DOI: 10.1002/pra2.313

SHORT PAPERS

Stigmatization in social media: Documenting and analyzing hate speech for COVID-19 on Twitter

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Abstract

As the COVID-19 pandemic has unfolded, Hate Speech on social media about China and Chinese people has encouraged social stigmatization. For the historical and humanistic purposes, this history-in-the-making needs to be archived and analyzed. Using the query "china+and+coronavirus" to scrape from the Twitter API, we have obtained 3,457,402 key tweets about China relating to COVID-19. In this archive, in which about 40% of the tweets are from the U.S., we identify 25,467 Hate Speech occurrences and analyze them according to lexicon-based emotions and demographics using machine learning and network methods. The results indicate that there are substantial associations between the amount of Hate Speech and demonstrations of sentiments, and state demographics factors. Sentiments of surprise and fear associated with poverty and unemployment rates are prominent. This digital archive and the related analyses are not simply historical, therefore. They play vital roles in raising public awareness and mitigating future crises. Consequently, we regard our research as a pilot study in methods of analysis that might be used by other researchers in various fields.

KEYWORDS

coronavirus, COVID-19, hate speech, pandemic, Twitter

1 | INTRODUCTION

As the COVID-19 pandemic has unfolded,[1] many local authorities have locked down cities through social distancing orders to slow down the speed of virus transmission. Consequently, daily routines and social norms have changed and social media platforms, such as Twitter, have emerged as one of the primary places where people create and exchange information relating to the virus.

Although people are physically distant, the information they have shared through social media streams during this global health and information crisis is influential (Xie et al., 2020). Some of the posts and commentaries being shared online, however, reflect or even amplify contemporary social stigmatization, discrimination and outright Hate Speech, especially directed at China and the Chinese people. To understand their potential to influence public opinion and behavior, these controversial tweets (Twitter posts) need to be documented and analyzed in a timely manner. In early February 2020, therefore, we began capturing and analyzing tweets related to the coronavirus and China, with a specific focus on Hate Speech.

In this paper, we present an initial analysis of the resulting archive of tweets together with the analytical methods we have used. Our broader goal has been to examine the role that an archive could play in informing the

83rd Annual Meeting of the Association for Information Science & Technology October 25-29, 2020.

public, educating the society, and preventing or smoothing future crises (Chew & Eysenbach, 2010). Furthermore, we are methodologically interested in identifying effective processes, from archiving to analyzing, that can be used in real time during a rapidly evolving crisis of this magnitude.

2 | STUDY DATA AND METHODS

2.1 | Data collection

2.1.1 | Building a database of tweets

We have been documenting tweets related to China since the start of the COVID-19 pandemic. “China” and “Coronavirus” are words that have been associated in the public mind ever since the Chinese authorities informed the World Health Organization (WHO)'s China office of the occurrence of pneumonia cases with unknown cause in Wuhan, China on December 31, 2019 (Ravelo & Jerving, 2020). During the critical period[2] between when the coronavirus emerged to the ensuing outbreaks, we have queried the Twitter API using “china+and+coronavirus” and have collected 3,457,402 English-language tweets (key tweets).

2.1.2 | External data collection

We have also been obtaining coronavirus cases information in the U.S. from the dataset provided by John Hopkins University.[3] To further detect whether there might be any systematic trend in Hate Speech within groups of states that share certain characteristics such as demographic composition, we have extracted supplementary information from the U.S. Census Bureau,[4] the U.S. Bureau of Labor Statistics[5] and the Federal Election Commission (Eileen & Leamon, 2017).

2.2 | Visualizing trends as a method for preliminary analysis

In this project, we utilize data visualization as an exploratory research method and have been able to effectively identify patterns and correlation among variables (e.g., new cases, number of hate tweets) by using barchart, gradient maps and word cloud.

2.2.1 | Hashtag trends

Word count tables and Word Clouds are straightforward representations of discourse. We have generated the word cloud in Figure 1 as a demonstration of the overall trend of tweets according to their hashtags, creating a summary of user input topics.

Among the top frequently used hashtags in the archive, several main categories can be discerned, including location, person, organization, and abstract concept. One clear trend is the occurrence of locations, as shown in Table 1 and Figure A1 in Appendix III. “wuhan”, with more than 24,000 occurrences, is the top hashtag used in this archive. Other locations used as hashtags include Italy, USA, Hong Kong, and Hubei (of which Wuhan is the capital). This preliminary finding confirms our intuition that analyzing the trend and speech discourse together with demographics could be productive.

In terms of contextual information, two of the frequently used hashtags, “chinesevirus” and “wuhanvirus”, are associated with discriminatory comments. Both hashtags are violations of the WHO's convention for naming new human infectious diseases (WHO, 2015). This preliminary finding suggests that Twitter users have often used discriminatory speech regarding specific groups, thus leading us to conduct further investigation using lexicon-based information extraction methods.

2.2.2 | The trend of tweets

Figure 2 provides an aggregated histogram[6] and line plot that analyze the relationship between the number of new cases versus the number of key tweets per day. We can observe an overall increasing trend for both the number of new cases and the number of key tweets over time. Interestingly, we can also observe a substantial surge in the number of key tweets from March 16 to March 19. We believe this occurrence might be caused by the burgeoning of confirmed cases in the U.S. and increasing media attention.

2.3 | Data pre-processing

After removing stop words and ignoring non-textural strings, we use lexicon-based methods for the primary data wrangling of both Hate Speech detection and aspect-based emotion scoring. For Hate Speech detection, we use the Hatebase[7] dictionary, which includes thousands of discriminatory words. For emotion extraction, we use an emotion lexicon created using crowdsourcing with Mechanical Turk (Mohammad & Turney, 2010).

