Inter-effect of Social Media and US Vaccine Progress

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Abstract

How does public opinion affect Covid-19 vaccination progress and vice versa? In this study, we conduct sentiment analysis on Covid-19 vaccine related tweets, extract hot tweet topics and tweet sentiment trend, and analyse the correlation between tweet sentiment and vaccination progress. We find that 1) Social media discussion focus differs from mainstream media news and articles. 2) The amount of positive tweets is highly positively correlated to vaccination trend. 3) Trend of daily positive tweet count lags behind vaccination trend.

Introduction

Twitter is one of the largest social media in the world. With COVID-19 sweeping the world, people have different attitudes towards vaccination due to the influence of social culture, national health level and other factors. Luo (Luo 2021) observed that the scientific events and non-scientific events were comparable in their ability to influence health belief trends on social media. We believe that people's opinions about vaccination on twitter have a great influence on others' attitude towards vaccination, which in turns affect the vaccination progress in the US.

In this study, we first perform sentiment analysis on Covid-19 vaccine related tweets from Dec. 2020 to Oct. 2021 and generated time series data reflecting the sentiment change of tweets regarding the vaccine. We conduct experiment with limited number of vaccine tweets with sentiment label, trained and evaluated our classifiers and generated sentiment predictions on the full tweet data. We choose VADER (Hutto and Gilbert 2014) and RoBERTa (Liu et al. 2019) as our sentiment classification models to experiment with. We evaluate both models and picked the model variation with the best accuracy to predict sentiment.

By extracting the time series data of US vaccination progression and the attitude change of people in Twitter towards Covid vaccines, we identify and investigate key timestamps which indicate major news and turning points of COVID-19 such as vaccination approvals and the Delta variant outbreak. We compare major events highlighted by mainstream media including CNN and CDC official news, to Twitter discussion topics mined from our Twitter dataset, and analyse how people on social media focus on different topics from mainstream media news and articles.

Finally, we analyze the Cross-Correlation (Time-Lagged Correlation) between social media sentiment regarding vaccines and the vaccination trend, to explore the role public opinions play in promoting or hindering vaccination in the pandemic.

Related Works

Prior works have been conducted to investigate the effect of COVID-19 through social media analysis. Fernandes (Fernandes 2020), and Baker et al. (Baker et al. 2020) studied the economy impact of COVID-19, while Zhang's study(Zhang et al. 2020) showed an significant increase in depression as people talk more about COVID-19 in Twitter. Those studies indicate that COVID-19 is closely related with social media, which reflects and affects public awareness and opinion about multiple aspect of the society. In addition, Li et al. (Li et al. 2020) concluded that internet searches and social media provided an accurate and timely prediction about the outbreak and progression of COVID-19. However, the direct impact of social media on vaccination progress and vice versa has not been studied yet. Using the most up-to-date twitter and vaccination data, we plan to decode the relationship between public opinion and COVID-19 vaccination progress, and we aim to predict future vaccination trends under the influence of social media.

VADER (Valence Aware Dictionary for Sentiment Reasoning) is a rule-based sentiment analysis tool that is that is sensitive to both polarity (positive/negative) and intensity (strength) of emotion. VADER does not require any training data and can understand the sentiment of a text containing emoticons, slangs, conjunctions, capital words, punctuations, which makes it the gold standard for traditional sentiment analysis tools. It works especially well on social media text. Elbagir et al. (Elbagir and Yang 2019) used VADER to classify sentiments expressed in Twitter data relating to 2016 election. The study showed good results in detecting ternary and multiple classes, indicating that VADER can serve as a reliable model in tweet sentiment classification.

