

**Topic correlation networks
inferred from open-ended responses
reveal signatures of ideology
behind carbon tax opinion**

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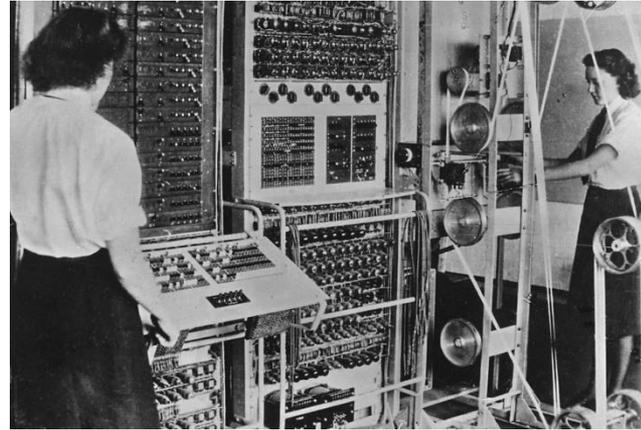


Stewardship of the Transition Zeitgeist

detect, track, and intervene on natural & engineered trends



Bletchley Park, 1941



Effectors (platform design, embedded agents, comms, etc.) supported by *social analytics*

Stewarding transition policy

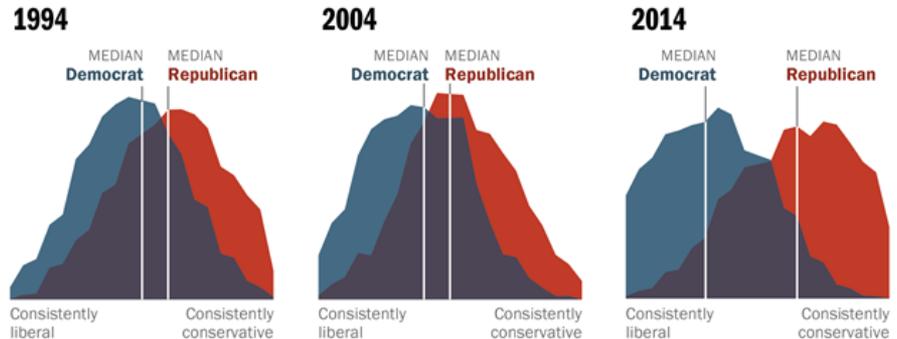
Policy development process:

- design policy
- deploy policy
- measure & analyze effectiveness
 - Public opinion: What do people think about it?
- ...

iterate



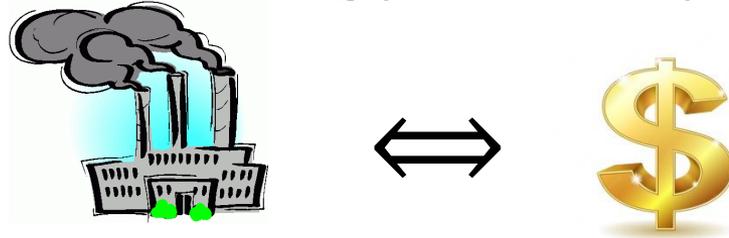
Backdrop: Polarization



Today's topic:

Public opinion of carbon pricing in Canada

A case study in ideology-driven policy opinions



The ‘price on pollution’/‘carbon tax’

- In Canada:
 - Polluters pay:*
 - carbon levy on fuel purchases
 - “big emitters” program for industrial facilities
 - rebate program for everyone:
 - \$ in tax return to 8/10 households in Canada
 - \$20/ton 2019
 - \$50/ton 2022
 - \$170/ton 2030
- Many economists agree: *flexible, simple, & easy to ramp up*
- Yet, **popularity low**—typically falling along political lines.

“Technology, not taxes, is the way forward to reduce emissions” –Conservative Party Leader

Intervening on beliefs with facts

Then just show them the data?

Total income tax deducted (amounts from all Canadian slips)	437	
Refundable Quebec abatement (See line 440 in the guide.)	440 +	
CPP overpayment (See line 308 in the guide.)	448 +	
Employment insurance overpayment (See line 312 in the guide.)	450 +	
Climate action incentive (Complete Schedule 14.)	449 +	457
Refundable medical expense supplement (Complete the Worksheet for the return.)	452 +	
Working income tax benefit (WITB) (Complete Schedule 6.)	453 +	
Refund of investment tax credit (Get and complete Form T2038(IND).)	454 +	
Part XII.2 trust tax credit (box 38 of all T3 slips and box 209 of all T5013 slips)	456 +	
Employee and partner GST/HST rebate (Get and complete Form GST370.)	457 +	
Flinnible educator school supply tax credit		



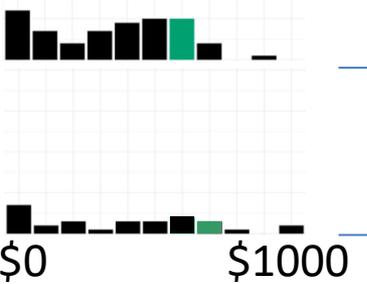
Guess at rebate size

Do they update their beliefs?

