W911NF-19-1-0217

Thrust 2: A Unified Theory of Group Decision Making

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Outline

- I. Group Decisions with resource constraints: Sharing belief samples instead of full belief *distributions:* [Vul, Goodman, Grifiths, Tenenbaum,2014]
  - Bayesian Social learning [Deshpande & Mossel,2020]
  - Bayesian Social learning without recall [Salhab, Ajorlou, Jadbabaie, Tenenbaum, 2020]
- II. From Persuasive campaigns to Polarization : curse of dimensionality [Hazla, Jin, Ramnarayan, Mossel 2020]
- III. Persuasion, news sharing and spread of misinformation [Hsu, Ajorlou, Jadbabaie 2020; Hsu, Ajorlou, Jadbabaie Yildiz 2020]

I. Group Decisions with Resource Constraints: Sparse Belief Samples

Yash Deshpande and Elchanan Mossel

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(Cog Sci 2020)

Extending Resource-Rationality to Group decision-making

REVIEW

Computational rationality: A converging paradigm for intelligence in brains, minds, and machines

Samuel J. Gershman[1,*], Eric J. Horvitz[2,*], Joshua B. Tenenbaum[3,*]
+ See all authors and affiliations

Science 17 Jul 2015:
Vol. 349, Issue 6245, pp. 273-278
DOI: 10.1126/science.aac6076

Article Figures & Data Info & Metrics eLetters PDF

Abstract

After growing up together, and mostly growing apart in the second half of the 20th century, the fields of artificial intelligence (AI), cognitive science, and neuroscience are reconverging on a shared view of the computational foundations of intelligence that promotes valuable cross-disciplinary exchanges on questions, methods, and results. We chart advances over the past several decades that address challenges of perception and action under uncertainty through the lens of computation. Advances include the development of representations and inferential procedures for large-scale probabilistic inference and machinery for enabling reflection and decisions about tradeoffs in effort, precision, and timeliness of computations. These tools are deployed toward the goal of computational rationality: identifying decisions with highest expected utility, while taking into consideration the costs of computation in complex real-world problems in which most relevant calculations can only be approximated. We highlight key concepts with examples that show the potential for interchange between computer science, cognitive science, and neuroscience.

Volume 43 2020 , e1

Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources

Falk Lieder (a1) and Thomas L. Griffiths (a2)

DOI: https://doi.org/10.1017/S0140525X1900061X Published online by Cambridge University Press: 04 February 2019

COGNITIVE SCIENCE
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One and Done? Optimal Decisions From Very Few Samples

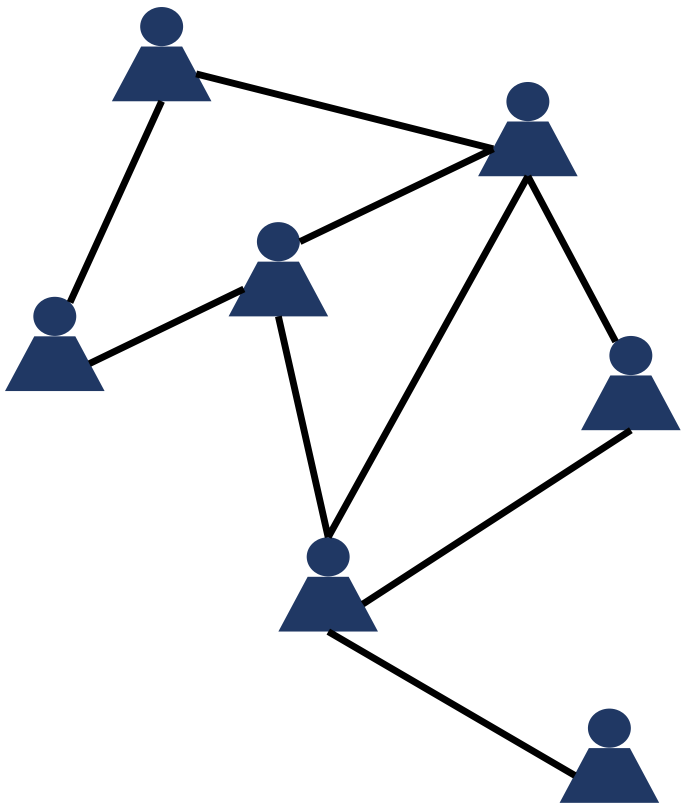
Edward Vul, Noah Goodman, Thomas L. Griffiths, Joshua B. Tenenbaum