For each tweet, we tabulate the number of words related to each element in the emotion dictionary and then generate 10 variables that include sentiments (*negative*, *positive*) and emotions (*anger*, *anticipation*, *disgust*, *fear*, *joy*, *sadness*, *surprise*, *trust*) and dividing them by the

FIGURE 1 Top 205 hashtags including in-appropriate naming of COVID-19. *Note*: An interactive version of the word cloud is available at: https://voyant-tools.org/?corpus=b60fb002d2b470b44fc7b0c3133cf9df&visible=205&view=Cirrus

TABLE 1 Selected highest occuring hashtags with frequency rank

Rank	Term	Count	Rank	Term	Count
1	wuhan	24080	9	taiwan	6009
2	italy	13536	10	chinesevirus	5191
6	hongkong	6643	12	wuhanvirus	4557
7	usa	6554	15	hubei	4208
8	iran	6212	16	russia	3895

tweet's word count to normalize. For tweets with words defined as hatewords, we label them as "Hate Speech".[8]

To identify location information, we use the *carmen* Python package based on geocoding tools (Dredze, Paul, Bergsma, & Tran, 2013). We extracted location information for 1,401,374 tweets from the archive and found that 40.53% of them are from the U.S.[9]

Finally, we average the normalized sentiment and emotion variables by date and state to create the aggregated datasets. Each dataset also contains the total number of key tweets and the percentage of Hate Speech on the aggregated levels. For the state-level dataset, we further introduce characteristic variables *PoliticalParty*, *AsianPercentage*, *UnemploymentRate*, and *PovertyRate*.[10]

2.4 | Statistical methods

2.4.1 | Decision tree classifier

Decision tree is a widely used machine learning technique that uses a tree-like model for making decisions and analyzing possible consequences. The target of building a decision tree is to minimize the entropy of each leaf so that it contains either only Hate Speech or Non-Hate Speech. Using Gini Impurity,[11] the decision tree model could also return the importance of features, from which we can identify the best Hate Speech indicator.

2.4.2 | Network methods

Another way to analyze and visualize Hate Speech behavior across each state is to use network methods. We can consider states to be nodes in a network and use methods such as modularity and centrality to evaluate the network. Network modularity is a measurement to show network homophily because similar nodes tend to connect with each other. If we assign groups to the states using some criterion (e.g., poverty), we can calculate the modularity of the network to show whether under such a criterion, states that are similar have homogeneity in Hate Speech behavior. Network centrality is a measurement to describe node property. Different centrality

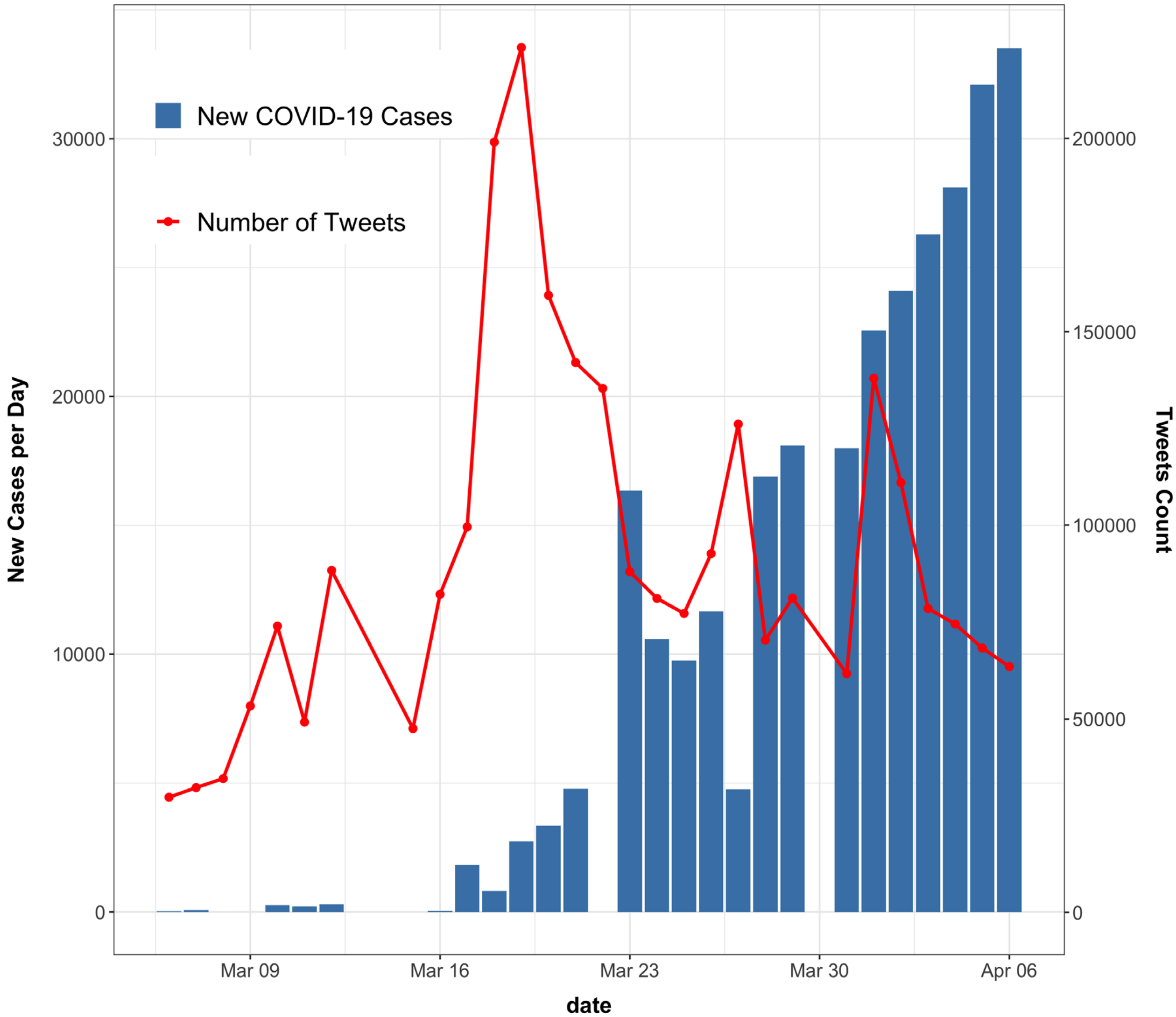

FIGURE 2 Number of new cases in the U.S. and Number of tweets per day in the U.S

measurements can describe different Hate Speech behavior of each state.