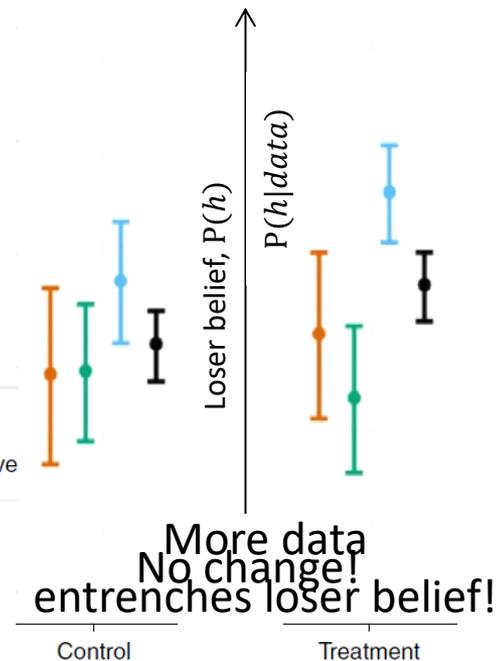
Systematic Underestimation

under-estimate the rebate size

for all **actual rebate sizes**



40

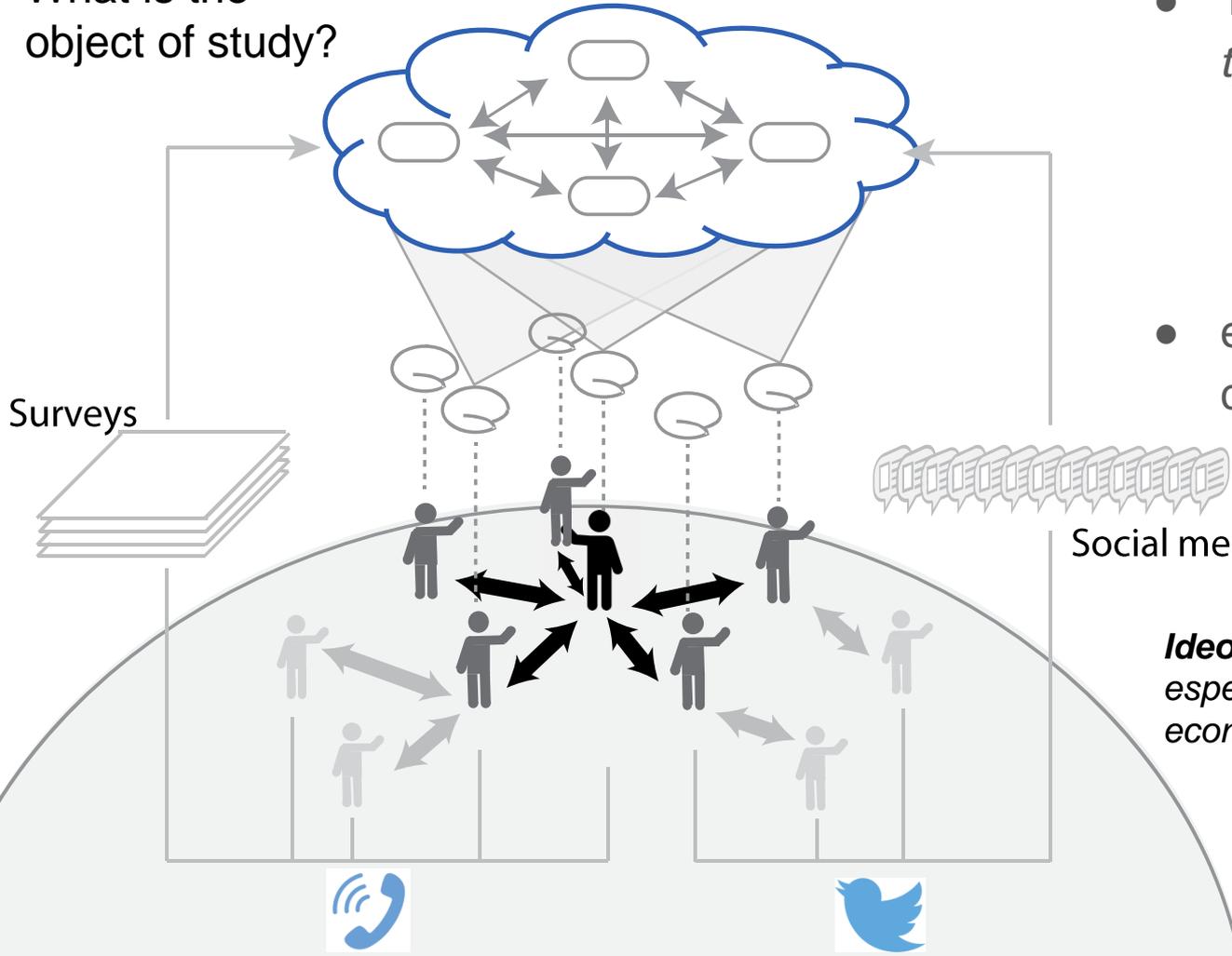


Not necessarily irrational!

strong prior for $h \Rightarrow P(h|data) \approx P(h)$!

