Social Media and COVID-19: Characterizing Anti-Quarantine Comments on Twitter

Abstract

Social media has become a mainstream channel of communication during the COVID-19 pandemic. While some studies have been developed on investigating public opinion on social media data regarding COVID-19 pandemic, there is no study analyzing anti-quarantine comments on social media. This study has collected and analyzed near 80,000 tweets to understand anti-quarantine social comments. Using text mining, we found 11 topics representing different issues such as comparing COVID-19 and flu and health side effects of quarantine. We believe that this study shines a light on public opinion of people who are against quarantine.

Introduction

As of June 4, 2020, the number of positive cases was more than 6.6 million globally, with over 390,000 deaths[1]. The outbreak has posed significant threats to international health and the economy. In the absence of treatment for this virus, US states imposed a quarantine period. In addition, the COVID-19 pandemic caused the largest global recession in history[2], and the US unemployment rate reached 14.7% in April 2020[3].

Social media has become a mainstream channel of communication. For example, 72% of U.S. adults use at least one social media site in 2019[4]. In the last decade, social media platforms such as Twitter have grown in popularity. Social media has received a great deal of academic interest to investigate public opinion on different issues such as politics and health (Karami, Lundy, et al., 2020). Some studies, such as (Abd-Alrazaq et al., 2020), have been developed on analyzing public opinion on social media data during the COVID-19 pandemic. While these studies have provided valuable insights, they didn't consider anti-quarantine comments on social media. This study characterizes tweets containing anti-quarantine hashtags with text mining to present a new perspective on public opinion during the COVID-19 pandemic.

Methodology

Data Collection and Preprocessing. We explored Twitter search to identify hashtags representing anti-quarantine semantic. We found six hashtags including #AntiLockdown, #AntiQuarantine, #ReOpenAmerica, #EndtheLockdown, #EndtheLockdown, and #ReOpenAmericaNow. Then, we utilized a data provider service (Brandwatch) to collect tweets containing at least one of the six hashtags. Next, we removed URLs, hashtags, username, duplicate tweets and tweets with less than 5 words. This process has provided 79,738 tweets.

Topic Discovery. In order to disclose hidden semantic layer in our data, we utilized topic modeling. This technique assigns words semantically related to each other into a cluster, called topic. Different topic models have been developed using Latent Dirichlet Allocation model (LDA) (Blei et al., 2003). LDA is an efficient and effective topic model that has been applied on different social media applications such as Twitter. The outputs of LDA for *n* documents (tweets), *m* words,

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[1] https://www.worldometers.info/coronavirus/
[2] https://www.businessinsider.com.au/countries-on-lockdown-coronavirus-italy-2020-3
[3] https://data.bls.gov/timeseries/LNS14000000
[4] https://www.pewresearch.org/internet/fact-sheet/social-media/

and t topics, are two matrices (Blei et al., 2003). The first one is the probability of each word in each topic or $P(W_i|T_k)$, and the second one is the probability of each of topic in each document or $P(T_k|D_j)$:

$$\begin{array}{ccc} & \text{Topics} & & & \text{Documents} \\ Words & \begin{bmatrix} P(W_1|T_1) & \cdots & P(W_1|T_t) \\ \vdots & \ddots & \vdots \\ P(W_m|T_1) & \cdots & P(W_m|T_t) \end{bmatrix} & \& & Topics & \begin{bmatrix} P(T_1|D_1) & \cdots & P(T_t|D_n) \\ \vdots & \ddots & \vdots \\ P(T_t|D_1) & \cdots & P(T_t|D_n) \end{bmatrix} \\ & P(W_i|T_k) & & & P(T_k|D_j) \end{array}$$

The $P(W_i|T_k)$ matrix output represents the probability of each word belonging to a specific topic, whereas the $P(T_k|D_j)$ matrix represents the probability of each topic belonging to a specific document. The top words in each topic based on the descending order $P(W_i|T_k)$ represent a topic. For example, the top words in topic 4 in Table 1 are *people, home, stay, sick, masks, live, care, risk, wear*, and *safe*, representing a theme related to wearing masks. We used a pre-processing step to find the optimal number of topics based on the level of consistency and coherence with the associated topic using the C_V method developed in the gensim Python package[5]. The estimation process offered the number of topics at 11. Next, we applied Mallet, a Java implementation of LDA, at 11 topics and 4000 interactions on our corpus.

Topic Analysis. We then moved to a qualitative coding process to inductively interpret topics. Our coding was based on reviewing the top related words within each topic using P(W|T) and the top related tweets within each topic using P(T|D).

Results

We found anti-quarantine tweets discussed in 11 topics, as seen in Table 1. The first topic showed discussions on the order of governors to close businesses and impose self-quarantine. These tweets argued that the order was unconstitutional because it was against people's liberty and freedom. The second topic represented arguments around the physical and mental health issues due to quarantine. The third topic focused on this question: "Why were big businesses (e.g., Walmart) open while small businesses were closed?"

