Visualizing relation between misinformation and public sentiment on Covid-19 vaccine

Ashiqur Rahman
Z-ID: **Z1874484**

09 December 2021

Abstract

Vaccine hesitancy is one of the significant obstacles to eradicating the Covid-19 and putting humanity back on track. Misinformation plays a vital role in creating this hesitancy. In this project, we visualized the topics frequently used in misinformation and public sentiment who are using those topics in vaccine related conversations.

Coordinator

Dr. David Koop
Assistant Professor
Department of Computer Science
Northern Illinois University

Contents

1 Introduction

Social media plays a vital role in modern life by communicating, disseminating information, and steering social conversations [40]. These features have more impact during a state of crisis [4]. We have seen this during major events like mass shootings, natural disasters, national elections, and even anti-vaccination campaigns [4], [8], [13], [14].
Due to the Coronavirus, the current pandemic created significant dependence on social media. While social media has an essential role in spreading updated information and creating public awareness, misinformation has spread with little to no oversight. As soon as the coronavirus emerged, racism, rumor, and fear-mongering started spreading like wildfire on different platforms [24]. This issue had some dire consequences like an overdose of Chloroquine in Nigeria, the suicide of a father of three in India, and the shortage of Hydroxychloroquine for Lupus patients as a direct influence of misinformation circulating the web [33], [51]. Well-intended dissemination of unsubstantiated information can do more harm than good [32]. Also, malicious characters try to take political, financial, or otherwise advantages using misinformation [14], [16]. The World Health Organization (WHO) has partnered with major tech giants such as Facebook, Google, LinkedIn, Microsoft, Reddit, and Twitter to fight against misinformation [36]. Social media giants like Facebook, Twitter, and YouTube are taking a more active role in preventing the spread of misinformation [26], [27], [29]. However, misinformation is still widely available on these platforms [47].
Although several precautionary techniques like masking, social distancing, and proper sanitization [43] remaining, history teaches us that vaccination is the most meaningful strategy to overcome this global pandemic [19]. While some promising vaccines are accessible around the world [48], it will require a significant percentage of the population to be vaccinated to achieve herd immunity [39]. In comparison, measles requires 95% vaccination, and polio requires 80% vaccination coverage to achieve this collective herd immunity [39] [45]. Unfortunately, Anti-vaxxers and conspiracy theorists are actively creating and disseminating misinformation about vaccination. This misinformation campaign can significantly thwart the effort to reach that goal of herd immunity and put this pandemic behind us [41]. A recent study found that the total monetary harm due to "non-vaccination" in the United States is between 50 to 300 million dollars per day **Bruns2021-tf**. So, it is crucial to study misleading information about Covid-19 vaccination and find the best way to combat the anti-vaccine campaigns.
In this project, we plan to analyze and visually explore Twitter data during this pan-

demic and find the most resonating misinformation topics among the general population which are driving them towards non-vaccination. Identifying these topics can give us the tools to better combat the misinformation campaign.

2 Contribution

Contributions of this project are:

1. A topic dataset related to Covid-19 vaccine containing words used to spread misinformation along with a scores of the words and number of tweets using each topic.
2. A tweet dataset related to Covid-19 vaccine containing user sentiment expressed in those tweets and a cumulative score over time.
3. An interactive tool to visualize the topics and user sentiments with interactive features.

Source code and the datasets relevant to this project can be found at this GitHub URL: https://github.com/ashiqur-rony/infoviz

3 Related Works

There is a thin line between fake news and misinformation. When verifiable false news is shared, that is called fake news [12]. On the other hand, misinformation is when false news is shared unintentionally [1], [37]. The mass population can genuinely believe fake news without verifying it and take part in spreading misinformation.

After analyzing 43.3 million tweets, Ferrara E. [28] found that automated social bots are used to disseminate misinformation and political conspiracy theories related to COVID-19. Al-Rakhami and Al-Amri [35] proposed a framework to use six different machine learning algorithms to detect misinformation. They collected the data using Twitter API at the beginning of the pandemic and manually labeled the data to train the models.

The vaccination to prevent COVID-19 is being debated widely, and the misinformation is spread by the opponents of vaccination more frequently compared to the proponents [30]. Although officials are taking steps to handle the misinformation regarding the vaccine [23], the efforts are still falling short [47] to tackle the diverse reasons [31] for the spread of misinformation.

