Extracting COVID-19 Events from Twitter

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Abstract

We present a corpus of 7,500 tweets annotated with COVID-19 events, including positive test results, denied access to testing, and more. We show that our corpus enables automatic identification of COVID-19 events mentioned in Twitter with text spans that fill a set of pre-defined slots for each event. We also present analyses on the self-reporting cases and user's demographic information. We will make our annotated corpus and extraction tools available for the research community to use upon publication at https:

//github.com/viczong/extract_
COVID19_events_from_Twitter.

1 Introduction

In December 2019, a novel coronavirus, SARS-CoV-2, emerged and began rapidly spreading around the world. In early 2020, many countries initiated social distancing measures and lockdowns to help slow the spread of the virus which has infected 5.5 million people and led to 347,864 deaths as of 2020/05/26. Because COVID-19 is a novel infectious disease, much is unknown about when and where it is safe to resume various activities. Official data on COVID-19, from agencies such as the World Health Organization (WHO) or Centers for Disease Control and Prevention (CDC) present aggregated views, such as the number of cases per city or county. However, these datasets do not capture statistics about more specific events that might be of interest, for instance people who were refused access to testing. On the other hand, people share a wide variety of information related to COVID-19 publicly on social media. For example, Twitter users often indicate when they might be at increased risk of COVID-19 due to a coworker or



Figure 1: Example tweet reporting a CAN-NOT-TEST event.

other close contact testing positive for the virus, or when they have symptoms but were denied access to testing. Moreover, news reports on public figures who are tested positive are also widely circulated on social media, such as British PM Boris Johnson and U.S. Senator Amy Klobuchar's husband.

In this paper, we show that it is possible to automatically extract structured knowledge on events related to COVID-19 from Twitter. We annotate a corpus of tweets describing positive/negative tests, denied access to testing, deaths due to COVID-19, etc. For each tweet that mentions one or more such events, we further annotate text spans within the tweet to fill a set of pre-defined slots that answer important questions (e.g., *Who tested positive? Where did they recently travel? Who is their employer?*)

There are a number of important factors to consider when using COVID-related information from Twitter. Facts should be independently verified before they are assumed to be true. However, we believe that event extraction may be useful for epidemiologists, journalists or policymakers, helping them find relevant pieces of information. Furthermore, our tools could enable new kinds of aggregate data analysis, which could prove useful so long as consumers of this information clearly understand its limitations. We will make our data available to the research community. To protect users' privacy we will only distribute IDs of the tweets in our dataset.

Inttps://www.nytimes.com/interactive/
2020/world/coronavirus-maps.html

2 COVID-19 Twitter Event Corpus

To extract structured knowledge from tweets about COVID-19, we formulate the problem as a slot filling task: given a tweet, first identify whether it corresponds to a relevant event, then find relevant text spans corresponding to a pre-defined list of slots associated with the event type (Benson et al., 2011). As an example, consider the tweet that reports a CAN-NOT-TEST event in Figure 1. In this case, the model should fill the LOCATION slot with "Houston" and also identify that the author of the tweet is currently experiencing COVID-19 symptoms. Table 1 shows the overall statistics of our corpus.

Data Collection. We consider five event types related to COVID-19: TESTED-POSITIVE, TESTED-NEGATIVE, CAN-NOT-TEST, DEATH, CURE & PRE-VENTION.² The first four events aim to extract structured reports of coronavirus related events, many of which are self-reported cases or come from news stories about public figures who have been exposed to the virus. As there is no widely accepted antiviral treatment or vaccine for COVID-19 as of 2020/06/01, we also dedicate one event type for CURE & PREVENTION to study how some potentially misleading information are perceived by public.

Event Type	# of Annotated Tweets	# of Slots
TESTED POSITIVE	2,500	9
TESTED NEGATIVE	1,200	8
CAN NOT TEST	1,200	5
DEATH	1,300	6
CURE & PREVENTION	1,300	3
TOTAL	7,500	31

Table 1: Statistics of COVID-19 Twitter Event Corpus.

We have been continuously collecting our data since 2020/1/15 by tracking keywords using the Twitter API.³ For example, "tested positive" is used as one of the keywords for TESTED-POSITIVE events. We have annotated 7,500 tweets sampled from 2020/01/15 and 2020/04/26. For duplicate tweets, we only keep the earliest post. We also use Jaccard similarity with a threshold of 0.7 to remove near-identical tweets that are posted same-day.

