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Racism is a Virus: Anti-Asian Hate and Counterspeech in Social Media during the COVID-19 Crisis

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***Abstract*—The spread of COVID-19 has sparked racism and hate on social media targeted towards Asian communities. However, little is known about how racial hate spreads during a pandemic and the role of counterspeech in mitigating this spread. In this work, we study the evolution and spread of anti-Asian hate speech through the lens of Twitter. We create COVID-HATE, the largest dataset of anti-Asian hate and counterspeech spanning 14 months, containing over 206 million tweets, and a social network with over 127 million nodes. By creating a novel hand-labeled dataset of 3,355 tweets, we train a text classifier to identify hateful and counterspeech tweets that achieves an average macro-F1 score of 0.832. Using this dataset, we conduct longitudinal analysis of tweets and users. Analysis of the social network reveals that hateful and counterspeech users interact and engage extensively with one another, instead of living in isolated polarized communities. We find that nodes were highly likely to become hateful after being exposed to hateful content in the year 2020. Notably, counterspeech messages discourage users from turning hateful, potentially suggesting a solution to curb hate on web and social media platforms. Data and code is available at http://claws.cc.gatech.edu/covid.**

I. Introduction

Hateful incidents throughout the world, such as acts of microaggression, physical and verbal abuse, and online harassment have increased during the COVID-19 pandemic [1]. Following the identified origin of COVID-19 in China, racially motivated hate crime incidents have increasingly targeted the Chinese and the broader Asian communities, resulting in over 6,603 racially-motivated hateful incidents in a year [2].

While there is mounting evidence of offline discriminatory acts and racism during COVID-19, the extent of such overtly hateful content on the web and social media is not widely known. Online hate speech has severe negative impact on the victims [3] and can lead to real-world crimes [4]. Meanwhile, while efforts to educate about, curb, and counter hate have been made via social media campaigns (e.g. the #RacismIsAVirus campaign), the success, effectiveness, and reach of counterspeech messages remain unclear. Thus, it is crucial to detect online hate speech to curb both online and physical harm, and monitor counterspeech messages to quantify their effectiveness, and inform future strategies to counter hate.

Recent research has been conducted on COVID-19-related hate online posts against Asians [5]–[10]. Building on these concurrent research works, we contribute several novel aspects to the understanding of this phenomenon. First, we conduct a long-term longitudinal study of the hate and counterspeech ecosystem on Twitter to monitor the changes in social perception and stance towards the Asian community as the pandemic progressed. Second, we study the combined ecosystem of hate and counterspeech messages on Twitter, as opposed to studying them in isolation. This is important because both coexist on the platform and influence each other simultaneously. Studying only one type of message (hate or counterspeech) is unable to uncover the influence they have on each other.

Our contributions. In this paper, we present COVID-HATE, the largest dataset of anti-Asian hate and counterspeech on Twitter in the context of the COVID-19 pandemic, along with a 14 month-long longitudinal analysis of the Twittersphere. We make the following key contributions:

- We create a dataset of COVID-19-related tweets, containing over 206 million tweets made between January 15, 2020 and March 26, 2021, and the social network of users, having over 127 million nodes and 910 million edges. The data and code is available at http://claws.cc.gatech.edu/covid.
- We hand-annotate 3,355 tweets based on their hatefulness towards Asians as hate, counterspeech, or neutral tweets to build highly accurate text classifier to identify hate and counterspeech tweets, finally identifying 1,227,116 hate and 1,154,289 counterspeech tweets.
- We conduct statistical, linguistic, and network analysis of tweets and users to reveal characteristic patterns of hate and counterspeech, and find counterspeech tweets lower the probability of neighboring nodes becoming hateful.

II. COVID-HATE: An Anti-Asian Hate and Counterspeech Dataset during COVID-19

We describe the COVID-HATE dataset. Table I shows the data statistics.

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Property	Statistic
Duration	Jan 15, 2020–Mar 26, 2021
Number of tweets	206,348,565
Number of (frac.) hate tweets	1,337,116 (0.64%)
Number of (frac.) counterspeech tweets	1,154,289 (0.55%)
Number of (frac.) neutral tweets	203,857,160 (98.81%)
Number of users	23,895,911
Number of (frac.) hate users	697,098 (2.91%)
Number of (frac.) counterspeech users	629,029 (2.63%)
Number of (frac.) neutral users	22,477,616 (94.06%)
Number of nodes in the social network	127,831,666
Number of edges in the social network	910,630,334

TABLE I: Statistics of `COVID-HATE` dataset, containing anti-Asian hate and counterspeech tweets and social network in the context of COVID-19.