3 | RESULTS

3.1 | Analyzing hate speech and emotions

To better understand the relationship between emotions and Hate Speech, we aggregate the negative sentiments[12] and observe a similar trend in the negative sentiment score and the number of Hate Speech over time, as shown in Figure 3.

To further analyze the relationship between emotions and Hate Speech, we implement a binary decision tree classifier to create a model that can infer whether a tweet is Hate Speech (negative class stands for Hate Speech). The decision tree model is built based on the eight emotion features in 3,461,929 positive samples and 25,467 negative samples (Train Set).

Based on Table 2 and Table 3, we believe that with a 100% specificity, our decision tree classifier could successfully detect all Hate Speech defined by the lexicon-based approach. With similar precision, our model's prediction of a tweet belonging to Non-Hate Speech is definite. Our negative predictive value is 87.87%, thus we can conclude that our model is proficient in detecting Hate Speech. Figure A2 in Appendix III provides an overview of the generated tree, from which we can also obtain the contributions of features in detecting Hate Speech.

In Table 4, based on the decision tree, we extract the feature importance of each emotion and conclude that surprise and fear are the two important Hate Speech indicators. As shown in Figure A2 in the Appendix IV, although the root node uses joy as a splitting criterion, it

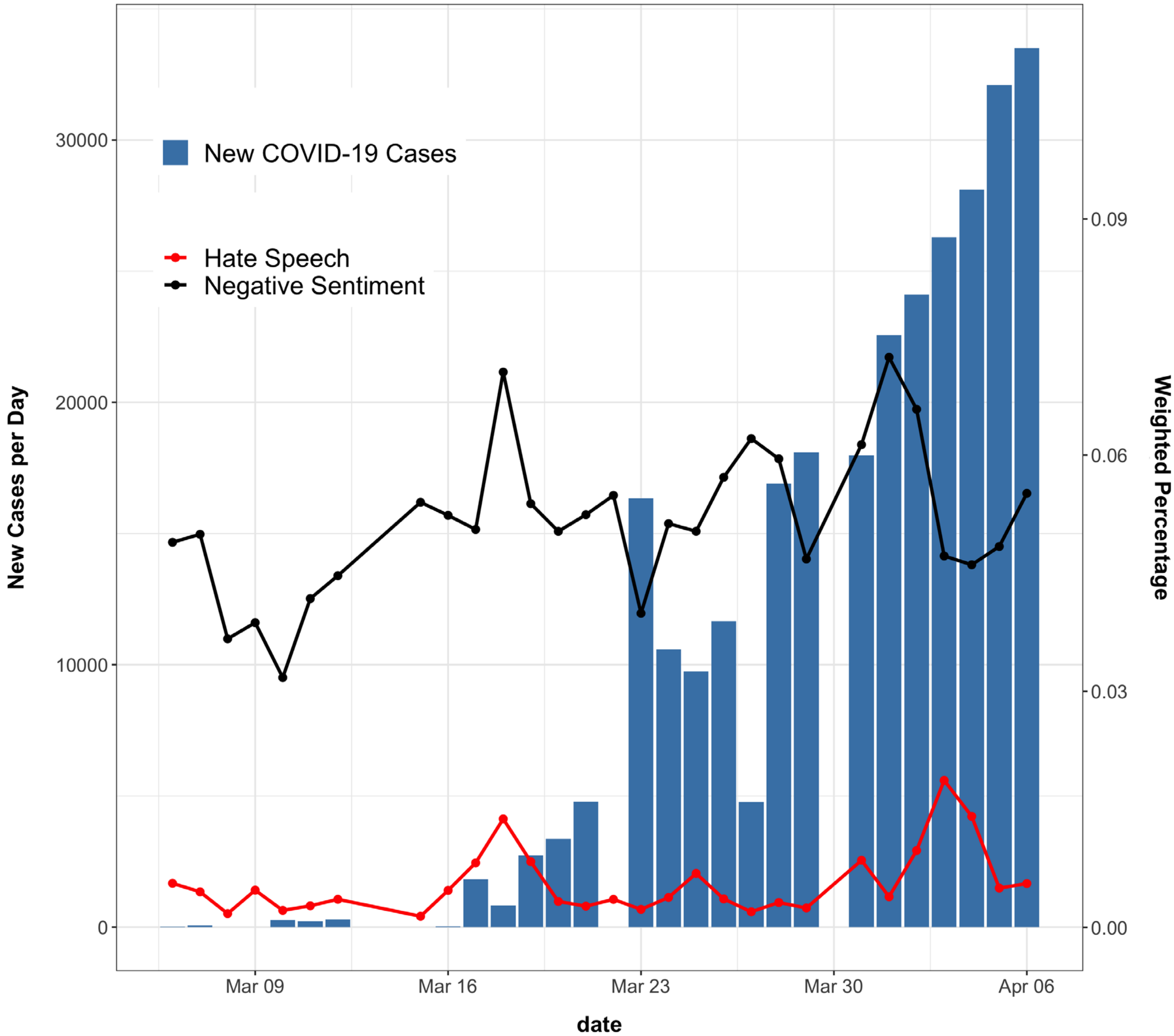

FIGURE 3 Number of New Cases per day in the U.S. (Blue Bars) and Sentiment and Hate Speech Trends

TABLE 2 Confusion Matrix of the Test Set

		Actual	
		Positive	**Negative**
Predicted	**Positive**	691877	0
	Negative	610	4418

TABLE 3 Confusion Matrix Measurements

Measurements	Value
Accuracy	99.91%
Sensitivity	99.91%
Specificity	100.00%
Precision	100.00%
NPV	87.87%

Note: NPV is Negative Predicted Value.

