

Twitter Sentiments on the Stayat-home Orders in the United **States**

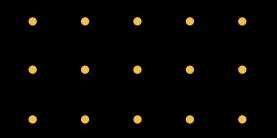
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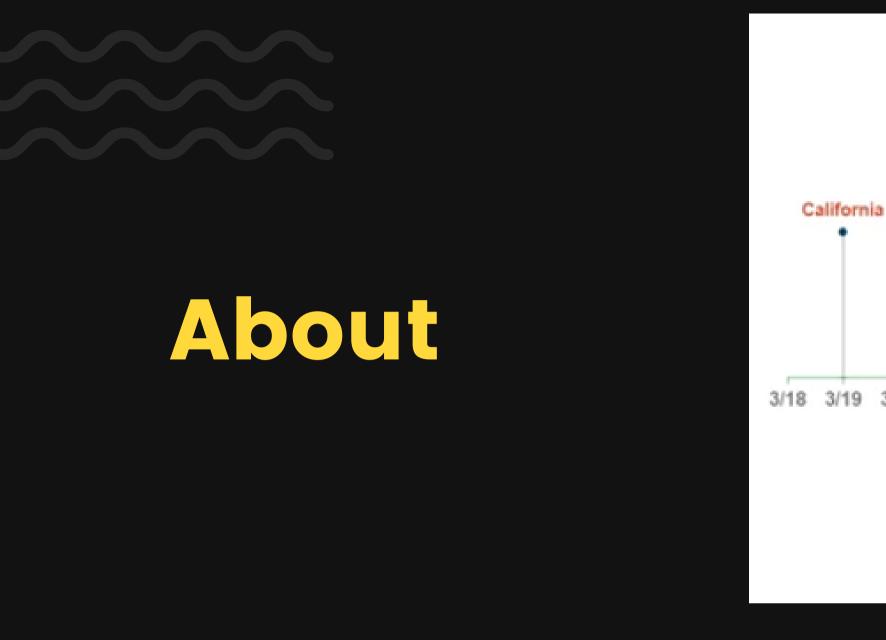
About

Stay-at-home orders were one of the controversial interventions to curb the spread of COVID-19 in the United States (US).

flatten the curve stay

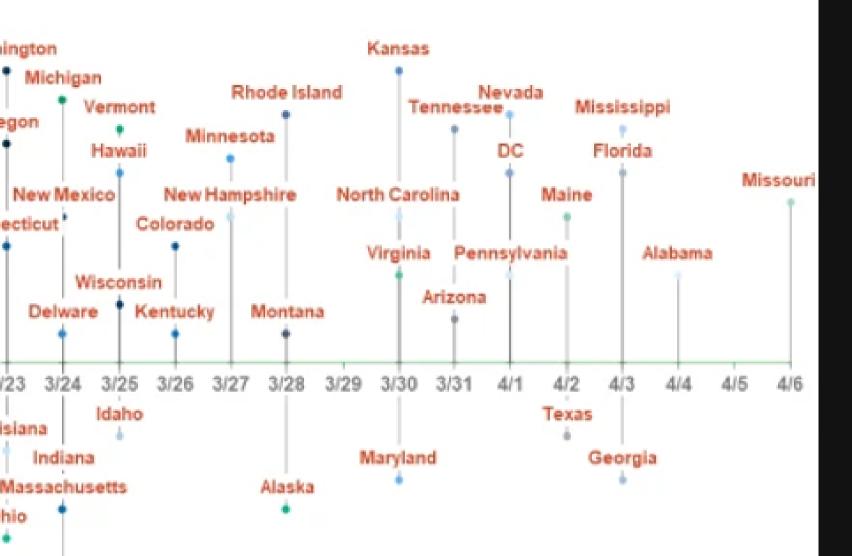


SARS-nCoV-2 isolate COVID-19■social d: coronav quarantine lockdown home curfew wash h virus self-isolate shelter in place test negative



The stay-at-home orders, implemented in 43 (out of 51) states and territories between 7 March to 30 June 2020, impacted the lives of individuals and communities and accelerated the heavy usage of online social networking sites.





