INTERNATIONAL JOURNAL OF TECHO-ENGINEERING

ISSN : 2057-5688

Quantifying COVID-19 Content in the Online Health Opinion War Using Machine Learning

VUYYURU ADITYA RAMA NARAYANA[1]

KLVGKMURTHY[2],

[1]MTech Student, Department of CSE, Priyadarshini Institute of Technology & Science, Chintalapudi-522 306

[2] Associate Professor MTech, Phd, Department of CSE, Priyadarshini Institute of Technology & Science, Chintalapudi-522 306

sAbstract: An immense number of potentially harmful COVID-19-related misinformation is surfacing on the internet. We use machine learning to assess COVID-19 information among the online people who oppose establishing health guidelines, particularly vaccines ("anti-vax"). We discover that the anti-vax group is forming a less narrow discussion on COVID-19 than its counterpart, those who are pro-vaccination ("pro-vax") group. The anti-vax group offers a greater variety of "flavors" of COVID-19-related topics. It, therefore, appeals to a more extensive range of those seeking COVID-19 advice on the internet, e.g., people who are hesitant about a compulsory speed-tracked COVID-19 vaccination or looking for alternative solutions. Thus, the anti-vax crowd is more likely to win new support in comparison to the pro-vax group. This is a concern because a widespread absence of the COVID-19 vaccine will result in the world falling short of achieving herd immunity, which leaves countries open to the possibility of future COVID-19 resurgences. We present a mechanistic model that interprets these findings and can assist in assessing the potential effectiveness of interventions. Our method is adaptable and thus addresses the pressing problem that social media platforms face of analyzing massive amounts of health-related online false information and disinformation.

Keywords: COVID-19, machine learning, topic modeling, mechanical model, social computing

I. Introduction

Experts agree that overcoming COVID-19 is dependent on the development of an effective vaccine. But, this assumes an adequate proportion of people will get a vaccine to ensure herd immunity is established. Because vaccines are less effective in older people, it will be necessary for the younger generation to receive high rates of COVID-19 vaccination to ensure the herd's immunity [11. There is already substantial opposition to the current vaccinations, e.g., against measles. Some parents are refusing to vaccinate their children. This opposition to vaccination has caused an increase in cases during the measles outbreak across the U.S. and beyond 2. The COVID-19 vaccine in the future is likely to face the same resistance [4]. The mandatory COVID-19 vaccinations required for children could lead to an international public health crisis. Understanding the opposition ahead of the COVID-19 vaccine is crucial for researchers, public health professionals, and government officials. Social media sites specifically, and the built-in communities which platform like Facebook (FB) offer, are now a popular place to allow vaccine opponents (anti-vax) to meet and communicate health (mis)information. This misinformation can be harmful to the health of individuals and public health [11, [4].

Additionally, supporters of vaccines (pro-vax) are also a part of these communities online to discuss and promote professional guidance on public health. Before COVID-19, there was already a significant online battle between anti-vax groups and pro-vax groups. Within the anti-vax community, the stories typically spread misinformation regarding formal medical advice and a distrust of the pharmaceutical industry, the government, and the latest technologies like 5G. In addition to fueling this fire, the birth in January 2020 of COVID-19 COVID-19 "infodemic" caused a flood of false information in social media about COVID-19, which directly threatened people's lives [66. For instance, dangerous "cures" were offered, including drinking additives to fish tanks, bleach, aqueous solution, or cow's urine, as well as coordinated threats against public health officials such as Dr. Anthony Fauci, director of the U.S. National Institute of Allergic and Infectious Diseases 7.

Additionally, false claims are being circulated that people with dark skin tone are not susceptible to COVID-19. This could have led to the more comfortable social distancing of certain minorities and consequently their high proportion as victims. For Chicago and Louisiana, at the beginning of April 2020, 70% of those killed occurred among African Americans even though this population only comprises 30 percent of the total population 8, [9]. Additionally, the world has seen a dramatic increase in COVID-19-related weaponization in the Asian group 10[10], (12). It is also apparent that this type of false information isn't an isolated phenomenon and could be popularly believed to be accurate by the population. A recent Pew survey discovered that 30% of Americans believe that the

COVID-19 virus originated in a lab, despite assertions from experts in infectious diseases contrary to.

The sheer amount of online Content being created and the speed at which it is spread means that social media companies struggle to stop the spread of health-related incorrect information. To make matters worse, individuals around the globe have been spending more of their time on social media because of social distancing that was imposed during the COVID-19 epidemic. This means of being exposed to misinformation, and, as a result, they could put themselves or their contacts at risk by consuming harmful COVID-19 cures, remedies, and lies.