(Bayesian confirmation theory)

What is the object of study?



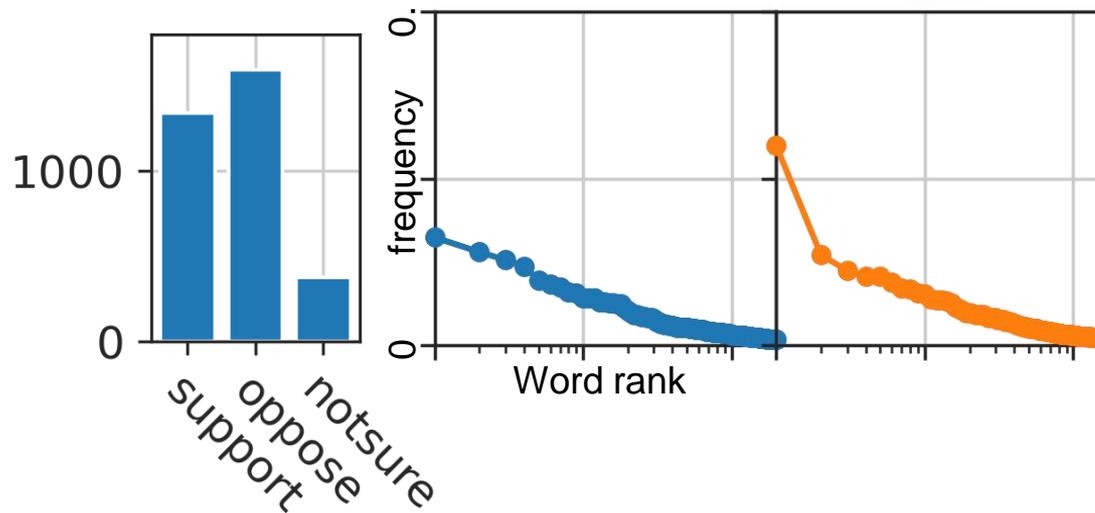
- Target Object:
type-conditioned distribution over a belief network
 - Inter-connected
 - Highly dynamic
 - Driven by many objectives
- expressed in what we collectively say and do

Ideology: “a system of ideas and ideals, especially one which forms the basis of economic or political theory and policy”

