An Approach to Quantify the COVID-19 Content in Online Health Opinion Conflicts

Varada Akash, Reddy Srinitya, Alapati Siddhartha, K Sai Pranay[1]
Ms.M.Sandhya Vani [2]

[1]UG Student, Department of Information Technology, Malla Reddy Engineering College, Hyderabad, Telangana-500100
[2]Assistant Professor, Department of Information Technology, Malla Reddy Engineering College, Hyderabad, Telangana-500100

Abstract

A huge amount of potentially dangerous COVID-19 misinformation is appearing online. Here we use machine learning to quantify COVID-19 content among online opponents of establishment health guidance, in particular vaccinations ("anti-vax"). We find that the anti-vax community is developing a less focused debate around COVID-19 than its counterpart, the pro-vaccination ("pro-vax") community. However, the anti-vax community exhibits a broader range of ``favors'' of COVID-19 topics, and hence can appeal to a broader cross-section of individuals seeking COVID-19 guidance online, e.g. individuals wary of a mandatory fast-tracked COVID-19 vaccine or those seeking alternative remedies. Hence the anti-vax community looks better positioned to attract fresh support going forward than the pro-vax community. This is concerning since a widespread lack of adoption of a COVID-19 vaccine will mean the world falls short of providing herd immunity, leaving countries open to future COVID-19 resurgences. We provide a mechanistic model that interprets these results and could help in assessing the likely efficacy of intervention strategies. Our approach is scalable and hence tackles the urgent problem facing social media platforms of having to analyze huge volumes of online health misinformation and disinformation

Keywords: LDA Model, Anti Vaccine, Pro Vaccine, COVID-19, Facebook, CNN, Random Forest.

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1. Introduction

Scientific experts agree that defeating COVID-19 will depend on developing a vaccine. However, this assumes that a sufficiently large proportion of people would receive a vaccine so that herd immunity is achieved. Because vaccines tend to be less effective in older people, this will require younger generations to have very high COVID-19 vaccination rates in order to guarantee herd immunity [1]. Yet there is already significant opposition to existing vaccinations, e.g. against measles, with some parents already refusing to vaccinate their children. Such vaccine opposition increased the number of cases in the 2019 measles outbreak in the U.S. and beyond [2]. Any future COVID-19 vaccine will likely face similar opposition [3][4]. Mandatory COVID-19 vaccinations for schoolchildren could trigger a global public health conflict. A better understanding of such opposition ahead of a COVID-19 vaccine is therefore critical for scientists, public health practitioners, and governments. Online social media platforms, and in particular the built-in communities that platforms like Facebook (FB) feature, have become popular fora for vaccine opponents (anti-vax) to congregate and share health (mis)information. Such misinformation can endanger public health and individual safety [1][4]. Likewise, vaccine supporters (pro-vax) also congregate in such online communities to discuss and advocate for professional public health guidance. Well before COVID-19, there was already an intense online conflict featuring anti-vax communities and pro-vax communities. Within anti-vax communities, the narratives typically draw on and generate misinformation about establishment medical guidance and distrust of the government, pharmaceutical industry, and new technologies such as 5G communications [1][4][5]. Adding fuel to this fire, the January 2020 birth of the COVID-19 "infodemic" has led to a plethora of misinformation in social media surrounding COVID-19 that directly threatens lives [6]. For example, harmful "cures" are being proposed such as drinking fish tank additives, bleach, or cow urine, along with coordinated threats against public health officials like

Dr. Anthony Fauci, director of the U.S. National Institute of Allergic and Infectious Diseases [7]. Moreover, false rumors have been circulating that individuals with dark skin are immune to COVID-19. Making matters worse, people around the world are spending more time on social media due to social distancing imposed during the COVID-19 pandemic. This increases the likelihood that they become exposed to such misinformation, and as a result they may put themselves and their contacts at risk with dangerous COVID-19 remedies, cures and falsehoods. Though much work still needs to be done, this study therefore provides a first step toward a fully automated but interpretable understanding of the growing public health debate concerning vaccines and COVID-19.

