Detecting Cognitive Dissonance & Belief Shift Over Time

Quantification of Cognitive Dissonance via Recursive Decision Forests

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YFA 2020

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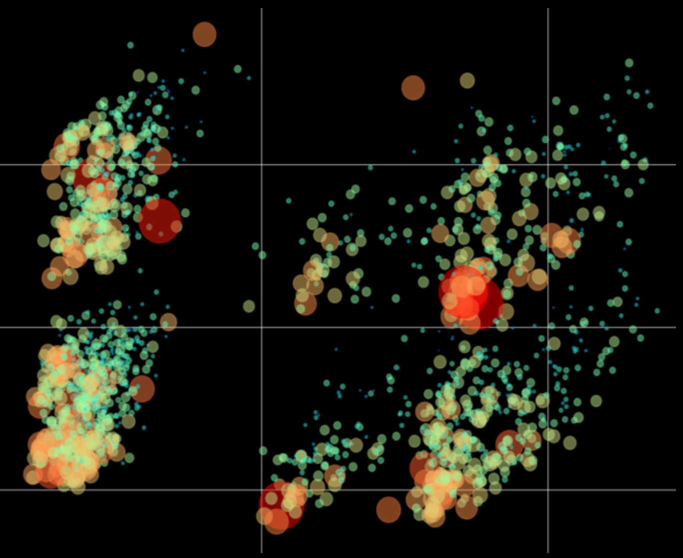
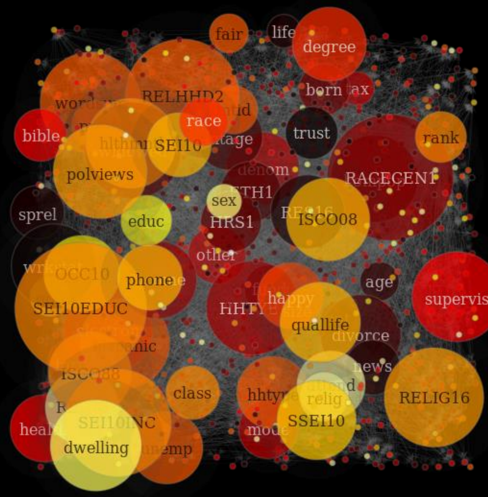
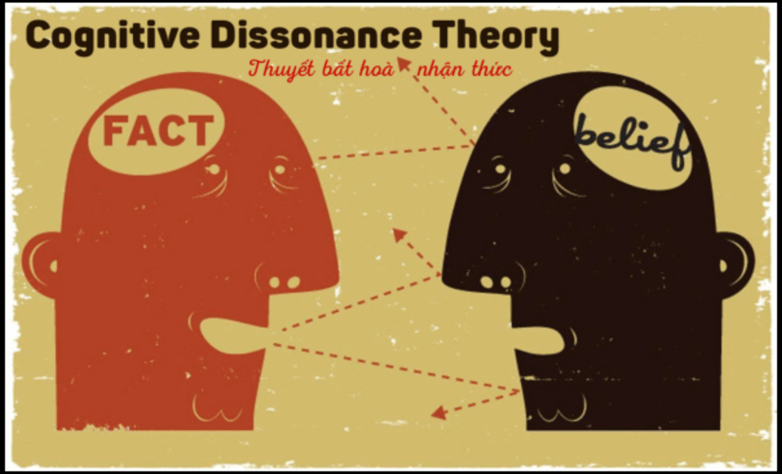




Cognitive dissonance [1,2] refers to the psychological stress arising from holding two or more contradictory beliefs, ideas or values.

Objectives

1. Identify & quantify cognitive dissonance in individuals, communities and societal subgroups
2. Model & predict shift of beliefs & opinions over time
3. Develop a general theory of belief shift, predicated by the need for cognitive consistency



1. Miller, M. K., Clark, J. D. & Jehle, A. Cognitive Dissonance Theory, 2015
2. Festinger, L. A Theory of Cognitive Dissonance. Mass communication series, 1962

Summary

We aim to detect and quantify cognitive dissonance in individuals, communities, and societal groups, and ultimately craft **a general theory of belief shift over time,** driven by the need to maintain and maximize cognitive consistency. We bring together psycho-social theory, stochastic processes, and large deviation analysis from information theory to predict likely choices and actions under cognitive conflict and chart the long-term stochastic dynamics of belief evolution. Our key innovation is the formulation of the notion of cognitive dissonance as a **information-theoretic measure of surprise**; computed as the deviation of an individual's opinions/beliefs from what is predicted by inferred models that optimally encode the responses of a wider random yet socially matched population. We develop a novel machine learning framework (**recursive decision forest**) to automatically seek out individuals with high dissonance, and topics around which significant dissonance exists in social groups. Precise mathematical formulation of a metric between opinion vectors allows us to view, model and predict real-world belief trajectories as they evolve. We develop and validate our models on the General Social Survey dataset (1972-2018), which provides a cross-section of the American Society spanning four decades.

Highlights | Accomplishments

Automated inference of complex emergent dependencies between opinions & beliefs using General Social Survey (1972-2018)

Recursive decision forest of conditional inference trees as a new tool for analyzing opinion surveys

Intrinsic metric on the space of opinions, with the provable property that closer opinions have higher odds of spontaneous shift

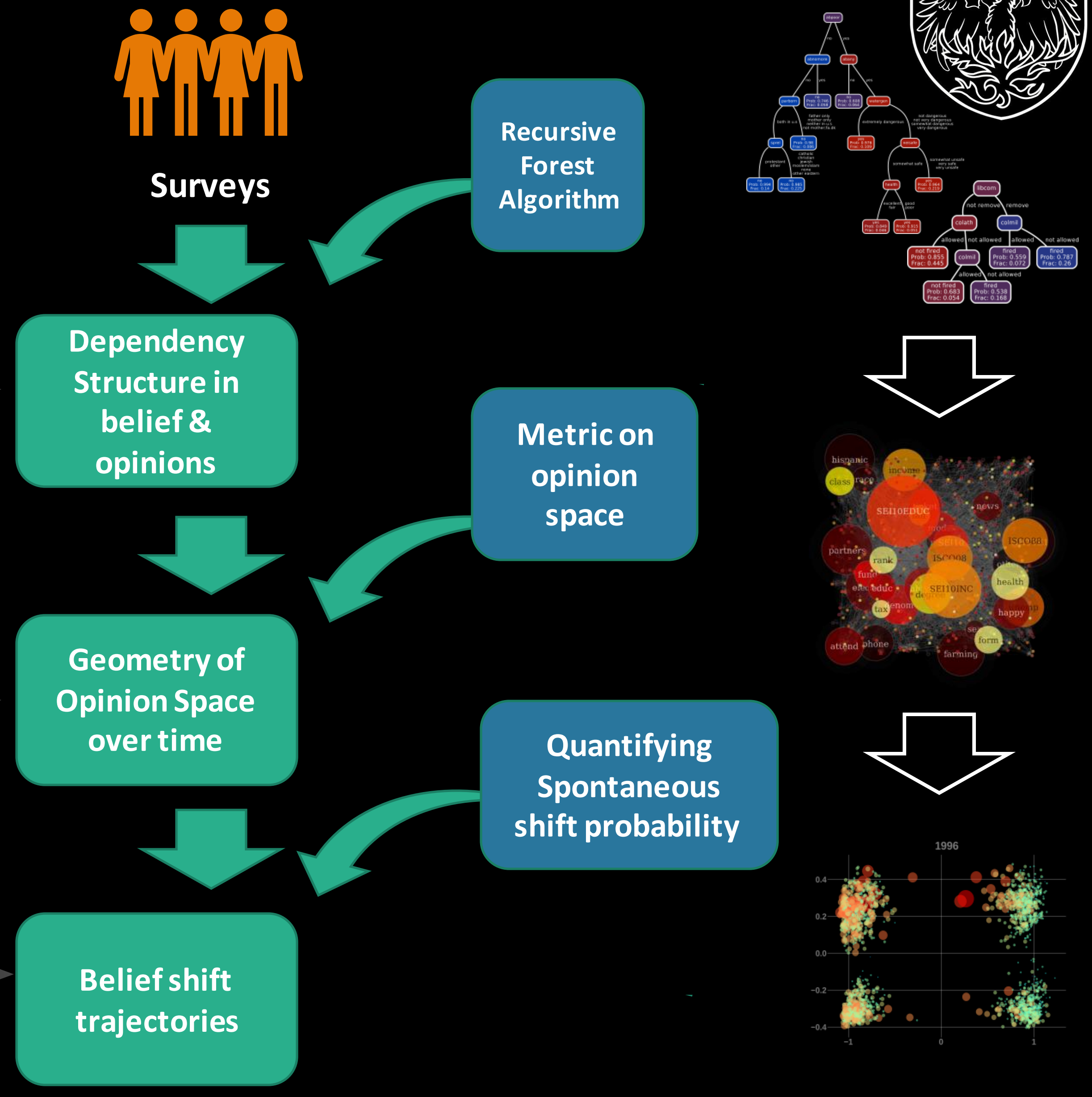
Application of large deviation theory to stochastic dynamics in opinion space, demonstrating belief shift trajectories over time

