Mining the Cause of Political Decision-Making from Social Media:
A Case Study of COVID-19 Policies across the US States

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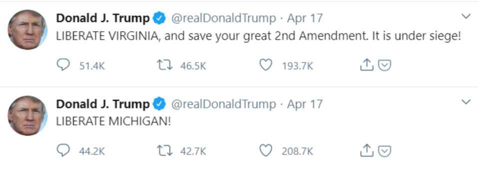
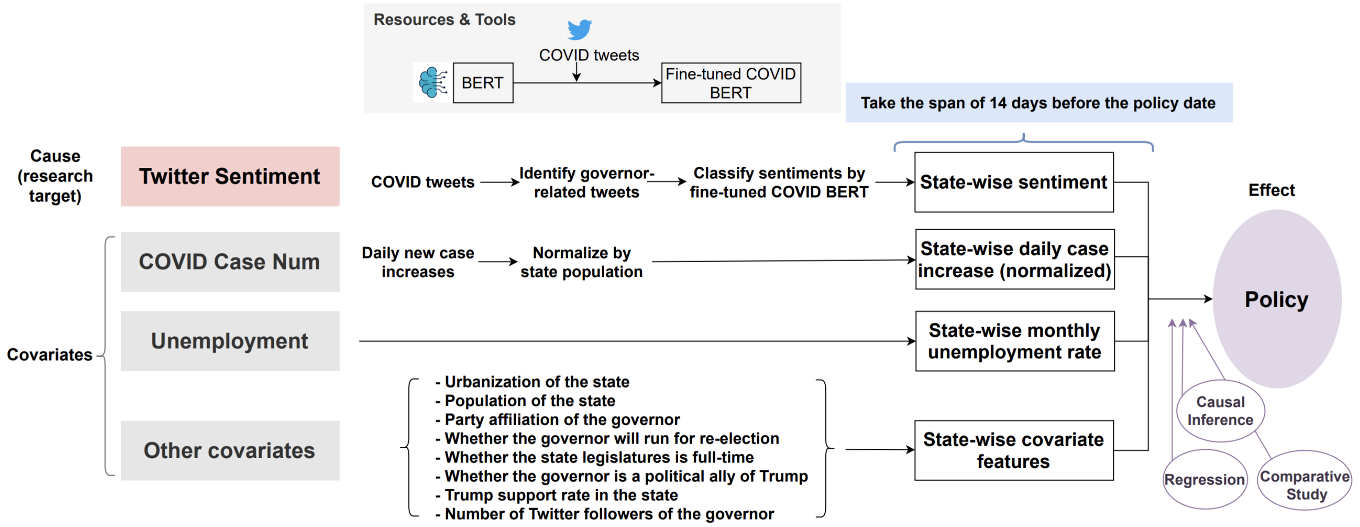
Key Research Question

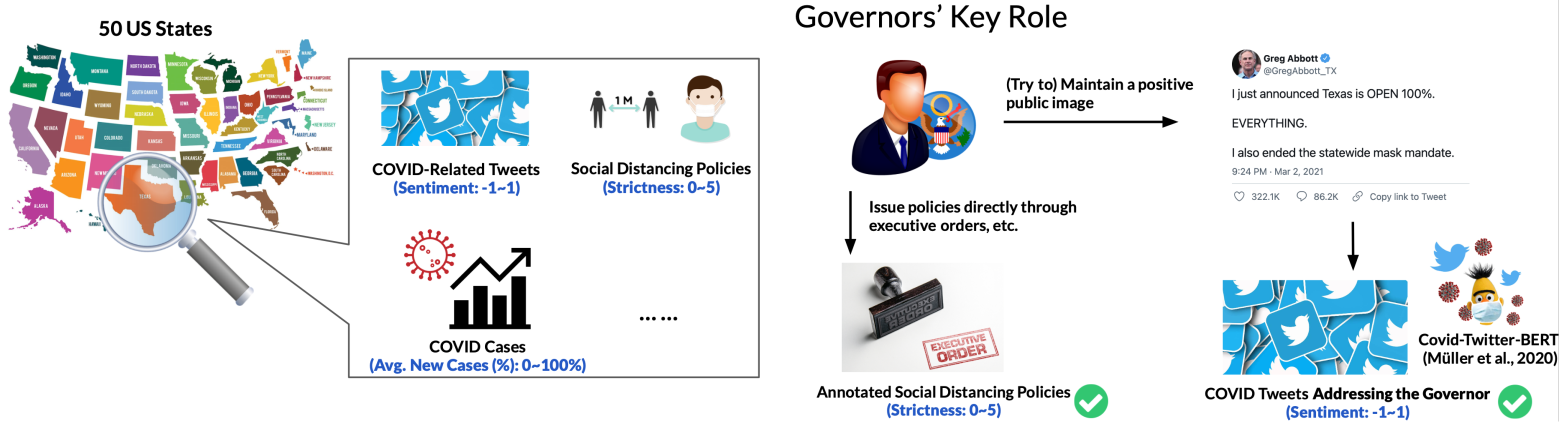
Are politicians overfitting **short-term public opinions?**