Washington

Oregon

Connecticut

3/23 3/24

Indiana

West Virginia

Louisiana

New York

3/22

Illinois

3/21

New Jersey

3/20

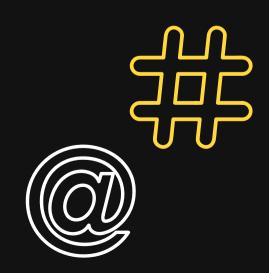
TWITTER INSIGHT

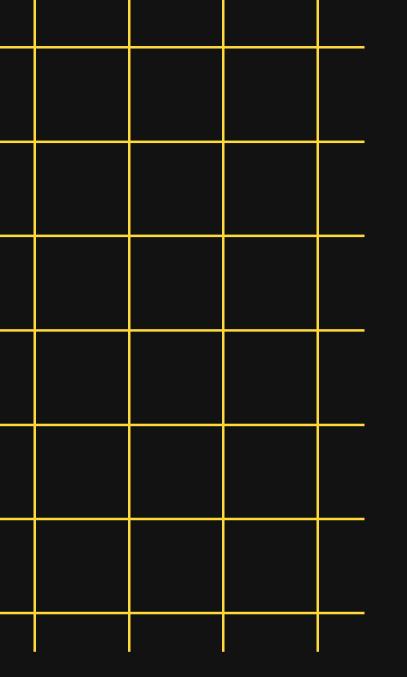
About

Twitter sentiment analysis can provide valuable insight into public health emergency response measures and allow for better formulation and timing of future public health measures to be released in response to future public health emergencies.







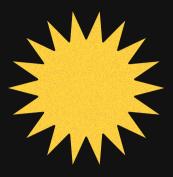


Objective

The purpose of the study was to evaluate how stay-at-home orders affect Twitter sentiment in the US. We particularly focused on vulnerable groups, including elderly groups, rural people, and lowincome groups.



RURAL VS URBAN ELDERLY





LOW INCOME







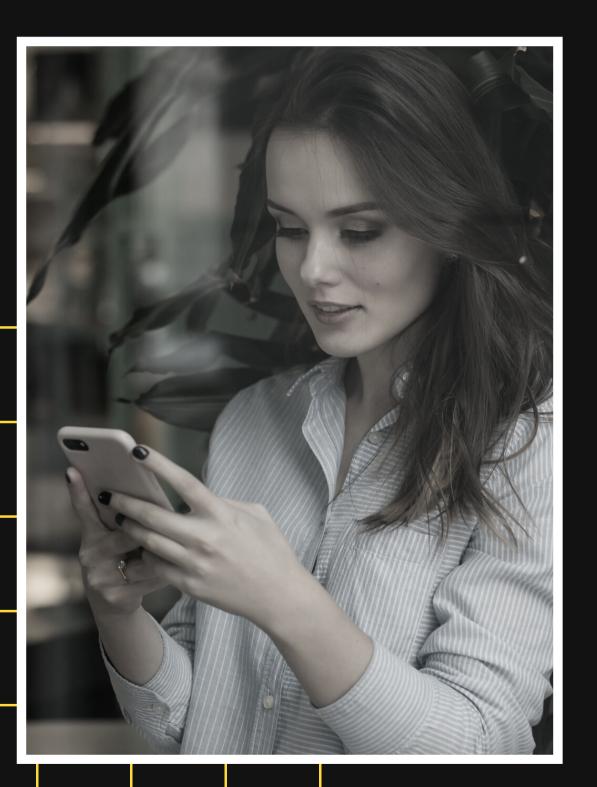


- A proxy for subjective well-being

- spanning time, geography, and 104 languages Harvard University)

• applying natural language processing techniques • a comprehensive archive of 10 billion geotagged tweets maintained (by the Center of Geographic Analysis at