Researchers found that vaccine hesitancy goes hand-in-hand with believing in vaccine related misinformation like "cause people to catch COVID-19," "more harmful than COVID-19," and "will be used to alter people's DNA" [46].

This seemingly unstoppable spread of misinformation can change the objectivity of the population towards vaccination. Sentiment analysis and stance detection can give us a clear overview of the impact on public opinion. Sentiment analysis is one of the major research areas in natural language processing (NLP) that analyzes people's attitudes and emotions from written language [6]. This can help us determine the overall perception of the population about any topic. Stance detection on the other hand is somewhat different from traditional sentiment analysis. While sentiment analysis can detect whether a block of text is positive, negative, or neutral, stance detection can classify someone's opinion as in favor or against a given target, which may or may not be present in the text [9].

Cotfas et al. [44] worked with tweets from the month following the Covid-19 vaccine announcement and found that the majority of tweets were in "neutral" territory and tweets in "favor" outpass "against" stance towards the vaccine.

Boon-Itt and Skunkan analyzed tweets to find the topics and sentiment related to Covid-19. They found the sentiment towards Covid-19 is mostly "negative". Although, they did not try to relate the sentiment with topics [20].

In our project, we want to visually represent the change of people's sentiment over time on the topic of Covid-19 vaccines and show how the spread of misinformation topics which are popular at that time impacts the opinion.

There are several works on visualizing topics including but not limited to word cloud, network, scatterplot, and heatmap [17]. "TopicPanaroma" [10], "Termite" [5] are two interesting tools to visualize topics.

Time series data visualization is also a widely researched area and many different methods like sequence chart, point chart, line chart, bar chart along with user interaction like zooming, brushing, linking presents a variety of options to represent time series data [2]. Brehmer et al. [11] discussed the design choices for temporal data to use a storytelling approach, which can better convey the message to the users from different narratives. They proposed 14 design choices in 3 dimensions and presented different visualization

approaches by combining those.
Wang et al. [38] proposed a visual analysis tool - “ConceptExplorer” to analyze the concept drift using the time series data from different sources. Their tool lets users choose a segment of the timeline for analysis and compares concepts in a correlation matrix.
Carvalho et al. [42] chronicled the progress in Covid-19 research in the first 12 months from the outbreak of Sars-Cov-2. Their work summarizes the significant achievement of scientists and researchers in a short period of time while also outlining the gaps in research. They used a very basic timeline visualization in their paper which shows that a bare minimum visualization can be enough to convey the message.
In our project we decided to go with a simple bubble chart to represent the data because it is easy to understand and we can convey several data points based on the position, size and color of the bubbles.

4 Methods

4.1 Preparing the datasets

We have prepared two separate datasets called the “Primary dataset” and the “Misinformation dataset” containing tweets during the Covid-19 pandemic. The datasets contain tweets, the date of the tweet, author locations in CSV format. Then we extracted the topics from the two and created the “Combined topic dataset”. Details of the three datasets are explained below.