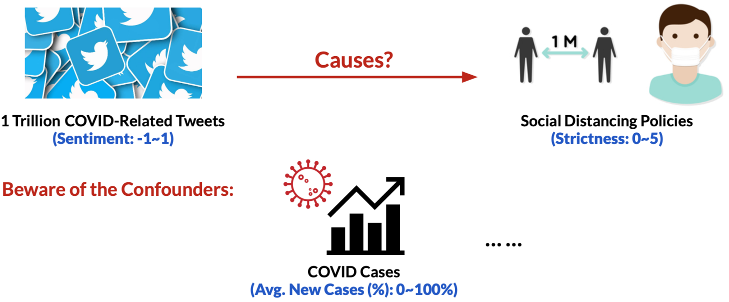
Goal: Detect and report important social issues

Step 1. Data Collection





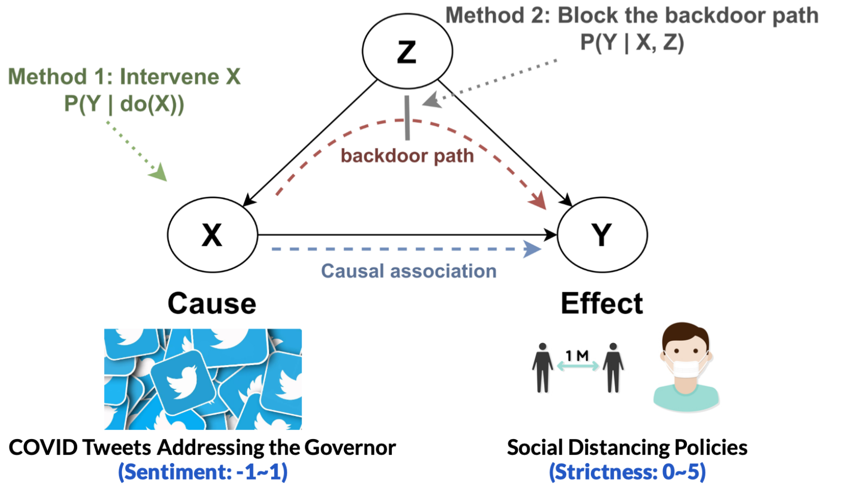
Problem Formulation



	Previous Work	This Work
Policy Type	Long-term, gradual (over decades)	Short-term (weekly/monthly)
Policy Sparsity	Less policies on the same topic	Many policies on the same topic across states
Data Source	Surveys	Trillions of tweets
Data Collection	–	NLP & Causality

Table 1: Comparison of the characteristics and paradigms of existing work versus our work.

Step 2. Causal Analysis



Backdoor Adjustment (Pearl, 1995)

Backdoor adjustment allows approximation of **interventional effect** by **observational data**

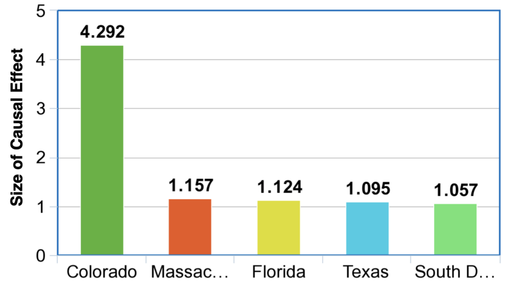
$$P(Y|\mathrm{do}(X)) = \sum_{Z} P(Y|X,Z)P(Z)\,.$$

The causal impact of **X** (i.e., positive or negative sentiment) on **Y** (i.e., policy change):

$$\begin{aligned}\beta &= \mathbb{E}[Y|\mathrm{do}(X=1)] - \mathbb{E}[Y|\mathrm{do}(X=-1)] \\ &= \sum_{Z} (\mathbb{E}[Y|X=1,Z] - \mathbb{E}[Y|X=-1,Z])P(Z) \\ &= \mathbb{E}_Z[\mathbb{E}[Y|X=1,Z] - \mathbb{E}[Y|X=-1,Z]]\,.\end{aligned}$$

Backdoor adjustment: Judea Pearl. 1995. Causal diagrams for empirical research.
Existing toolboxes: *DoWhy: An End-to-End Library for Causal Inference (2020). Amit Sharma, Emre Kiciman.*

Step 3. Connecting Back to Real-World Politics



Colorado · Massachusetts

- **High support rate** for the democratic governors compared to the Republican competitors
- Policies align with **most people's support the COVID restrictions**

South Dakota · Texas · Florida

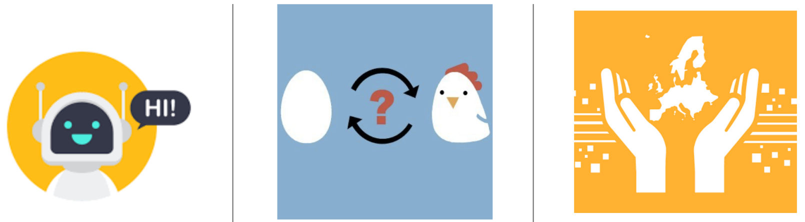
- **High demand to open the state**
- **Policies align with general sentiment across the states to refuse restrictions**

State	Change in β before and after June 1
Montana	+9.39
Washington	+4.03
Georgia	+3.15
Tennessee	+2.94
Indiana	+2.53

Table 7: Top 5 states with the most change in the causal impact of sentiment on policies from March to June 1, 2020, versus from June 1, 2020 to April, 2021.

Future Pursuit

"Introducing *causality* to *NLP*, to address tasks for *social good*"



NLP · Causality · Social Good

NLP for Social Good

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