The fourth topic was about the uselessness of wearing a mask for safety. The fifth topics considered blocking a republican bill that added small business loans by senate democrats. The sixth and seventh topics showed requests for open businesses and the Opening Up America, respectively. The next topic illustrated debates on fake news and wrong models on predicting COVID-19 related issues. The ninth topic was about protests again quarantine in different US states such as California and Michigan. The next topic was discussion on political consequences of the COVID-19 quarantine in elections. The last topic compared flu and COVID-19 based on different statistics such as the number of deaths. Table 2 also provides an example tweet for each of topics.

Discussion and Conclusion

This study investigated anti-quarantine tweets to understand hidden topics Twitter with a cost and time effective approach. Our findings show the anti-quarantine tweets were about different issues

[5] https://radimrehurek.com/gensim/models/coherencemodel.html

related to the COVID-19 quarantine. Our research shines a light on US public opinion regarding anti-quarantine efforts.

While this study provided a new perspective in public opinion mining, we didn't study non-English tweets and this paper was limited to six hashtags. Future work could investigate non-English tweets and consider more hashtags.

Table 1: Topics of Anti-Quarantine Tweets

ID	Label	Words per Topic
T1	Unconstitutional Order	rights governors freedom government state people orders constitution free unconstitutional
T2	Health Issues	economy end lockdown virus people lives health worse time risk
T3	Small Business	open essential social businesses time closed politicians small stores corrupt
T4	Masks	people home stay sick masks live care risk wear safe
T5	Blocking Small Business Support	businesses money pay families reason government political save democrat bills
T6	Open Businesses	back america work time country reopen business save open jobs
T7	Opening Plan	reopening reopen states plan time testing weeks economy start trump
T8	Wrong Models and Fake News	news media wrong science data models daily truth stop fake
T9	Protests	state protest governor reopen today california rally patriots michigan join
T10	Political Consequences	trump president hell love thing democrats party white hoax election
T11	Flu vs COVID-19	deaths people covid flu cases million virus rate numbers population

Table 2: Tweet Examples

Topic	Tweet Example	Topic	Tweet Example
Unconstitutional Order	Please support Elon Musk @elonmusk as he battles against Leviathan (the government) for our rights and liberty as individuals and private businesses. A true revolutionary is one who defies the State at his potential peril. #business #tesla #covid #california #ReopenAmericaNow	Open Businesses	America MUST get back to work. Click here to sign the petition to save jobs, small business, and America as we know it! #reopenamerica #reopenamericanbusiness
Health Issues	Absolutely & we MUST also remember those that have lost their lives during this dangerous lockdown due to addiction, suicide & other reasons, all due to the extended unnecessary lockdown. The lockdown has caused immense harm to MANY ! #ReOpenAmerica	Opening Plan	President Trump unveiled 'Opening Up America' plan, aims for May 1. The guidelines were developed by #coronavirus task force members, Drs. Birx & Fauci in coordination with CDC & Prevention chief Robert Redfield. #ReopenAmerica
Small Business	Ian Smith, owner of Atilis Gym, is right "enough is enough". Small business are just as "essential" as big box stores like Wal-Mart. If big box stores servicing over a 100 customers can take the necessary precautions to remain open so can small businesses. #ReopenAmericaNow	Wrong Models and Fake News	🕵️👮😳An analysis from Bot Sentinel, a bot tracking platform, found that bots and trolls have been stoking sentiments online that have fueled the protests, using hashtags like #ReopenAmericaNow and #StopTheMadness.
Masks	Absolutely & we MUST also remember those that have lost their lives during this dangerous lockdown due to addiction, suicide & other reasons, all due to the extended unnecessary lockdown. The lockdown has caused immense harm to MANY ! #ReOpenAmerica	Protests	There are protests planned in California, Oregon, Washington, Arizona, New Mexico, Colorado, Kansas, Minnesota, Iowa, Missouri, Illinois, Wisconsin, Indiana, Michigan, Kentucky, Tennessee, Ohio, Pennsylvania, N.Carolina, Delaware and Maine. #ReopenAmerica
Blocking Small Business Support	You're not making lists of US taxpayers. #ReopenAmericaNow! Democrats withheld critical funding for the people who pay their salaries; who are struggling to feed their families, pay their bills, save their businesses. You did it for political gain, without missing a paycheck.	Political Consequences	Trump now losing ground in a key swing state. Remember, even Winston Churchill got crushed right after he won World War Two! Want to reelect Trump? #ReopenAmerica
Flu vs COVID-19	@realDonaldTrump TESTS are not even required to confirm deaths as Coronavirus. Total deaths for each week in March as compared to FOUR prior years are DOWN. Many flu & pneumonia deaths are coded falsely as coronavirus. That is the only logical conclusion. #ReopenAmericanow		

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References

Abd-Alrazaq, A., Alhuwail, D., Househ, M., Hamdi, M., & Shah, Z. (2020). Top concerns of Tweeters during the COVID-19 pandemic: Infoveillance study. *Journal of Medical Internet Research*, *22*(4), e19016.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, *3*(Jan), 993–1022.

Karami, A., Lundy, M., Webb, F., & Dwivedi, Y. K. (2020). Twitter and research: A systematic literature review through text mining. *IEEE Access*, *8*, 67698–67717.

Karami, A., White, C. N., Ford, K., Swan, S., & Spinel, M. Y. (2020). Unwanted advances in higher education: Uncovering sexual harassment experiences in academia with text mining. *Information Processing & Management*, *57*(2), 102167.