2.1 Annotation Process

We use crowd workers on Amazon Mechanical Turk to annotate our dataset. We provide annotation interface in Appendix B. Each tweet is annotated by 7 workers in two steps:

- 1. **Specific Events.** Some tweets are generic news reports, however, we are more interested in capturing tweets with fine-grained information, especially the self-reporting cases. Therefore, we first ask the annotators to decide whether a tweet is regarding an individual or a group of people.⁴ Annotators proceed to the next step only if they answer yes to this question.
- 2. Slot Filling. In this second step, we ask questions to collect factual information and user's opinions for filling our designated slots (Table 2). We provide the annotators with a list of candidate answers, which include all noun chunks and name entities extracted by a Twitter tagging tool (Ritter et al., 2011). We also combine noun chunks if they are adjacent or separated by a preposition phrase.⁵ We include "author of the tweet" as an additional option for who questions and "near author of tweet" for where questions. For each tweet, annotators have an average of 10 to 11 possible answers to choose from, and are allowed to choose more than one answers for WH-questions. We also collect Wikipedia links for public figures involved in the events.

Inter-annotator Agreement. During annotation, we track crowd workers' performances by comparing their annotations with the majority votes and remove workers whose F1 scores fall below 0.65. In addition, we independently annotated 100 tweets (20 tweets for each event) and compared them with the majority votes of crowdsourcing workers. We observe an average of 0.76 Cohen's Kappa (Artstein and Poesio, 2008) for specific-event questions and an average F1 score of 0.74 for slot-filling.

3 Automatic Event Extraction

We develop models to automatically extract structured information as slot-filling tasks for COVID-19 related events (Table 2). We set up each slot filling task \mathbb{T} as a binary classification problem:

²We are actively expanding the list to include more event types, such as WAITING-FOR-THE-TEST-RESULTS, HOSPI-TALIZATION, ICU, RECOVERY, and REOPENING.

³We list all keywords for data collection in Appendix A.

⁴For CURE & PREVENTION, we ask annotators if the tweet describes a cure or prevention for COVID-19.

⁵We notice in some cases our provided chunks are not perfect and may include some extra words. We provide explicit guidelines for annotators stating that an option should only be chosen when it contains no more than two extra words.

Event Type	Slot Abbr.	Slot Filling Questions
TESTED POSITIVE TESTED NEGATIVE	who c. contact relation employer recent v. when / where age / gender duration	Who is tested positive (negative)? Who is in close contact with the person tested positive (negative)? Does the infected person have a relationship with the author of the tweet? Who is the employer of the people tested positive? Where did the people tested positive recently visit? {When, Where} is tested positive (negative) cases reported? What is the {age, gender} of the people tested positive (negative)? How long does it take to get to know the test results?
CAN NOT TEST	who relation when / where symptoms	Who can not get a test? Does the untested person have a relationship with the author of the tweet? {When, Where} is can't-be-tested situation reported? Is the untested person currently experiencing any COVID-19 related symptoms?
DEATH	who relation when / where age symptoms	Who is dead for coronavirus? Does the deceased person have a relationship with the author of the tweet? {When, Where} is the dead case reported? What is the age of the people who is dead of COVID-19? Did the person who was dead experience COVID-19 related symptoms?
CURE & PREVENTION	opinion what who	Does the author of tweet believe the cure method is effective? What is the cure for coronavirus mentioned by the author of the tweet? Who is promoting the cure for coronavirus?

Table 2: Slot filling questions used for annotation.

given the tweet t and the candidate slot s, the classification model $f(t,s) \to \{0,1\}$ predicts whether s answers its designated question. To keep the evaluation consistent for all $\mathbb{T}s$, we convert the nonbinary slot "gender" (with labels M, F, NA) into two independent binary classification tasks.

3.1 Models and Baseline

LR model. We use a logistic regression classifier as a baseline, using n-gram (n = 1, 2, 3) features. We replace the slot s in the tweet t with a special token <TARGET> before computing the n-grams.

