Hyperparameters of the classifiers are selected by Bayesian optimization (see Section 3.4). Once the classifier with its set of hyperparameters giving the highest cross-validation classification performance is selected, the classifier is trained with full dataset of 4,919 observations.
With this model, inference on 26,759,164 samples of Twitter data embeddings is performed.

3.4. Bayesian Hyperparameter Optimization

Typically, machine learning algorithms have several hyperparameters that require tuning for the specific task to avoid sub-optimal predictive performance. Most influential hyperparameters of k-nearest neighbour classifier are $k$ (number of neighbours) and distance metric (e.g., cosine, euclidean, manhattan, etc.). For logistic regression and support vector machine classifiers, $l_2$ regularization coefficient, $\lambda$, is the most crucial hyperparameter. We formulate the problem of finding the optimal set of classifier hyperparameters, $\hat{\theta}$, as a Bayesian optimization problem:

$$\hat{\theta} = \arg\max_{\theta} f(\theta),$$

where $f(\theta)$ is the average of cross-validation accuracies for a given set of hyperparameters, i.e., $\frac{1}{N} \sum_{i=1}^{N} ACC_i$. For our experiments $N = 10$ as we perform 10-fold cross-validation. We use Gaussian Processes for the surrogate model of the Bayesian optimization by which we emulate the statistical relationships between the hyperparameters and model performance, given a dataset. We run the optimization scheme for 30 iterations (each iteration corresponds to one full cross-validation) for each classifier.

Bayesian optimization is especially beneficial in settings where the function to be minimized/maximized, $f(\theta)$, is a black-box function without a known closed-form and expensive to evaluate. As $f(\theta)$ corresponds to cross-validation performance in our case, it indeed is a black-box function that is computationally expensive to evaluate. That is our motive for employing Bayesian hyperparameter optimization instead of manual tuning or performing grid-search over a manually selected hyperparameter space.

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3Although, not an official distance metric as it violates triangle inequality.
Figure 2: UMAP visualization of language-agnostic embeddings belonging to 4,919 observations among 11 COVID-19 discourse categories.
### Table 3: Cross-validation results of three classifiers.

| Classifier | Accuracy (%) | AUROC  |
|------------|--------------|--------|
| kNN        | 82.76        | 0.964  |
| LR         | 86.05        | 0.980  |
| SVM        | 86.92        | 0.986  |

#### 3.5. Evaluation

For visual inspection of LaBSE embeddings, we utilize Uniform Manifold Approximation and Projection (UMAP) to map the 768-dimensional embeddings to a 2-dimensional plane [79]. UMAP is a frequently used dimensionality reduction and visualization technique that can preserve global structure of the data better than other similar methods [79]. In their recent study, Ordun et al. employ UMAP visualization of COVID-19 tweets as well [32].

Evaluation of classifiers and their sets of hyperparameters are performed by 10-fold cross-validation. Randomness (seed) in cross-validation splits are fixed in order to perform fair comparison. Average accuracy (%) and Area Under the Receiver Operating Characteristic (AUROC) curve scores across 10 folds are reported for all classifiers (for their best performing set of hyperparameters). AUROC scores are calculated in a one-vs-rest manner and macro averaging. As SVMs do not directly provide probability estimates required for AUROC calculation, Platt scaling is used for probabilistic output estimation [80]. Confusion matrix for the best performing classifier is reported as well. After running inference on Twitter data to classify 26.8 million tweets into 11 categories with the best performing classifier, we aggregate the overall distribution of Twitter chatter into percentages. We also show tweet examples from each predicted category.

#### 4. Results

UMAP visualization of LaBSE embeddings of the training data is depicted in Figure 2. Most visibly distinctive clusters belong to categories Donate, Share,
and Travel. A cumulative of 88 hours of GPU computation was performed for extracting language-agnostic embeddings for the 26.8 million tweets which roughly corresponds to a carbon footprint of 9.5 kgCO$_2$eq (estimate by following [81]).