2019 Response statistics

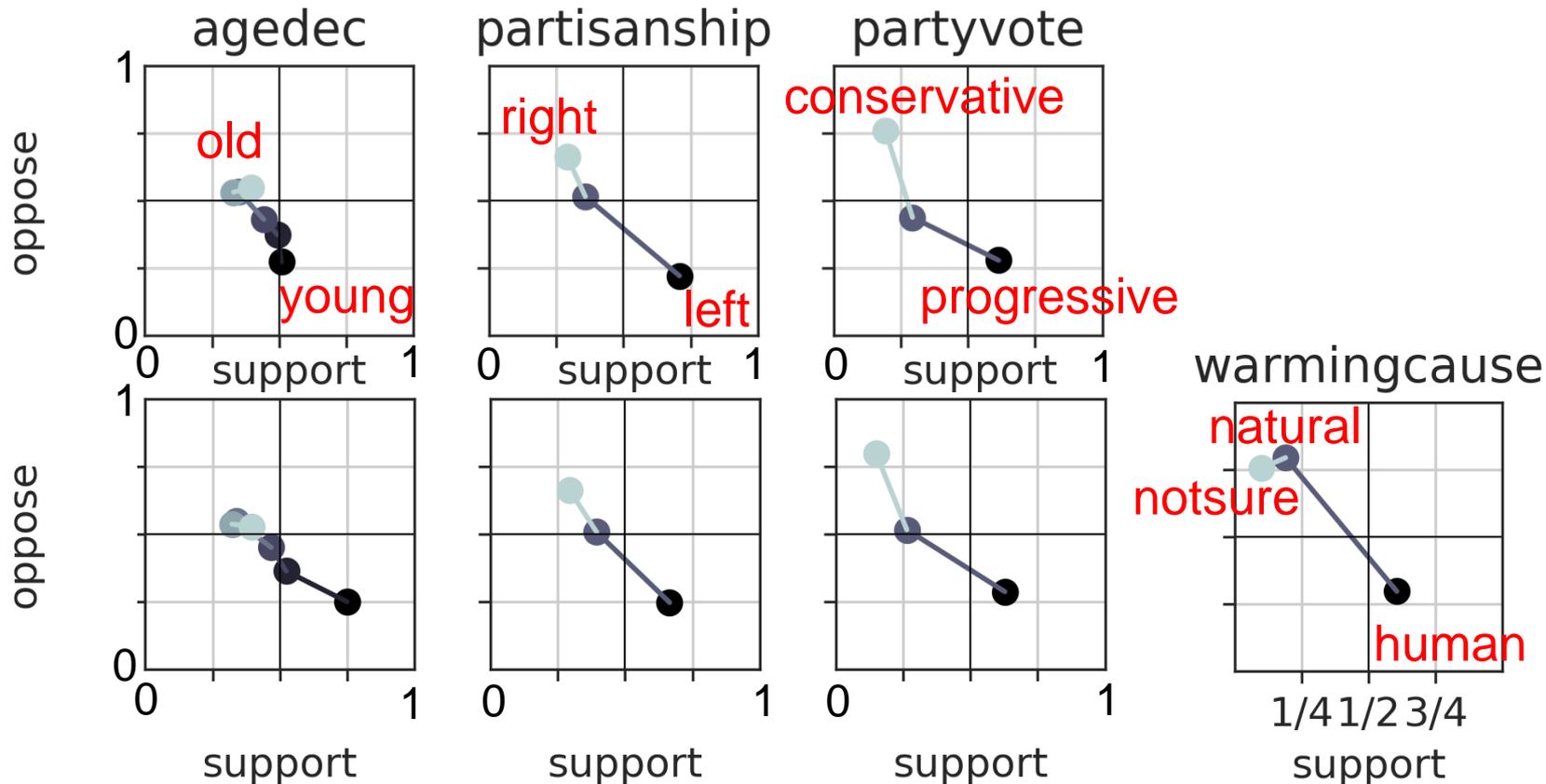
support

oppose



Support shifts strongly with political views/voting

2019



2022

Topic Models are generative models

Vocabulary—an indexed set of words $\{w_1, \dots, w_N\}$

Topic, $\mathbf{t} = (p_1, \dots, p_N)$ —sample probabilities over a vocabulary

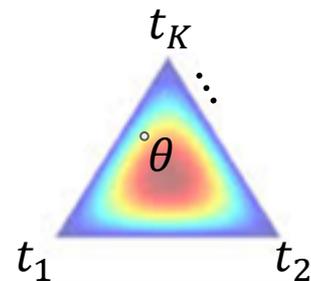
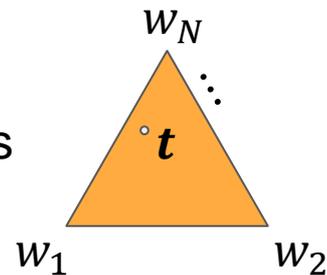
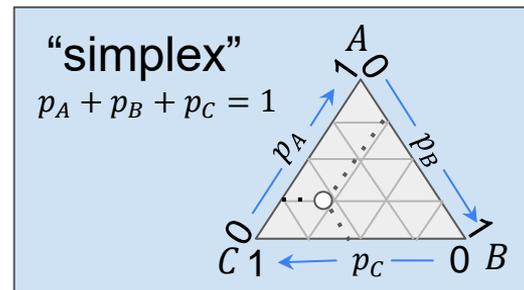
Topic mixture, $\boldsymbol{\theta} = (q_1, \dots, q_K)$ —sample probabilities over K given topics

Topic mixture prior, $P_s(\boldsymbol{\theta})$ —a distribution on $\boldsymbol{\theta}$, given respondent type s

Process to generate a response:

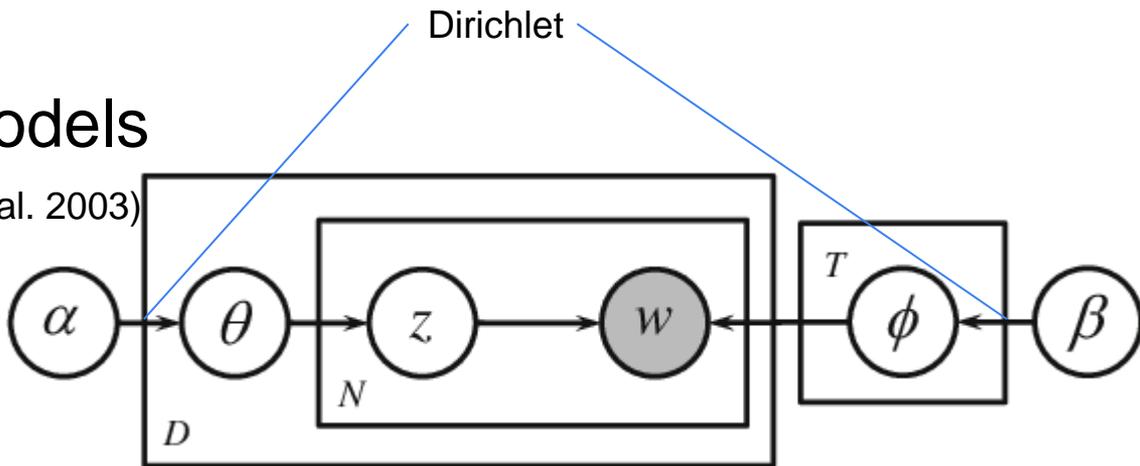
- Step 1: Sample a topic mixture $\boldsymbol{\theta}$, given s
- Step 2: Sample a topic id, given $\boldsymbol{\theta}$
- Step 3: Sample a word id, given \mathbf{t}