Software: python package https://pypi.org/project/quasinet/

Paper draft under preparation

Core Idea:

1. Opinions have dependencies
2. Infer these dependencies using a novel ML framework called **recursive forests of conditional inference trees**
3. Visualize dependency graphs among opinions over time
4. Define a metric on space of opinions, to visualize the opinion geometry of the US society over time
5. Measure the probability of spontaneous shift, leading to a theory of belief shift with the ability to simulate/forecast belief trajectories



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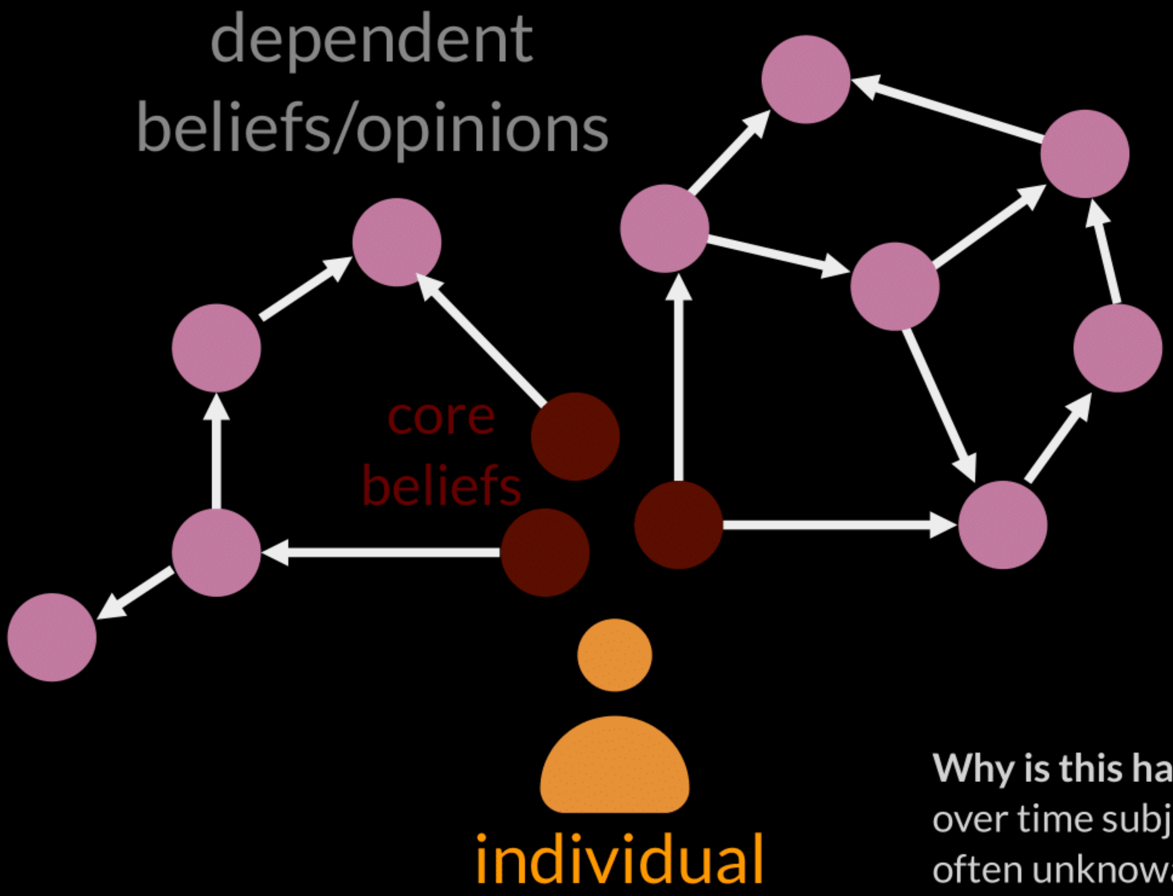
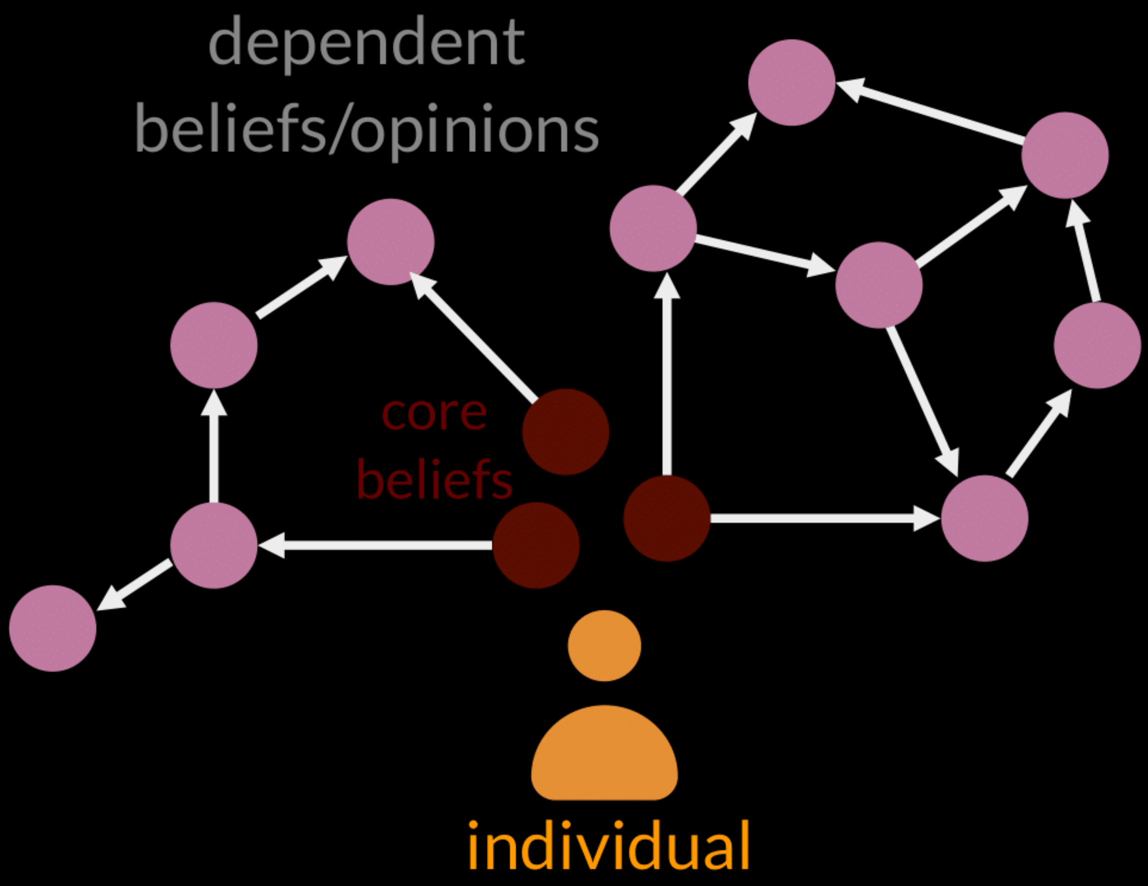
Framework & Background