TABLE 4 Importance of Each Emotional Feature in Picking Hate Speech

Emotion	Feature Importance
Surprise	28.28%
Fear	22.78%
Anticipation	13.43%
Anger	10.99%
Disgust	7.80%
Trust	7.77%
Sadness	6.83%
Joy	2.11%

makes little contribution to finding Hate Speech.[13] The actual nodes that contribute the most to detecting Hate Speech are shown in Figure 4; thus, tweets satisfying all

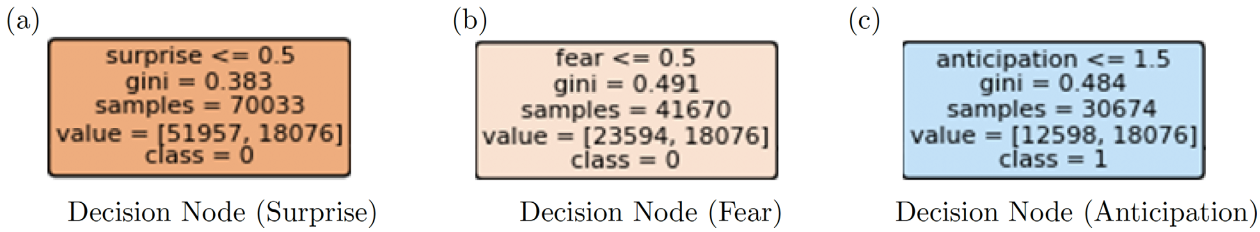

FIGURE 4 Important Decision Nodes

TABLE 5 Basic Rules of Emotion to Distinguish Hate Speech

Emotion	Low (0 ~ 0.5)	Medium (0.5 ~ 1.5)	High (1.5 ~)
Surprise		✓	
Fear		✓	✓
Anticipation		✓	
Anger	✓		
Disgust	✓	✓	
Trust		✓	✓
Sadness		✓	
Joy	✓	✓	

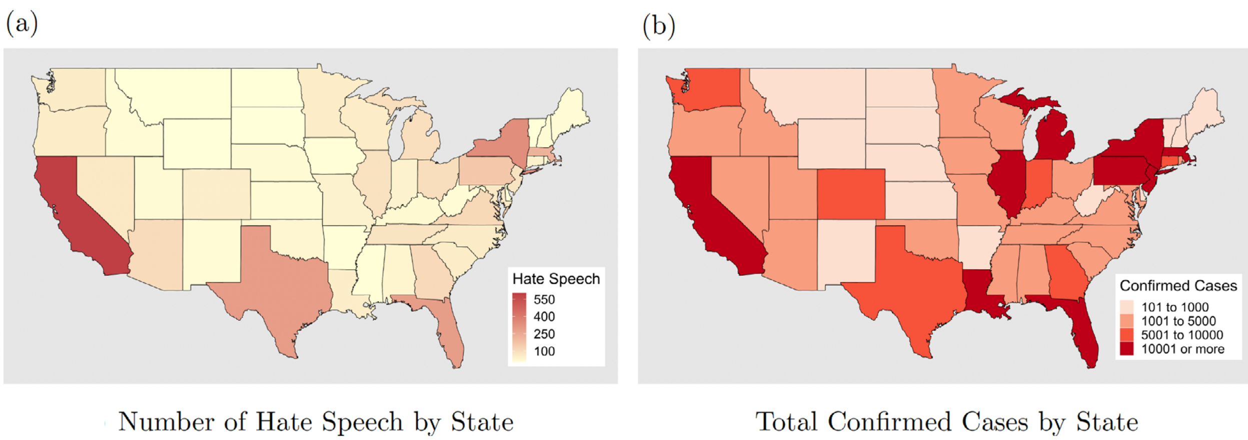

FIGURE 5 Comparison between the Number of Occurrences of Hate Speech and Confirmed Cases: California, Texas, Florida and New York, all states with high number of confirmed cases, are also the locations associated with large numbers of Hate Speech

three splitting criteria are likely to be Hate Speech. Moreover, tweets satisfying attributes demonstrated in Table 5 are likely to be Hate Speech.

3.2 | Analyzing hate speech and demographics

Using the aggregated state-level dataset, we compare the number of Hate Speech occurrences against the number of confirmed cases of COVID-19 by state. The gradient maps show a high correlation between the two, suggesting that shared characteristics across states might influence the number of Hate Speech occurrences and confirm cases simultaneously. To further investigate and visualize homogeneity between states and factors associated with Hate Speech, we build a network model and conduct modularity and centrality analyses.

According to the steps and conditions[14] specified in Figure 6a, we visualize the resulting network in Figure 6b.

3.2.1 | Network modularity analysis

The modularity of our network, Q, indicates whether our grouping criteria, for example state poverty rate, are informative in revealing each state's Hate Speech behavior:

$$Q=\sum_{i=1}^{r}\left(e_i-a_i^2\right) \tag{1}$$

where e_r and a_i[15] are the proportion and the expected proportion of similar states pairs[16] within each group. If $Q>0$, the similarity of states within groups is comparatively larger than that of between groups, which indicates that our method of splitting the groups is informative in revealing each state's different Hate Speech behavior.