[" _____ "]

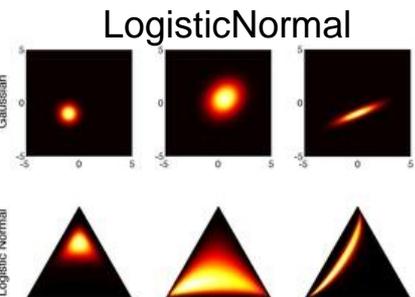


Generative Topic Models

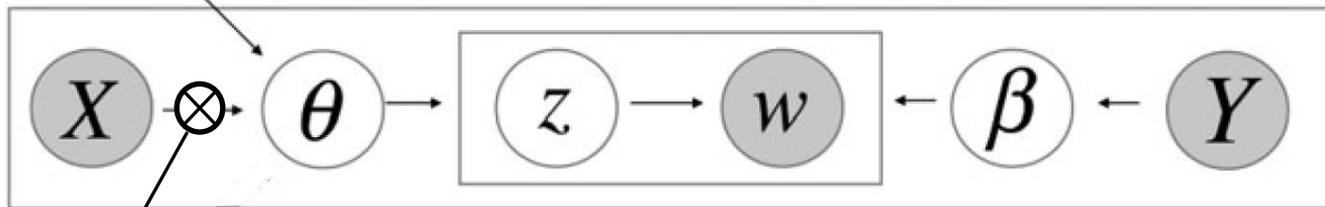
Latent Dirichlet Allocation (LDA) (Blei et al. 2003)



Correlated Topic Model (CTM)
(Blei & Lafferty, 2005)



Σ Document-topic proportions Per-word topic assignment Observed word Topic word distribution Content covariates



γ Structural Topic Model (Roberts et al. 2014)

$$\beta \propto \exp(m_v + \kappa_{k,v}^{(r)} + \kappa_{y_d,v}^{(c)} + \kappa_{y_d,k,v}^{(i)})$$

Coefficients

Topic Quality Assessment

Exclusivity

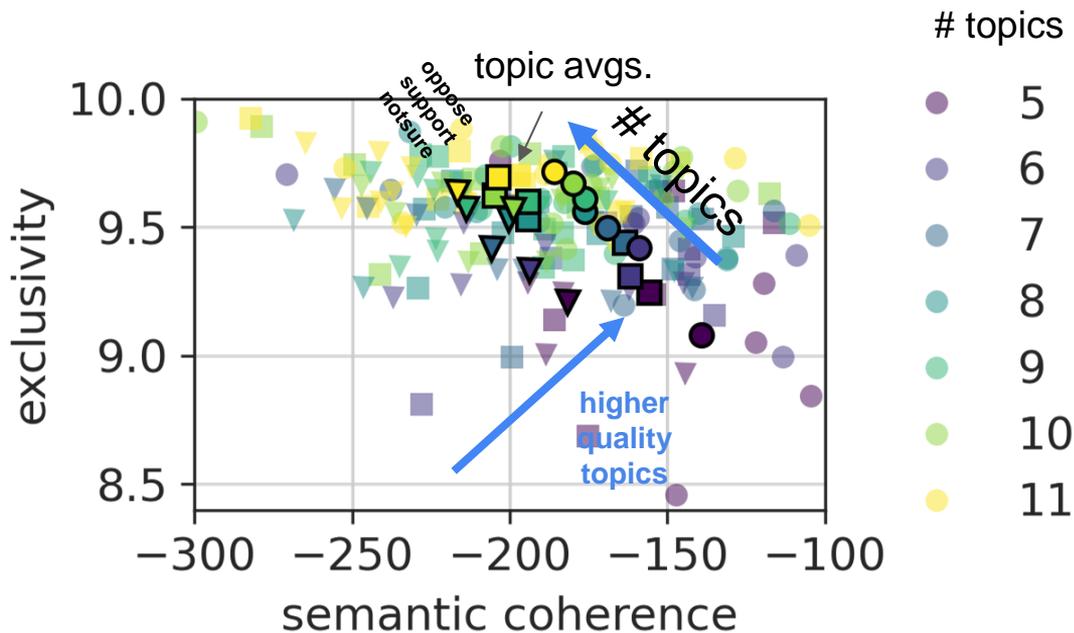
High when a topic's frequent words
are exclusive to that topic

$$\text{FREX}_{k,v} = \left(\frac{\omega}{\text{ECDF}(\beta_{k,v} / \sum_{j=1}^K \beta_{j,v})} + \frac{1 - \omega}{\text{ECDF}(\beta_{k,v})} \right)^{-1}$$