On the other hand, the transformer architecture enabled various state-of-the-art pretraining approaches to achieve amaz- ing results on language understanding task including sentiment classification. BERT (Devlin et al. 2019) is a popular transformer-based deep learning technique for NLP pretraining developed by Google. BERT had been the gold standard in deep learning NLP area. In recent years, multiple variations of BERT emerged and achieved even better performance. Among which, RoBERTa by Y. Liu is a retraining of BERT with improved training methodology, more data and compute power. In Piyush et al.'s (Ghasiya and Okamura 2021) paper, RoBERTa achieved 90% validation accuracy on newspaper articles sentiment analysis. Considering the small amount of training data used in our study, we think that RoBERTa can be a reliable method for our sentiment analysis task given its improved robustness.

Methodology

To investigate the relation between tweet sentiment trend towards vaccination and the US vaccination trend, we accomplish two major tasks in this study: sentiment analysis on tweet text and time series analysis on tweet sentiment and vaccination progress.

Sentiment Analysis

In this task, we selected VADER and RoBERTa as candidate classifiers to generate tweet sentiment labels.

VADER VADER is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media. VADER uses a combination of A sentiment lexicon that is a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation as either positive or negative. Given an input sequence, VADER generates a compound score, a metric that calculates the sum of all the lexicon ratings which is then normalized between -1 (most extreme negative) and +1 (most extreme positive). By tuning the threshold of the compound score, we are able to label the sentence with sentiments and evaluate the classification accuracy.

RoBERTa We then built and trained a RoBERTa-base model on the training set. RoBERTa is a state-of-the-art Transformer that learns contextual relations between words in text via an attention mechanism. The Transformer architechture includes two main components, an encoder that reads the input test, and a decoder that makes prediction for the tasks. Unlike LSTM models which read the text input sequentially (or bi-directionally for bi-directional LSTM), we can consider RoBERTa as non-directional, since RoBERTa was trained by putting [MASK] on words on random locations in texts to learn their contextual relations. Vanilla RoBERTa inputs two sentences, with a [CLS] token placed at the beginning of the first sentence, and an [SEP] token between the two sentences. However for text sequence classification tasks, the input should consist only of [CLS] token, tokenized sequence data, and an [SEP] token. For our sentiment classification task, we introduced a compact pre-trained RoBERTa model: RoBERTa-Base, Uncased with 125M parameters. We tokenized input texts by mapping words to a word IDs using the vocabulary file from RoBERTa. Then we padded the tokenized data to a maximum sequence length of 512 with [CLS] and [SEP] tokens inserted. To output the predicted sentiment, we used the output from [CLS] token and added a dense layer with Dropout on top. The model outputs a vector of length 3, corresponding to the 3 sentiment classes negative, neutral, positive.

Time Series Analysis

In this paper, we use cross-correlation to analyse the vaccination progress and the obtained sentiment trend. Cross-correlation is a measure of similarity of two series as a function of the displacement of one relative to the other. Formally, for continuous period function f and g of period T, the cross-correlation is defined as:

$$(f \star g) = \int_{t_0}^{t_0+T} \overline{f(t)} g(t+\tau) d_t$$

In our work, the cross-correlation reflects whether the sentiment trend boosts or hinders vaccination (or vice versa), as well as how much delay (in days) such effect takes place.

Experiments

Data Overview

World Vaccination Progress The data is collected daily from Our World in Data GitHub repository[1], merged and uploaded by Kaggle user Gabriel Preda[2]. The data contains daily vaccination records for all countries and regions with dates ranging from 11/30/2020 to 10/25/2021. Important attributes of this data include:

- **Country** - The country for which the vaccination information is provided.
- **Total number of vaccinations** - The absolute number of total immunizations in the country.
- **Total number of people vaccinated** - A person, depending on the immunization scheme, will receive one or more (typically 2) vaccines; at a certain moment, the number of vaccination might be larger than the number of people.
- **Total number of people fully vaccinated** - Number of people who completed the vaccination, usually after 1, 2, or 3 doses depending on the type of vaccines.
- **Daily vaccinations (raw)** - For a certain data entry, the number of vaccination for that date/country.
- **Vaccines used in the country** - Total number of vaccines used in the country (up to date).