BERT model. We fine-tune a BERT (Devlin et al., 2019) based classifier that takes a tweet t as input and encloses the candidate slot s, within the tweet, inside special entity start <E> and end </E> markers. The BERT hidden representation of token <E> is then processed through a fully connected layer with softmax activation to make the binary prediction for a task \mathbb{T} (Baldini Soares et al., 2019). By design, many slots within an event are semantically related to each other. For example, "gender" slot is directly related to the "who" slot. To leverage this, we jointly train the final softmax layers of all the Ts in an event by sharing their BERT model parameters. We use $BERT_{base}$ cased model and HuggingFace PyTorch implementation (Wolf et al., 2019). All the shared BERT models are fine-tuned

with 2×10^{-5} learning rate using Adam (Kingma and Ba, 2015) algorithm for 8 epochs. This model has $\approx 110M$ parameters.

3.2 Evaluation

For all the slots and events, the gold labels are assigned based on the annotators' majority votes. We use a 60/15/25 ratio for train/dev/test. The best threshold for each \mathbb{T} is found by grid search on dev data. We report the model performance by precision (P), recall (R) and F1 score in Table 3. The BERT-based classifier significantly outperforms logistic regression on all the slot filling tasks. By exploiting the shared BERT representations across the slots of the same event, the BERT model is able to get reasonably good F1 scores, even on slots that have a limited amount of labeled training data.

4 Additional Analysis

Our annotations can be potentially used for other analytical purposes besides event slot filling.

Tracking Self-reporting Cases. One feature of our dataset is that it enables tracking of self-reporting cases. We consider tweets with "who"

⁶Candidate thresholds for grid-search $\in \{0.1, 0.2, ..., 0.9\}$

⁷We excluded several slots that have too few annotations, such as "duration" for TESTED NEGATIVE events and "when" for CAN NOT TEST, from the evaluation.

TESTED POS	SITIVE	LR		BERT			
slot	#	P	R	F1	P	R	F1
who	450	.51	.48	.49	.76	.74	.75
c. contact	33	0.0	0.0	0.0	.33	.42	.37
relation	11	0.0	0.0	0.0	.60	.55	.57
employer	61	.32	.15	.20	.40	.39	.40
recent v.	27	0.0	0.0	0.0	.50	.37	.43
age	15	0.0	0.0	0.0	.56	.93	.70
where	133	.27	.20	.23	.51	.59	.55
gender m.	124	.31	.29	.30	.73	.60	.65
gender f.	45	0.0	0.0	0.0	.71	.64	.67
when	14	0.0	0.0	0.0	.28	.69	.40
TESTED NEC	GATIVE		LR			BERT	1
slot	#	P	R	F1	P	R	F1
who	134	.33	.33	.33	.49	.61	.55
relation	26	.08	.04	.05	.63	.46	.53
where	18	1.0	.06	.11	.33	.17	.22
gender m.	47	.31	.32	.32	.58	.70	.63
gender f.	22	.12	.05	.07	.55	.55	.55
CAN NOT	TEST	LR		BERT			
slot	#	P	R	F1	P	R	F1
who	110	.19	.22	.20	.49	.31	.38
relation	39	.62	.13	.21	.60	.62	.61
where	23	.12	.04	.06	.54	.61	.57
symptoms	36	.29	.06	.09	.62	.44	.52
DEATH	I		LR			BERT	
slot	#	P	R	F1	P	R	F1
who	141	.31	.38	.34	.65	.60	.62
relation	29	0.0	0.0	0.0	.57	.43	.49
when	32	0.0	0.0	0.0	.58	.47	.52
where	51	.31	.10	.15	.52	.60	.56
age	31	.50	.03	.06	.68	.90	.78
CURE & P	REV.		LR			BERT	1
slot	#	P	R	F1	P	R	F1
opinion	73	.28	.15	.20	.37	.53	.44
what	136	.47	.24	.32	.59	.61	.60
who	65	.25	.02	.03	.30	.48	.37
micro avg	. F1		.30			.59	
(dev) micro a	wg. F1		.31			.61	

Table 3: Slot-filling task test evaluations for logistic regression (LR) and BERT-based classifiers. P, R and F1 are the precision, recall and F1 score. # is the count of gold annotations in the test data for each slot type. The last two rows reports the test and dev micro-average F1 score of classifiers for all 27 slot types combined.

slot annotated with "I", "we" or "author of the tweet" as self-reporting cases. Table 4 presents the number of such cases for each event. We note a much higher percentage of users tends to report their CAN NOT TEST situations online. We can also automatically detect self-reported cases by training a binary classifier using our annotated corpus. A simple logistic regression with bigram and unigram features can achieve a 0.64 F1 score based on

5-fold cross validation on CAN-NOT-TEST data.