Semantic Coherence

High when a topic's frequent words co-occur often

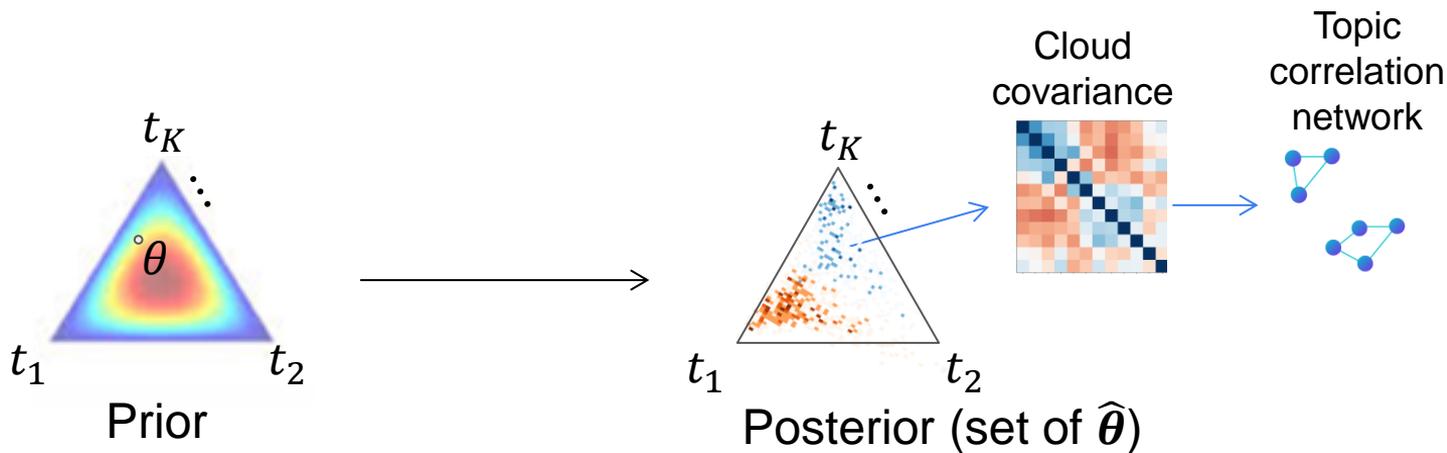
$$C_k = \sum_{i=2}^M \sum_{j=1}^{i-1} \log \left(\frac{D(v_i, v_j) + 1}{D(v_j)} \right)$$



Conclusion: No *single* number of topics stands out.

Posterior Inference of STMs

- Given parameters, compute the most probable topic mixture, $\hat{\theta}$, for each response



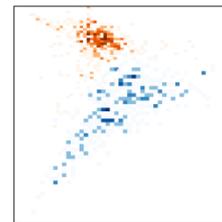
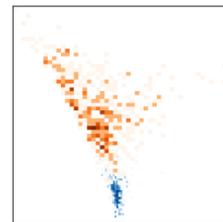
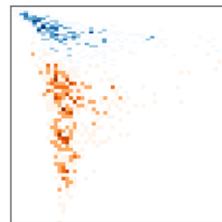
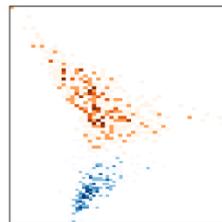
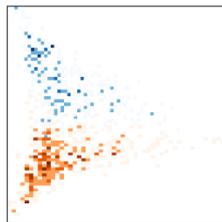
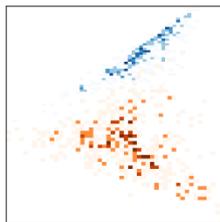
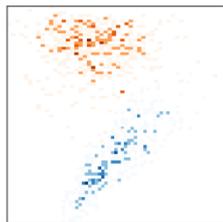
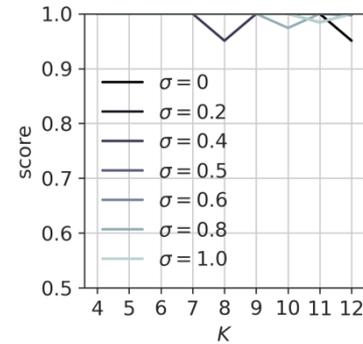
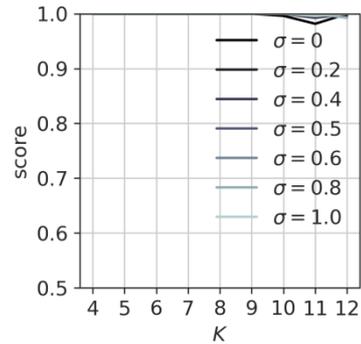
How to analyze these type-conditioned $\hat{\theta}$ -data clouds?