We analyze the effects of four grouping criteria on Hate Speech behavior: political party, poverty rate, Asian percentage, and unemployment rate. For political party, we group the states by Republican states and Democratic states according to the 2016 Presidential Election Results. For the other factors, we group all the states into quadrisections. According to the division, we calculate the modularity of each criterion (Table 6). We conclude that the poverty rate and the unemployment rate of each state are informative factors in studying the Hate Speech behavior of each state.

3.2.2 | Network centrality analysis

Centrality of a network is a measurement to describe the importance of each node. In our case, we are interested

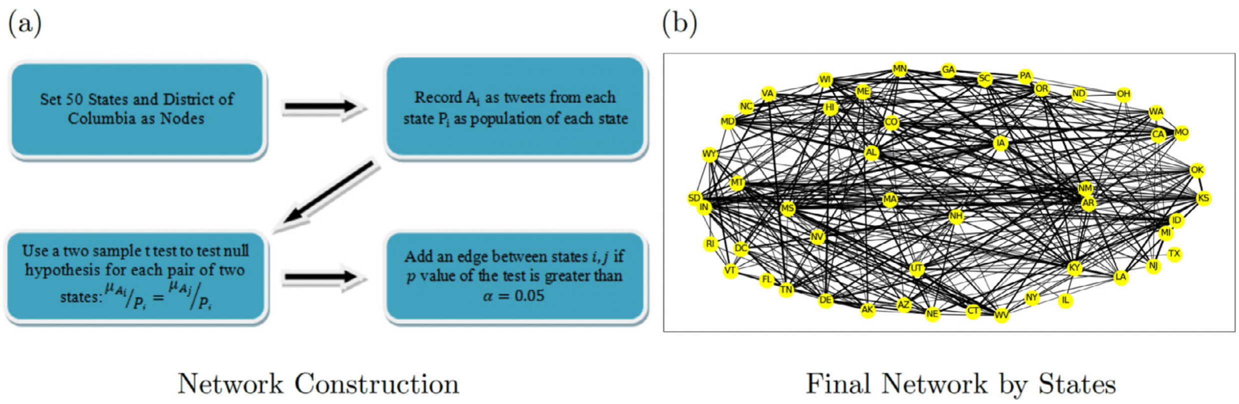

FIGURE 6 Network Construction and Result

TABLE 6 Modularity of the Network by Different Grouping Criterion

Factor	Political Party	Poverty Rate	Asian Percentage	Unemployment Rate
Modularity	−0.0624	0.0244	−0.0013	0.0399

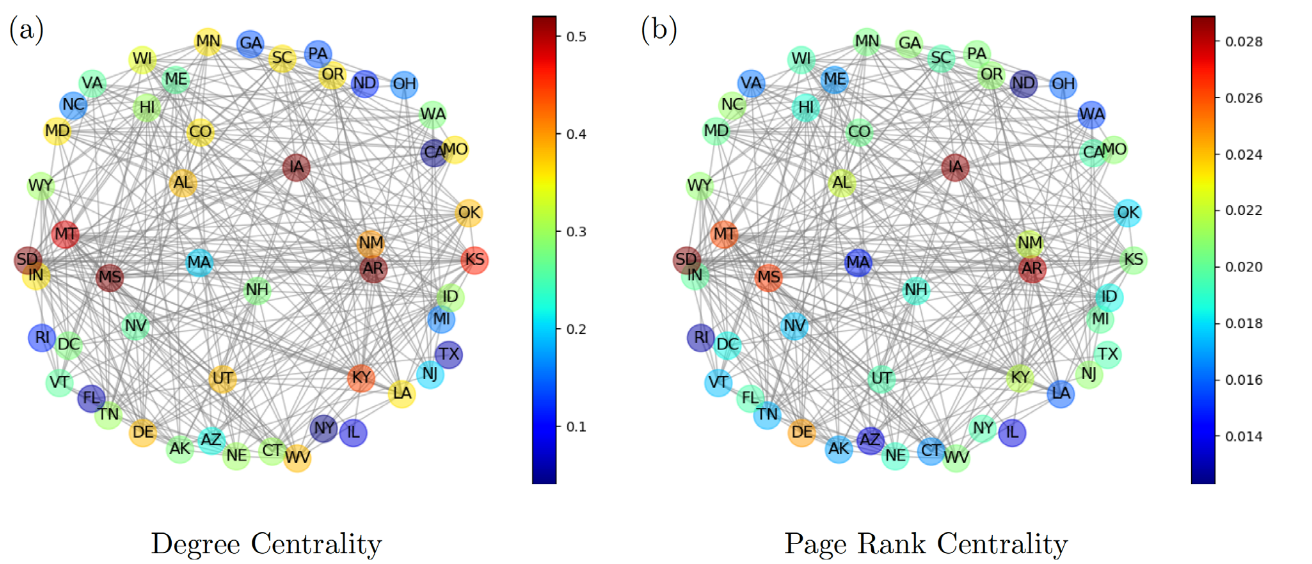

FIGURE 7 Centrality Measurements of Network

in the degree centrality and page rank centrality of each node. Degree centrality vector, σ_C, can be used to measure the number of states that have similar Hate Speech behavior with another state:

$$\sigma_C = \frac{A\mathbf{1}}{|V|} \tag{2}$$

where A means the adjacency matrix; $\mathbf{1}$ means the all-one vector; $|V|$ means the number of nodes. In our case, higher degree centrality means the state's Hate Speech behavior is common among all states. Otherwise, the state may have a unique Hate Speech behavior (either too high or too low).

Compared with degree centrality, page rank centrality, σ_P, gives high centrality to nodes that connected with high centrality notes, that is page rank centrality groups "potentially" similar states in a more extreme way. Therefore, for those states that have low page rank centrality, their Hate Speech behaviors have higher levels of distinctions. For the centrality of each state:

$$\sigma_{P,i} = \alpha \sum_{j=1}^{n} A_{ij} \frac{\sigma_{P,i}}{k_j} + \beta \tag{3}$$

where A refers to the adjacency matrix, k_j refers to the degree of node j, and α, β are constants.