This study is driven by two needs: (1) the need for a better understanding of the relationship between the online opposition to vaccination and the debate on the internet surrounding COVID-19, as well (2) the necessity for an automated process due to the volume of new material posted online each day renders manual analysis an unsustainable option in the future. We employ an automated machine-learning approach that overcomes the limitations of scalability that come with a manual analysis of Content. Although the paper presented here is only the beginning step towards a more challenging objective, the automated method that we have given lets the following questions be considered What did COVID-19 due to the discussion on the internet within the groups that were pro-vaccination or anti-vaccination over two months in early 2020, when the disease was an international threat? And what does the shift in the topic that we see in the anti-vax and pro-vaccination online communities' online narratives suggest about their respective abilities to gain new support to the cause in the future?

In contrast to other studies, the study does not use Twitter research data (16, 17), [17] as it is widely known that Twitter is primarily an online platform for broadcasting individual shout-outs. Discussions and narratives are developed in online communities exclusive to platforms like Facebook (e.g., fan pages) [18]. Twitter is not a platform with community spaces built into it. Based on the current method that is derived from and the data gathered from these communities on the internet, specifically Facebook Pages that are pro-vaccination or pro-vaccination opinions. The information is available to the public and doesn't require personal information, thus eliminating privacy concerns like knowing the contents of a discussion among many people in real-time; open public space is not dependent on knowing any personal information regarding the people in that crowd. The specifics of our methodology are presented in the appendix. The third distinction in this study from previous studies is that machine-learning results are evaluated as mechanistic models that can capture the general trends for the coherence of online conversation over time. Although there is still a lot of work to be completed, the study provides an initial step towards an automated but readable understanding of the ever-growing public health debate on vaccines and COVID-19.

II. DATA AND MACHINE LEARNING ANALYSIS

The words "Facebook Page"' and "cluster' are interchangeable here as every Page on Facebook Page is a collection of users. Facebook Pages, also referred to as public or fan pages, are accounts used to represent causes, organizations or communities, or public people. According to Facebook's guidelines, "Content posted to a Page is available to the public and can be seen by anyone who can view the Page. It is important to note that a Facebook Page is distinct from an individual Facebook individual account. Personal accounts are private to individuals. Their posts and activities are more private and targeted towards the immediate friends of their users. The paper is not a study of information from personal accounts. Our method follows [19and [19] as well as [20[19] and [20] by analyzing the Content that is public on Facebook Pages that are the anti-vaccination ("anti-vax") as well as vaccination ("pro-vax") community. The public Content of these online communities is collected using a snowball method that starts with the seed of manually identified pages discussing vaccines, public policy regarding vaccination, or the pro-vs.-anti-vaccination debate. Their links to other fan sites are tracked. New clusters that follow each step are analyzed using an amalgamation of human code and computer-assisted filtering. To determine whether a cluster is being (1) pro-vax or anti-vax and (2) having COVID-19 information or Content, we analyzed the pages' posts and "about" area. Anti-vax and pro-vax classifications require at least (a) minimum two of the 25 most recent posts discussed the debate between anti-vax and pro-vax and (b) the title and "about" section stated it was either pro-vax or against-vax. Two researchers at least classified each cluster separately. If they disagreed on their proposed classification, A third researcher analyzed the articles, and all three reviewers debated the case. The three reviewers reached an agreement in each instance. This allowed us to differentiate between Content intended to be severe and not just humorous. Self-weeding within Facebook Pages is a way to cut down on the number of fake profiles. Our study was concentrated on English. However, this could be generalized by using our identical method. In addition, our research was global and not restricted to a specific region.

