

Mapping Belief Landscapes in Social Media

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Extended Abstract

How beliefs develop, change, and spread within populations is a long standing object of scientific study with broad interest across research disciplines [2]. In an information era characterized by rampant misinformation, increasing polarization, and the rejection of conventional epistemologies, this investigation takes on new urgency. One established vehicle for this study, pioneered in the field of political science, is the analysis of a longitudinal data from opinion surveys such as the American National Election Studies (ANES) [1, 3]. The approach has yielded important findings about Americans' political attitudes but is limited to the analysis of political beliefs sampled at long time intervals and omits consideration of the communications networks that likely drive shifting beliefs at the individual level.

Data collected from social platforms holds the potential to address these limitations. People use social platforms to profess their beliefs about a wide range of concerns, including political issues, religion, science, financial markets, celebrities, consumer goods, and many others. These beliefs can be observed longitudinally at high resolution and across a range of sociotechnical contexts. Leveraging this data could revolutionize research on belief dynamics, leading to new theories about how populations organize their beliefs and adapt them over time in different sociotechnical contexts.

We have begun to develop such an approach, using conversations about climate change on Twitter. Our analysis offers us a map of the "belief landscape" inhabited by our study population, identifying regions that are both densely and lightly populated and illuminating the pathways people frequently travel as they move from one area of this belief landscape to another. Here, we will present our current method, and preview our results.

Data, Methods & Findings

For this analysis, we collected a convenience sample of data from Twitter from 23rd May 2020 to 27th October 2020 using the streaming API for a series of terms related to climate change (e.g., climate, climate change, global warming, etc). We chose to examine this topic because it involves a diverse set of concerns (politics, social welfare, the economy, science) and views (including skepticism about climate change itself, its impact, whether it is driven by human activity, and how to address it). We were particularly interested in observing how likely it is for people to move between opposing views within this topic. The collected tweets discussed various subjects including climate change, science, the earth, Covid, Biden, Trump, Greta Thunberg, etc. The dataset contains 29.3 million tweets and 2.67 million users.

Our method follows the process in Figure 1. The final output of this pipeline is a transition matrix or graph that captures the likelihood of moving from one belief state to another given a study population. A sample of data from our initial analysis is show in Figure 2. The figure illustrates a subset of observed belief transitions. Each node is a belief state (the size of a node reflects the proportion of people expressing this belief), and each link indicates that some percentage of the population moved from one belief state to another in our data (the width of the link indicates the relative number of times that transition was made). The subgraph captures potential pathways between seemingly opposed belief states.

The node labelled “A” is a dominant, pro-science view in the data sample. The node labelled “B” is a less widely held anti-science position, frequently observed amongst individuals that draw a connection between climate-change and Covid-19. The path between A and B is mediated by beliefs that focus on the limits of humans’ ability to influence nature.