Country, State/Province, and County/City level in 164 countries

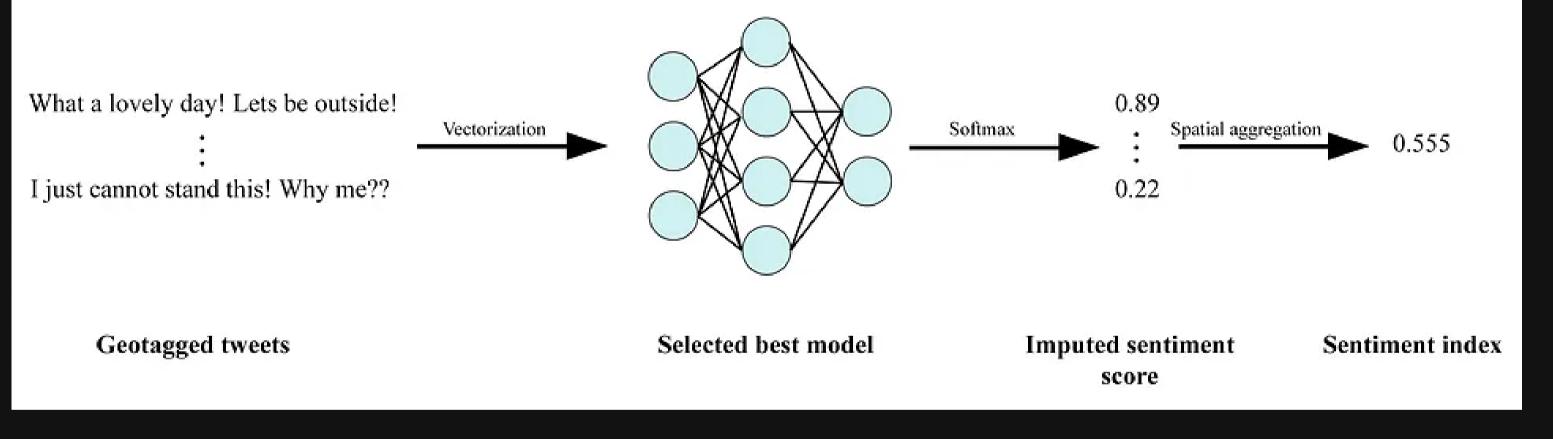


Daily sentiment scores in 10 year coverage (2012 to 2022)



83% sentiment classification accuracy by using neural network model

Generate sentiment index



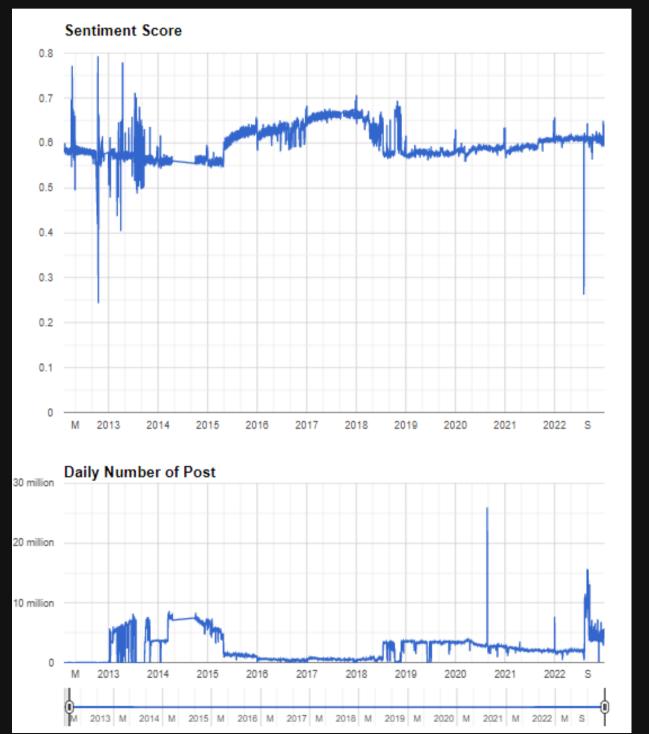
The sentiment index for global geotagged tweets was made in the following steps:

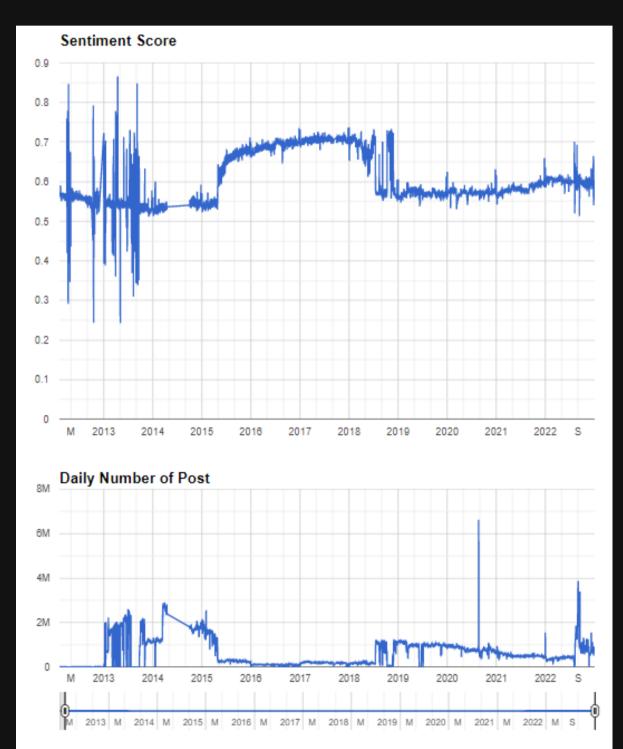
- 1. They vectorized the text into a 768 dimensions vector.
- 2. They fed the vector into a trained neural classifier to get the single sentiment score.
- 3. They aggregated the scores in different administrative areas to represent the local subjective well-being.

Picture source: https://gis.harvard.edu/twitter-sentiment-geographical-index-tsgi-dataset-global-high-frequency-dataset-monitoring