The Content from the clusters was later bundled separately for both anti-vax and the pro-vax community. the two sets of Content were analyzed by using machine learning. In particular, we applied an unsupervised method of machine learning known as Latent Dirichlet Allocation (LDA) [2222 to study the rise and development of topics related to COVID-19. The LDA method models papers as distributors of subjects and issues as word-based distributions. In the course of training, the allocations are adjusted to conform to the set of data. It is crucial to understand that the LDA method is explained correctly on Wikipedia in the form of [2323] "[quote[quote]. A model of statistical generative that allows the observations of a set to be explained by non-observed groups to explain why certain portions of the data are alike. In the case of observations, for instance, if they are words incorporated into documents, it is believed that every document is made up of a limited number of subjects and that every word's existence is due to one of the topics in the document. LDA can be described as a topic model part of the machine learning toolbox, and more broadly to the AI toolbox." A coherence score offers a quantitative method to determine the alignment of words in a subject (see [22]). It is calculated by an entirely different algorithm applied to a previous model that has been trained LDA model. The total coherence score of an individual model is the average of its coherences per topic. There are a variety of coherence metrics that can be used to measure the coherence per topic. We employ which constructed using sliding windows with a one-set segmentation for the top words, and another indirect measure of confirmation that employs regularized point-wise mutual information and that of cosine similarities. It is a collection of probabilities measurements of how frequently top-ranked words from topics are found to occur together in the context of examples of the subjects. The study is referred to as for a complete explanation and analysis. Machine learning automation could assist in tackling the significant issues that confront social media platforms by selecting Content that needs to be analyzed from the vast plethora of Content available online. While this can help reduce the spread of misinformation online, it is essential to inquire whether it is reliable and accurate compared to human analysts. The issue has been addressed. We employ the same coherence metrics () as the authors. They addressed the issue that previous topical analysis models had not assured the ability to interpret their output. Mainly, they developed a variety of benchmark datasets that included human judgments on the interoperability of topics. They also discovered results that were superior to existing methods about ratings from humans. They did this by comparing 237,912 measures of coherence on six different benchmarks for topic coherence, making it the most comprehensive study of coherences between topics at the time. In addition, we've conducted our survey of the overall subject of online hate and have discovered a comparable level of coherence.

III. Results of the proposed model

The primary focus was the COVID-19 discussion in the early stages of the global epidemic and before the first reported U.S. COVID-19-related death in February 2020 (2525. We, therefore, have gathered Facebook public posts for the period between 1/17/2020 and 2/28/2020. To determine the evolution over time, the period was broken down into intervals of time. Because having longer time intervals will result in smaller quantities of data in each one, which would result in more fluctuations, and because we only care about the changes over time and not the change over time, we chose two intervals that were of equal duration, the T1 interval, and the T2. The first time interval 1/7/2020-2/27/2020 (T1) comprises 774 total pro-vax posts and replies and the total number of anti-vax posts and replies. The second time interval of 2/7/2020-2/28/2020 (T2) comprises 673 total pro-vax posts and answers and 3200 total anti-vax posts and responses. So, our two equal time windows have identical amounts of information. We tested our results to ensure that they were remarkably similar to other options of time intervals. Incredibly, T1 is roughly the period when COVID-19 was mainly viewed as a concern in Asia, and T2 compares to the period when it became a significant issue in Europe. To ensure that our data were representative of COVID-19 discussions in these time frames Also, we checked whether the split in data is comparable to the division for COVID-19 mentions in articles from all over the world in English newspapers worldwide Google trends.

It was found that the LDA model was trained on posts from the four distinct categories: anti-vaccination posts within T1, anti-vaccination postings at T2, anti-vaccination postings in T1, and pro-vaccination posts in T2. Ten particular LDA models were trained in each seat using the number of topics parameters between 3-20, resulting in an aggregate of 180 models for all four categories. More details can be found in the appendix. This CV algorithm for coherence was executed over all of these models. The coherence scores were averaged across several subjects. The average scores are shown in Figures 1B and1C. Figure 1A illustrates the results of the same method applied to all posts in our database, as well as for all posts against vaccination and all posts that promote vaccination.

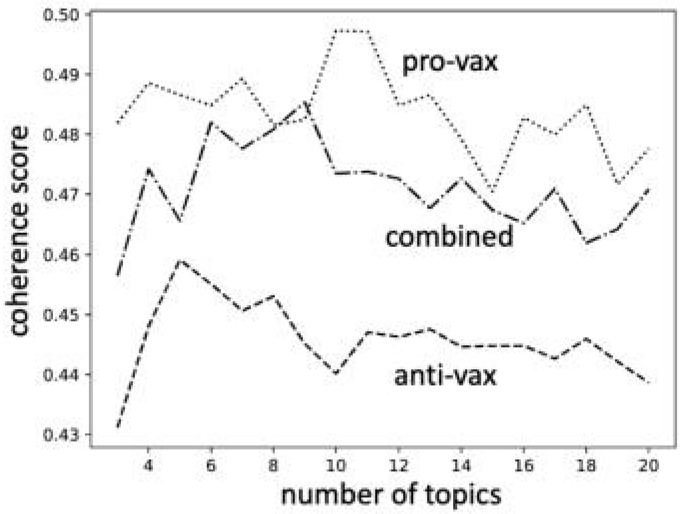

Fig. 1: Coherence scores CV for (A) anti-vax (dashed line), pro-vax Content (dotted line), and anti-vax combined with pro-vax (dashed-dotted line), calculated over the entire period of study (T1+T2).