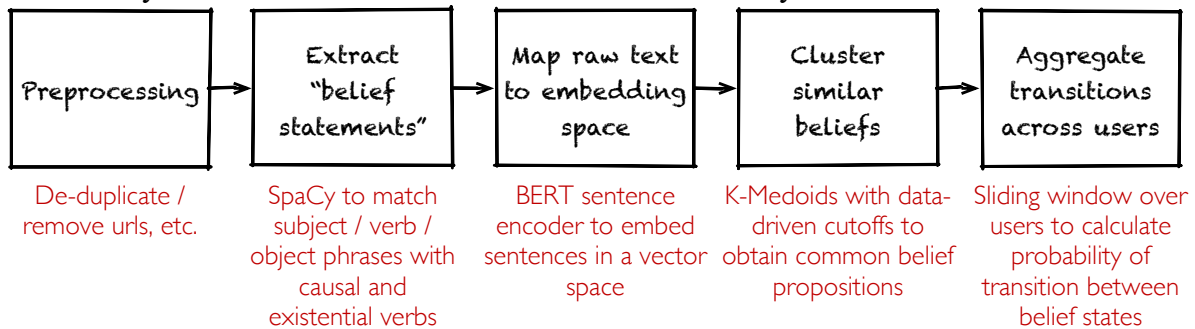


Figure 1: Summary of the algorithmic pipeline for belief landscape analysis

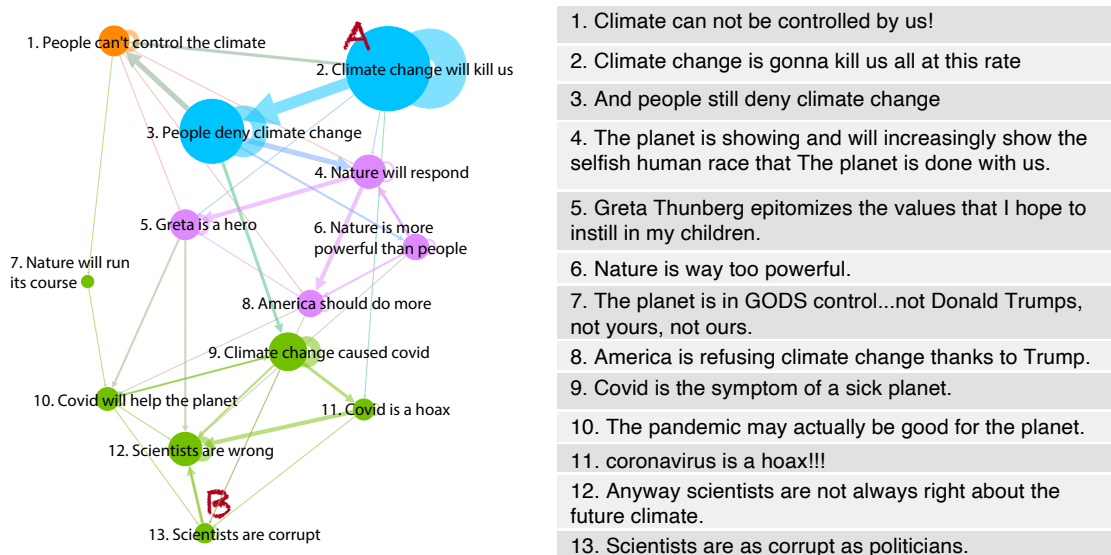


Figure 2: Sub-graph of belief change map; nodes have been labeled manually, table on the right contains text from tweets near the centroid of each labeled belief state. Node size reflects number of people expressing that belief, link width reflects number of transitions made by the sample population. Labeled nodes (A, B) capture opposing views regarding science.