t the single sentiment score. areas to represent the local

World



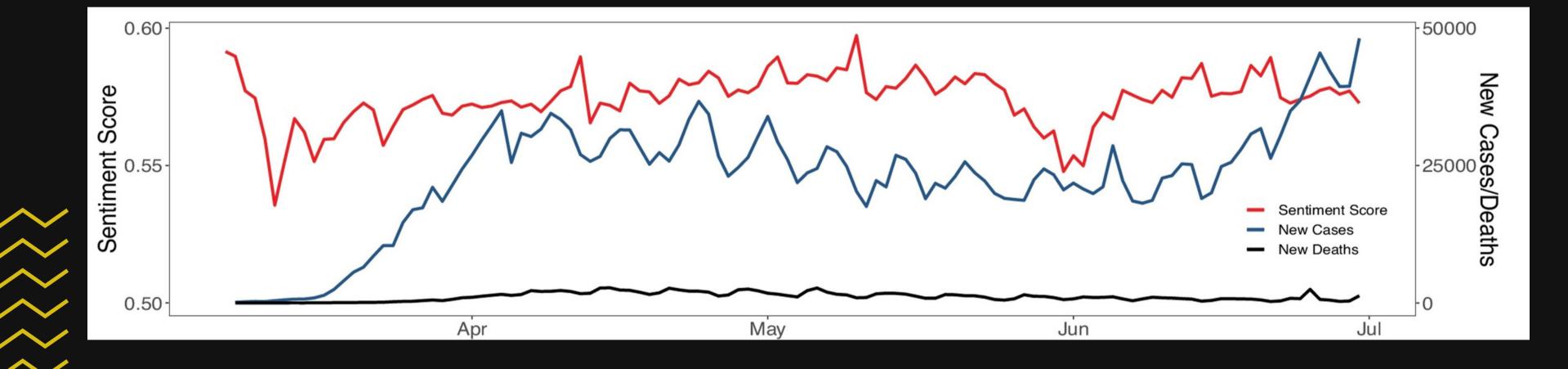


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United States

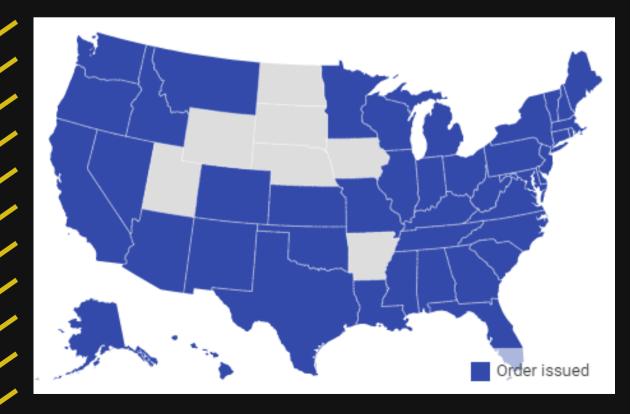


Preliminary results: Sentiment + + score vs. New cases/deaths + + + +





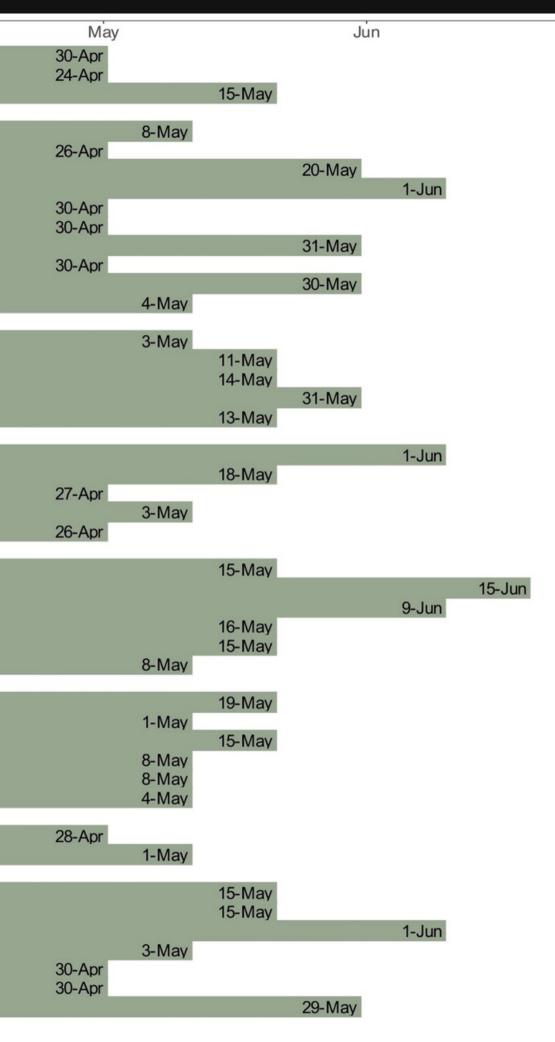
Stay-athome related policy timeline



Alabama Alaska Arizona Arkansas California Colorado Connecticut Delaware Florida Georgia Hawaii Idaho Illinois Indiana lowa Kansas Kentucky Louisiana Maine Maryland Massachusetts Michigan Minnesota Mississippi Missouri Montana Nebraska Nevada New Hampshire New Jersey New Mexico New York North Carolina North Dakota Ohio Oklahoma Oregon Pennsylvania Rhode Island South Carolina South Dakota Tennessee Texas Utah Vermont Virginia Washington West Virginia Wisconsin Wyoming **District of Columbia**

Apr		
		4-Apr
	28-Mar	тир
	31-Mar	
19-Mar		
	26-Mar	
	23-Mar	
	24-Mar	
		3-Apr
	05.14	3-Apr
	25-Mar	
	25-Mar	
	21-Mar	
	24-Mar	
	30-Mar	
	26-Mar	
	23-Mar	
	20 1110	2-Apr
	30-Mar	
	23-Mar	
	27-Mar	
		3-Apr
		6-Apr
	28-Mar	
		4 4
	27-Mar	1-Apr
	21-Mar	
	23-Mar	
	22-Mar	
	30-Mar	
	23-Mar	
	25-Mar	
	23-Mar	
		1-Apr
	28-Mar	
		7-Apr
	04 14-	
	31-Mar	2 Apr
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	25-Mar	
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1-Apr