2. Literature Survey

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. The Internet plays a large role in disseminating anti-vaccination information. This paper builds upon previous research by analyzing the arguments proffered on anti-vaccination websites, determining the extent of misinformation present, and examining discourses used to support vaccine objections. Arguments around the themes of safety and effectiveness, alternative medicine, civil liberties, conspiracy theories, and morality were found on the majority of websites analyzed; misinformation was also prevalent. The most commonly proposed method of combating this misinformation is through better education, although this has proven ineffective. Education does not consider the discourses supporting vaccine rejection, such as those involving alternative explanatory models of health, interpretations of parental responsibility, and distrust of expertise. Anti-vaccination protestors make postmodern arguments that reject biomedical and scientific “facts” in favour of their own interpretations. Pro-vaccination advocates who focus on correcting misinformation reduce the controversy to merely an “educational” problem; rather, these postmodern discourses must be acknowledged in order to begin a dialogue.

With morbidity and mortality from vaccine-preventable diseases [VPDs] having reached record lows [1], vaccines are one of the most successful tools for biomedical science and public health. Yet paradoxically, the effectiveness of vaccination has led to the reemergence of anti-vaccination sentiments. Vaccines may be seen as unnecessary or dangerous because incidence rates of VPDs in developed countries have plummeted. Vaccine “reactions” – negative health events following vaccination, attributed to the vaccine – then appear to be more common than the diseases themselves [2]. In this way, vaccines can be considered victims of their own success. The media plays a large role in disseminating and sensationalizing vaccine objections. Such objections are part of what has been called the “anti-vaccination movement”, which has had a demonstrable impact on vaccination policies, and individual and community health [3].

3. Materials and Methods

The terms 'Facebook Page' and 'cluster' are used interchangeably here since each Facebook Page is a cluster of people. Our methodology analyzing the public content of Facebook Pages for both anti-vaccination (“anti-vax”) and pro-vaccination (“pro-vax”) communities. The publicly available content of these online communities is obtained using a snowball approach, starting with a seed of manually identified pages discussing vaccines, public policies about vaccination, or the pro-vs-anti vaccination debate. Then their connections to other fan pages are indexed. At each step, new clusters are evaluated through a combination of human coding and computer-assisted filters. To classify a cluster as being (1) anti-vax or pro-vax and (2) including COVID-19 content or not, we reviewed its posts and the Page’s “about” section between content that is intended to be serious versus merely satirical. The self-weeding tendency within Facebook Pages tends to reduce material from bots and fake profiles. We kept the present study focused on English, though this can be easily generalized using our same procedure. Beyond that, our study was global and not limited to a particular region.The content of these clusters was then bundled together separately for the anti-vax community and the pro-vax community, and the two resulting sets of content were analyzed using machine learning. We use CV which is based on a sliding window, one-set segmentation of the top words and an indirect confirmation measure that uses normalized point-wise mutual information and the cosine similarity.

It comprises collections of probability measures on how often top words in topics co-occur with each other in examples of the topics.

i. LDA Model
ii. Convolutional Neural Networks

i. LDA Model

LDA focuses primarily on projecting the features in higher dimension space to lower dimensions. You can achieve this in three steps:

Firstly, you need to calculate the separability between classes which is the distance between the mean of different classes. This is called the between-class variance.

$$S_b = \sum_{i=1}^{g} N_i (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})^T$$

Secondly, calculate the distance between the mean and sample of each class. It is also called the within-class variance

$$S_w = \sum_{i=1}^{g} (N_i - 1) S_i = \sum_{i=1}^{g} \sum_{j=1}^{N_i} (x_{i,j} - \bar{x}_i)(x_{i,j} - \bar{x}_i)^T$$

Finally, construct the lower-dimensional space which maximizes the between-class variance and minimizes the within-class variance. P is considered as the lower-dimensional space projection, also called Fisher's criterion.

$$P_{lda} = \arg\max_{P} \frac{\left|P^T S_b P\right|}{\left|P^T S_w P\right|}$$

ii. Convolutioal Neural Networks

A **Convolutional Neural Network (ConvNet/CNN)** is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area. The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image. ConvNets need not be limited to only one Convolutional Layer. Conventionally, the first ConvLayer is responsible for capturing the Low-Level features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the High-Level features as well, giving us a network which has the wholesome understanding of images in the dataset, similar to how we would. There are two types of results to the operation — one in which the convolved feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same. This is done by applying Valid Padding in case of the former, or Same Padding in the case of the latter.