Predictive power of mixture space

Left-learning/
Right-leaning

Progressive Voting/
Conservative Voting

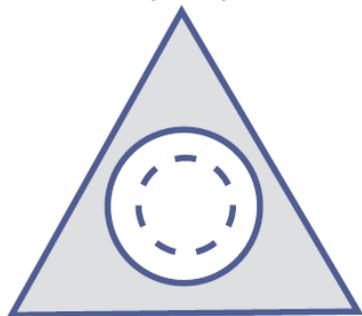
- How well does a linear classifier do?



Characterizing Ideology

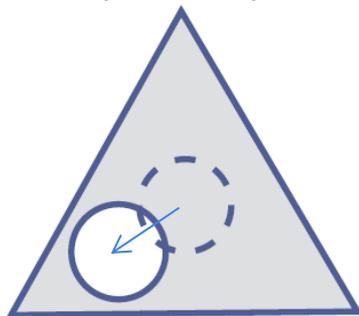
- Previously: subjective labelling of topics from interpreting top words.
- But, “ideological” strength *should be* independent of topic semantics...
- Solution: *geometry of mixture data cloud*

(size)



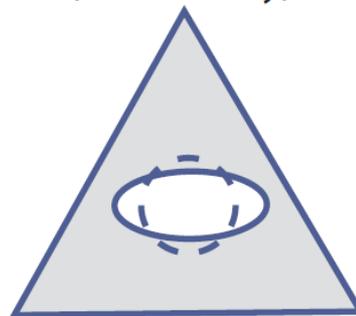
(K-1)-dim. Volume
from covariance

(location)



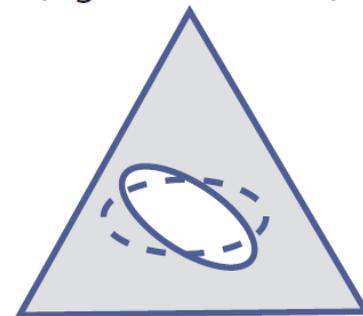
Distance to center
 $\langle H(\hat{\theta}) \rangle / H_{\max}$

(eccentricity)

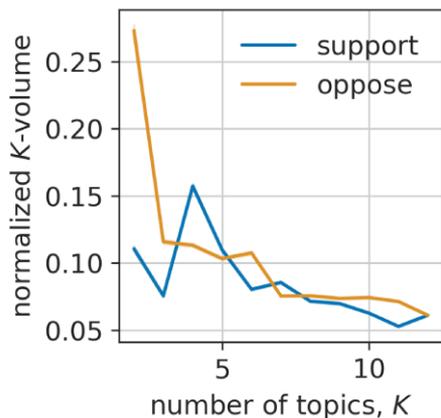
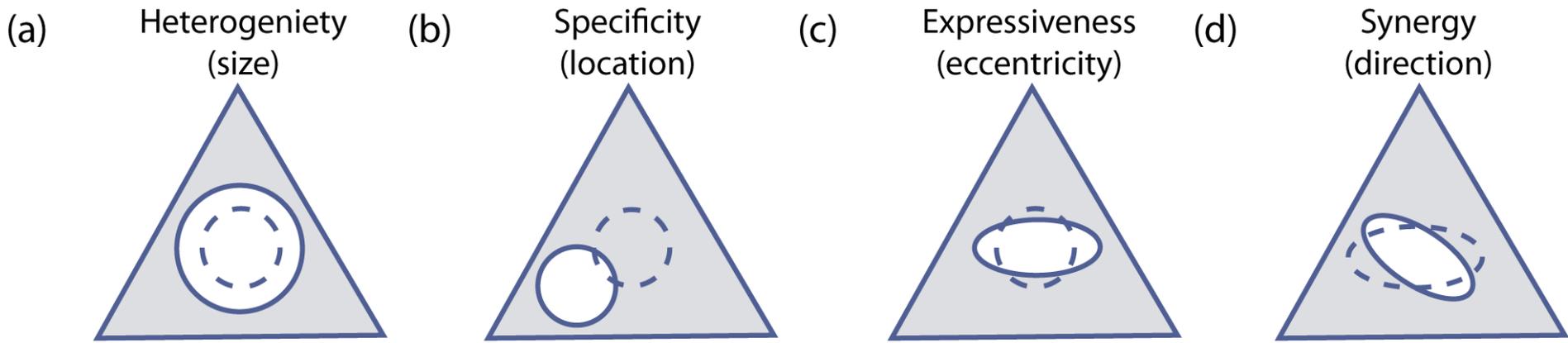