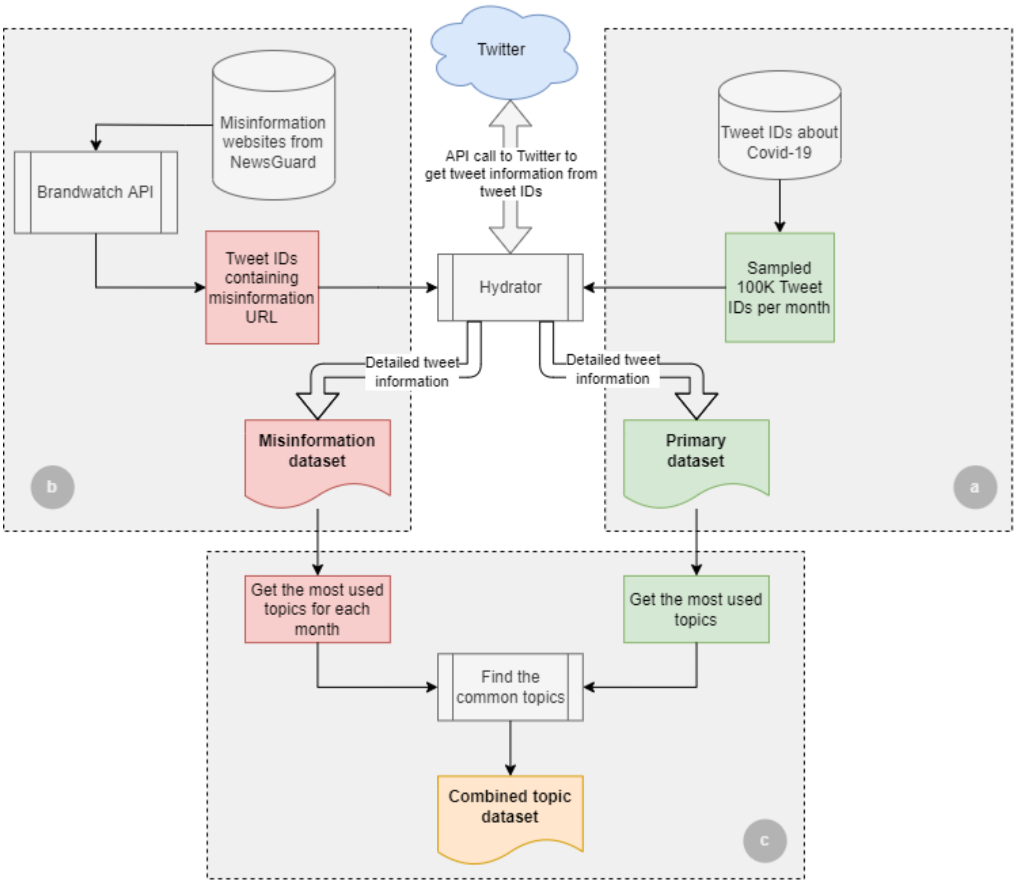

Figure 1: a) Creating the "Primary dataset" using Tweets from Chen et al., b) Building "Misinformation dataset" using the curated list from NewsGuard, c) Using Top2Vec and creating the "Combined topic dataset"

Primary dataset

We have collected 6.2 million tweets between January 2020 and March 2021 that contain information about Covid-19 (SARS-COV-2). We have used the data from Chen et al. [22] and gathered the Tweet IDs from their GitHub repository [21]. Chen et al. used several keywords to search for the Covid-19 related tweets. Then we randomly sampled IDs from each month to fetch the detailed tweets. Finally used the Hydrator API tool [25] to collect all the tweet information. This is the primary dataset for the study.
Due to the rate limit of Twitter API [51], we sampled 100,000 tweets from each week and collected the complete tweet data using the above process. At the end of the process, we had 6,224,762 tweets in our dataset. Figure Figure 1(a) shows the steps to prepare

the primary dataset.

Misinformation dataset

To identify the prominent topics in misinformation, we first need to create a dataset containing the misinformation tweets relating to Covid-19. To achieve this, we collected the list of websites curated by NewsGuard [50] that are spreading Covid-19 related misinformation. Tweets that contain links to these potential misinformation websites possibly contain misinformation content. We collected random tweet IDs from the year 2020 that contain any of the misinformation URLs, using the Brandwatch API [49], a web-based tool to collect historical social media data, to create the misinformation dataset. We used the Hydrator API tool to get the tweets from the tweet IDs. At the end of the process, we had 509,460 tweets in the misinformation dataset. Figure 1(b) shows the steps of preparing the misinformation dataset.

Combined topic dataset

We used Top2Vec [18] to create the topic models from our datasets and find the common topics among the "primary" and "misinformation" datasets. Although Latent Dirichlet Allocation (LDA) [3] is one of the most popular algorithms to do topic analysis, we found Top2Vec to be more beneficial for our purpose. Top2Vec is superior to LDA because unlike LDA, Top2Vec trains the document and word vector jointly in a single semantic space, we do not need to know the number of topics before the training, and removal of stop-words is not necessary [18], [34], [45].
In this step we extracted the topics related to "vaccine" in English language tweets from both the datasets and grouped by unique words. Then we matched the common words between the two datasets to find the misinformation topics present in the generic twitter conversations. The more frequent words and words with higher topic scores are given higher priority in this step. After this step, we had 9 unique topics with 918 unique words in the dataset. Figure 1(c) shows the steps of preparing the combined topic dataset.