Dissonance:
Inconsistency in the logical dependency structure

Why is this hard: Opinions and dependencies change over time subject to new information, ground truth is often unknowable

Framework & Background



Knowledge is important to experience and detect dissonance

no cognitive dissonance

1. Smoking is not bad for health
2. I am health conscious
3. I smoke

cognitive dissonance

1. **Smoking causes lung cancer**
2. I am health conscious
3. I smoke

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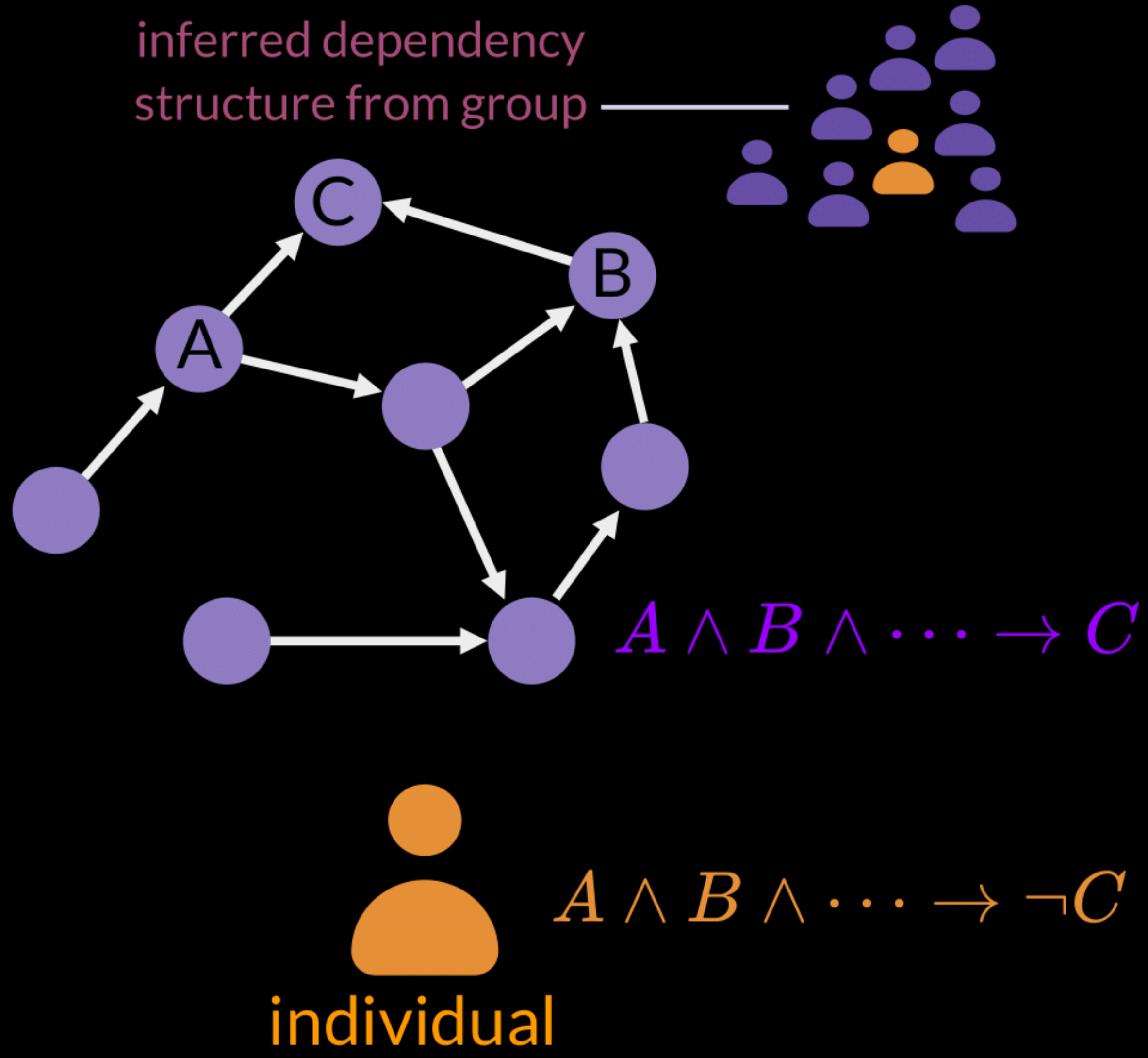
Framework & Background



- Everyone has access to same facts/knowledge
- Rational beings, with possibly different core beliefs / axioms
- Individual reaches different conclusion suggests breakdown of logical consistency