Category	Keywords
COVID-19	coronavirus, covid 19, covid-19, covid19, corona virus
Hate keywords	#CCPVirus, #ChinaDidThis, #ChinaLiedPeopleDied, #ChinaVirus, #ChineseVirus, chinese virus, #ChineseBioterrorism, #FuckChina, #KungFlu, #MakeChinaPay, #wuhanflu, #wuhanvirus, wuhan virus, chink, chinky, chonky, churka, cina, cokin, communistvirus, coolie, dink, niakoué, pastel de flango, slant, slant eye, slopehead, ting tong, yokel
Counterspeech keywords	#IAmNotAVirus, #WashTheHate, #RacismIsAVirus, #IAmNotCovid19, #BeCool2Asians, #StopAAPIHate, #ActToChange, #HateIsAVirus

TABLE II: The list of keywords and hashtags used for comprehensive data collection.

A. Tweet Dataset

We adopted a keyword-based approach to collect relevant COVID-19 tweets through Twitter's official APIs. Specifically, we used a collection of keywords and hashtags belonging to three sets: (a) `covid-19 keywords` are terms referring to COVID-19 which are used to collect tweets related to the pandemic, (b) `hate keywords` are keywords and hashtags indicating anti-Asian hate amidst COVID-19. To compile this list, we first took the hate keywords from existing papers and news articles [11]. We then expanded this list by including co-occurring hate hashtags observed in an initial tweet crawl. We also included Asian slurs listed in Hatebase[1]. Finally, (c) `counterspeech keywords` are keywords and hashtags that were used to organize efforts to counter hate speech and support Asians. These keywords were listed in news articles covering counterspeech efforts during the initial phases of the data collection setup [12]. In total, we used 42 keywords as shown in Table II. After getting the keywords, we utilized Twitter's Streaming API to collect real-time tweets (from March 28, 2020) and Twitter's Search API (for data between January 15, 2020 to March 27, 2020). Finally, we collected 206,348,565 English-language tweets made by 23,895,911 users between January 15, 2020 and March 26, 2021, which do not contain retweets.

Twitter Network Construction: In addition to the tweets, we crawled the ego-network (i.e., the followers and followees) of a randomly-sampled subset of 489,011 users who made at least one COVID-19 tweet by Twitter's GET API, as shown in Table I.

[1]https://hatebase.org/

B. Annotating Anti-Asian COVID-19 Hate and Counterspeech

Since keyword-based selection can be inaccurate, to accurately categorize tweets, we developed a rigorous annotation process to hand-label a subset of tweets and create a textual classifier to label the rest. We labeled the tweets into the following three broad categories, as we define below.

Compared to the concurrent work by Vidgen et al. [5], which only contains 116 counterspeech tweets, we aim to create a more balanced labeled dataset.

Anti-Asian COVID-19 Hate Tweets: We build on previous studies of racial hate literature that showed that hate speech casts targets as "legitimate objects of hostility" and "others", i.e., isolates the target group [13]–[17]. Building on this, we define anti-Asian COVID-19 hate as antagonistic speech that is directed towards an Asian entity (individual person, organization, or country), and *others* the Asian outgroup through intentional opposition or hostility in the context of COVID-19. We distinguish hate from criticism and do not consider the motivation or reason behind hate speech (e.g., a conspiracy theory) while labeling hate. One overt example of anti-Asian hate we considered is (censorship ours):

> *F*ck Chinese scums of the Earth disgusting pieces of sh*t learn how to not kill off your whole population of pigs, chickens, and humans. coronavirus #wuhanflu #ccp #africaswine #pigs #chickenflu nasty nasty China clean your f*****g country.*

COVID-19 Counterspeech Tweets: This category of tweets either: (a) explicitly identify, call out, criticize, condemn, challenge, or oppose racism, hate, or violence towards an Asian entity or (b) explicitly support, express solidarity towards, or defend an Asian entity. These tweets can either be direct replies to hateful tweets or be stand-alone tweets, but they must be explicit. Implicit counterspeech is not considered here. An example of a tweet in this category is as follows:

> *The virus did inherently come from China but you can't just call it the Chinese virus because that's racist. or KungFlu because 1. It's not a f*****g flu it is a Coronavirus which is a type of virus. And 2. That's also racist.*

Neutral and Irrelevant Tweets: These tweets neither explicitly nor implicitly convey hate, nor counterspeech, but are related to COVID-19. Tweets in this category also include news, advertisements, or outright spam. One example of a tweet in this category is:

> *COVID-19: #WhiteHouse Asks Congress For $2.5 Bn To Fight #Coronavirus: Reports #worldpowers #climatesecurity #disobedientdss #senate #politics #news #unsc #breaking #breakingnews #wuhan #wuhanvirus https://t.co/XipNDc*

Annotation process: We trained two undergraduate annotators to recognize anti-Asian COVID-19 hate tweets, COVID-19 counterspeech tweets, and neutral/irrelevant tweets using the above definitions. Both annotators are of Asian descent (one Chinese and one Indian). One co-author supervised the annotation process. After practicing on a set of 100 tweets and discussing disagreements with the supervising co-author, the

Feature set	Precision	Recall	F1 score
Anti-Asian hate tweet detection			
Linguistic	0.541	0.233	0.323
Hashtag	0.100	0.002	0.005
BERT	0.765	0.760	0.762
Counterspeech tweet detection			
Linguistic	0.483	0.189	0.267
Hashtag	0.800	0.029	0.056
BERT	0.839	0.868	0.853
Neutral tweet detection			
Linguistic	0.632	0.891	0.739
Hashtag	0.591	0.999	0.743
BERT	0.886	0.874	0.880

TABLE III: Tweet classification performance of different feature sets with a neural network classifier. The BERT model has the best classification performance in all three tasks.

annotators each independently labeled the same set of 3,255 tweets, which were randomly sampled from the collected dataset. Since the majority of tweets were expected to be neutral, we over-sampled tweets that contained anti-Asian hate, and counterspeech terms. This ensured our labeling process yielded sufficient hate and counterspeech tweets to train a classifier. The annotation process took six weeks.

The two annotators agreed on 68% of the data, with Cohen's Kappa score of 0.448 for hate and 0.590 for counterspeech, indicating a moderate inter-rater agreement that is typical of hate speech annotation [5], [18]. We removed the tweets where the two annotators disagreed and were left with 429 hate, 517 counterspeech, and 1,344 neutral tweets. The annotators also identified 110 tweets containing hatefulness or aggression towards non-Asian groups, which we drop too.

C. Anti-Asian Hate and Counterspeech Text Classifier

We use the annotated tweets to train a text-based machine learning classifier to categorize tweets using the following features: (1) **Linguistic Features.** This set contains a total of 90 features including stylistic, metadata, and psycholinguistic patterns [14]; (2) **Hashtag features.** These features represent the number of occurrences of each hashtag and keyword listed in Table II; (3) **Bert Tweet Embeddings.** To incorporate word and sentence-level semantics, we embed each tweet using the BERT base uncased text embedding model, with fine-tuning, and use a feed-forward layer for classification [19].

Model training. Similar to the BERT classifier, one-layer feed-forward neural network classifiers are trained using linguistic features and hashtag features. We conducted five-fold cross validation and reported the performance in Table III, finding BERT has the superior performance. Thus, we use the BERT model to label the rest of the tweets, resulting in 1.337M hate and 1.154M counterspeech tweets, which are used for downstream analysis.

III. Longitudinal Characterization of COVID-19 Hate and Counterspeech

To characterize the temporal changes in trends, we compare the statistics from the year 2020 (from January 15, 2020 to December 31, 2020) and the year 2021 (from January 1, 2021 to March 26, 2021).

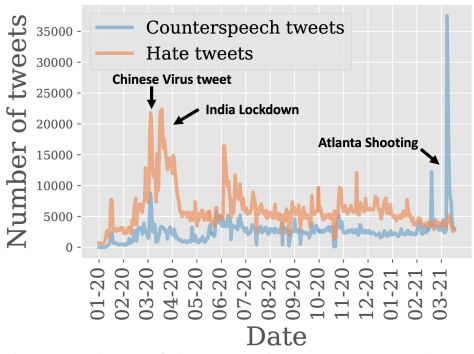


Fig. 1: The number of hate and counterspeech tweets from January 15, 2020–March 26, 2021.

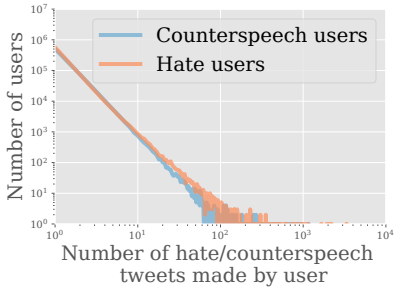


Fig. 2: Distribution of the number of hate and counterspeech tweets made by users shows a long tail pattern.