4.2 Sentiment Analysis

To find the change in public sentiment, we extracted the English language tweets from the "Primary" dataset and used VADER (Valence Aware Dictionary and sEntiment Reasoner) [7] sentiment analysis tool to find sentiment scores. We chose VADER because it works well with the social media text by taking different social media norms, common slang words, emojis, and emoticons into consideration. This process gave us sentiment scores for each of the tweets. The Score data contained four fields - "pos", "neg", "neu", and "compound". The "pos", "neg", and "neu" represent the ratio of positive, negative, and neutral parts of the texts. The sum of these three fields becomes 1. The "compound" score is the most meaningful metric to measure the sentiment of the tweets. The compound score ranges between -1 and 1. The score between -1 and -0.5 is considered negative, the score between -0.5 and 0.5 is considered neutral, and the score above 0.5 is considered positive. We calculated the cumulative compound score over time to understand if one person is getting more polarized over time. Then we isolated the tweets that contain vaccine related keywords to focus our visualization to vaccine related sentiment.

4.3 Interactive visualization tool

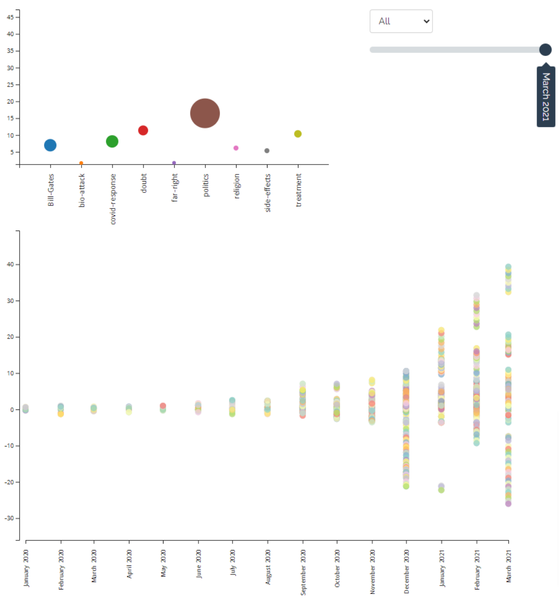

Figure 2: Visualization tool to explore topics and sentiments

We developed a multiple-view visualization tool to explore the topics and sentiments from the Covid-19 vaccine related dataset prepared above. Figure 3 shows a screenshot from the tool. The interactive tool can be accessed using the URL: https://ashiqur-rony.github.io/infoviz/

We have explained each of the views present in the tool below.

Visualizing topics

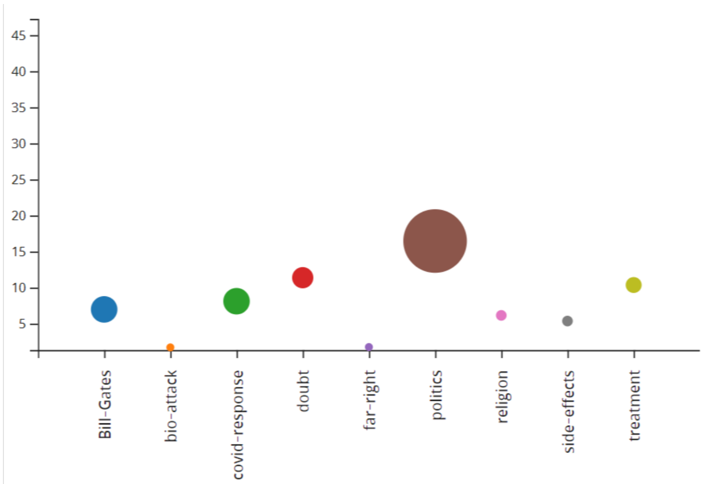

Figure 3: Topics visualized using bubble charts

We used bubble charts to display the topics at any time. The horizontal axis represents the topics, while the vertical axis represents the topic score calculated in the combined topic dataset. The size of the bubbles represents the total number of tweets in that topic at the selected time segment. We used different colors to better isolate the topics in the visualization.

We used animation to change the view when the user changes their selection (see user controls section). "Hover effect" is also present to highlight the tweets in the sentiment visualization related to that topic.