10-fold cross-validation results for the classifiers with the highest scoring set of hyperparameters are shown in Table 3. Best hyperparameters for k-nearest neighbour classifier were found to be $k = 7$ and cosine distance. Optimal regularization coefficients for logistic regression and support vector machine classifiers were found to be $4.94 \times 10^3$ and 5.07, respectively. Best performing classifier was found to be support vector machine classifier with 86.92 % accuracy and 0.986 AUROC. Confusion matrix of this classifier out of cross-validation predictions can be examined from Figure 3. In parallel to visual findings on Figure 2, Donate, Share, and Travel classes reach high accuracies of 97.1 %, 98.1 %, and 94.0 %, respectively. Classifier has the highest error rate for the Prevention and Speculation classes, both staying below 80 % accuracy. Our results show that more than 15 % of samples belonging to Speculation category have been misclassified as Transmission.

Figure 4 depicts the timeline of normalized daily category distributions obtained by running inference on tweets posted between 26 January and 5 April 2020. Transmission and travel-related chatter as well as speculations (opinions on origin of COVID-19, myths, and conspiracies) show significance presence throughout the pandemic. What Is Corona?, i.e. questions and inquiries regarding what exactly COVID-19 is, shows a presence in the early stages of the pandemic but decreases through time, possibly due to gained scientific knowledge about the nature of the disease. On the contrary, prevalence of Prevention related tweets increase through time especially after the declaration of pandemic by WHO on March 11. Similarly, chatter for Donation discussions are observed only starting from March. Timeline curves become smoother (less spiky) with increasing date as the percentage changes between consecutive days gets smaller. This is intuitive as the total number of tweets in January is several magnitudes lower than that of April and sudden percentage jumps in January can be at-
Figure 3: Normalized confusion matrix of SVM classifier predictions across cross-validation folds.
5. Discussion

Adequate risk management in crisis situations has to take into account not only the threat itself but also the perception of the threat by the public [82]. In digital era, public heavily relies on social media to inform their level of risk perception, often in a rapid manner. In fact, social media enhances collaborative problem-solving and citizens ability to make sense of the situation during disasters [4]. With this paradigm in mind, we attempt to perform large-scale classification of 26.8 million COVID-19 tweets using natural language processing and machine learning. We utilize state-of-the-art language-agnostic tweet representations coupled with simple, lightweight classifiers to be able to capture COVID-19 related discourse during a span of 13 weeks.

Our first observation of increasing Twitter activity with increased COVID-
| Tweet                                                                 | Predicted Class |
|----------------------------------------------------------------------|-----------------|
| China Providing Assistance To Pakistani Students                     | Donate          |
| Trapped in Wuhan: Ambassador - #Pakistan                              |                 |
| Results are in. State health officials say three suspected cases      | News & Press    |
| of Coronavirus have tested NEGATIVE. There is a forth possible case    |                 |
| from Washtenaw County being sent to the CDC.                          |                 |
| what are good steps to protect ourselves from the Coronavirus?        | Prevention      |
| The first coronavirus case has been confirmed in the U.S. #virus      | Reporting       |
| Share this and save lives #coronavirus #SSOT                         | Share           |
| #coronavirus Dont let these ignorant people make you believe          | Speculation     |
| that this corona virus is any different than SARS IN 2003 which was   |                 |
| contained after a few months. They want you to panic as they have     |                 |
| ulterior motives such as shorting the stock market etc.              |                 |
| I have a rushing sound in my ears. It doesn’t seem to match the      | Symptoms        |
| symptoms for the #coronavirus so perhaps it is the sound of the      |                 |
| #EU leaving my body...                                                |                 |
| what animals can carry Wuhan coronavirus?                             | Transmission    |
| can we ban flights from wuhan pls?!?                                 | Travel          |
| Qu medicamento nos colar en est ocasin la industria                  | Treatment       |
| farmacutica para combatir al coronavirus?                            |                 |
| Oque coronavirus?                                                     | What Is Corona? |