Event Type	Specific Events	Self-report
TESTED POSITIVE	1,798 (71.9%)	29 (1.2%)
TESTED NEGATIVE	632 (52.7%)	113 (9.4%)
CAN NOT TEST	540 (45.0%)	207 (17.3%)
DEATH	495 (38.1%)	1 (0.1%)
CURE & PREVENTION	573 (44.1%)	/
TOTAL	4,038	350

Table 4: Number and percentage of tweets on specific events and self-reporting cases in our corpus.

Demographics of Users. Based on the public profiles of the 348 unique users who posted these 350 self-reporting tweets, we observe the following interesting trends: (1) The gender of self-reported users is roughly evenly split (female 55.7% versus male 44.3% for 271 users with gender information). (2) The top two categories for race are white (171 users) and black (34 users), excluding 92 users that we are not able to identify race. (3) Among 153 users whose political inclinations can be identified, 143 are democrats. (4) 55.6% of the 223 users who are reporting their ages are from age group 25-50. (5) 69.0% of the 348 users who self-reported information related to COVID-19 also disclose their geolocation information on Twitter. 74.2% of these users are located in the United States and 10.8% in European countries.

Bots and Organization Accounts. Within 7,326 unique users in our corpus, 2.4% are potentially bots, as identified by the Botometer API (Varol et al., 2017). We also note 4.1% of tweets about CURE & PREVENTION are potentially posted by bots. 8 18.5% of user accounts belong to organizations, according to the Humanizr (McCorriston et al., 2015).

Perceived Cures and Treatments. There are 219 different descriptions of cure or prevention methods for COVID-19 in our corpus, including widely discussed ones "toilet paper" and "alcohol". The top 5 cure or prevention methods that Twitter users believe effective are "social distancing", "vitamin c", "hydroxychloroquine", "chloroquine" and "bathroom hygiene".

5 Conclusions

In this paper, we present an annotated corpus of 7,500 tweets for COVID-19 events, including positive/negative tests and denied access to testing. We

 $^{^8}$ A user is considered as a bot if its Complete Automation Probability (CAP) from Botometer is ≥ 0.6 .

demonstrated that our corpus supports accurately identifying COVID-19 events in Twitter. We further demonstrated that we are able to extract text spans for filling a set of pre-defined slots specific to each event. Finally we showed that our annotated corpus could be used for analyzing self-reporting cases and user demographics.

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References

- Ron Artstein and Massimo Poesio. 2008. Inter-coder agreement for computational linguistics. *Computational Linguistics*.
- Livio Baldini Soares, Nicholas FitzGerald, Jeffrey Ling, and Tom Kwiatkowski. 2019. Matching the blanks: Distributional similarity for relation learning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL)*.
- Edward Benson, Aria Haghighi, and Regina Barzilay. 2011. Event discovery in social media feeds. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (ACL)*.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL).
- Diederick P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *International Conference on Learning Representations (ICLR)*.
- James McCorriston, David Jurgens, and Derek Ruths. 2015. Organizations are users too: Characterizing and detecting the presence of organizations on twitter. In *Proceedings of the 9th International AAAI Conference on Weblogs and Social Media (ICWSM)*.

- Alan Ritter, Sam Clark, Mausam, and Oren Etzioni. 2011. Named entity recognition in tweets: An experimental study. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.
- Onur Varol, Emilio Ferrara, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2017. Online human-bot interactions: Detection, estimation, and characterization. In *Proceedings of the Eleventh International AAAI Conference on Web and Social Media (ICWSM)*.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rmi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface's transformers: State-of-the-art natural language processing. *arXiv* preprint arXiv:1910.03771.

A Keywords Used for Collecting Data

Event Type	Start From	Keywords
TESTED POSITIVE	2020/01/15	(test OR tests OR tested) positive AND VIRUS
TESTED NEGATIVE	2020/02/15	(test OR tests OR tested) negative AND VIRUS
CAN NOT TEST	2020/01/15	(can't OR can not) get (tested OR test OR tests) (can't OR can not) be tested (couldn't OR could not) get (tested OR test OR tests) (couldn't OR could not) be tested
DEATH	2020/02/15	(died OR pass away OR passed away) AND VIRUS
CURE & PREVENTION	2020/03/01	(cure OR prevent) AND VIRUS

Table A.1: Keywords used for each event type. For VIRUS, we consider the following variants: $VIRUS = (COVID19 \ OR \ COVID-19 \ OR \ corona \ OR \ coronavirus)$.