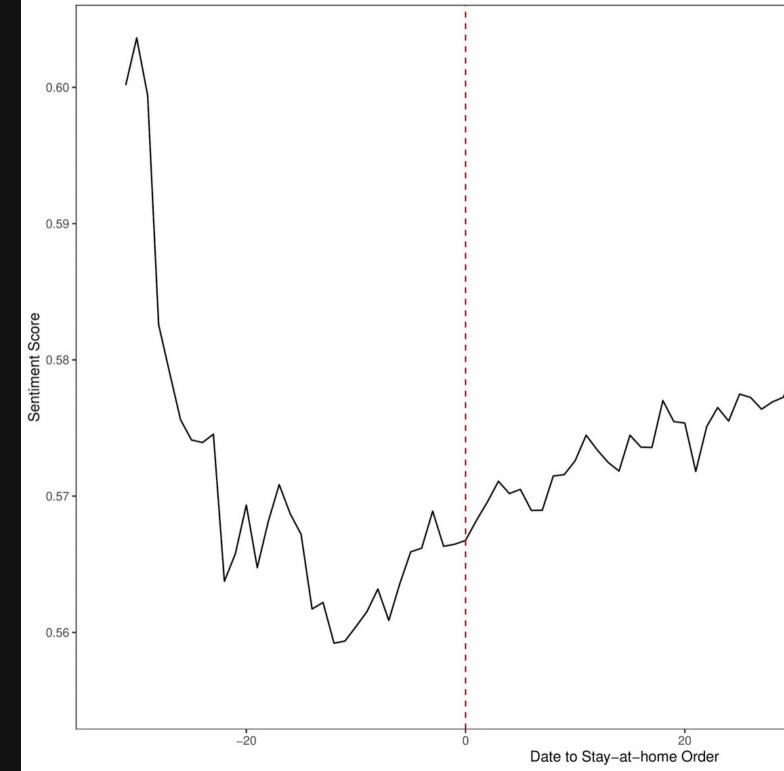


Stay-at-Home Order Period

Jul



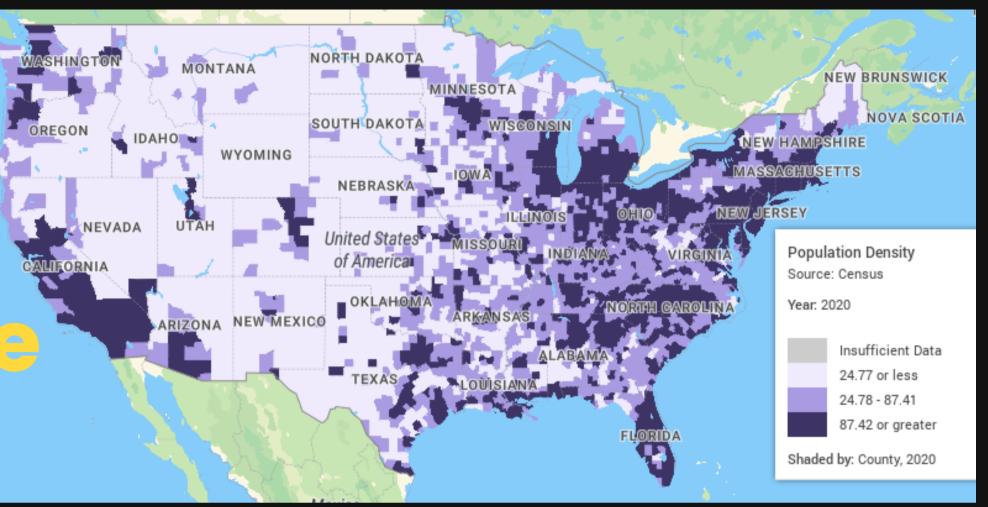
Sentiment scores before and + after the stay-at-home orders +