From Figure 7a,b we can discern the states that perform "uniquely" in Hate Speech. We can observe that California, New York, Florida, Texas, Pennsylvania, Illinois (from degree centrality), and Massachusetts, Rhode Island, North Dakota (from page rank centrality) have low centrality compared with other states. Combined with Figure 5, we observe that those states either have extremely high confirmed cases (such as New York, Massachusetts, Illinois, California) or have extremely low confirmed cases (such as North Dakota). Therefore, further study might usefully compare the Hate Speech behaviors of different states.

4 | CONCLUSION

We observe that many hashtags, the user-defined topic of tweets, include inappropriate naming conventions and discriminate against certain ethnic or geographic groups. Moreover, by taking the U.S. as an example group of English language Twitter users, we find associations between the amount of Hate Speech and sentiments/state demographic factors, where surprise, fear, poverty and unemployment rates are of greater importance. These initial findings provide us with a base for more focused investigation, ideally associating our dataset with news during this period.

It is also important to reiterate that this tweet archive and the related analyses are not purely historical in nature or importance. They have a central role to play in making rational voices heard by the public and raising awareness about social and humanistic issues during crises. It is our hope that the knowledge we gain and the methodological approaches we develop will be helpful also to other researchers working to anticipate and mitigate social tensions during global crises.

5 | DISCUSSIONS AND FUTURE WORK

5.1 | Related work and our focus

We realize that our dataset could be a good complement to the "COVID-19-TweetIDs" dataset, which has a more general scope (Chen, Lerman, and Ferrara, 2020). We also notice that scholars from various fields are analyzing COVID-19-related Twitter datasets by using topic modeling methods and characterizing individual user behaviors (Chen, Yang, et al., 2020). Compared to these investigations, our scope is more comprehensive, encompassing archival, analytical, and methodological processes, and including utilizing machine learning and network methods for visualization and analysis.

5.2 | Limitation and discussion of data scope

With the Twitter API's limitations[17] on continuity of searching, we have several data gaps. Since we either normalize the variables or analyze correlations, we expect this discontinuity to have minimal influence on our analysis. While the number of key tweets quickly drops then slowly increases after March 19th, this drop may be due to delayed adoption of the term "COVID-19" in place of "coronavirus", thus potentially diverting much of the information stream.

5.3 | Limitation and improvement in information extraction

Restricted by the scope of the dictionaries, lexicon-based methods likely underestimate the sentiment/emotion score by failing to identify malformed words and colloquial expressions (e.g., gr8, RIP) (Taboada, Brooke, Tofiloski, Voll, & Stede, 2011). Itis also not sufficiently sophisticated to capture overall context and complex syntax scenarios (e.g., ironic language use). To combat these limitations and extract more precise indicators for Hate Speech, we plan to create a manually labelled dataset and employ other supervised learning models such as a support vector machine.

ACKNOWLEDGMENTS

We thank Prof. Anne Gilliland for supervising our research and providing generous help. We also thank Prof. Todd Presner, Prof. Ashvin Gandhi, and Dr. Heather Zinn-Brooks for their inspiring suggestions.

ENDNOTES

[1] By April 26, 2020, 2,810,325 confirmed cases and 193,825 deaths had been reported as shown by WHO COVID-19 dashboard at https://covid19.who.int/

[2] January 31, 2020 to April 7, 2020, approximately 40 days

[3] https://systems.jhu.edu/research/public-health/ncov/

[4] https://www.census.gov/programs-surveys/acs; https://www.census.gov/programs-surveys/saipe.html

[5] https://www.bls.gov/lau/data

[6] Twitter is a US-based social media platform, so the apparent bias is not surprising. Because most of the tweets in this archive are in English and most of the users are located in the U.S., we associate the number of tweets with the number of new cases in the U.S.

[7] https://hatebase.org/

[8] Examples of Hate Speech are presented in Appendix I Table A1

[9] Some unincorporated territories of the U.S. such as Guam and USVI are dropped due to insufficient sample size.

[10] Descriptive results for the state level dataset are presented in Appendix II Table A2

[11] For a set of items with J classes, where $p_i$is the fraction of items labeled with class $i$in the set, the Gini Impurity of the class is $I_G(p) = 1 - \sum_{i=1}^{J} p_i^2$. The decision tree algorithm chooses one feature that could minimize Gini Impurity and uses it as the decision criterion.

[12] *Fear*, *Anger*, and *Disgust* could be directed at haters as well as Hate Speech, and *Sad* indicates negative emotions which are related but not limited to hate. For the convince of the first and overall result, we aggregate them together, while distinguish them in later analyses.

[13] The Joy node only separates out a large amount of Non-Hate Speech (the left branch), and a significant amount of Non-Hate Speech remain unidentified.

[14] We normalize the number of Hate Speech tweets by dividing them into the population of each state/district.

[15] Here, $e_r = \frac{1}{2m}\sum_{i=1}^{n}\sum_{j=1}^{n} A_{ij}\delta_{g_i,r}\delta_{g_j,r}$ and $a_r = \frac{1}{2m}\sum_{i=1}^{n} k_i \delta_{g_i,r}$, where $m$stands for the number of edges, $r$stands for the number of groups, Astands for the adjacency matrix, δ_{ij}stands for the Kronecker delta, and k_i stands for the degree of node i; $g_i$stands for group i.

[16] Similar states pair stands for two states that share the same or similar feature. For example, both states are Democratic States; both states have high poverty rate.