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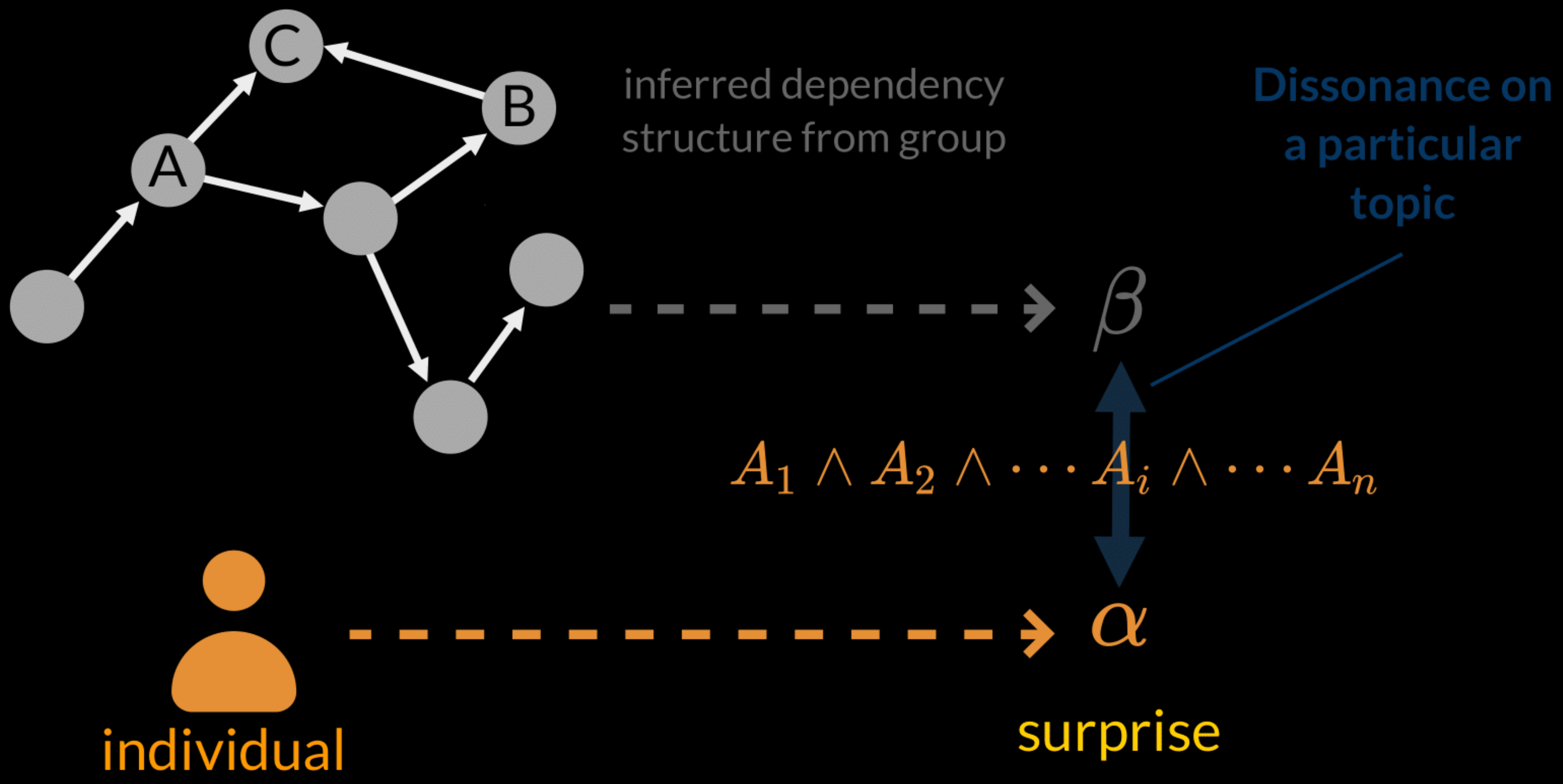
Framework & Background



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Theory

Collection of all such conditional inference trees is the recursive forest, answering the following question:

If we have n questions/topics $X_1, \cdots, X_n$,

and we have a subject responding with

$$x_1, \cdots, x_{i-1}, x_{i+1}, \cdots, x_{n-1},$$

then the distribution of responses to question X_i is given by

$$\Phi_i : \prod_{j \neq i} \Sigma_j \to \mathcal{D}(\Sigma_i)$$

where $\mathcal{D}(\Sigma_i)$ is the set of all possible distributions over the set of all possible responses Σ_i

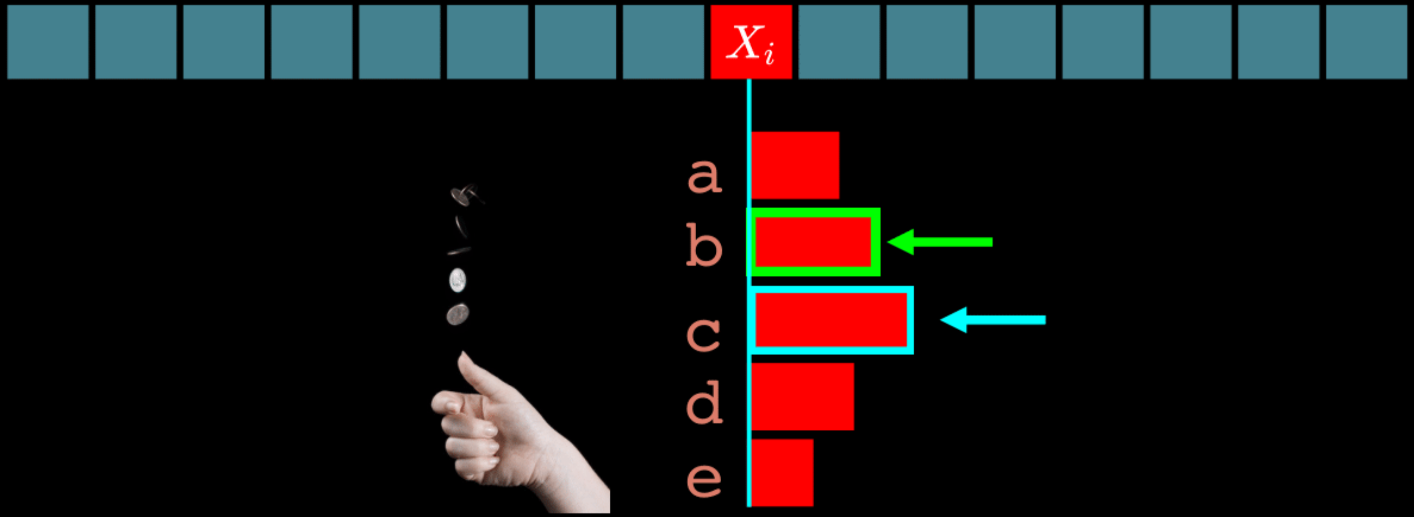
Intrinsic metric between opinion vectors

For two opinion vectors x, y

$$\theta(x, y) \triangleq \mathbf{E}_i \left(\mathbb{J}^{\frac{1}{2}} \left(\Phi_i^P(x_{-i}), \Phi_i^Q(y_{-i}) \right) \right)$$

where P, Q are possibly two distinct populations
with distinct qnets, such that
$x \in P, y \in Q$ and
J is the Jensen-Shannon divergence

Towards A Formulation for Spontaneous Shifts



Similar opinion vectors can spontaneously switch:

intrinsic metric quantifies the odds of this spontaneous switch

Three Fundamental Equations for Opinion Geometry Inference and Belief Shift Dynamics

Recursive Forest

$$\Phi_i : \prod_{j \neq i} \Sigma_j \rightarrow \mathcal{D}(\Sigma_i)$$

Metric

$$\theta(x,y) \triangleq \mathbf{E}_i \left(\mathbb{J}^{\frac{1}{2}} \left(\Phi_i^P(x_{-i}), \Phi_i^Q(y_{-i}) \right) \right)$$