A. The Ebb and Flow of Hate and Counterspeech

Here, we analyze the spread pattern of hate and counterspeech, as shown in Figure 1. In 2020, the number of hate and counterspeech tweets was negligible-to-low during the early phases of the pandemic in January, 2020 and February, 2020. Later, the number increases and hate tweets outnumber counterspeech tweets throughout the timeline during 2020. Furthermore, we observe the spike in hate speech between March 16, 2020 and March 19, 2020. However, after the Atlanta Spa shooting on March 16, 2021 [20], there was a dramatic increase in the number of counterspeech tweets in March, 2021. Counterspeech tweets increased within one week, while we observed that hateful tweets also surprisingly rose. The spike in counterspeech signals the Twittersphere expressing sympathy and solidarity towards the Asian community.

B. User Activity and Interaction Behavior

We analyze the properties of the users who produce hate and counterspeech tweets. Following the tweet categorization labels, we categorize users, based on their tweets, into one of the following: *hate*, *counterspeech*, *dual*, or *neutral*. Hate users make at least one hate tweet but no counterspeech tweets. Similarly, counterspeech users make at least one counterspeech tweet but no hate tweet. Users who tweet from both categories are categorized as dual users. Finally, users who make at least one COVID-19 tweet (and thus, are part of our dataset), but no hate or counterspeech tweets, are labeled as neutral. Among

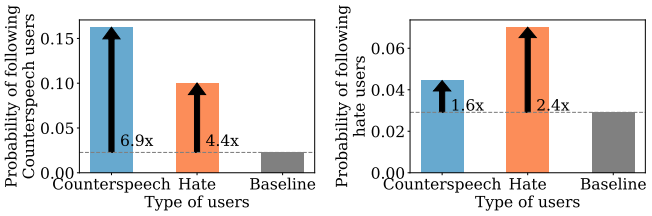


Fig. 3: Social network of hate and counterspeech users: Hate and counterspeech users are highly interconnected and exhibit homophily.

the 23,895,911 users in the dataset, most of the users (94.06%) are neutral, 697,098 (2.92%) are hateful, 629,029 (2.63%) are counterspeech users, and a very small fraction of users (0.39%) are dual. This distribution mimics the category-wise tweet distribution. Our following analysis focuses on hate, counterspeech, and neutral user categories. Due to low volume, we do not emphasize on the dual users here.

Figure 2 shows the distribution of the number of hate tweets (counterspeech tweets) made by hate users (counterspeech users). We observe both distributions exhibit a long tail, showing most users make few relevant tweets and only a handful of users are responsible for spreading most of the hate propaganda and counterspeech messages.

C. Social Network Connectivity Structure

We examine the user-user social connectivity in the hate and counterspeech ecosystem. As described previously, we crawled the social network containing over 127 million nodes and 910 million edges. Out of these, 1,380,613 nodes have made at least one COVID-19-related tweet. The rest of the nodes are part of the network as they are neighbors of these nodes.

To understand the differences in how hateful and counterspeech users behave, we compare their ego-networks. We find that on average, counterspeech users are better connected than hate users—counterspeech users follow more users compared to hate users (1201.84 vs. 828.40; $p < 0.001$) and are followed more by other users (1249.42 vs. 759.96; $p < 0.001$).

Intragroup and intergroup connectivity. We analyze the connectivity of users within and across the different groups to establish if nodes express homophily or form echo chambers. Simply comparing their probability of creating edges to nodes of a certain group is not sufficient as it is confounded by the node degrees and node distribution across categories. Thus, we create a network baseline preserving the node property to model the expected behavior of nodes and compare against this baseline [21]. The baseline networks are created by randomly shuffling the edges, while keeping the set of nodes the same. The node degrees and number of COVID-19 neighbors are preserved. Aggregate ego-network statistics are computed across 100 runs.

We compare the observed and the baseline behavior using the probability of connecting to hate, counterspeech, and neutral nodes. Figure 3 presents the results.

Nodes exhibit homophily. First, we examine the propensity for hate and counterspeech nodes to connect with nodes within their own group. In Figure 3 (left), we show that counterspeech users are 6.92× more likely to connect to other counterspeech users compared to the baseline behavior. Similarly, the right figure shows that hateful users connect with other hateful users 2.42× more than expectation. Thus, nodes are preferentially connected to other nodes in the same group.