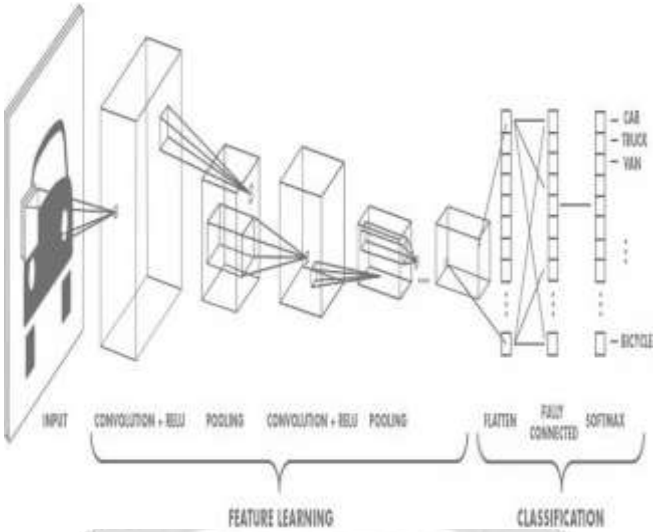

Fig-1: Convolutioal Neural Networks

Machine learning automation can, in principle, help address the significant issues facing social media platforms by mechanically picking out material that requires attention from the huge haystack of online content. While this could help to better curtail online misinformation, one might rightly ask about its accuracy and reliability as compared to human analysts. This has been recently addressed in Ref. [24]. We use the same coherence metric (CV) as these authors. They addressed the problem that topic models had previously given no guarantee on the interpretability of their output. Specifically, they produced several benchmark datasets with human judgments of the interpretability of topics and they found results that outperformed existing measures with respect to correlation to human ratings. They achieved this by evaluating 237,912 coherence measures on 6 different benchmarks for topic coherence, making this the biggest study of topic coherences at that time. Separately, we have done our own comparison for the general area of online hate and have found comparable consistency.

The LDA models were trained over posts in the following distinct groups: anti-vaccination posts in T1, anti-vaccination posts in T2, pro-vaccination posts in T1, and pro-vaccination posts in T2. For each of these sets, 10 separate LDA models were trained with the number of topics parameter ranging from 3-20, for a total of 180 models in each of the four groups. Fuller details are given in the Appendix. The CV coherence algorithm was then run over each of these models and the coherence scores were averaged for each number of topics. These averaged scores are plotted in Figures 1B and 1C. Figure 1A shows the result of the same procedure applied to all posts in our dataset, and to all anti-vaccination posts, and to all pro-vaccination posts

4. Result and Discussion

To run project double click on 'run.bat' file to get below screen

Fig-2: Initial Configuration of Application

In above screen click on ‘Upload Facebook Posts Dataset’ button to load dataset

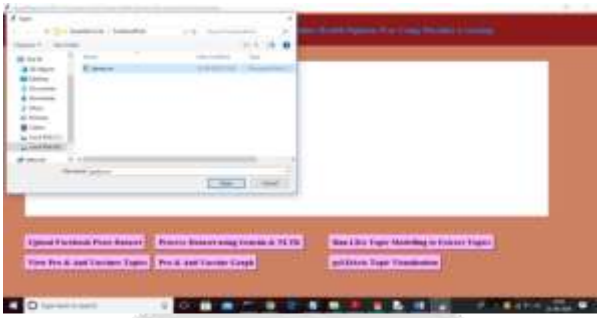

Fig-3: Upload Facebook Posts Dataset

In above screen uploading ‘Posts.csv’ file and then click on ‘Open’ button to load dataset and after loading dataset click on ‘Process Dataset using Gensim & NLTK’ button to read dataset and to clean dataset

Fig-4: Showing the Content of Dataset

In above screen after cleaning will get above text from all posts and now click on ‘Run LDA Topic Modelling to Extract Topics’ button to extract topics from all posts

Fig-5: Probability Score of Each Word

In above screen we can see TOPIC and its probability score for each word from POSTS and now click on ‘View Pro & Anti Vaccines Topics’ button to view all topics with coherence score