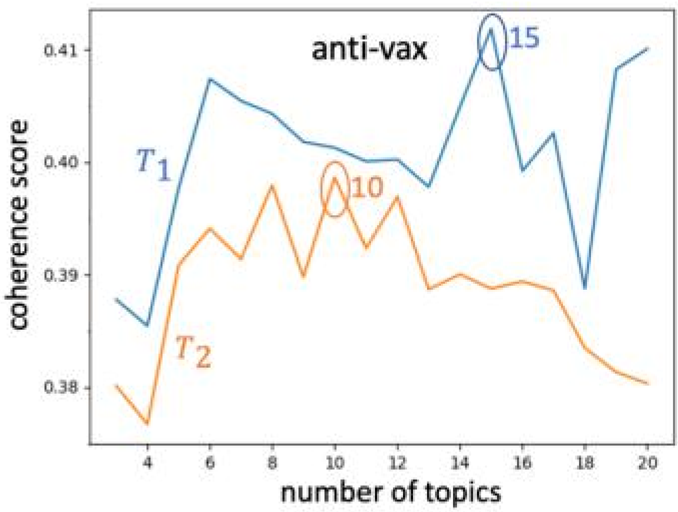

Fig. 2: Anti-vax Content for the separate periods T1 (blue line) and T2 (orange line).

IV. A MECHANISTIC MODEL INTERPRETATION

We have developed a mechanical framework that further validates these findings empirically and offers an in-depth analysis of the output of machine learning. In particular, we created the computer model of an online community's ecology. Elements of the more extensive community content. Each of these is identified by an x-axis x=(x1 2), x2) ...) where each component xi indicates the importance of a particular element that is a part of the online health controversy, e.g., government control. The specific nature of these components does not require a particular definition, i.e., whether they are short phrases. It's just important to note that there exists a wide variety of such components. Although it appears to be very simple, the mechanical model represents the evidence and research on the subject of online discussion on vaccination opposition, as outlined and analyzed in detail in the work of Kata in Ref. [1]. Then, we run the simulation in which these components are randomly chosen to create Content. Components form clusters (or they cluster with their collections if they already are in the same group) if the x-values of their components are comparable (i.e., homophile as in Fig. 3A) or different (i.e., the heterophobia in Fig. 3B). To show the results the model produces, figure. 3 illustrates a one-dimensional model. We tested whether two-dimensional versions yield similar results, but it's visually more complex due to having the time component in three dimensions. It also produces plots that look identical to the ones in Fig. 2, as is evident in Fig. 3.

Homophile (similar to building a unidirectional discussion with a few flavors identical to the pro-vax community) has a more rapid convergence rate, as can be seen in the Figures. 1 and 2. These are for the pro-vax community. In contrast, the heterophony situation (which is similar to having discussions on diverse topics with a variety of kinds, such as those in the community against vax) is more difficult to unite and is in line with the anti-vax crowd in Figs. 1 and 2. The horizontal red line in Figures. 3A and 3B indicate the current stage in the simulation, which is generally in line with the Figs. 2D and 2B represent the anti-vax and pro-vax communities and vice versa.

V. RECOMMENDATIONS AND LIMITATIONS OF THE PROPOSED STUDY

There are several limitations of this research. Many other digital platforms on social networks, aside from Facebook, need to be investigated, but Facebook is the most popular. Similar behavior patterns are expected to emerge on any platform on which communities may develop. It could provide a fascinating instance to examine our findings compared to other studies focusing on Twitter, a platform where messages are typically in the form of brief, individual posts. The study also found that people are more likely to make short, personal statements. It is also a matter of the influence of external agents or organizations. But the social media communities tend to be supervised for bot-like or troll behavior. More analysis is needed of the specifics and Content. This requires more than only text, and maybe even beyond LDA, as memes and images can often share information.

Additionally, the output of the generative model must be evaluated in detail with the speed of change of topics. More research is needed to convert the results from all platforms into precise and actionable outcomes for policymakers. These shortcomings are to be addressed in future research.