[17] https://developer.twitter.com/en/docs/tweets/search/overview/s

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How to cite this article: Fan L, Yu H, Yin Z. Stigmatization in social media: Documenting and analyzing hate speech for COVID-19 on Twitter. *Proc Assoc Inf Sci Technol*. 2020;57:e313. https://doi.org/10.1002/pra2.313

APPENDIX I.

TABLE A1 Examples of Hate Speech on Twitter

Tweet ID	Date	Tweet
122348490476099****	2/1/2020	After SARS, Bird Flu, Swine flu and all that, how could something like coronavirus be allowed to spread for so long that the first person to get it is elusive? China do not f**k around, one c**t starts coughing the whole province is in masks in minutes.
123718116467216****	3/10/2020	What do we call this China Coronavirus then what it is and you Idiot's call us Racist I put it where it should belong at the feet of the China Government we did not get this from another Country it came from China now we are all in it's path so keep on being ignorant about this
123795213637523****	3/12/2020	If they diagnosed all these people with the coronavirus in China 2 months ago then why TF DID THEY EVEN LET THEM LEAVE CHINA, WHAT IDIOT LET THESE PEOPLE GO AROUND THE WORLD AND SPREAD IT
123815218206889****	3/12/2020	Well, yes, the novel coronavirus COVID 19 did, in fact, originate from Wuhan, China probably from filthy Commie Ch*nk s open air meat markets the Wuhan Virus is a foreign virus. Call it the ChineseVirus, perhaps. And, out of spite, Americans should boycott Chinese stuff.
123815202117115****	3/12/20	Down ~£5 k on my investments because some mad c**t eat a bat in China and started the coronavirus. Mad ting
124076900418213****	3/19/2020	Anyone who thinks China the pestilence nation is a leader in this is an idiot China covered this up for at least 2 months and let it fester. If anything they declared biological war on the planet. FoxNews
124255771854143****	3/24/2020	Anyone who believes Russia's numbers is an idiot. And I do not believe China's numbers either. Bullshit COVID19 coronavirus

Note: Hate Speech occurrences are marked red with parts masked for the sake of the scholarly audience; the last four digits of Tweet IDs are masked for privacy reasons.

APPENDIX II

TABLE A2 Descriptive Statistics of State Level Data

		Mean		95% CI Upper
State	Total Tweets (Key word containing)	13466.80	7995.17	18938.43
	Hate Speech Percentage	0.00594	0.00520	0.00653
Emotion	Anger Score	0.01905	0.01882	0.01929
	Anticipation Score	0.02252	0.02234	0.02269
	Disgust Score	0.01635	0.01611	0.01660
	Fear Score	0.02708	0.02670	0.02745
	Joy Score	0.00882	0.00872	0.00892
	Sad Score	0.02432	0.02393	0.02470
	Surprise Score	0.01710	0.01691	0.01729
	Trust Score	0.02763	0.02739	0.02786
	Positive Score	0.03213	0.03193	0.03232
	Negative Score	0.05219	0.05158	0.05280
Demographic	Asian Percentage	0.04195	0.02661	0.05729
	Unemployment Rate	0.03562	0.03318	0.03806
	Poverty Rate	0.12864	0.12085	0.13643
Political Party			Percentage	
	Democratic		0.38	
	Republican		0.62	

APPENDIX III: DAILY MOST FREQUENT HASHTAGS

Date	Top 1	Frequency1	Top 2	Frequency2	Top 3	Frequency3	Top 4	Frequency4	Top 5	Frequency5
1/31/20	wuhan	513	communist	379	hubei	256	breaking	241	cats	159
2/1/20	wuhan	1135	tfboys	896	xiaozhan	896	wangyibo	896	warning	390
2/2/20	wuhan	1072	tfboys	925	xiaozhan	925	wangyibo	925	taiwan	893
2/3/20	wuhan	1627	pandemic	623	wangyibo	593	hongkong	524	communist	367
2/4/20	latest	1962	wuhan	737	hongkong	477	infected	334	sars	171
2/5/20	latest	1254	wuhan	1118	breaking	245	chinese	226	virus	206
2/6/20	wuhan	1336	latest	1128	tencent	374	wuhanvirus	308	everydayhero	254
2/7/20	wuhan	1063	wuhanvirus	468	liwenliang	246	virus	239	latest	238
2/8/20	wuhan	676	taiwan	617	chinese	284	ccp	235	virus	161
2/9/20	wuhan	795	virus	230	flu	215	sars	197	vindman	156
2/10/20	wuhan	565	virus	227	sars	225	flu	208	vindman	199
2/11/20	wuhan	543	sars	233	virus	231	flu	205	vindman	198
2/12/20	wuhan	1020	hongkong	323	virus	222	sars	216	flu	201
2/13/20	wuhan	1199	hongkong	1147	hubei	645	virus	265	ccp	252
2/14/20	wuhan	1023	breaking	349	ccp	304	uyghur	222	eastturkistan	221
2/15/20	wuhan	368	sars	188	virus	173	flu	156	tiktok	156
2/16/20	taiwan	383	hongkongprotesters	327	wuhan	321	quarantine	258	新型コロナウイルス	255
2/17/20	who	85	wuhan	61	taiwan	39	sars	34	hongkongprotesters	32
3/3/20	iran	64	russia	63	trump	9	wuhan	6	chinese	6
3/4/20	iran	963	russia	780	italy	155	wuhan	134	censorship	104
3/5/20	wuhan	210	iran	182	ccp	151	wuhandiary	140	us	87
3/6/20	breaking	249	apple	126	uyghur	122	wuhan	98	update	84
3/7/20	iran	364	collapse	325	quanzhou	325	irgc	310	dogs	250
3/8/20	italy	456	iran	238	wuhan	179	uyghur	111	update	95
3/9/20	italy	187	wuhan	125	locusts	87	southkorea	79	uyghur	67
3/10/20	wuhanvirus	312	wuhan	259	chucktheschmuck	167	saudiarabia	163	ksrelief	159
3/11/20	italy	1484	chongqing	674	breaking	309	pandemic	266	chucktheschmuck	250
3/12/20	almightygod_kabir	660	italy	279	trump	273	iran	256	wuhanvirus	251
3/15/20	italy	435	iran	246	ccp	238	donaldtrump	226	trade	222
3/16/20	italy	364	ccp	238	wuhan	193	trade	188	iran	183
3/17/20	chinesevirus	1533	borisresign	446	us	428	uk	420	trump	402
3/18/20	chinesevirus	839	us	678	iran	652	hongkong	640	ccp	584
3/19/20	italy	2206	breaking	1912	ccp	762	russia	585	hongkong	458
3/20/20	italy	706	wuhan	544	hongkong	512	standwithhk	470	ccp	322
3/21/20	taiwan	1363	who	894	breaking	636	vaccine	619	newyork	604
3/22/20	italy	714	trump	615	who	518	wuhan	489	chinese	439
3/23/20	italy	943	iran	753	vaccine	323	india	272	trump	215
3/24/20	hantavirus	1056	italy	436	wuhan	402	who	315	usa	307
3/25/20	italy	714	wuhan	380	who	371	spain	333	hantavirus	290
3/26/20	italy	615	chinesevirus	521	usa	417	us	410	breaking	394
3/27/20	usa	1540	italy	1265	ccp	608	ccpvirus	573	hubei	543
3/28/20	ccpvirus	1122	wuhan	460	usa	429	chongqing	290	europe	279
3/29/20	ccpvirus	787	xijinping	532	usa	380	italy	332	wuhan	236
3/31/20	wuhan	1330	ccp	866	chian	480	us	473	shanghai	445
4/1/20	tiktok	1096	ccp	879	usa	735	s	360	wuhan	353
4/2/20	putin	2731	shenzhen	1341	gravitas	232	carefulpakistan	224	ccp	203
4/3/20	breaking	1435	trump	462	democrats	382	putin	328	shenzhen	321
4/4/20	ccp	597	wechat	517	wuhan	316	tiktok	266	taiwan	202
4/5/20	charleslieber	807	ccp	440	australia	290	liberal	271	labor	271
4/6/20	ppe	460	wuhan	255	chinese	222	charleslieber	111	ccp	78
4/7/20	ppe	419	usa	233	chinese	84	sars	51	uk	48