First published: 28 January 2014 | https://doi.org/10.1111/cogs.12101 | Citations: 113

- People often appear to make decisions based on just one or a few samples from the appropriate posterior probability distribution, rather than using the full distribution
- Acting based on a few samples can be easily reconciled with optimal Bayesian inference
- Can groups learn if they only communicate samples?

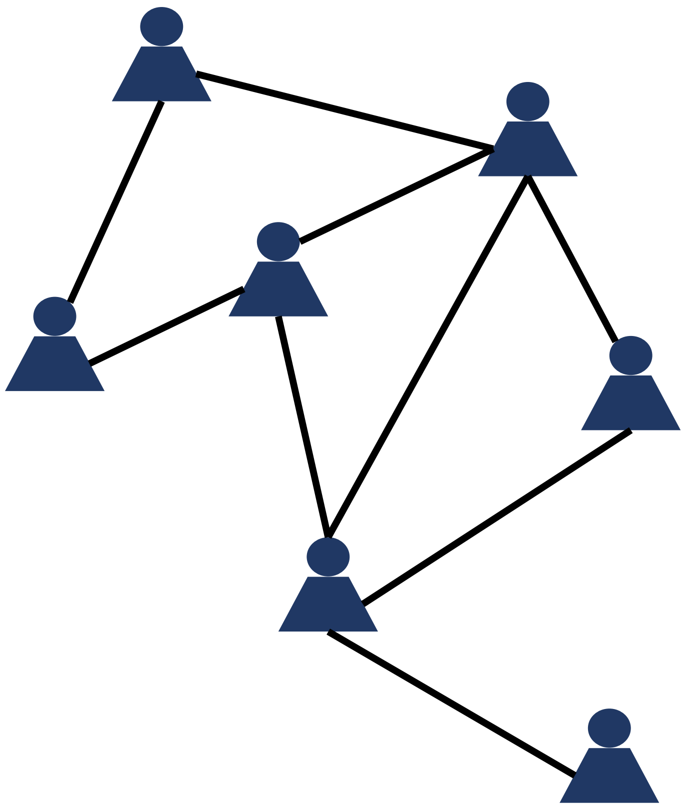
Bayesian Social Learning with Sampling

- social learning in the framework of Vul, Goodman, Griffiths, Tenenbaum 2015
- A group of fully Bayesian agents with private observations communicate a single sample from their belief distribution at each round
- Questions:
  - Do agents aggregate information?
  - If so, how well and how quickly?
  - Is it computationally tractable?