Table 4: Example tweets and predicted classification categories.
19 spread throughout the globe” (Figure 1) is in parallel with other studies. For instance, Bento et al. show that Internet searches for "coronavirus" increase on the day immediately after the first case announcement for a location [83]. Wong et al. correlates announcement of new infections and Twitter activity [84]. Similar associations have been discovered between official cases and Twitter activity by causal modeling as well [69]. Secondly, we show that language-agnostic embeddings can be utilized in an out-of-the-box fashion (without requiring task-specific fine-tuning of BERT models) even by a simple nearest neighbour classifier which achieves 0.964 AUROC. A SVM classifier reaches 86.92% accuracy and 0.986 AUROC for classification into 11 topic categories. Finally, we show that overall public discourse shifts through the pandemic. Questions of "what coronavirus is" leave their place to donation and prevention related discussions as the disease spreads into more and more countries especially during March 2020. Tweets related to donation increase especially around 13 March 2020 when WHO and the United Nations Foundation start a global COVID-19 donation fund [85].

When compared to existing studies that often employ unsupervised topic modeling, our approach tries to perform public attention surveillance with a more automated perspective as we formulate the problem as a supervised learning one. Topic modeling with LDA, which has been employed by majority of previous studies, relies on manual/qualitative inspection of discovered topics. Furthermore, plain LDA fails to accommodate contextual representations and does not assume a distance metric between discovered topics as it is based on the notion that words belonging to a topic are more likely to appear in the same document. With language-agnostic embeddings, we also include tweets from languages other than English to our analysis, hence decrease the selection bias.

Utilization of large-scale social media data for extracting health insights is even more pertinent during a global pandemic such as COVID-19, as running randomized control trials becomes less practical. Moreover, traditional surveys for public attention surveillance may further stress the participants whose men-
tal health and overall well-being might have been affected by lockdowns, associated financial issues, and changes in social dynamics [86, 87, 88]. Once accurate estimation of global or national discourse is possible, social media can also be used to direct people to trusted resources, counteract misinformation, disseminate reliable information, and enable a culture of preparedness [89]. Assessment of effectiveness of public risk communication and interventions is also feasible with properly designed computational systems. Guided by machine learning insights, some of these interventions can be made on social media itself.

Our study has several limitations. First, the training data consists of single label annotations while in reality a tweet can have several topics simultaneously, e.g. Prevention and Travel. Secondly, we do not employ a confidence threshold for categorizing tweets which forces our model to classify every observation into one of the 11 categories. Considering some Twitter discourses related to COVID-19 may not be properly represented by our existing categories, a probability threshold can be introduced for the final classification decision. Finally, we discard retweets in our analysis, which in fact contributes to public attention on Twitter.

Future research includes running similar analysis for a more granular category set or sub-categories. For instance, Speculation category can be divided into conspiracies related to origin of the disease, transmission characteristics, and treatment options. Including up-to-date Twitter data (after April 2020) as well as extracting location-specific insights will be performed in future analyses as well.

6. Conclusions

Transforming social media data into actionable knowledge for public health systems face several challenges such as advancing methodologies to extract relevant information for health services, creating dynamic knowledge bases that address disaster contexts, and expanding social media research to focus on health response activities [90]. We hope our study serves this purpose by prov-
ing methodologies for large-scale, language-agnostic discourse classification on Twitter.

References

[1] D. Cucinotta, M. Vanelli, Who declares covid-19 a pandemic., Acta Biomедica: Atenei Parmensis 91 (1) (2020) 157–160. [doi:10.23750/abm.v91i1.9397]

[2] E. Dong, H. Du, L. Gardner, An interactive web-based dashboard to track covid-19 in real time, The Lancet Infectious Diseases. [doi:10.1016/S1473-3099(20)30120-1]

[3] E. Mahase, Coronavirus: covid-19 has killed more people than sars and mers combined, despite lower case fatality rate (2020). [doi:10.1136/bmj.m641]