B Annotation Interface

A portion of our annotation interface is shown in Figure A.1.

[1242765840069455872] @SwetaSinghAT Coronavirus latest news: Prince Charles tests positive fo https://www.telegraph.co.uk/global-health/science-and-disease/coronavirus-uk-lockdown-news-nhsvolunteers/	
Part 1	
Does the above tweet report an individual (or a small group of people) who is tested positive for coronavirus?	
YES - it reports an individual (or a small group of people) who is tested positive.	
Part 2	
Who is(are) tested positive? Not Specified ★ Please provide the corresponding Wikipedia page link if the people tested positive is a public figure (separated by comma if multiple):
e.g., https://en.wikipedia.org/wiki/Tom_Hanks	,
<u>Who</u> is(are) in close contact with the person tested positive? Not Specified ★ Please provide the corresponding <u>Wikipedia page link</u> if the <u>people who are in close contact with tested positive cases</u> is a public multiple):	figure (separated by comma if
e.g., https://en.wikipedia.org/wiki/Tom_Hanks	
Does the person who tested positive have <u>personal relationship(s)</u> with the author of the tweet?	
Not Specified *	
Who is(are) the employer of the people tested positive? ☐ Not Specified × ☐ Not S	
When is the tested positive case reported? Not Specified ▼	
Where is(are) the tested positive case(s) reported from? Not Specified *	
<u>Where</u> did the people tested positive recently visit? Not Specified ★	_
What are the <u>age</u> of the people tested positive? Not Specified Not Spec	
What is(are) the gender of the people tested positive? Not Specified	

Figure A.1: A portion of the annotation interface shown to Mechanical Turk workers for TESTED-POSITIVE tweets.

C Model Implementation and Training Details

The **BERT model** for each $\mathbb T$ is trained on a single GeForce RTX 2080 Ti GPU with average training time per epoch ≈ 2 minutes.

D Examples of Our Annotations

We provide some examples of our annotated tweets for each category in Tables A.2-A.6. We mark a tweet's slot filling annotation as "Not Applicable" if annotators do not think it describes a specific event (discussed in Section 2.1). Please refer to Table 2 for complete slot filling questions.

Event Type: TESTED POSITIVE			
Tweet	Slot Filling Annotations		
My wife's grandmother tested positive for coronavirus in an old persons home in CZ. 9 others tested positive. afaik 1 died. After 1 death they tested all residents and staff. Residents confined to rooms. They got extra staff. The grandmother has recovered now. Why is UK so bad?	WHO GENDER - F, WHERE RELATION - Y		
My eldest daughter tested positive for COVID-19 on Tuesday, a temperature of 40.2, she was hallucinating for hours. Now my 3 year old son looks like this. And my 5yr old girl is now showing symptoms. Still think this is a joke?!?!?!? [URL]	WHO GENDER - F WHEN C. CONTACT		
apparently the staff of brikama hospital is now in isolation because a nurse tested positive for covid19	WHO EMPLOYER		
These numbers are being fluffed. They count everyone who tested positive not necessarily actually that was the cause of death. Asymptomatic people could've died for an unrelated reason and they tally it as a covid19 death. And they are saying asymptomatic people are very common.	NOT APPLICABLE		
#Karnataka — A 26-year-old man returning from #Greece tested positive for #COVID19, becoming the fifth positive case in the state, a health official said on Thursday. #CoronavirusPandemic #COVID #COVID19india #CoronavirusOutbreak #coroanvirus [URL]	WHO GENDER - M AGE WHERE RECENT V.		

Table A.2: Examples of our annotated tweets in TESTED POSTIVE category.