Intrinsic
dimensionality
from covariance

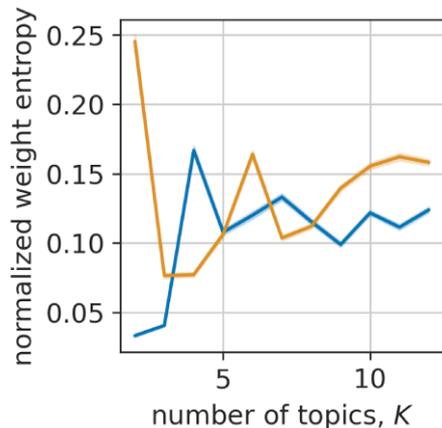
(signed direction)



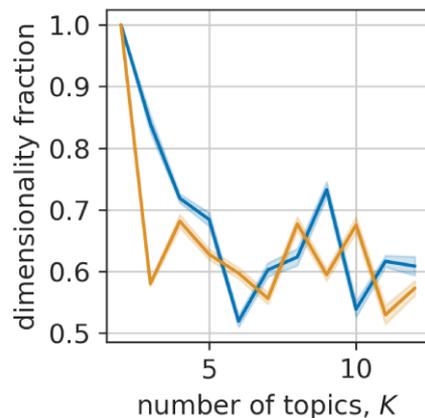
Fraction of
positive pairwise
correlations



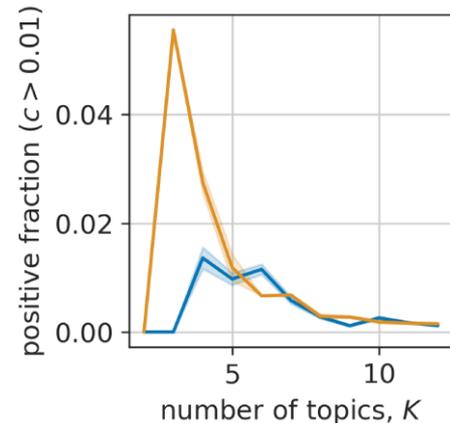
Oppose types are more similar to each other



inconclusive (with this distance metric)



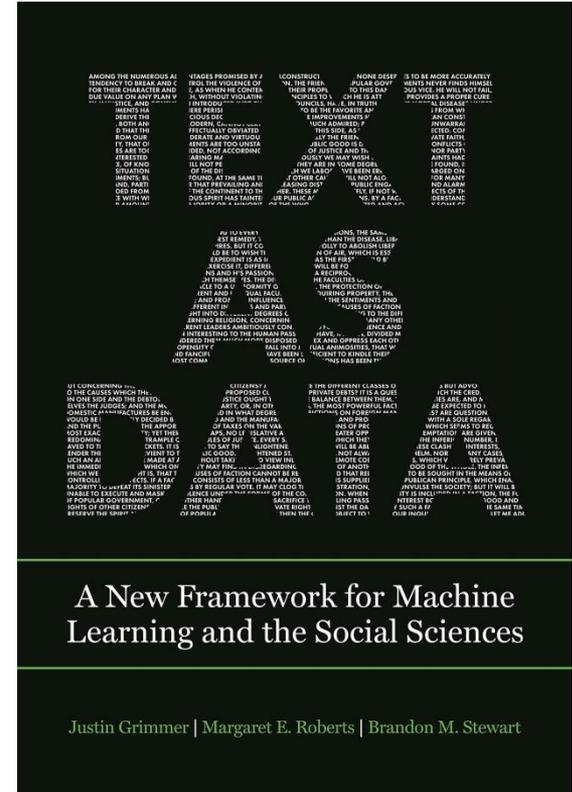
oppose types mix in fewer ways



oppose types recruit more mutually enforcing topics

Quantitative social science

- **Datastreams:** [text, behaviour,...] *as data*
 - social media, news media, transcripts, internet,
- **Models:** Multiscale, many-agent system models
 - e.g. Sociophysics with neural network components
- **Infra:** pipelines for now-casting/data management
- **Methods:** statistical inference/deep learning
- **Mathematical theory:**
 - Control theory/reinforcement learning theory
 - Game theory (esp. mechanism design)
 - evolutionary game theory/statistical mechanics
- **Disciplines:** psychology/public policy/political science/economics/sociology



A New Framework for Machine Learning and the Social Sciences

Justin Grimmer | Margaret E. Roberts | Brandon M. Stewart

Policy Implications

- Better design/better communication
 - Meet people where they are.
- A response to “no one is driving the bus”
 - discourse evolving in unintended ways
 - Many trying to sculpt the narrative
- Stewardship ethics best developed in open science setting

Acknowledgements

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