Fig-6: PRO and ANTI with count value

In above screen we can see all topics of PRO and ANTI with count value and now click on ‘Pro & ANTI Vaccine Graph’ button to get below graph and to quantify number of peoples are in favour of PRO or ANTI

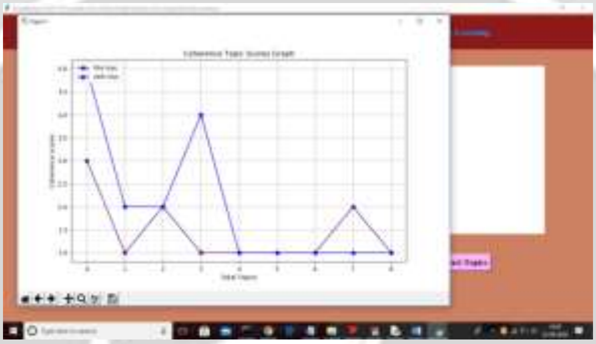

Fig-7: “Number of Topics Vs Coherence” Graph

In above graph x-axis represents number of topics and y-axis represents coherence score and in above graph blue line refers to ANTI and indigo colour line refers to PRO vaccine and from above graph we can conclude more peoples are discussing ANTI topics about vaccine. Now click on ‘pyLDAvis Topic Visualization’ to get visualization of all topics in browser.

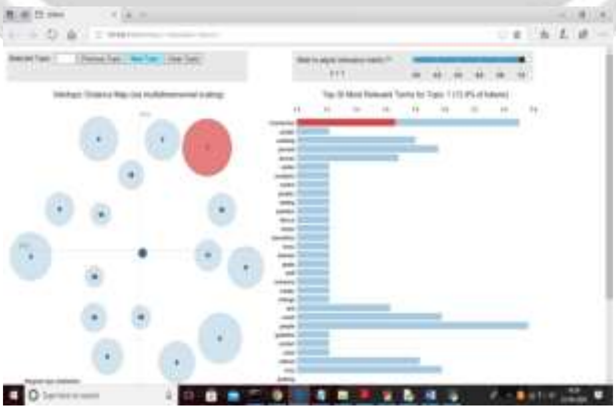

Fig-8: Graph with Topic Count within the Circle

In above graph large circle refers that topic occurs more number of time and if occur less number of times then its circle will be in small size. In right size we can see all topics from that posts and u can click on ‘Next Topic’ button from top side of window to get next topic visualization. In above graph

each circle represents 1 topic
In above screen for topic 1 coronavirus topic appears more times in all posts. Above graph u can see in browser only.

5. Conclusion

These findings suggest that the online anti-vax community is developing a more diverse and hence more broadly accommodating discussion around COVID-19 than the pro-vax community. As a result, the pro-vax community runs the risk of making itself less engaging to the heterogeneous ecology of potential new users who join the online COVID-19 discussion, and who may arrive online with a broad set of concerns, questions, and possibly pre conceived notions, misinformation and even falsehoods. The analysis in this paper also provides a first step toward eventually either replacing, or at least supplementing, the non-scalable efforts of human moderators tasked with identifying online misinformation. In addition, the mechanistic model (Fig. 3) could be used for what-if scenario testing of how quickly coherence develops and what the impact would be of breaking up the coherence around certain topics, e.g. by counter-messaging against individuals ingesting bleach or the even newer 'COVID Organics' that are circulating as a cure in Madagscar, Africa and beyond. This can be achieved by using the \empirical analysis in Fig. 2 -- repeated over multiple consecutive time intervals -- to identify the growth of topics around new words which may be gaining popularity as a home cure (e.g. "bleach"). Then Facebook, for example, could post ads that specifically target these specific new words and topics, rather than blanket vanilla messaging promoting establishment medical science narratives. Overall, this approach shows that a machine-learning algorithm, the LDA algorithm, identifies plausible topics within collections of posts from online communities surrounding the vaccine and COVID-19 debate. In addition to being able to handle large quantities of data, its results emerge quickly using statistical grouping techniques, instead of having to rely on potentially biased, slow and costly human labeling.

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