Event Type: TESTED NEGATIVE		
Tweet	Slot Filling Annotations	
Sigh of relief. My wife 's COVID-19 test came back negative today. The Lord has been gracious. One of my favorite pics I took of her. #thankful. [URL]	WHO GENDER - F WHEN RELATION - Y	
Live updates: Boris Johnson tested negative for Covid-19 on leaving hospital, says Downing Street #coronavirus — #COVID19 [URL] [URL]	WHO GENDER - M	
What good would that do? One could pick covid19 up at the place one gets the test, or one could pick it up sometime after one tests negative. I suggest that one pretend that everyone has covid19 and act accordingly. Also, pay attention to the CDC. [URL]	NOT APPLICABLE	
truly, thank you. I tested negative, but I think it was wrong. Had most of the symptoms except for high temp. On the mend. Hope you are too, and thanks so much for sharing, it could save lives.	WHO - AUTHOR	
My best friend is locked down in The Maldives with his lovely wife, and had access to a test to find out hes negative for Corona. Where did my life go so horribly wrong? [URL]	WHO GENDER - M	

Table A.3: Examples of our annotated tweets for TESTED NEGATIVE event.

Event Type: CAN NOT TEST			
Tweet	Slot Filling Annotations		
Thank you so very much for you're honesty involving this virusthank you also for helping that sweet mom at home taking care of her family. My 35 yr old daughter and 2 of my grandbabies have been sick for weekscould not get testedoklahoma case counts are inaccurate	WHO RELATION - Y SYMPTOMS - Y		
Yeah same in French Guiana. I'm sick not heavily but it's concerning since we can't be tested. I've to work a little friday & saturday. The few 'left' to work seems also sick. This is really a mess	WHO – AUTHOR WHERE SYMPTOMS – Y		
Nurse working in ITU couldnt get tested, & was told that the test was very expensive, so he couldnt have a test. [URL]	WHO		
Yep! I'm sick can't shake it. Dr. Doesn't want me in there. Chest pressure but moderate not severe. Sent me to ER. They tested me for everything under the sun EXCEPT. North Florida can't get tests our numbers are low but it's rampant I'm sure getting worse. We all know why	WHO – AUTHOR WHERE SYMPTOMS – Y		
Curiously they have immediate access to testing while all we hear from the media is that people cant get tested.	NOT APPLICABLE		

Table A.4: Examples of our annotated tweets for CAN NOT TEST event.

Event Type: DEATH	
Tweet	Slot Filling Annotations
Yes. My friends mom died in Oregon and was never tested even though she was in the hospital with clear COVID-19 symptoms.	WHO SYMPTOMS – Y WHERE RELATION – Y
Martin Douglas loved the steel pan's jangly sound and he loved its versatility, and he could play any song, just name it Penny Lane was a particular favorite. He has died of Covid-19. He was 72. [URL]	WHO AGE
A third Chicago Police officer has died of COVID-19, the department announced Friday.	WHO WHEN WHERE
#TopChef Masters' winner Floyd #Cardoz dies after #coronavirus diagnosis World-renowned chef Floyd Cardoz died Wednesday in New Jersey at age 59. Cardoz admitted himself to the hospital on March 17 after feeling feverish. #COVID19 #Death [URL]	WHO AGE WHERE SYMPTOMS – Y
Well, people are not going to ER for stroke/heart attack either. My uncle recently died of a heart attack; he did not have COVID-19, but he was too afraid to go the hospital.	(NOT APPLICABLE)

Table A.5: Examples of our annotated tweets for Death event.

Event Type: Cure & Prevention	
Tweet	Slot Filling Annotations
chewing tobacco cures coronavirus. i've been chewing non stop all week.	WHAT WHO - AUTHOR OPINION - EFFECTIVE
Folks, many people are telling me that tear gas prevents coronavirus [URL]	WHAT WHO OPINION - EFFECTIVE
Mutahi Kagwe insists that social distancing and washing hands as some of the best ways to prevent the local transmission of #Covid_19 'follow them diligently.' @MOH_Kenya #Stay-Homekenya	WHAT WHO OPINION - EFFECTIVE
Hello Eric! Listerine mouth rinse is not indicated to prevent or treat COVID-19. You should follow the preventive measures issued by the World Health Organization. Give us a call at 1-888-222-0182 Mon - Fri from 9 AM - 5:30 PM ET so we can learn more about your experience.	WHAT OPINION - NOT EFFECTIVE
Still have no shame for some companies no worries for their employees no any attention to prevent covid - 19 please understand as you are forcing them to travel in peak hour #shame @FluperOfficial @IAnshulShr	NOT APPLICABLE

Table A.6: Examples of our annotated tweets for Cure & Prevention event.