[4] M. Jurgens, I. Helsloot, The effect of social media on the dynamics of (self) resilience during disasters: A literature review, Journal of Contingencies and Crisis Management 26 (1) (2018) 79–88. [doi:10.1111/1468-5973.12212]

[5] J. J. Van Bavel, K. Baicker, P. S. Boggio, V. Capraro, A. Cichocka, M. Cikara, M. J. Crockett, A. J. Crum, K. M. Douglas, J. N. Druckman, et al., Using social and behavioural science to support covid-19 pandemic response, Nature Human Behaviour 4 (2020) 460–471. [doi:10.1038/s41562-020-0884-z]

[6] B.-L. Zhong, W. Luo, H.-M. Li, Q.-Q. Zhang, X.-G. Liu, W.-T. Li, Y. Li, Knowledge, attitudes, and practices towards covid-19 among chinese residents during the rapid rise period of the covid-19 outbreak: a quick online cross-sectional survey, International journal of biological sciences 16 (10) (2020) 1745. [doi:10.7150/ijbs.45221]
[7] A. Signorini, A. M. Segre, P. M. Polgreen, The use of twitter to track levels of disease activity and public concern in the us during the influenza a h1n1 pandemic, PloS One 6 (5). doi:10.1371/journal.pone.0019467.

[8] X. Ji, S. A. Chun, J. Geller, Monitoring public health concerns using twitter sentiment classifications, in: IEEE International Conference on Healthcare Informatics, IEEE, 2013, pp. 335–344. doi:10.1109/ICHI.2013.47.

[9] X. Ji, S. A. Chun, Z. Wei, J. Geller, Twitter sentiment classification for measuring public health concerns, Social Network Analysis and Mining 5 (1) (2015) 13. doi:10.1007/s13278-015-0253-5.

[10] C. Weeg, H. A. Schwartz, S. Hill, R. M. Merchant, C. Arango, L. Ungar, Using twitter to measure public discussion of diseases: a case study, JMIR Public Health and Surveillance 1 (1) (2015) e6. doi:10.2196/jmir.3953.

[11] L. Mollema, I. A. Harmsen, E. Broekhuizen, R. Clijnck, H. De Melker, T. Paulussen, G. Kok, R. Ruiter, E. Das, Disease detection or public opinion reflection? content analysis of tweets, other social media, and online newspapers during the measles outbreak in the netherlands in 2013, Journal of Medical Internet Research (JMIR) 17 (5) (2015) e128. doi:10.2196/jmir.3863.

[12] S. E. Jordan, S. E. Hovet, I. C.-H. Fung, H. Liang, K.-W. Fu, Z. T. H. Tse, Using twitter for public health surveillance from monitoring and prediction to public response, Data 4 (1) (2019) 6. doi:10.3390/data4010006.

[13] H. Rosenberg, S. Syed, S. Rezaie, The twitter pandemic: the critical role of twitter in the dissemination of medical information and misinformation during the covid-19 pandemic, Canadian Journal of Emergency Medicine 22 (4) (2020) 418–421. doi:10.1017/cem.2020.361.

[14] E. Chen, K. Lerman, E. Ferrara, Covid-19: The first public coronavirus twitter dataset, arXiv preprint arXiv:2003.07372.
[15] Z. Gao, S. Yada, S. Wakamiya, E. Aramaki, Naist covid: Multilingual covid-19 twitter and weibo dataset, arXiv preprint arXiv:2004.08145.