Dissonance

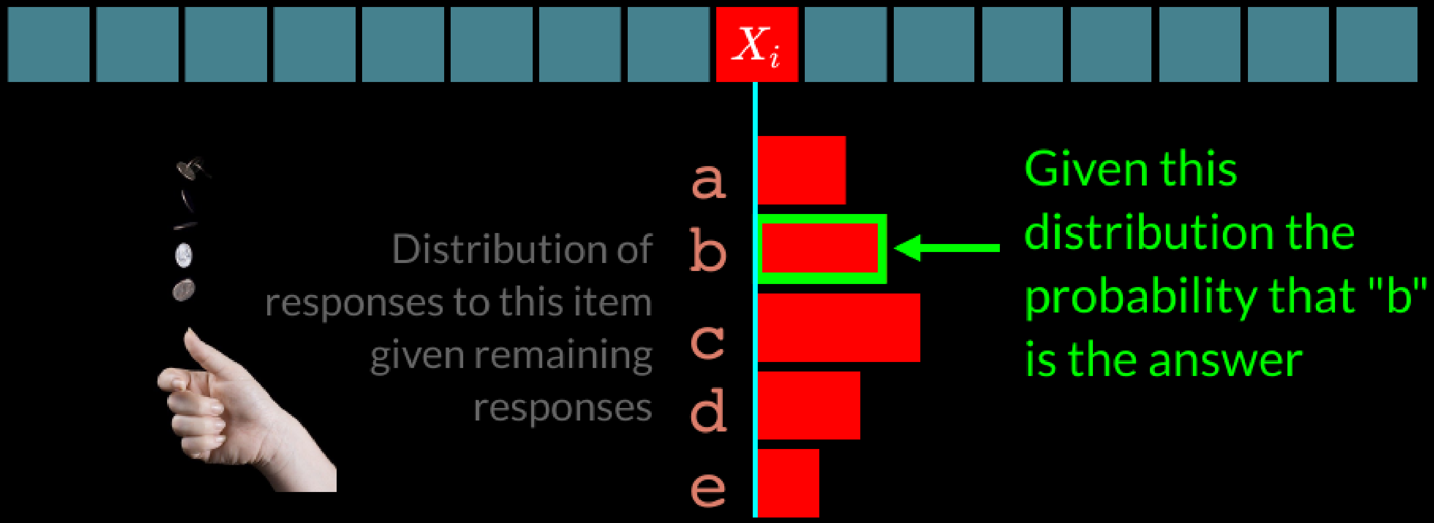
$$\mathbb{D}^P(x,i) \triangleq 1 - \Phi_i^P(x_{-i})|_{x_i}$$

Assume that one question

X_i

is unanswered.

questions/opinions $X_1, X_2, \cdots, X_i, \cdots, X_N$



Follows from first principles: $$Pr(x \in P \rightarrow y \in Q) = \prod_{i=1}^{N} \Phi_i^P(x_{-i})\big|_{y_i}$$

$$\theta(x,y) \triangleq \mathbf{E}_i \left(\mathbb{J}^{\frac{1}{2}} \left(\Phi_i^P(x_{-i}), \Phi_i^Q(y_{-i}) \right) \right)$$

Distance metric such that log-likelihood of jump scales as the distance

theorem

$$\omega_y e^{\frac{\sqrt{8}N^2}{1-\alpha}\theta(x,y)} \geq Pr(x \in P \rightarrow y \in Q) \geq \omega_y e^{-\frac{\sqrt{8}N^2}{1-\alpha}\theta(x,y)}$$

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Dynamic Modeling & Spectral Analysis

Average Dissonance for sample:

$$D_x \triangleq \mathbf{E}_i D(x,i)$$

Transition Matrix between samples:

$$P_{xy} = \begin{cases} \omega_y e^{-\frac{\sqrt{8}N^2}{1-\alpha}\theta(x,y)} \frac{D_x}{D_y} & \text{if } x \neq y \\ 1 - \sum_{x \neq y} P_{xy} & \text{otherwise} \end{cases}$$

prob. of x's belief changing to y's

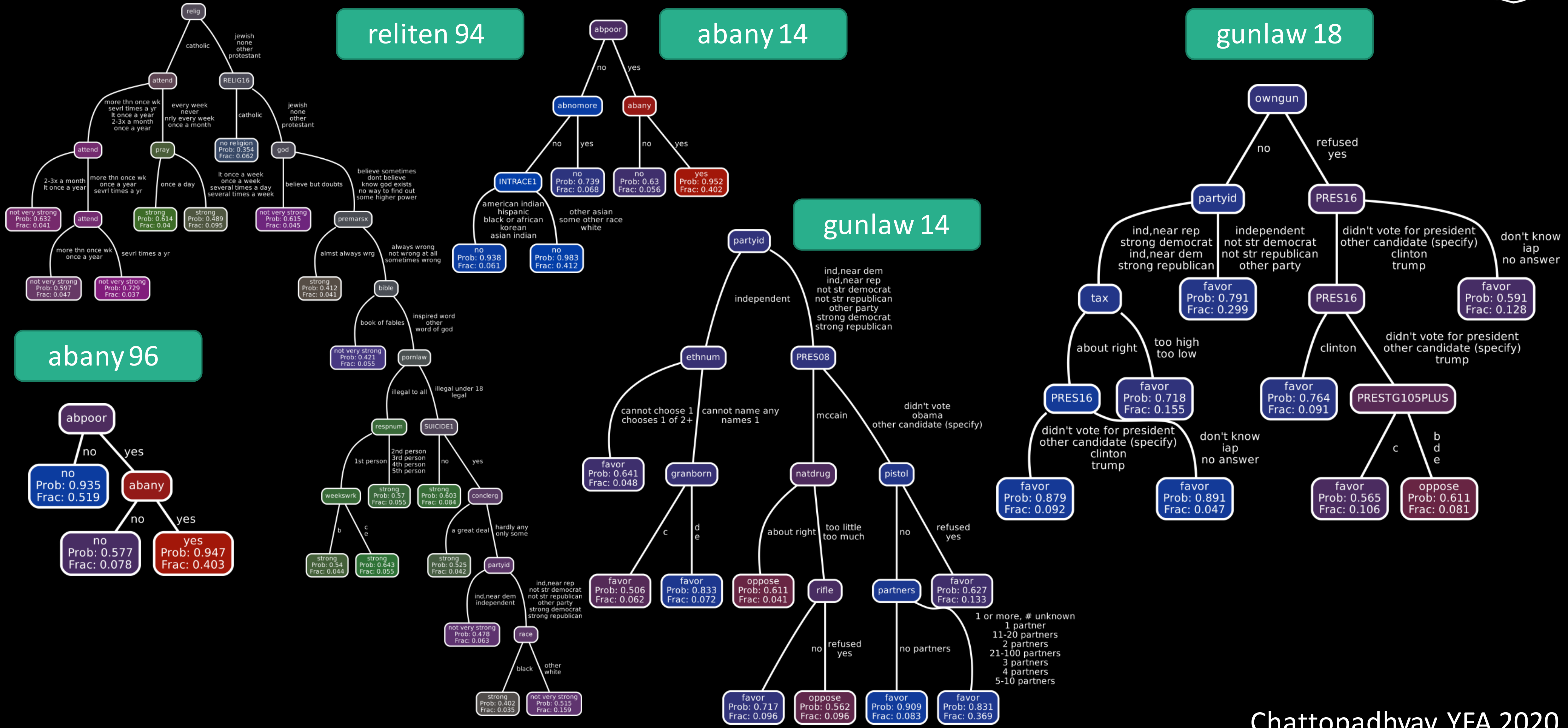
N: number of questions, $\alpha =$ significance level (.95)

Belief Spectrum on population:

$$\nu P = \nu$$

Results

Component Conditional Inference Trees Computed for specific GSS Variables for Different Years