Visualizing sentiment

We used bubble charts to visualize the cumulative sentiment over time. Each bubble in the visualization represents one tweet. The color of the bubble differentiates the users. User selection of month can highlight the cumulative sentiment up to that month, and

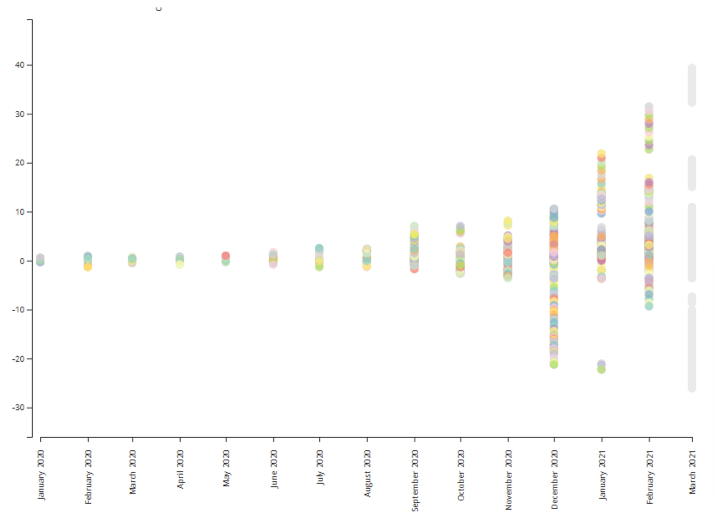

Figure 4: Cumulative sentiment over time visualized using a bubble chart

the rest is grayed out. Users can also choose to highlight a single user in the whole visualization (see user controls section).

We used animation to change the view when the user changes their selection. Hovering the mouse pointer on a bubble shows detail about that tweet.

User controls

There are several user controls present in the visualization. A user can choose to highlight a certain month, user, topic, or tweets.

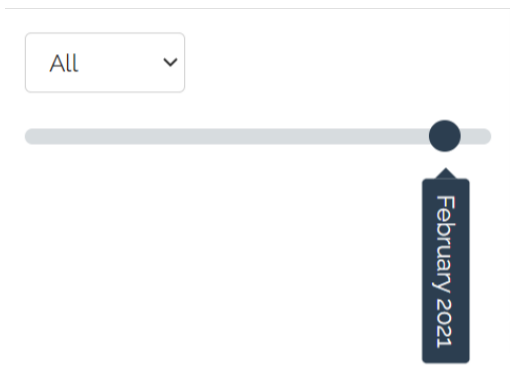

Figure 5: User controls at the top-right

Primary user control is the selection and the slider at the top right of the visualization (or in the middle of two visualizations on mobile devices). Using the range slider, we can select the month to display in the topic visualization and highlight the cumulative sentiment up to that month. From the dropdown we can select the user to highlight in the sentiment visualization. Both the controls have animation effects attached to it while changing the visualizations.

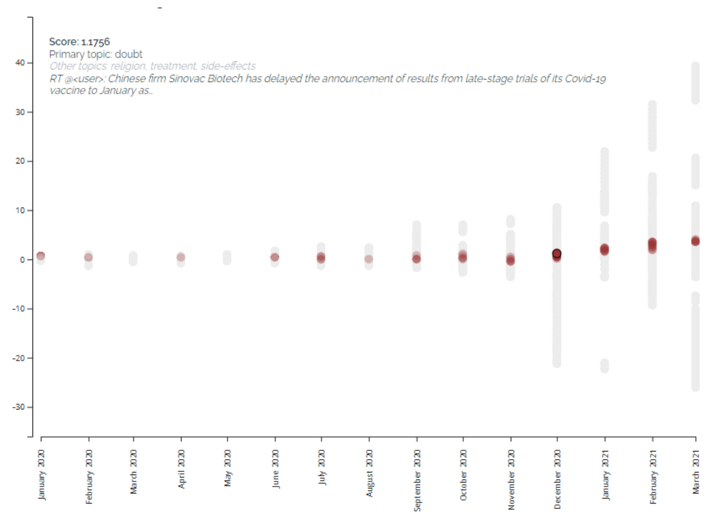

Figure 6: Highlighting only one user in the sentiment visualization and displaying the detail at the top-left after mouse hover

There are also mouse hover effects attached to both topic and sentiment visualization. When we hover our mouse on a topic, brushing techniques highlight that topic from the topic visualization at the top and highlight only the tweets using that topic from the sentiment visualization at the bottom.