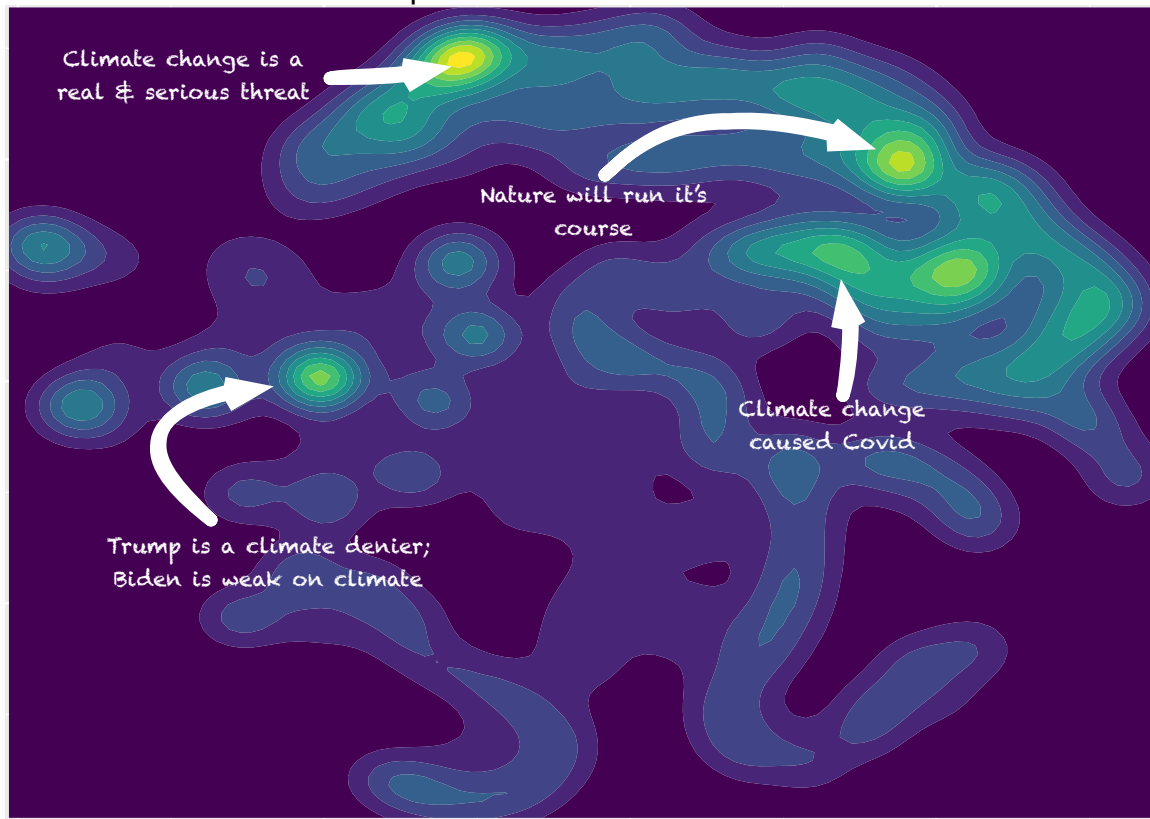
In addition to providing insights about how some beliefs can play a transitional role between seemingly opposed viewpoints, macro-scale analyses of belief-dynamics (e.g., Figure 3), which we offer in a full presentation of this work, illustrate how populations shift beliefs over time and in response to events and support predictive modeling at both the population and individual level.

References

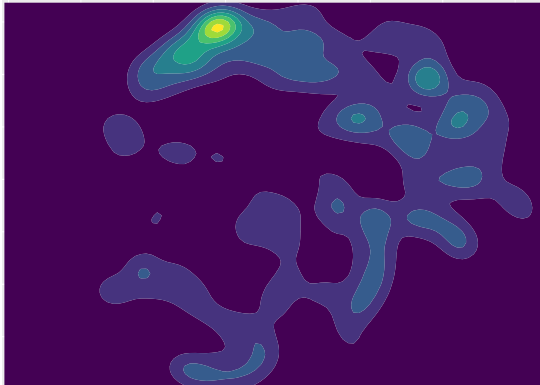
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- [3] American National Election Studies, University of Michigan, & Stanford University.

Appendix

A. Overall Belief Landscape



B. Frequent Twitter Users



C. Infrequent Twitter Users

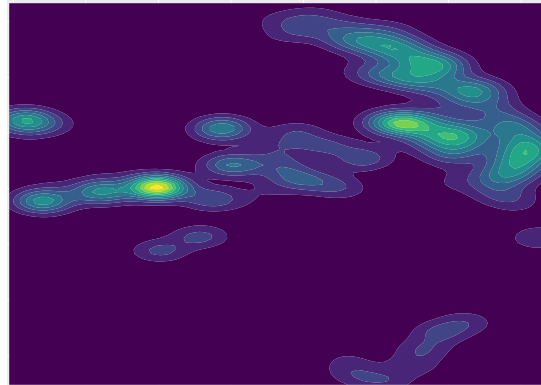


Figure 3: Visual inspection of the belief landscape. Landscape visualization produced using tSNE, a stochastic algorithm that captures proximity relationships in high dimensional data. Notable belief regions are labeled. A) Kernel density plot of overall population on the visualized belief landscape. B) Kernel density plot of users with more than 49 tweets in the dataset. C) Density plot of users with less than 50 tweets.