[16] R. Lamsal, Corona virus (covid-19) tweets dataset (2020). doi:10.21227/781w-ef42
URL http://dx.doi.org/10.21227/781w-ef42

[17] N. Aguilar-Gallegos, L. E. Romero-García, E. G. Martínez-González, E. I. García-Sánchez, J. Aguilar-Ávila, Dataset on dynamics of coronavirus on twitter, Data in Brief 30 (2020) 105684. doi:10.1016/j.dib.2020.105684

[18] E. Chen, K. Lerman, E. Ferrara, Tracking social media discourse about the covid-19 pandemic: Development of a public coronavirus twitter data set, JMIR Public Health and Surveillance 6 (2) (2020) e19273. doi:10.2196/19273

[19] A. Abd-Alrazaq, D. Alhuwail, M. Househ, M. Hamdi, Z. Shah, Top concerns of tweeters during the covid-19 pandemic: infoveillance study, Journal of Medical Internet Research 22 (4). doi:10.2196/19016

[20] H. R. Rao, N. Vemprala, P. Akello, R. Valecha, Retweets of officials alarming vs reassuring messages during the covid-19 pandemic: Implications for crisis management, International Journal of Information Management (2020) 102187. doi:10.1016/j.ijinfomgt.2020.102187

[21] H. W. Park, S. Park, M. Chong, Conversations and medical news frames on twitter: Infodemiological study on covid-19 in south korea, Journal of Medical Internet Research 22 (5) (2020) e18897. doi:10.2196/18897

[22] F. Feng, Y. Yang, D. Cer, N. Arivazhagan, W. Wang, Language-agnostic bert sentence embedding, arXiv preprint arXiv:2007.01852.

[23] D. R. Dewhurst, T. Alshaabi, M. V. Arnold, J. R. Minot, C. M. Danforth, P. S. Dodds, Divergent modes of online collective attention to the covid-
19 pandemic are associated with future caseload variance, arXiv preprint arXiv:2004.03516.

[24] M. Thelwall, S. Thelwall, Retweeting for covid-19: Consensus building, information sharing, dissent, and lockdown life, arXiv preprint arXiv:2004.02793.

[25] T. Alshaabi, J. R. Minot, M. V. Arnold, J. L. Adams, D. R. Dewhurst, A. J. Reagan, R. Muhamad, C. M. Danforth, P. S. Dodds, How the world’s collective attention is being paid to a pandemic: Covid-19 related 1-gram time series for 24 languages on twitter, arXiv preprint arXiv:2003.12614.

[26] T. C. Hamamsy, R. Bonneau, Twitter activity about treatments during the covid-19 pandemic: case studies of remdesivir, hydroxychloroquine, and convalescent plasma., medRxiv . doi:10.1101/2020.06.18.20134668

[27] L. Singh, S. Bansal, L. Bode, C. Budak, G. Chi, K. Kawintiranon, C. Padden, R. Vanarsdall, E. Vraga, Y. Wang, A first look at covid-19 information and misinformation sharing on twitter, arXiv preprint arXiv:2003.13907.

[28] C. E. Lopez, M. Vasu, C. Gallemore, Understanding the perception of covid-19 policies by mining a multilanguage twitter dataset, arXiv preprint arXiv:2003.10359.

[29] R. Kouzy, J. Abi Jaoude, A. Kraitem, M. B. El Alam, B. Karam, E. Adib, J. Zarka, C. Traboulsi, E. W. Akl, K. Baddour, Coronavirus goes viral: quantifying the covid-19 misinformation epidemic on twitter, Cureus 12 (3). doi:10.7759/cureus.7255

[30] P. Wicke, M. M. Bolognesi, Framing covid-19: How we conceptualize and discuss the pandemic on twitter, arXiv preprint arXiv:2004.06986.

[31] A. Jarynowski, M. Wójta-Kempa, V. Belik, Trends in perception of covid-19 in polish internet, medRxiv . doi:10.1101/2020.05.04.20090993
[32] C. Ordun, S. Purushotham, E. Raff, Exploratory analysis of covid-19 tweets using topic modeling, umap, and digraphs, arXiv preprint arXiv:2005.03082.

[33] R. J. Medford, S. N. Saleh, A. Sumarsono, T. M. Perl, C. U. Lehmann, An "infodemic": Leveraging high-volume twitter data to understand public sentiment for the covid-19 outbreak, medRxiv. doi:10.1101/2020.04.03.20052936.