VI. CONCLUSION

These results indicate that the online anti-vax community is creating an affluent and more broad-based discussion on COVID-19 than the pro-vax community. This means that the pro-vax group runs the possibility of becoming less responsive to the heterogeneous ecosystem of potential new users who are joining the COVID-19 online discussion and who might arrive with a wide range of concerns, questions, and even misconceptions, misinformation, or even lies. The study can be a start towards eventually replacing, or at the very least, enhancing the ineffective efforts of human moderators charged with identifying fake news online. Furthermore using the model of mechanistic (Fig. 1) can be utilized for scenarios that test how short coherence is developed and what the consequences are of breaking the coherence surrounding certain subjects, e.g., through counter-messaging to people who consume bleach or even the newer COVID Organics that are used as a treatment within Madagascar, Africa and beyond. This can be accomplished through the analysis shown in Fig. 2. It is repeated at multiple periods to detect the increase in subjects centered around new words gaining popularity as a cure for home (e.g., "bleach"). Facebook could, for instance, can create ads that focus on these particular terms and topics instead of bland, generic messages that promote the establishment of medical science theories. In the end, this method demonstrates how a machine-learning program, known as the LDA algorithm, can identify plausible topics in the collection of posts on social media sites that relate to COVID-19 and the vaccine. Additionally, it can handle large amounts of data; its findings are quickly uncovered by using statistical grouping methods instead of relying on possibly biased, slow, and expensive human labeling.

References

[1] J. Guy, "East Asian student, assaulted in 'racist' coronavirus attack in London," CNN.com, 2020.

[2] H. Yan, N. Chen, and D. Naresh, "What's spreading faster than coronavirus in the US? Racist assaults and ignorant attacks against Asians," CNN.com, 2020.

[3] M. Rajagopalan, "Korean interpreter says men yelling 'Chinese' tried to punch her off her bike," BuzzFeed News, 2020.

[4] K. Schaeffer, "Nearly three-in-ten Americans believe COVID-19 was made in a lab," Pew Fact Tank, 2020.

[5] R. Iyengar, "The coronavirus is stretching Facebook to its limits," CNN Business, 2020.

[6] S. Frenkel, D. Alba, and R. Zhong, "Surge of virus misinformation stump Facebook and Twitter," 2020.

[7] D. A. Broniatowski et al., "Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate," Am. J. Public Health, pp. e1–e7, 2018, DOI: 10.2105/AJPH.2018.304567.

[8] Y. Lama, T. Chen, M. Dredze, A. Jamison, S. C. Quinn, and D. A. Broniatowski, "Discordance between human papillomavirus Twitter images and disparities in human papillomavirus risk and disease in the United States: Mixed-Methods Analysis," J. Med. Internet Res., vol. 20, no. 9, Sep. 2018, DOI: 10.2196/10244.

[9] T. Ammari and S. Schoenebeck, "'Thanks for your interest in our Facebook group, but it's only for dads:' Social roles of stay-at-home dads," in Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing - CSCW '16, 2016, vol. 27, pp. 1361–1373, DOI: 10.1145/2818048.2819927.

[10] N. F. Johnson et al., "Hidden resilience and adaptive dynamics of the global online hate ecology," Nature, vol. 573, no. 7773, pp. 261–265, Sep. 2019, DOI: 10.1038/s41586-019-1494-7.

[11] N. F. Johnson et al., "New online ecology of adversarial aggregates: ISIS and beyond," Science, vol. 352, no. 6292, pp. 1459–1463, Jun. 2016, DOI: 10.1126/science.aaf0675.

[12] Facebook, "Pages, groups and events policies," Facebook Policies, 2020. [Online]. Available: https://www.facebook.com/policies/pages_groups_ev ents.

[13] A. Kata, "A postmodern Pandora's box: Anti-vaccination misinformation on the Internet," Vaccine, vol. 28, no. 7, pp. 1709–1716, Feb. 2010, DOI: 10.1016/j.vaccine.2009.12.022.

[14] L. Givetash, "Global measles cases surge amid stagnating vaccinations," NBC News, 2019.

[15] B. Martin, “Texas anti-vaxxers fear mandatory COVID-19 vaccines more than the virus itself,” Texas Monthly, 2020.

[16] H. Larson, "Blocking information on COVID-19 can fuel the spread of misinformation," Nature vol. 580, no. 306, March 2020, DOI: 10.1038/d41586-020- 00920-w

[17] R. Schraer and E. Lawrie, “Coronavirus: scientists brand 5G claims ‘complete rubbish,’” BBC News, 2020. [Online]. Available: https://www.bbc.com/news/52168096. [Accessed: 05-Apr-2020].

[18] World Health Organization, “Coronavirus disease (COVID-19) advice for the public: myth busters,” World Health Organization, 2020.

[19] K. Benner and M. Shear, “After threats, Anthony Fauci to receive enhanced personal security,” The New York Times, 2020.

[20] S. Almasy, H. Yan, and M. Holcombe, “Coronavirus pandemic hitting some African-American communities extremely hard,” CNN Health, 2020.

[21] A. Maqbool, “Coronavirus: why has the virus hit African Americans so hard?,” BBC News, 2020. [Online].