Covid-19 Vaccine Tweets The data[3] is collected with Twitter API, which contains 213k tweets about Pifzer/BioNTech, Sinopharm, Sinovac, Moderna, Oxford/Astra-Zeneca, Covaxin and Sputnik V vaccines. Relevant attributes include:

- **User_location** - Location of the twitter user.
- **User_followers** - Number of user followers.
- **Text** - Tweet contents in text format.
- **Date** - Timestamps indicating the time user tweeted.

[1]https://github.com/owid/covid-19-data/tree/master/public/data
[2]https://www.kaggle.com/gpreda
[3]https://www.kaggle.com/gpreda/all-covid19-vaccines-tweets

id	tweet_text	label
0	4,000 a day dying from the so called COVID-19 vaccine @DailyBeast reports. #vaccine #PfizerVaccine #Moderna	1
3	Lab studies suggest #Pfizer, #Moderna vaccines can protect against #coronavirusvariant	3

Table 1: Tweet with sentiment annotation

Vaccine Tweet with Sentiment Annotation This data is sampled from Covid-19 Vaccination Tweets, and it[4] contains a collection (6000 entries) of tweets related to COVID-19 vaccines with manually annotated sentiments (negative, neutral, positive). Negative sentiment is labeled as 1, neutral as 2, and positive as 3. We use this data set to train a sentiment extraction model to predict the sentiment for the full vaccine tweets data. Example entry is shown in Table 1.

Data Pre-processing

Missing Data World Vaccination Progress contains missing data since actual vaccination numbers are not reported on certain dates. However, given the continuity of the vaccination data, it is safe to fill in missing data via interpolation. To be specific, we apply linear interpolation for missing entries in *Total number of vaccinations* and *Total number of people vaccinated*. Linear interpolation takes two data points, (x_a, y_a), (x_b, y_b):

$$y = y_a + (y_b - y_a) * \frac{x - x_a}{x_b - x_a}$$

which calculates the missing data value y on date x given the previous known data y_a on date x_a and the next know data y_b on date x_b.

Unbalanced Data It is ideal to train our RoBERTa model with balanced data. However, the sentiment class distribution of the labeled tweet data is highly unbalanced (Figure 1). The number of neutral tweets far exceeds the number of positive and negative tweets (the two classes we care the most). Thus, we over-sampled negative and positive class to mitigate the effect of unbalanced data, and to improve the prediction accuracy on negative and positive class.

Feature Construction We believe that the trend in number of people taking the first does of vaccine best reflects the public's decision and opinion towards vaccination. therefore, we constructed the attribute *Daily people vaccinated* from *Total number of people vaccinated*. We also constructed the attribute *Daily people fully vaccinated* from *Total number of people fully vaccinated* to see how likely people are to complete the vaccination after taking the first dose.

To compare and analyse tweet sentiment trend and US vaccination trend, we label every tweet text entry in the Covid-19 Vaccine Tweets data as negative, neutral, and positive with our classifier which is discussed in the next sections.

[4]https://www.kaggle.com/datasciencetool/covid19-vaccine-tweets-with-sentiment-annotation

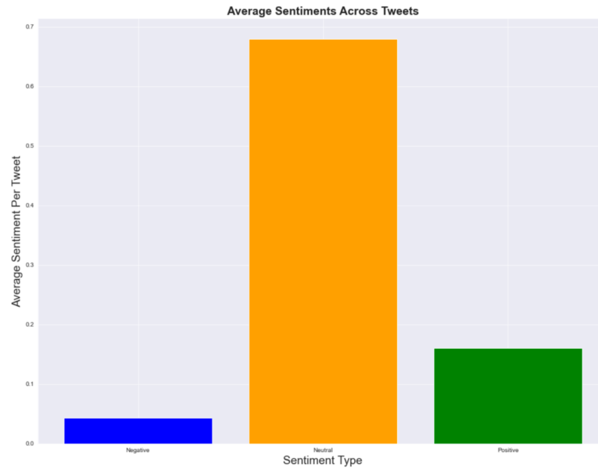

Figure 1: Unbalanced Training Data

Tweet Text Cleaning Since we have a relatively small amount of labeled tweet data to train our classifiers, in order to obtain a high accuracy, we followed *Preprocessing BERT* on Kaggle[5] to clean our tweet text. Specifically, the cleaning process includes:

- Convert text to lower case
- Remove Stopwords
- Normalize characters and dots
- Remove 'control' chars
- Convert or remove Bad Symbols
- Remove hrefs
- Remove html tags
- Remove links
- Duplicated dots, question marks and exclamations
- Remove underscore for spam words
- Combine short words
- Break long words
- Find and replace acronims
- Remove emojis

An example comparison between raw tweet and the cleaned tweet is shown below:

- Raw: Here we go! Grateful to be among the first group of vaccinated healthcare workers in Tampa/FL against #COVID19 emoji{folded-hands} ... https://t.co/kGyeHA1KOj
- Clean: Here we go ! Grateful to be among the first group of vaccinated healthcare workers in Tampa / FL against #COVID19 ...

[5]https://www.kaggle.com/kyakovlev/preprocessing-bert-public

Sentiment Analysis

Study shows that human performance on sentence sentiment analysis is around 80% to 85% accuracy. Therefore, we aim to obtain a model with a performance as close to the above accuracy as possible to serve as a robust classifier to label our full tweet dataset.

VADER Tuning First we evaluate VADER's performance on our labeled tweets using the default compound score threshold. That is, we label tweets with compound score no less than 0.05 as positive and no larger than -0.05 as negative, and others between -0.05 and 0.05 as neural sentiments. However, the accuracy is only 46.32%, with nearly half of neural sentiments labeled as positive. Tuning the positive threshold leads to an increase in overall accuracy and true positive rate but a decrease in false positive rate. The model reached the highest overall accuracy when the positive threshold is set to 0.45 and the negative threshold at -0.43. The final VADER classification accuracy is 57.43% on our labeled vaccine tweet dataset, which we do not consider to be robust enough to conduct sentiment analysis. Therefore, we continue to explore RoBERTa based models as our sentiment classifier.

RoBERTa We train our vanilla RoBERTa model with the additional classification layer on the Vaccine Tweet with Sentiment Annotation dataset with a 80-20 train-test split. After moderate model tuning, the best accuracy we obtained is 72%. We do not consider it to be robust enough for sentiment labeling. Therefore, we continue to experiment with a similar model that is more attuned to tweet texts. The model we chose, Twitter-RoBERTa-base [6], is a RoBERTa-base model trained on 58 million tweets, described and evaluated in the TweetEval benchmark. Again, we apply the same classification layer on top of this model, and fine-tuned the model on Vaccine Tweets with Sentiment Annotation data. This time we obtained a test accuracy of 78.1% and F1 scores of 77.3, 75.4, and 81.3 for negative, neutral, and positive class respectively. Though we could not obtain a model with accuracy comparable to human performance given the limited amount of training data, we argue that this model is robust enough to generate tweet sentiment labels for downstream analysis tasks. Figure 2 shows the sentiment distribution of the labeled full tweet dataset.

Time Series Analysis

From the full tweet dataset we obtained, we extract time-series data including daily count of negative, neutral, and positive vaccine related tweets. For certain outstanding dates where daily tweet count spikes or the sentiment shifts dramatically, we try to label them with corresponding important Covid-19 vaccine news and facts reported by mainstream media. Then we generate WordCloud from tweets tweeted on such dates and see whether the topics of Twitter discussion align with mainstream media topics. Finally we investigate the 60-day cross-correlation between US vaccination trend and the time series sentiment data we extracted. Result is discussed in the following section.