[34] L. Chen, H. Lyu, T. Yang, Y. Wang, J. Luo, In the eyes of the beholder: Sentiment and topic analyses on social media use of neutral and controversial terms for covid-19, arXiv preprint arXiv:2004.10225.

[35] M. Cinelli, W. Quattrociocchi, A. Galeazzi, C. M. Valensise, E. Brugnoli, A. L. Schmidt, P. Zola, F. Zollo, A. Scala, The covid-19 social media infodemic, arXiv preprint arXiv:2003.05004.

[36] P. Hosseini, P. Hosseini, D. A. Broniatowski, Content analysis of persian/farsi tweets during covid-19 pandemic in iran using nlp, arXiv preprint arXiv:2005.08400.

[37] H. Jang, E. Rempel, G. Carenini, N. Janjua, Exploratory analysis of covid-19 related tweets in north america to inform public health institutes, arXiv preprint arXiv:2007.02452.

[38] M. Saad, M. Hassan, F. Zaffar, Towards characterizing the covid-19 awareness on twitter, arXiv preprint arXiv:2005.08379.

[39] M. Odlum, H. Cho, P. Broadwell, N. Davis, M. Patrao, D. Schauer, M. E. Bales, C. Alcantara, S. Yoon, Application of topic modeling to tweets as the foundation for health disparity research for covid-19, Studies in health technology and informatics 272 (2020) 24–27. doi:10.3233/SHTI200484.

[40] S. Park, S. Han, J. Kim, M. M. Molaie, H. D. Vu, K. Singh, J. Han, W. Lee, M. Cha, Risk communication in asian countries: Covid-19 discourse on twitter, arXiv preprint arXiv:2006.12218.
[41] J. Xue, J. Chen, R. Hu, C. Chen, C. Zheng, T. Zhu, Twitter discussions and concerns about covid-19 pandemic: Twitter data analysis using a machine learning approach, arXiv preprint arXiv:2005.12830.

[42] R. K. Gupta, A. Vishwanath, Y. Yang, Covid-19 twitter dataset with latent topics, sentiments and emotions attributes, arXiv preprint arXiv:2007.06954.

[43] X. Wang, C. Zou, Z. Xie, D. Li, Public opinions towards covid-19 in california and new york on twitter, medRxiv . doi:10.1101/2020.07.12.20151936.

[44] Y. Feng, W. Zhou, Is working from home the new norm? an observational study based on a large geo-tagged covid-19 twitter dataset, arXiv preprint arXiv:2006.08581.

[45] H. Yin, S. Yang, J. Li, Detecting topic and sentiment dynamics due to covid-19 pandemic using social media, arXiv preprint arXiv:2007.02304.

[46] L. McQuillan, E. McAweeney, A. Bargar, A. Ruch, Cultural convergence: Insights into the behavior of misinformation networks on twitter, arXiv preprint arXiv:2007.03443.

[47] Y. Omoya, M. Kaigo, Suspicion begets idle fears–an analysis of covid-19 related topics in japanese media and twitter, Available at SSRN 3585532 . doi:10.2139/ssrn.3585532.

[48] K. Sharma, S. Seo, C. Meng, S. Rambhatla, A. Dua, Y. Liu, Coronavirus on social media: Analyzing misinformation in twitter conversations, arXiv preprint arXiv:2003.12309.

[49] M. Kabir, S. Madria, et al., Coronavirus: A real-time covid-19 tweets analyzer, arXiv preprint arXiv:2004.13932.

[50] K. D. Rosa, R. Shah, B. Lin, A. Gershman, R. Frederking, Topical clustering of tweets, Proceedings of the ACM SIGIR: SWSM 63. doi:10.1.1.207.4287.
[51] S. B. Kaleel, A. Abhari, Cluster-discovery of twitter messages for event detection and trending, Journal of Computational Science 6 (2015) 47–57. doi:10.1016/j.jocs.2014.11.004

[52] S. L. Lo, R. Chiong, D. Cornforth, An unsupervised multilingual approach for online social media topic identification, Expert Systems with Applications 81 (2017) 282–298. doi:10.1016/j.eswa.2017.03.029

[53] Q. Le, T. Mikolov, Distributed representations of sentences and documents, in: International conference on machine learning, 2014, pp. 1188–1196.