We can also do the selection from the other end. Hovering on a bubble from the sentiment visualization at the bottom highlights a single tweet and displays the cumulative sentiment score, tweet text, highest ranked topic, and other lower ranked topics from that tweet text at the top-left corner. This also highlights the highest ranked topic in the topic visualization at the top.

5 Discussion

By analyzing misinformation topics on Twitter and user sentiment regarding Covid-19 vaccine, we noticed that users were getting more polarized as time went on. We noticed while the number of tweets related to the topic - “politics” is always the highest, most negative sentiment tweets had “doubt” or “religion” in the highest scoring topics in them. We also noticed that some users jumped into the twitter conversation right around the time when the vaccines were rolled out and drove the conversations to the extreme ends (e.g., *user_32*). Some extreme tweets were also just trying to take advantage of the highly debated conversation and promote their products (e.g., *user_31*).

6 Future Works

There are several possible improvements to the study. First of all, we can use stance detection techniques [15] and take user stance into consideration instead of cumulative sentiment because users can express extreme sentiment in their tweet while in favor or against a topic.

Secondly, we matched words to identify the topics of a tweet. This is not an effective method because the same words can be used in totally different topics. We need to use a better approach to identify the topics of individual tweets.

Finally, we can collect more data and increase the duration of the analysis. We can test if the trend changed after the end of the “election year”, widespread vaccine mandate, and vaccination of a large segment of the population.

7 Conclusion

In conclusion, this is an important research area in our opinion and should be further continued to understand and prevent the spread of misinformation during Covid-19 pandemic. The methods derived from this project can also be extended for any future crisis and tackle the misinformation campaign.

References

[1] J. H. Kuklinski, P. J. Quirk, J. Jerit, D. Schwieder, and R. F. Rich, “Misinformation and the currency of democratic citizenship,” *J. Polit.*, vol. 62, no. 3, pp. 790–816, 2000.

[2] M. Weber, M. Alexa, and W. Müller, “Visualizing time-series on spirals,” in *Infovis*, vol. 1, ieg.ifs.tuwien.ac.at, 2001, pp. 7–14.

[3] D. M. Blei, A. Y. Ng, and M. I. Jordan, “Latent dirichlet allocation,” *J. Mach. Learn. Res.*, vol. 3, no. Jan, pp. 993–1022, 2003.

[4] L. Palen, *Online social media in crisis events*, https://er.educause.edu/articles/2008/8/online-social-media-in-crisis-events, Accessed: 2020-8-8, Aug. 2008.

[5] J. Chuang, C. D. Manning, and J. Heer, “Termite: Visualization techniques for assessing textual topic models,” in *Proceedings of the International Working Conference on Advanced Visual Interfaces*, ser. AVI ’12, Capri Island, Italy: Association for Computing Machinery, May 2012, pp. 74–77.

[6] B. Liu, “Sentiment analysis and opinion mining,” *Synthesis Lectures on Human Language Technologies*, vol. 5, no. 1, pp. 1–167, May 2012.

[7] C. Hutto and E. Gilbert, “VADER: A parsimonious Rule-Based model for sentiment analysis of social media text,” en, *ICWSM*, vol. 8, no. 1, pp. 216–225, May 2014.

[8] E. Housholder and H. L. LaMarre, “Political social media engagement: Comparing campaign goals with voter behavior,” *Public Relat. Rev.*, vol. 41, no. 1, pp. 138–140, Mar. 2015.

[9] S. Mohammad, S. Kiritchenko, P. Sobhani, X. Zhu, and C. Cherry, “SemEval-2016 task 6: Detecting stance in tweets,” pp. 31–41, Jun. 2016.

[10] X. Wang, S. Liu, J. Liu, J. Chen, J. Zhu, and B. Guo, “TopicPanorama: A full picture of relevant topics,” en, *IEEE Trans. Vis. Comput. Graph.*, vol. 22, no. 12, pp. 2508–2521, Dec. 2016.