[6]https://huggingface.co/cardiffnlp/twitter-roberta-base

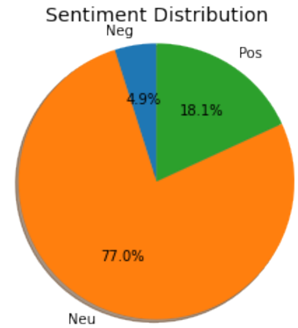

Figure 2: Sentiment Distribution

Results and Analysis

Twitter Discussion VS Mainstream Media Figure 3 shows the daily count of Covid-19 vaccine related tweets with three major events highlighted by mainstream media. The three outstanding timestamps includes:

- 2021-03-03: J&J authorization
- 2021-04-21: Fear of supply outstripping demand & CDC discussion of J&J bloodclots
- 2021-06-29: Discussion of vaccine protection against delta variant.

In comparison to Twitter discussion topics (Figure 10, 11, and 12 in Appendix) we extracted via WordCloud from the corresponding dates, we see that mainstream media and Twitter discussion only shares the delta variant discussion.

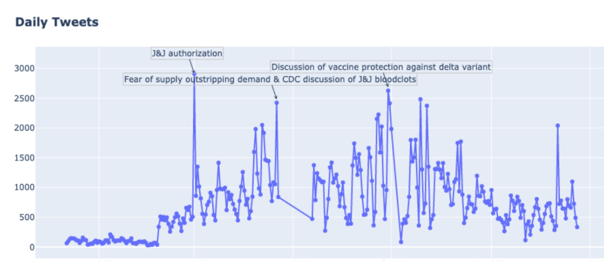

Figure 3: Daily Tweet Count

To further investigate this misalignment between Twitter discussion and maintream media focus, Figure 4 shows the daily count of positive tweets versus negative tweets (in proportion to the total number of tweets per day). Again, we generated WordClouds (Figure 13, 14, 15 in Appendix) for outstanding dates and searched for key Covid-19 events happened on such dates. The hot topics caught by tweet WordCloud and actual news and facts highlighted by mainstream media is listed below (shared events are in bold text):

- Tweet Catch:
  - 01/17/2021: 29 died within few days of vaccination

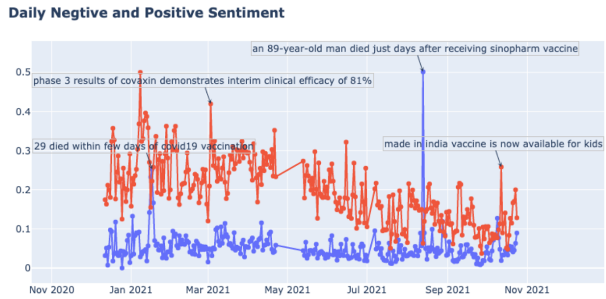

Figure 4: Daily Negative & Positive Tweet Count in Percentage (Red = Positive, Blue = Negative)

- 03/03/2021: Dolly Parton gets vaccination she helped fund. **Phase 3 results of covaxin demonstrates interim clinical efficacy of 81%**
- 04/21/2021: 'Double mutant' COVID-19 variant appears in B.C. Canada
- 06/29/2021: **Discussion of vaccine protection against delta variant**
- 08/13/2021: An 89-year-old man died just days after receiving Sinopharm vaccine.
- 10/12/2021: India vaccine available to kids

• Mainstream News and Articles

- 01/20/2021: Biden halts the US' withdrawal from WHO
- 03/01/2021: J&J authorization
- 03/03/2021: **Phase 3 results of covaxin demonstrates interim clinical efficacy of 81%**
- 04/21/2021: Fear of supply outstripping demand & CDC discussion of J&J bloodclots
- 06/29/2021: **Discussion of vaccine protection against delta variant**
- 08/13/2021: The FDA authorizes an additional Covid-19 vaccine dose for certain immunocompromised people

Comparing the two lists, we can see that Twitter users cares more about local and personal topics. They are particularly sensitive to extreme cases of Covid vaccines, especially people dying from getting vaccinated. Twitter topics also catches celebrity related news (Dolly Parton), which mainstream media does not care. In contrast, mainstream media highlights global situations and progression of Covid vaccines, together with official and political news about the vaccine, to which Twitter users show less interest.