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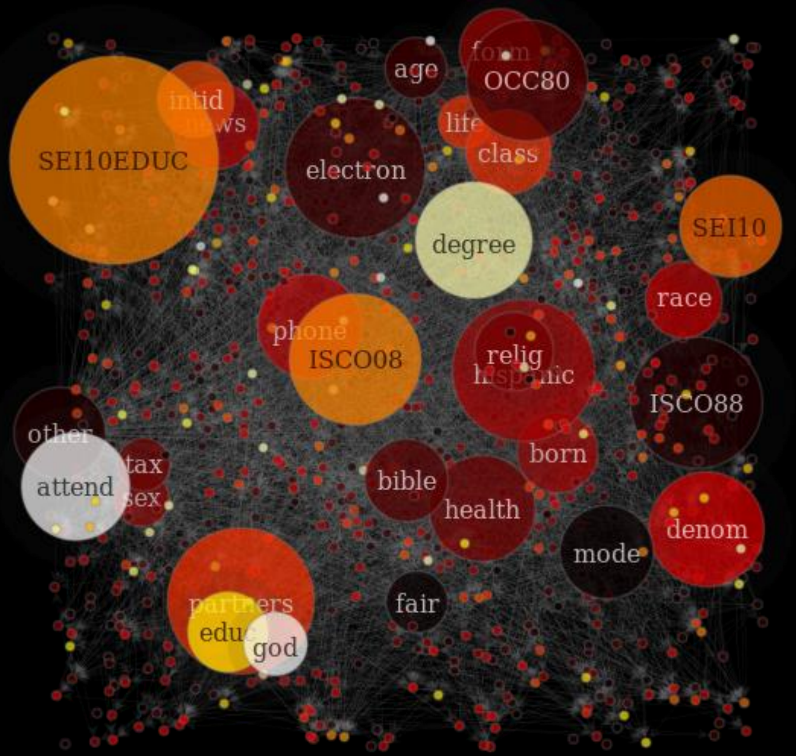
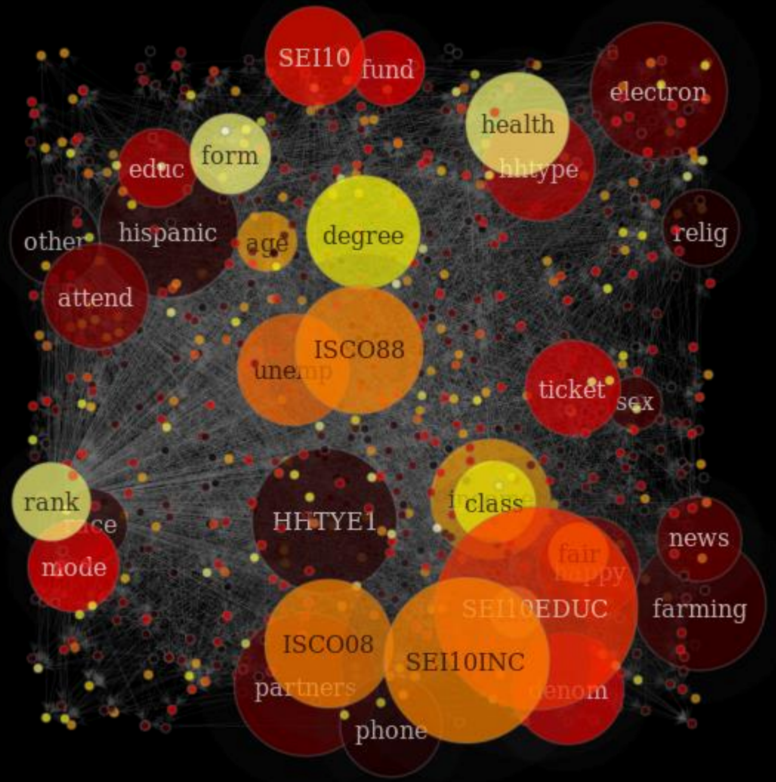
Inferred Dependency Structures (shown for three years)

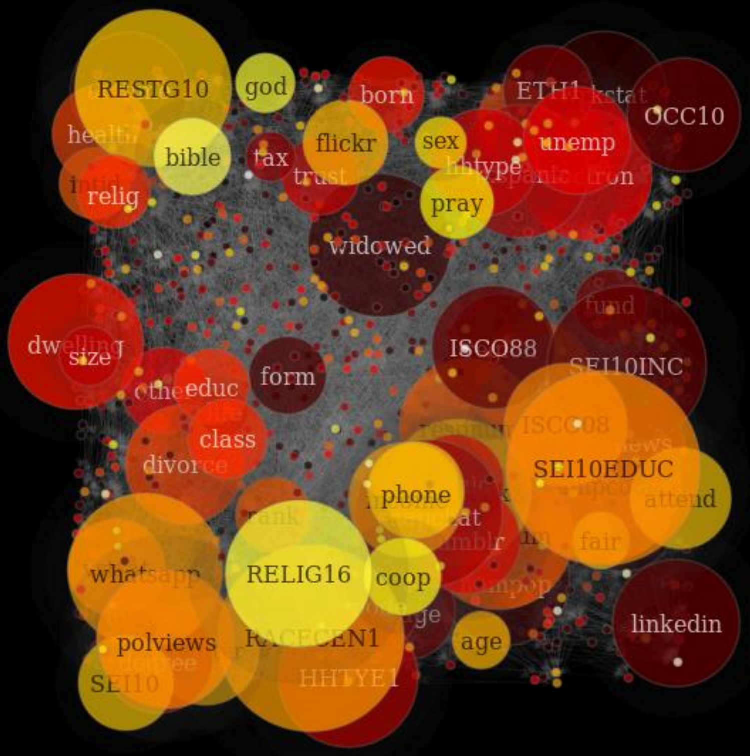
YEAR 2008



YEAR 2012



YEAR 2016



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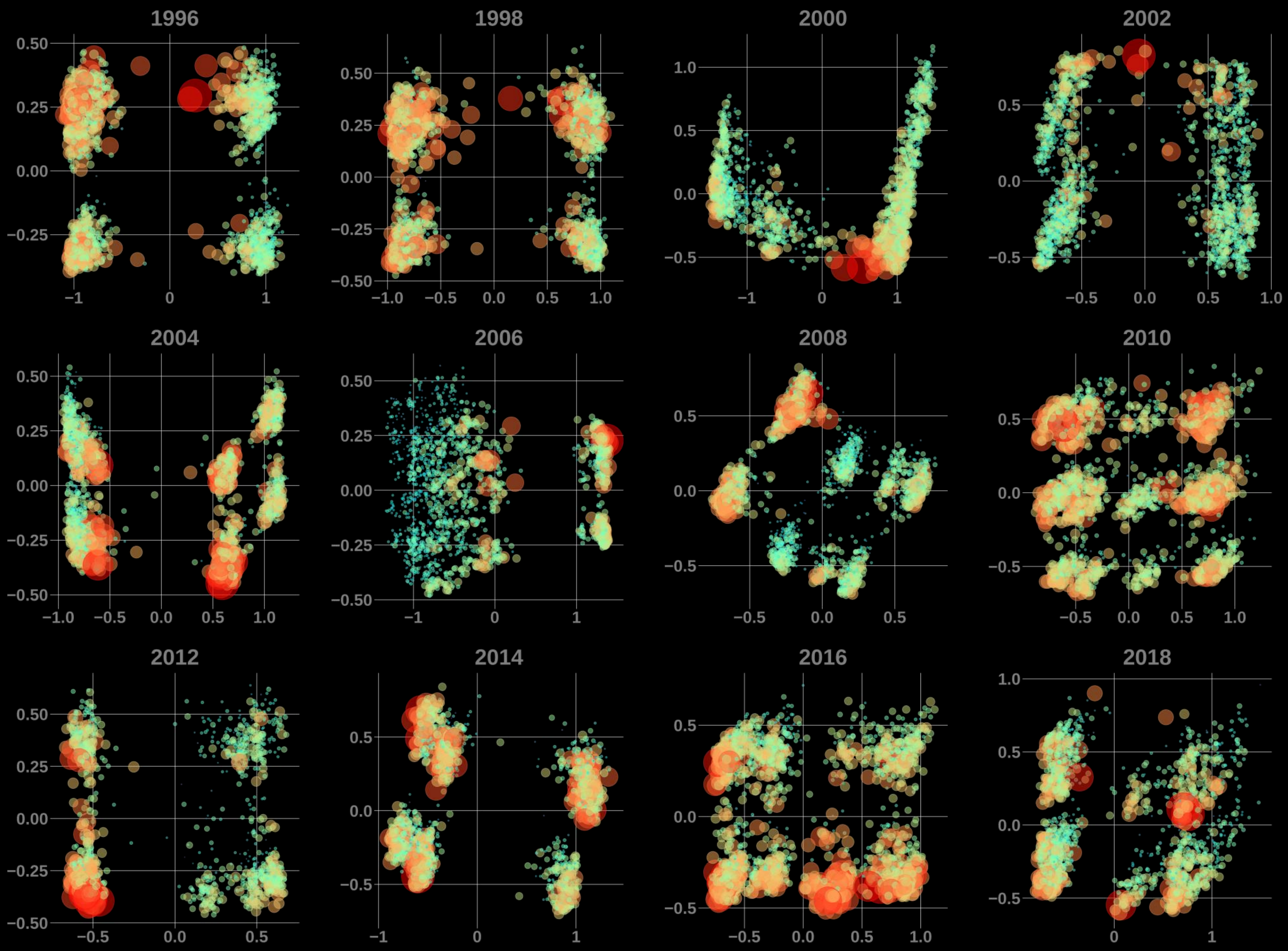