[11] M. Brehmer, B. Lee, B. Bach, N. H. Riche, and T. Munzner, “Timelines revisited: A design space and considerations for expressive storytelling,” en, *IEEE Trans. Vis. Comput. Graph.*, vol. 23, no. 9, pp. 2151–2164, Sep. 2017.

[12] K. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu, “Fake news detection on social media: A data mining perspective,” *SIGKDD Explor. Newsl.*, vol. 19, no. 1, pp. 22–36, Sep. 2017.

[13] A. Badawy, E. Ferrara, and K. Lerman, “Analyzing the digital traces of political manipulation: The 2016 russian interference twitter campaign,” in *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, Aug. 2018, pp. 258–265.

[14] D. A. Broniatowski, A. M. Jamison, S. Qi, *et al.*, “Weaponized health communication: Twitter bots and russian trolls amplify the vaccine debate,” en, *Am. J. Public Health*, vol. 108, no. 10, pp. 1378–1384, Oct. 2018.

[15] K. Dey, R. Shrivastava, and S. Kaushik, “Topical stance detection for twitter: A Two-Phase LSTM model using attention,” in *Advances in Information Retrieval*, Springer International Publishing, 2018, pp. 529–536.

[16] V. L. Kitzie, E. Mohammadi, and A. Karami, ““life never matters in the DEMOCRATS MIND”: Examining strategies of retweeted social bots during a mass shooting event,” *Proc. Assoc. Info. Sci. Tech.*, vol. 55, no. 1, pp. 254–263, Jan. 2018.

[17] C. Zhang, Z. Li, and J. Zhang, “A survey on visualization for scientific literature topics,” *Journal of Visualization*, vol. 21, no. 2, pp. 321–335, Apr. 2018.

[18] D. Angelov, “Top2Vec: Distributed representations of topics,” Aug. 2020. arXiv: 2008.09470 `[cs.CL]`.

[19] BBC News, “How do pandemics end?” *BBC*, Oct. 2020.

[20] S. Boon-Itt and Y. Skunkan, “Public perception of the COVID-19 pandemic on twitter: Sentiment analysis and topic modeling study,” en, *JMIR Public Health Surveill*, vol. 6, no. 4, e21978, Nov. 2020.

[21] E. Chen, *COVID-19-TweetIDs*, https://github.com/echen102/COVID-19-TweetIDs, Accessed: 2021-9-9, May 2020.

[22] E. Chen, K. Lerman, and E. Ferrara, “Tracking social media discourse about the COVID-19 pandemic: Development of a public coronavirus twitter data set,” en, *JMIR Public Health Surveill*, vol. 6, no. 2, e19273, May 2020.

[23] W. Cornwall, “Officials gird for a war on vaccine misinformation,” en, *Science*, vol. 369, no. 6499, pp. 14–15, Jul. 2020.

[24] A. Depoux, S. Martin, E. Karafillakis, R. Preet, A. Wilder-Smith, and H. Larson, "The pandemic of social media panic travels faster than the COVID-19 outbreak," en, *J. Travel Med.*, vol. 27, no. 3, May 2020.

[25] Documenting the Now, *Hydrator API*, 2020.

[26] E. Douek, "The internet's titans make a power grab," *The Atlantic*, Apr. 2020.

[27] ——, "The year that changed the internet," *The Atlantic*, Dec. 2020.

[28] E. Ferrara, "What types of COVID-19 conspiracies are populated by twitter bots?" en, *First Monday*, May 2020.

[29] T. Hatmaker, "Twitter broadly bans any COVID-19 tweets that could help the virus spread," *TechCrunch*, Mar. 2020.

[30] A. M. Jamison, D. A. Broniatowski, M. Dredze, A. Sangraula, M. C. Smith, and S. C. Quinn, "Not just conspiracy theories: Vaccine opponents and proponents add to the COVID-19 'infodemic' on twitter," *HKS Misinfo Review*, Sep. 2020.

[31] S. Loomba, A. de Figueiredo, S. J. Piatek, K. de Graaf, and H. J. Larson, "Measuring the impact of exposure to COVID-19 vaccine misinformation on vaccine intent in the UK and US," Oct. 2020.

[32] G. Pennycook, J. McPhetres, Y. Zhang, J. G. Lu, and D. G. Rand, "Fighting COVID-19 misinformation on social media: Experimental evidence for a scalable Accuracy-Nudge intervention," en, *Psychol. Sci.*, vol. 31, no. 7, pp. 770–780, Jul. 2020.