Sentiment Trend VS US Vaccine Trend Figure 5 shows the daily number of people who gets their first Covid vaccine shot and Figure 6 shows the daily number of people who fully completed the vaccination. From the plots, we can see that the raw data fluctuates a lot, because people tend not to get vaccinated on weekends, leading to big drops in number of daily vaccinations. Thus, we applied a 7-day rolling mean to smoothen the raw data for further analysis. Figure 7 shows the cross-correlation between *daily people vaccinated* and textitdaily people fully vaccinated is reaching 0.9 given time lag of 28/21 days. This indicates that most people do complete the vaccination process in 3-4 weeks, which solidifies our assumption that *daily people vaccinated* best serves as the key indicator of people's decision to take the vaccine.

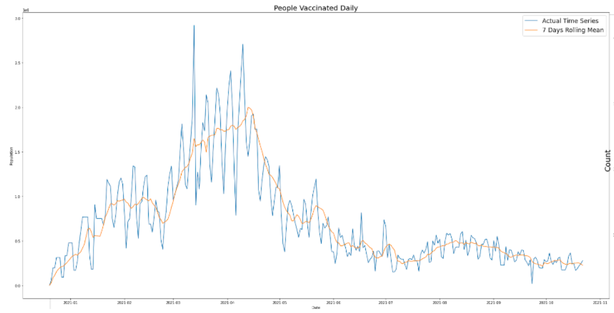

Figure 5: Daily People Vaccinated

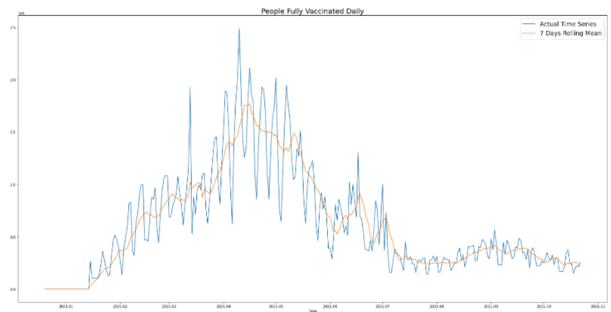

Figure 6: Daily People Fully Vaccinated

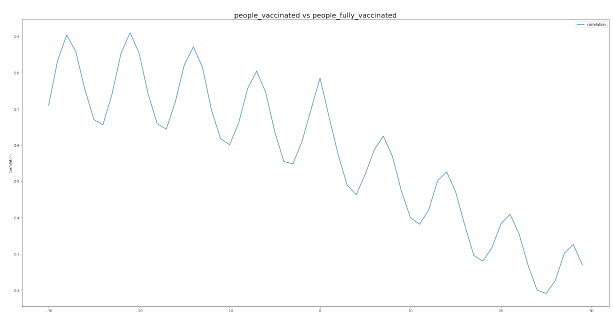

Figure 7: Cross-Correlation Vaccinated vs Fully Vaccinated

Finally, we plot the cross-correlation between vaccination trend and multiple sentiment trend features we extracted in Figure 8. Result shows that the raw daily counts of positive Covid vaccine related tweets is highly positively correlated to the daily number of people getting vaccinated. However, the highest correlation coefficient 0.88 (Figure 9)is achieved at a time lag of 4 to 18 days, which means that tweet sentiment trend trails behind vaccination trend by 4-18 days. It is expected that tweet sentiment trend is correlated with vaccination trend, while the we did not expect to see that the sentiment trend lags behind the vaccination trend. Intuitively, positive discussion on social media could encourage people getting vaccinated, but the opposite phenomenon discovered by our study contradicts this intuition. The causality of such phenomenon is left to be discussed and studied.