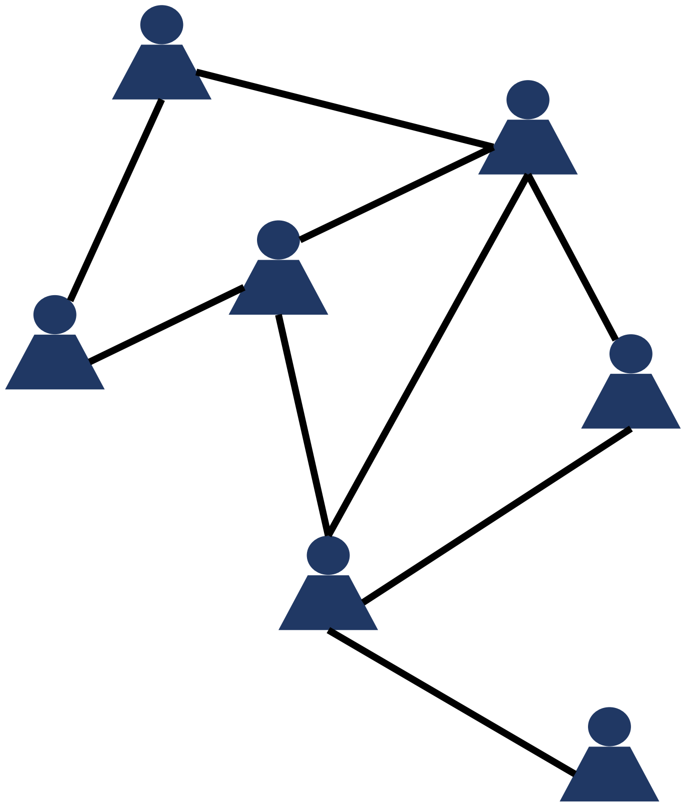
Bayesian Social Learning with belief sampling

- Surprisingly, there is *no informational cost* to sampling from beliefs.
- Bayesian agents aggregate information efficiently: as if all private signals were publicly known
- Sampling beliefs by fully Bayesian agents *does not* cause herding, polarization or confirmation bias. It only potentially slows convergence
- Not true in Non-Bayesian setting



A general model of social learning with belief samples

- State of the world $\theta \sim \nu$
- Agents get private signals $S_i \sim \mathbb{P}_i(\cdot|\theta)$
- At time t, agent i
  - computes posterior $\nu_i(t)$
  - generates sample $Y_i(t) \sim \nu_i(t)$
  - communicates to neighbors $Y_i(t)$

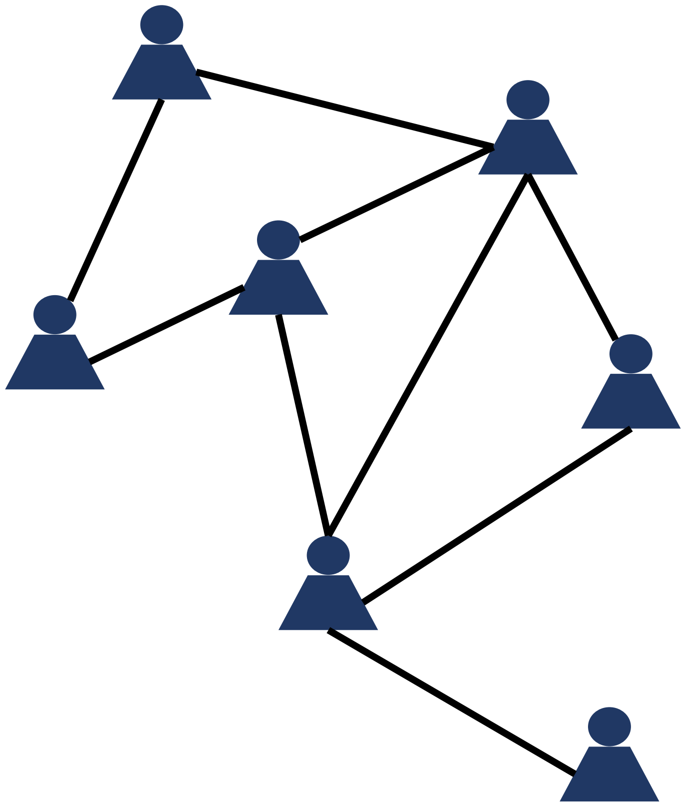


- **Efficient aggregation**: agents learn as if *private signals are public*

i.e. $\nu_i(t) \to \nu|S_1, \ldots, S_n$

Gaussian model

- State of the world $\theta \sim \nu$ (flat prior on $\mathbb{R}^d$)
- Agents get private signals $S_i \sim N(\langle a_i, \theta \rangle, 1)$
- At time t, agent i
  - computes posterior $\nu_i(t)$
  - generates sample $Y_i(t) \sim \nu_i(t)$
  - communicates to neighbors $Y_i(t)$