Geometry of Opinion Space with Belief Spectrum

Larger dots represent thought leaders

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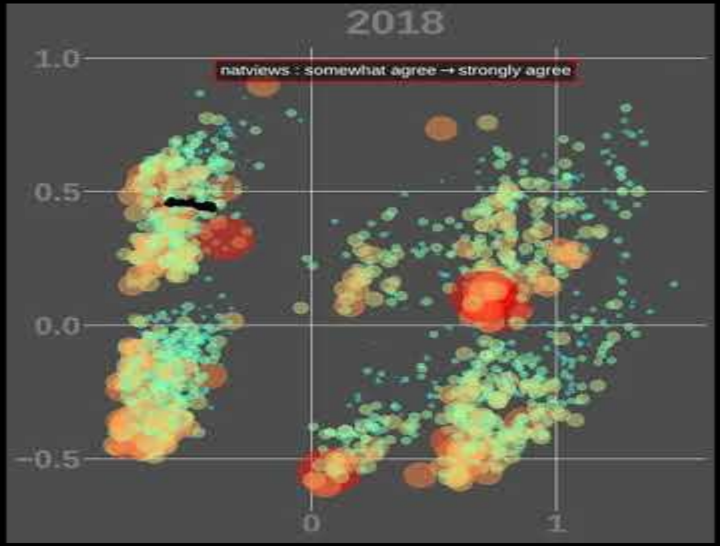
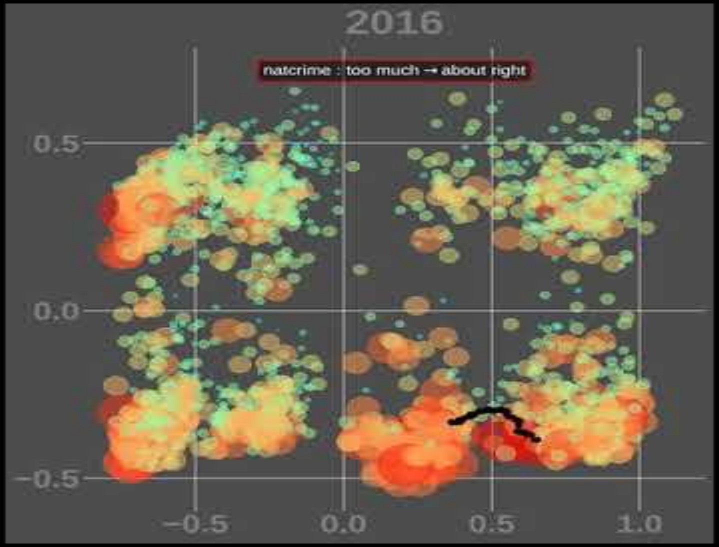
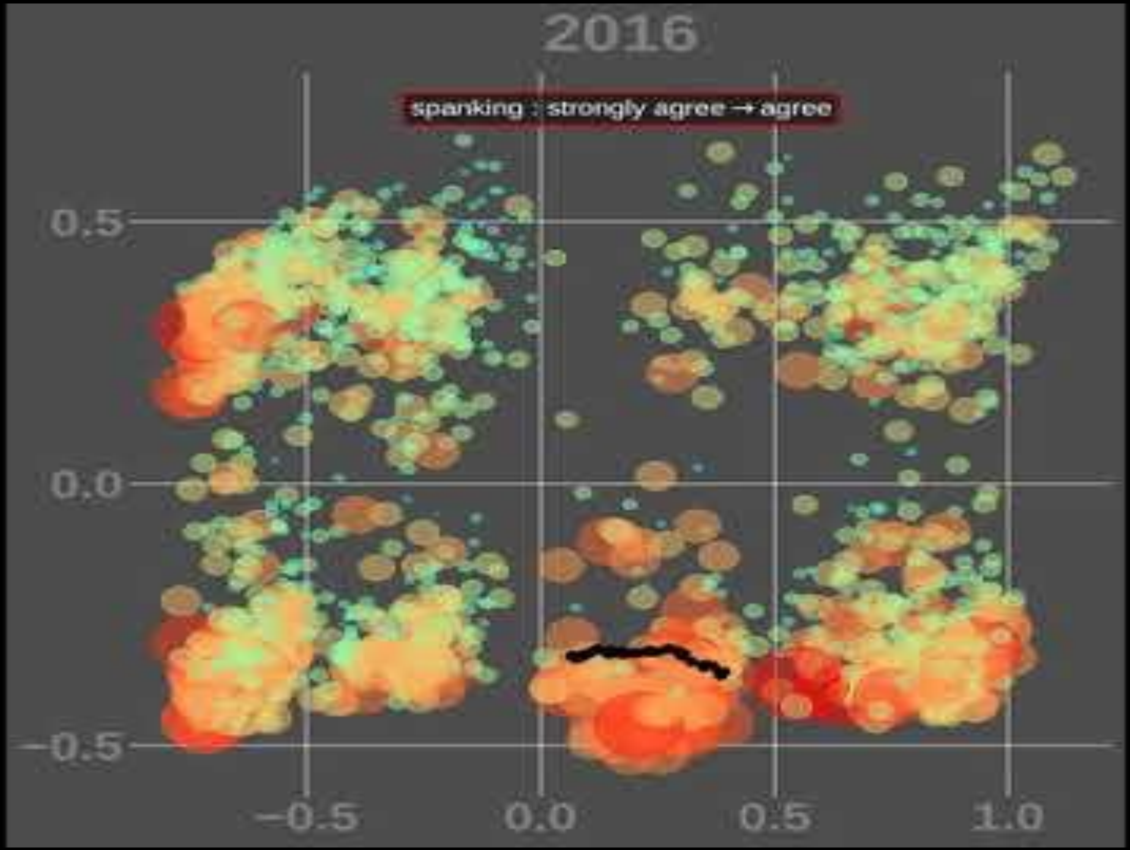
Belief Shift Trajectories Simulated with correspoding local shifts