[54] J. Pennington, R. Socher, C. Manning, Glove: Global vectors for word representation, in: Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), 2014, pp. 1532–1543. doi:10.3115/v1/D14-1162

[55] S. Vosoughi, P. Vijayaraghavan, D. Roy, Tweet2vec: Learning tweet embeddings using character-level cnn-lstm encoder-decoder, in: Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval, 2016, pp. 1041–1044. doi:10.1145/2911451.2914762

[56] B. Dhingra, Z. Zhou, D. Fitzpatrick, M. Muehl, W. Cohen, Tweet2vec: Character-based distributed representations for social media, in: Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), 2016, pp. 269–274. doi:10.18653/v1/P16-2044

[57] J. Liu, Z. He, Y. Huang, Hashtag2vec: learning hashtag representation with relational hierarchical embedding model, in: Proceedings of the 27th International Joint Conference on Artificial Intelligence, 2018, pp. 3456–3462. doi:10.5555/3304222.3304248

[58] M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee,
L. Zettlemoyer, Deep contextualized word representations, in: Proceedings of NAACL-HLT, 2018, pp. 2227–2237. doi:10.18653/v1/N18-1202.

[59] J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding, in: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 2019, pp. 4171–4186. doi:10.18653/v1/N19-1423.

[60] O. Gencoglu, Deep representation learning for clustering of health tweets, arXiv preprint arXiv:1901.00439.

[61] J. Zhu, Z. Tian, S. Kübler, Um-iu@ ling at semeval-2019 task 6: Identifying offensive tweets using bert and svms, arXiv preprint arXiv:1904.03450.

[62] J. Ray Chowdhury, C. Caragea, D. Caragea, Keyphrase extraction from disaster-related tweets, in: The world wide web conference, 2019, pp. 1555–1566. doi:10.1145/3308558.3313696.

[63] J. R. Chowdhury, C. Caragea, D. Caragea, On identifying hashtags in disaster twitter data, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34, 2020, pp. 498–506. doi:10.1609/aaai.v34i01.5387.

[64] K. Roitero, V. Cristian Bozzato, G. Serra, Twitter goes to the doctor: Detecting medical tweets using machine learning and bert, in: Proceedings of the International Workshop on Semantic Indexing and Information Retrieval for Health from heterogeneous content types and languages, Vol. 2619, 2020.

[65] B. Mazoyer, J. Cagé, N. Hervé, C. Hudelot, A french corpus for event detection on twitter, in: Proceedings of The 12th Language Resources and Evaluation Conference, 2020, pp. 6220–6227.

[66] D. Q. Nguyen, T. Vu, A. T. Nguyen, Bertweet: A pre-trained language model for english tweets, arXiv preprint arXiv:2005.10200.
[67] M. Müller, M. Salathé, P. E. Kummervold, Covid-twitter-bert: A natural language processing model to analyse covid-19 content on twitter, arXiv preprint arXiv:2005.07503.

[68] N. Reimers, I. Gurevych, Sentence-BERT: Sentence embeddings using Siamese BERT-networks, in: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 2019, pp. 3982–3992. doi:10.18653/v1/D19-1410

[69] O. Gencoglu, M. Gruber, Causal modeling of twitter activity during covid-19, medRxiv. doi:10.1101/2020.05.16.20103903

[70] R. Baly, G. Karadzhov, J. An, H. Kwak, Y. Dinkov, A. Ali, J. Glass, P. Nakov, What was written vs. who read it: News media profiling using text analysis and social media context, arXiv preprint arXiv:2005.04518.

[71] H. Kim, D. Walker, Leveraging volunteer fact checking to identify misinformation about covid-19 in social media, Harvard Kennedy School Misinformation Review 1 (3). doi:10.37016/mr-2020-021

[72] O. Gencoglu, Cyberbullying detection with fairness constraints, arXiv preprint arXiv:2005.06625.