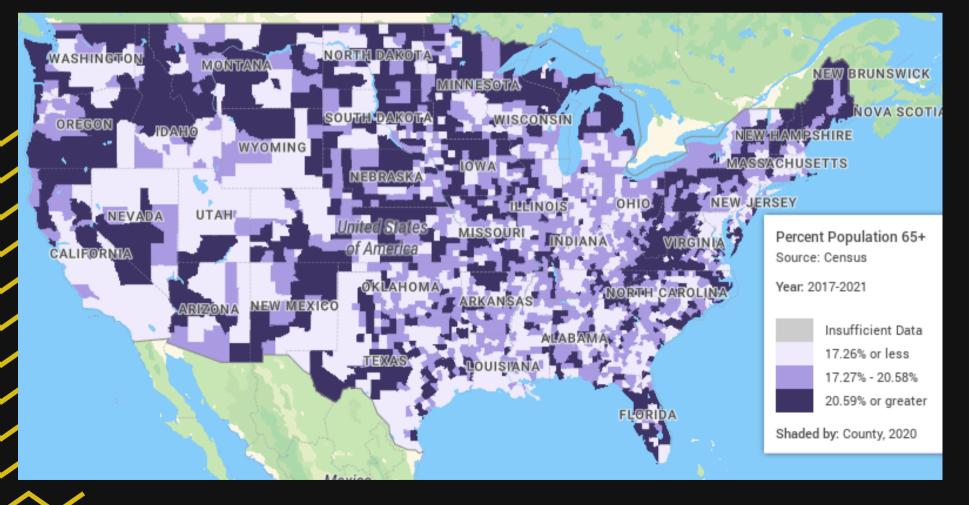


Vulnerabl groups

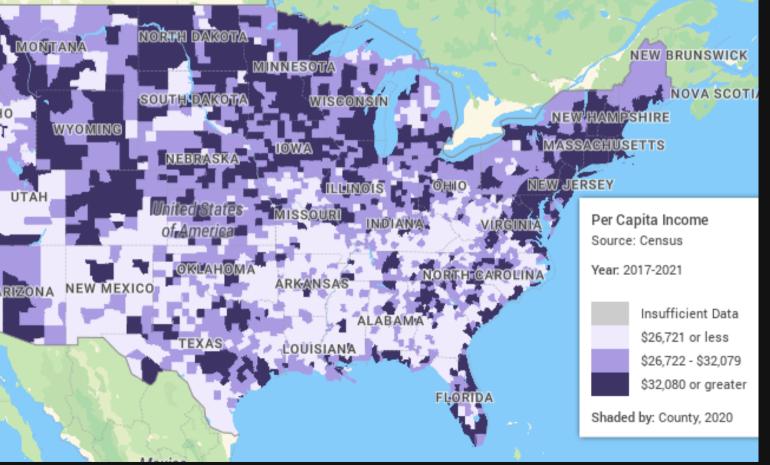


ADA

IFORNI



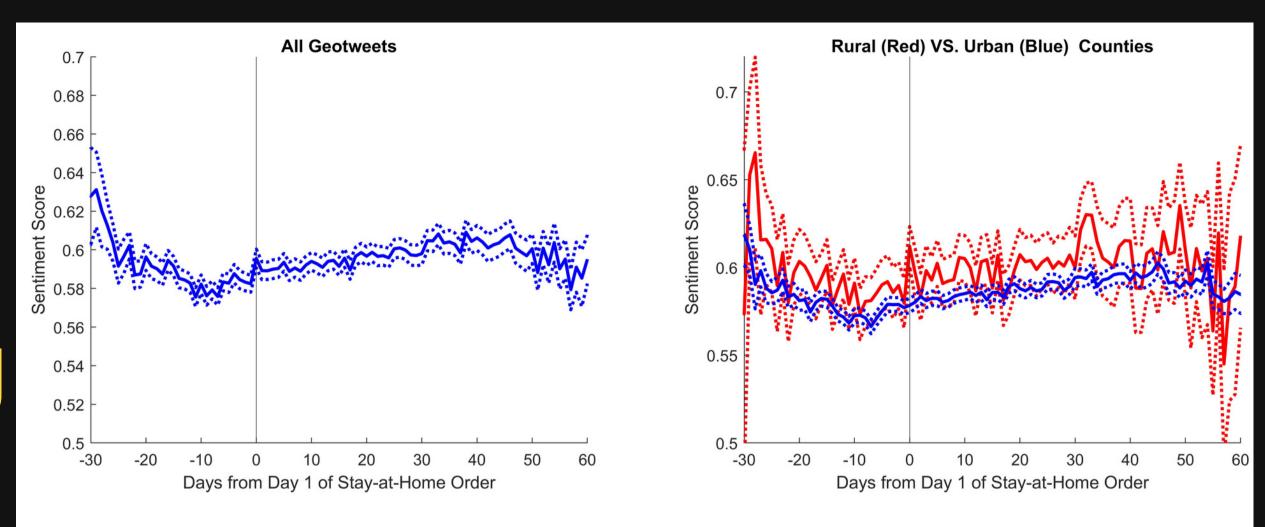
+ + + + + +



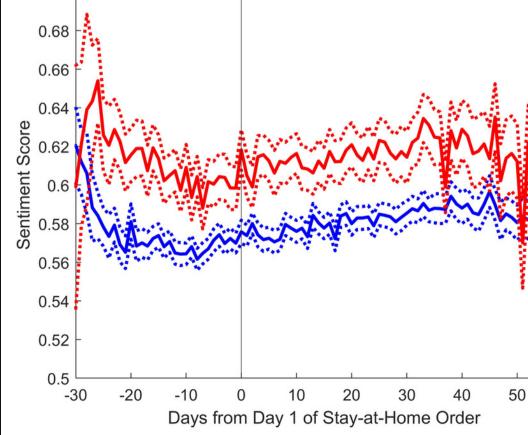
Picture source: Policymap.com

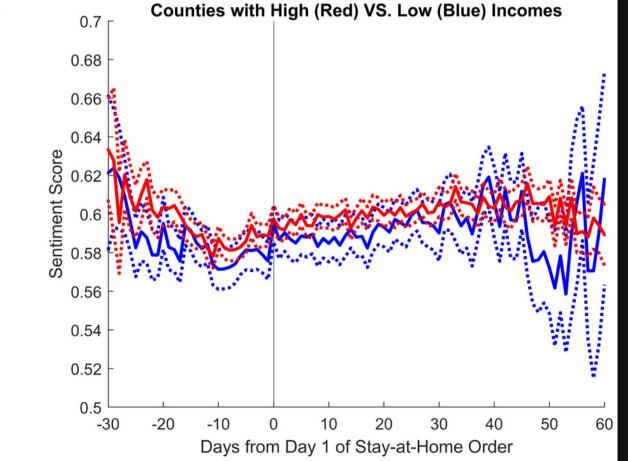


Sentiment scores among vulnerable groups









60

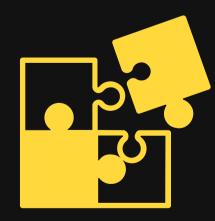
Summary

- Stay-at-home orders received a positive response and contributed to an improvement in Twitter sentiments.
- However, counties faced more significant difficulties in an urban (versus rural) setting, with a lower concentration of elderly individuals, or lower incomes during the pandemic.
- This study offers a sociological perspective, informed by large-scale Twitter data, for monitoring changes in public opinion, evaluating the impact of social events, and understanding the disaster management of pandemic shocks.



Next Steps

Methodology



Research topics



- The difference in differences (DID) regression model
- Topic modeling

• Natural disasters (e.g., hurricanes)

Т

 The efficiency of policies (stay-at-home orders in the US vs lockdowns in China)







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Contact me for more questions.

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