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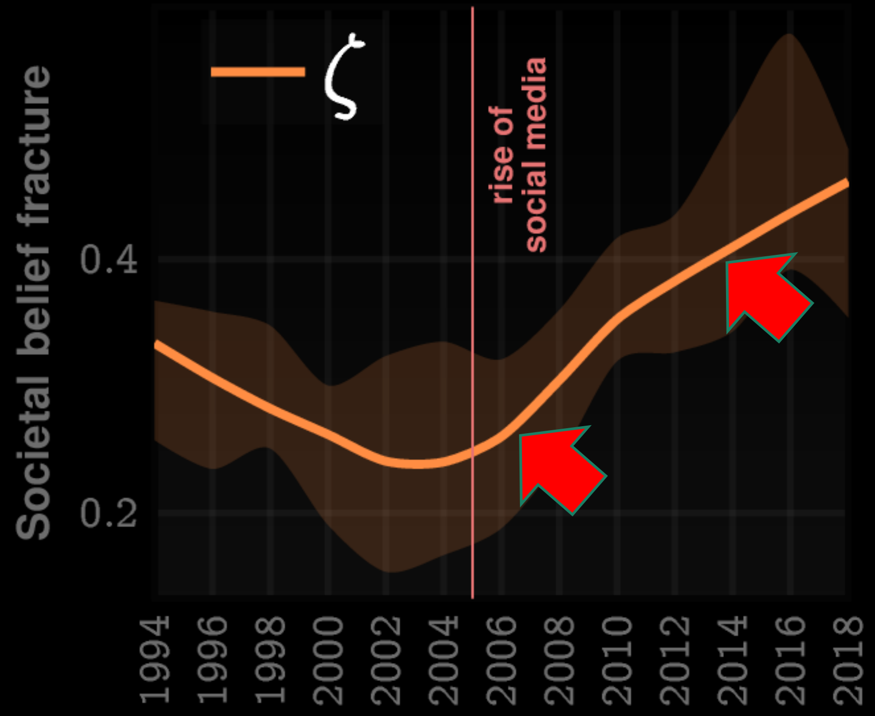
Worsening Societal Fracture: Association with Rise of Social Media

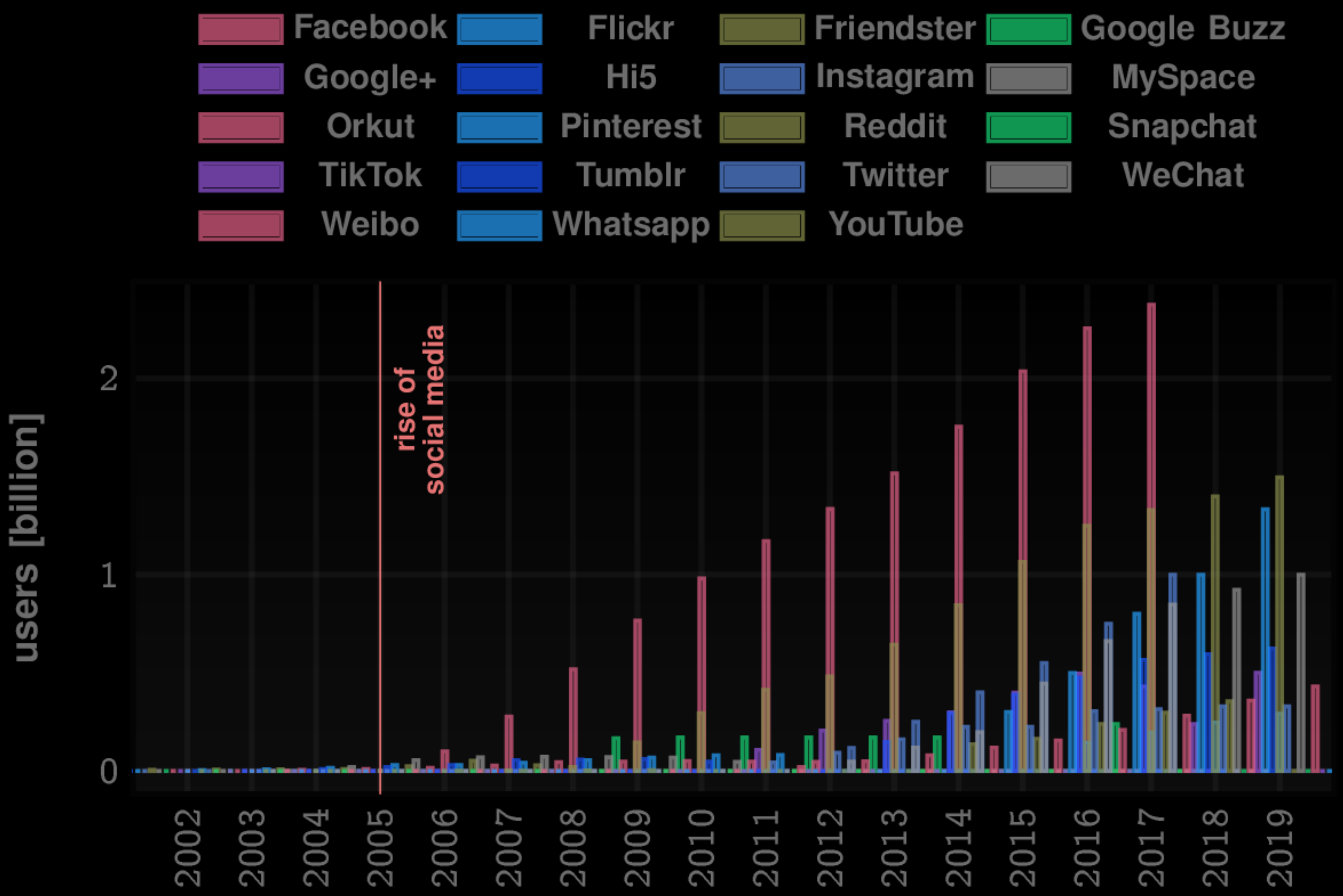
Measure of fracture:

$$\zeta = \mathbf{E}_\alpha \left(\frac{1}{|X(\alpha)|} \sum_{x_i, x_j \in X(\alpha)} \Theta_{ij}^2 \right)^{\frac{1}{2}}$$

where set of samples:

$$X(\alpha) = \{x : Pr(x) > \alpha\}$$





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Ongoing & Future Work

Ongoing Validation

1. Validate forecasting of societal shifts in opinion distributions for key contentious GSS variables
2. Use true longitudinal datasets to validate opinion shifts in individuals over time
3. Design optimal intervention strategies

Future Work

1. Validate interventions
2. Experiment with local cohorts
3. Investigate cross-talk effects between inferred geometry of opinion space and external socio-economic variables
4. Apply to data beyond US and Western nations

Biography

Ishanu Chattopadhyay is an Assistant Professor of Medicine at the University of Chicago. His research focuses on the core algorithmic principles in large-scale data analysis with minimal human intervention, or where there is little prior domain expertise. Leading the laboratory for Zero Knowledge Discovery, Prof. Chattopadhyay is interested in unravelling complex phenomena in biology, biomedicine, clinical decision-making, epidemiology of complex diseases, and human social interactions. Dr. Chattopadhyay's work resides at the cusp of several disciplines - artificial intelligence, statistical theory, formal languages, dynamical systems, machine learning, and computational social science; formulating tools that work with little prior experience, and hopefully answering questions that we have not yet thought to ask. Dr. Chattopadhyay earned his doctorate at the Pennsylvania State University, along with multiple graduate degrees in Mathematics and Engineering, and completed his post-doctoral training at Cornell University, before joining the University of Chicago as an expert in data science. in late 2016. He has served as PI in several large grants from DoD and DARPA.