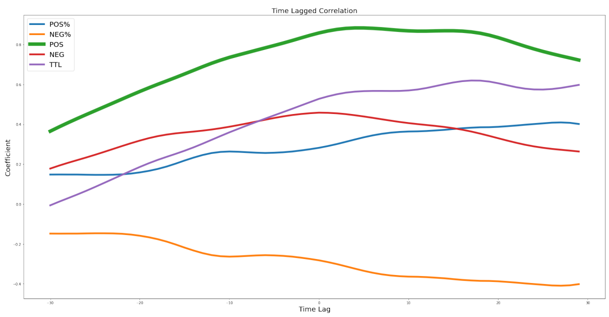

Figure 8: Cross-Correlation Sentiment vs Vaccination

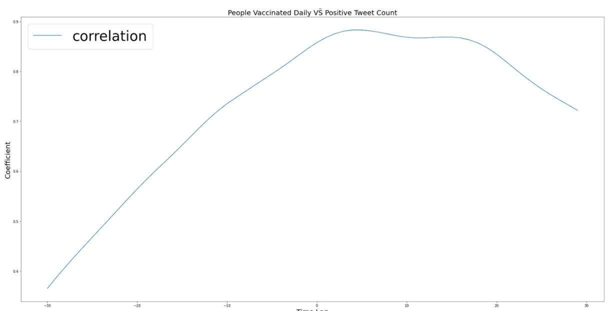

Figure 9: Cross-Correlation Positive Count vs Vaccination

Conclusion

In this work, we studied the inter-effect between social media and Covid-19 vaccine by mining sentiment and discussion topics on vaccine related tweets, and by performing time series analysis on the observed sentiment trend and vaccination trend. We concluded that: (1) social media discussion focuses on different aspect of Covid-19 vaccine comparing to mainstream media, whereas social media cares more about personal, local, and negative facts; (2) Number of positive tweet is positively correlated to number of people getting vaccinated; (3) However tweet sentiment trend follows the vaccination trend, which is counter-intuitive.

In future work, we are particularly interested in looking into the causality of finding (3), and investigating how vaccination trend affects public opinion on Covid vaccine. We will incorporate Covid infection data and vaccine scheduling wait time data to study this problem.

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Appendix

Figure 10: 2021-03-03: Phase 3 Results of Covaxin & Dolly Parton

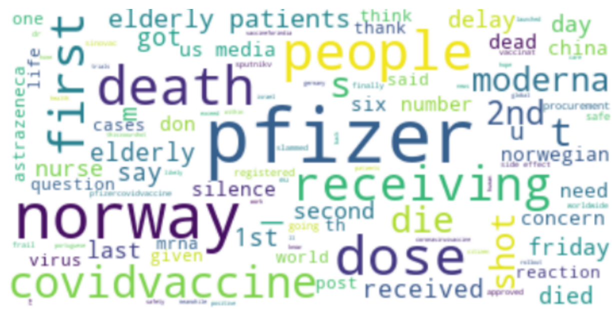

Figure 13: 2021-01-16: Deaths in elderly vaccine recipients in Norway

Figure 11: 2021-04-21: Double Mutant Variant in B.C, Canada

Figure 14: 2021-08-13: 89-year-old man died just days after receiving Sinopharm vaccine

Figure 12: 2021-06-29: Delta Variant Discussion

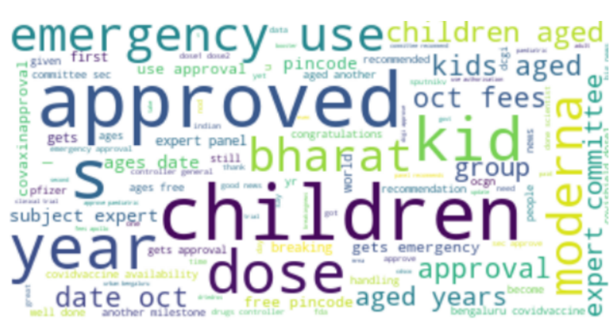

Figure 15: 2021-10-12: India vaccine now available for kids