Do hateful and counterspeech users form polarized communities? Figure 3 illustrates the empirically-observed network behavior. Both hate and counterspeech nodes are more likely to connect with one another than expected. Precisely, hateful users follow counterspeech users 4.45× more than expected (left figure) and counterspeech users are 1.62× more likely to follow hateful users compared to the baseline (right figure). These indicate that hateful and counterspeech users are highly engaged and closely interact with each other.

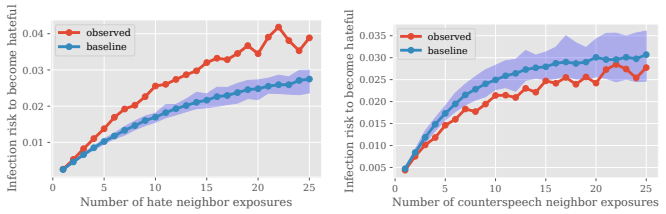
IV. Influence of Counterspeech on the Spread of Hate

Here we quantify influence as the likelihood of a user to become hateful (i.e., writing an anti-Asian hate tweet for the first time) after a user is exposed to any number of hate or counterspeech tweets from his or her neighbors. Similarly, we also explore the effect of neighborhood messages on a node's likelihood to start writing counterspeech tweets for the first time. We refer to a user's change of state from the neutral state to hate/counterspeech state after observing neighbors' messages as an *infection*. We model the dynamics of hate/counterspeech infection as an event cascade. The cascade is a temporally-ordered sequence of events of the nodes that transition from neutral to hate or counterspeech states. Each cascade is associated with a function $Risk_{s\to s'}(n)$ that quantifies the probability that a user transitions from neutral to category $s' \in \{hate, counterspeech\}$ after n neighbors have become part of category $s \in \{hate, counterspeech\}$. Neighbors are obtained from the social network. The infection risk function is calculated as:

$$Risk_{s\to s'}(n) = \frac{|Infected_{s'} \cap Exposed_s(n)|}{|Exposed_s(n)|} \quad (1)$$

where $Infected_{s'}$ is the set of users already infected with type s' and $Exposed_s(n)$ is the set of users with at least n neighbors of type s.

The infection risk in a network is conflated not only by users' influence on one another, but also by homophily—the tendency of similar users to cluster in the network. We have already shown in the previous sections that hate and counterspeech users exhibit homophily. To tease out the effect of influence from homophily, we create a null model that measures the baseline risk of infection solely due to homophily, without any user-to-user influence. We follow the technique by [22] for this analysis. We randomly shuffle the order of cascade events and calculate the infection risk in the random cascade. The social network remains fixed. We compare the mean baseline infection risk observed across 100 shuffled cascades to the empirically observed infection risk. If the empirical infection risk exceeds the baseline risk, then social contagion is



(a) Hate → hate (b) Counterspeech → hate

Fig. 4: The impact of hate speech and counterspeech on the spread of hate

responsible for the spread of infection (hate or counterspeech). On the other hand, if the empirical infection risk is lower than the baseline risk, then social contagion inhibits the spread of infection. The results are shown in Figure 4.

Figure 4(a) shows that exposure to hate speech increased the likelihood of adopting hate speech, compared to the baseline. Moreover, the likelihood of hate adoption increased with the number of exposures. It indicates that when people see more hate speech tweets, chances are high that they will be hateful and tweet some hate speech messages. On the other hand, the effect of counterspeech on hate speech contagion is crucial to investigate as it can shed light on potential counter-measures. Counterspeech significantly deterred the spread of hate speech compared to the baseline, as shown in Figure 4(b). It shows low social inhibition effect, indicating that when exposed to counterspeech messages, people will be influenced and possibly send less hate speech tweets.

V. Related Work

Due to the long-lasting societal effect of COVID-19 pandemic and infodemic [1], [3], [10], some researchers studied hate speech [6], [8], [14] and analyzed its spread pattern in the context of COVID-19 [7], [9]. But, counterspeech is ignored in those research, which is the gap we address in this paper. Moreover, counterspeech messaging is qualitatively shown to be one effective to curb hate speech [23]. But those works are quite generic and not placed in a pandemic, e.g., the COVID-19 pandemic. Additionally, contemporaneous work by [5] released a large hand-labeled dataset of hatespeech and counterspeech tweets. However, they do not conduct any analysis of the hate and counterspeech Twittersphere, which we present in this work, in addition to creating a complementary hand-labeled dataset.

VI. Conclusions

Our findings shed light on societal problems caused by the COVID-19 pandemic. Notably, we observe that counterspeech reduced the probability of neighbors becoming hateful. It paves the way towards the use of public counterspeech messaging campaigns as a potential solution against hate speech.

Acknowledgements

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