FIGURE A1 Top five hashtags per day and their numbers of occurrences

APPENDIX IV: DECISION TREE CLASSIFIER FOR DISTINGUISHING HATE SPEECH

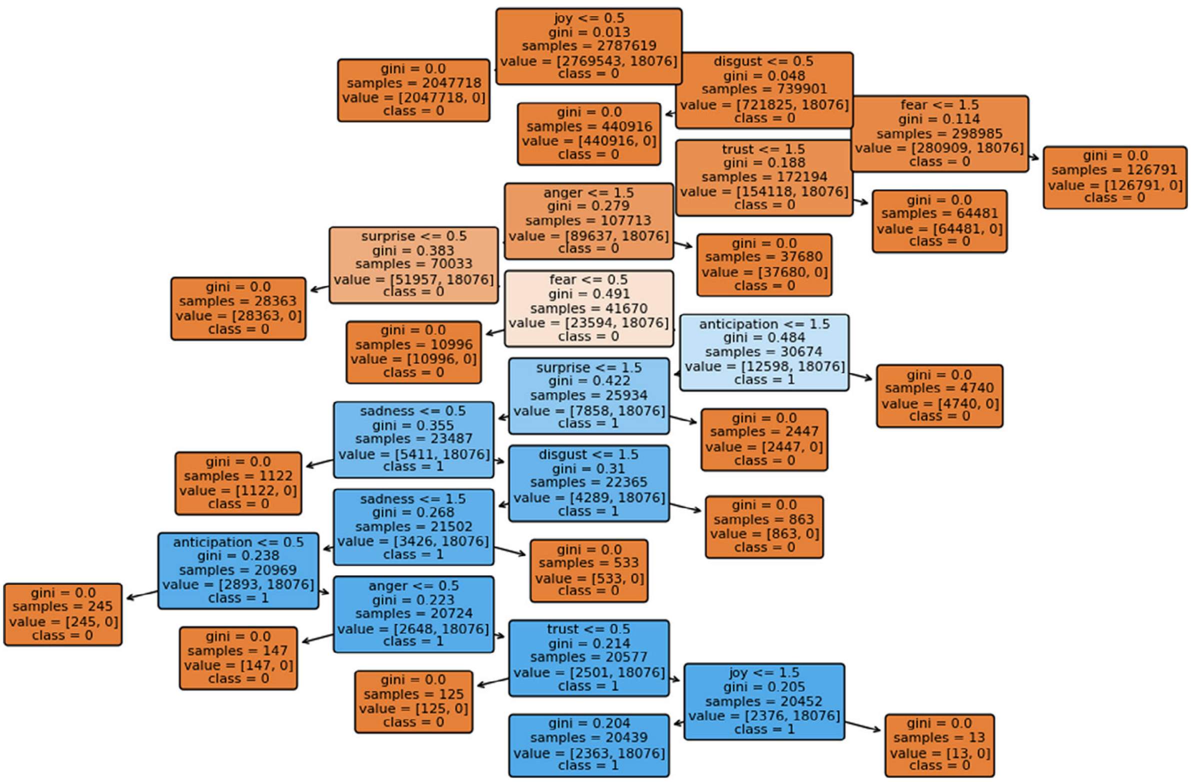

FIGURE A2 Decision Tree Classifier generated by classifying Hate Speech using training data