[33] C. A. Peschken, "Possible consequences of a shortage of hydroxychloroquine for patients with systemic lupus erythematosus amid the COVID-19 pandemic," en, *J. Rheumatol.*, vol. 47, no. 6, pp. 787–790, Jun. 2020.

[34] S. Pundir, *TOP2VEC: New way of topic modelling*, https://towardsdatascience.com/top2vec-new-way-of-topic-modelling-bea165eeac4a, Accessed: 2021-6-25, Oct. 2020.

[35] M. S. Al-Rakhami and A. M. Al-Amri, "Lies kill, facts save: Detecting COVID-19 misinformation in twitter," *IEEE Access*, vol. 8, pp. 155 961–155 970, 2020.

[36] S. Tasnim, M. M. Hossain, and H. Mazumder, "Impact of rumors or misinformation on coronavirus disease (COVID-19) in social media," Mar. 2020.

[37] E. K. Vraga and L. Bode, "Defining misinformation and understanding its bounded nature: Using expertise and evidence for describing misinformation," *Political Communication*, vol. 37, no. 1, pp. 136–144, Jan. 2020.

[38] X. Wang, W. Chen, J. Xia, *et al.*, "ConceptExplorer: Visual analysis of concept drifts in multi-source time-series data," in *2020 IEEE Conference on Visual Analytics Science and Technology (VAST)*, Oct. 2020, pp. 1–11.

[39] WHO, *Coronavirus disease (COVID-19): Herd immunity, lockdowns and COVID-19*, https://www.who.int/news-room/q-a-detail/herd-immunity-lockdowns-and-covid-19, Accessed: 2021-3-4, Dec. 2020.

[40] X. Ye, B. Zhao, T. H. Nguyen, and S. Wang, "Social media and social awareness," in *Manual of Digital Earth*, H. Guo, M. F. Goodchild, and A. Annoni, Eds., Singapore: Springer Singapore, 2020, pp. 425–440.

[41] C. Aschwanden, "Five reasons why COVID herd immunity is probably impossible," en, *Nature*, vol. 591, no. 7851, pp. 520–522, Mar. 2021.

[42] T. Carvalho, F. Krammer, and A. Iwasaki, "The first 12 months of COVID-19: A timeline of immunological insights," en, *Nat. Rev. Immunol.*, vol. 21, no. 4, pp. 245–256, Apr. 2021.

[43] CDC, *How to protect yourself & others*, https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html, Accessed: 2021-9-16, Sep. 2021.

[44] L.-A. Cotfas, C. Delcea, I. Roxin, C. Ioanăş, D. S. Gherai, and F. Tajariol, "The longest month: Analyzing COVID-19 vaccination opinions dynamics from tweets in the month following the first vaccine announcement," *IEEE Access*, vol. 9, pp. 33 203–33 223, 2021.

[45] Z. Khanjari Nezhad Jooneghani, "COMPARISON OF TOPIC MODELING METHODS FOR ANALYZING TWEETS ON COVID-19 VACCINE," 2021.

[46] K. Kricorian, R. Civen, and O. Equils, "COVID-19 vaccine hesitancy: Misinformation and perceptions of vaccine safety," en, *Hum. Vaccin. Immunother.*, pp. 1–8, Jul. 2021.

[47] C. Wardle and E. Singerman, "Too little, too late: Social media companies' failure to tackle vaccine misinformation poses a real threat," en, *BMJ*, vol. 372, n26, Jan. 2021.

[48] WHO, *Coronavirus disease (COVID-19): Vaccines*, https://www.who.int/news-room/q-a-detail/coronavirus-disease-(covid-19)-vaccines, Accessed: 2020-10-28, Jun. 2021.

[49] Brandwatch, *Brandwatch: A new kind of intelligence*, https://www.brandwatch.com/, Accessed: 2021-1-27.

[50] NewsGuard, *Coronavirus misinformation tracking center - NewsGuard*, https://www.newsguardtech.com/coronavirus-misinformation-tracking-center/, Accessed: 2021-1-27.

[51] Twitter, *Twitter developer*, https://developer.twitter.com/, Accessed: 2020-1-25.