[73] J. M. Banda, R. Tekumalla, G. Wang, J. Yu, T. Liu, Y. Ding, G. Chowell, A twitter dataset of 150+ million tweets related to covid-19 for open research (2020). doi:10.5281/zenodo.3738018

[74] Covid-19 twitter chatter dataset for scientific use, http://www.panacealab.org/covid19/ accessed: 2020-07-30.

[75] A. Arora, A. Shrivastava, M. Mohit, L. S.-M. Lecanda, A. Aly, Cross-lingual transfer learning for intent detection of covid-19 utterances OpenReview preprint. URL https://openreview.net/pdf?id=vP-CQG-ap-R
[76] J. Wei, C. Huang, S. Vosoughi, J. Wei, What are people asking about covid-19? a question classification dataset, arXiv preprint arXiv:2005.12522.

[77] C. E. Rasmussen, Gaussian processes in machine learning, in: Summer School on Machine Learning, Springer, 2003, pp. 63–71. doi:10.1007/978-3-540-28650-9_4.

[78] J. Mockus, On bayesian methods for seeking the extremum, in: Optimization Techniques IFIP Technical Conference, Springer, 1975, pp. 400–404. doi:10.1007/3-540-07165-2_55.

[79] L. McInnes, J. Healy, N. Saul, L. Großberger, Umap: Uniform manifold approximation and projection, Journal of Open Source Software 3 (29) (2018) 861. doi:10.21105/joss.00861.

[80] J. Platt, et al., Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods, Advances in large margin classifiers 10 (3) (1999) 61–74.

[81] A. Lacoste, A. Luccioni, V. Schmidt, T. Dandres, Quantifying the carbon emissions of machine learning, arXiv preprint arXiv:1910.09700.

[82] P. M. Sandman, Responding to community outrage: Strategies for effective risk communication, AIHA, 1993.

[83] A. I. Bento, T. Nguyen, C. Wing, F. Lozano-Rojas, Y.-Y. Ahn, K. Simon, Evidence from internet search data shows information-seeking responses to news of local covid-19 cases, Proceedings of the National Academy of Sciences 117 (21) (2020) 11220–11222. doi:10.1073/pnas.2005335117.

[84] C. M. L. Wong, O. Jensen, The paradox of trust: perceived risk and public compliance during the covid-19 pandemic in singapore, Journal of Risk Research (2020) 1–10. doi:10.1080/13669877.2020.1756386.

[85] Covid-19 solidarity response fund, https://www.who.int/emergencies/diseases/novel-coronavirus-2019/donate, accessed: 2020-07-30.
[86] C. Wang, R. Pan, X. Wan, Y. Tan, L. Xu, C. S. Ho, R. C. Ho, Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (covid-19) epidemic among the general population in china, International Journal of Environmental Research and Public Health 17 (5) (2020) 1729. doi:10.3390/ijerph17051729

[87] W. Cullen, G. Gulati, B. Kelly, Mental health in the covid-19 pandemic, QJM: An International Journal of Medicine 113 (5) (2020) 311–312. doi:10.1093/qjmed/hcaa110

[88] S. K. Brooks, R. K. Webster, L. E. Smith, L. Woodland, S. Wessely, N. Greenberg, G. J. Rubin, The psychological impact of quarantine and how to reduce it: rapid review of the evidence, The Lancet 395 (2020) 912–920. doi:10.1016/S0140-6736(20)30460-8

[89] R. M. Merchant, N. Lurie, Social media and emergency preparedness in response to novel coronavirus, Journal of the American Medical Association (JAMA) 323 (20). doi:10.1001/jama.2020.4469

[90] J. L. Chan, H. Purohit, Challenges to transforming unconventional social media data into actionable knowledge for public health systems during disasters, Disaster medicine and public health preparedness (2019) 1–8. doi:10.1017/dmp.2019.92