Main result: agreement & efficient aggregation

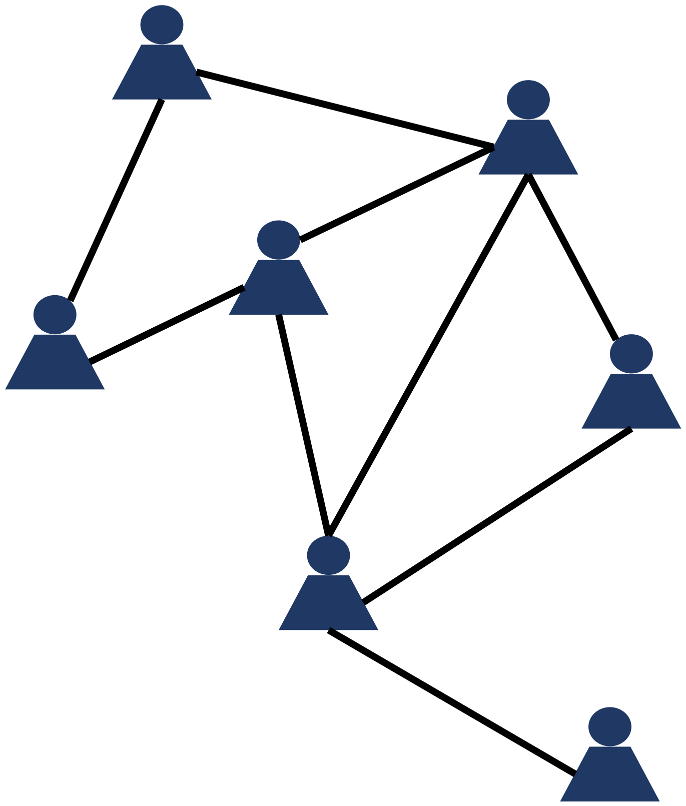
Theorem

In a connected network, agents eventually agree and efficiently aggregate information. Namely, almost surely, for every agent *i*:

$$\nu_i(t) \to \nu | S_1, \dots, S_n$$

- General model needs mild regularity on signal distributions $\mathbb{P}_i(\cdot|\theta)$
- Convergence above is in weak topology generally,
  can prove convergence in Wasserstein distance for Gaussian model

Gaussian model is computationally tractable



- State of the world $\theta \sim \nu$ (flat prior on $\mathbb{R}^d$)
- Agents get private signals $S_i \sim \mathrm{N}(\langle a_i, \theta\rangle, 1)$
- Posteriors $\nu_i(t)$ are Gaussian

$$\nu_i(t) = \mathrm{N}(X_i(t), \Sigma_i(t))$$

  - $X_i(t)$: linear function of signal, samples
  - $\Sigma_i(t)$: deterministic, precomputable
- It suffices to keep track of Cov$(X_i(t), X_j(t))$

Gaussian setting: an explicit description

Theorem

Almost surely, for every agent i: $\nu_i(t) \to \nu | S_1, \ldots, S_n$

- Since agents get linear observations $S_i \sim \mathrm{N}(\langle a_i, \theta \rangle, 1)$, the posterior distribution is given by least squares:

$$\nu | S_1, \ldots, S_n = \mathrm{N}(\mu_*, \Sigma_*)$$

$$\mu_* = (A^T A)^{-1} A^T S, \;\; \Sigma_* = (A^T A)^{-1}$$

$$A = \begin{bmatrix} a_1^T \\ a_2^T \\ \vdots \\ a_n^T \end{bmatrix}$$

Belief sampling with non-Bayesian updates

- Fully Bayesian agents aggregate information efficiently from samples
- In the Gaussian setting, this is computationally easy: *linear* updates
- Open questions:
  - How do information and network geometry affect speed of learning?
  - Social sampling and communication limits *do not* yield herding, polarization or confirmation in Bayesian agents. When can this occur?
  - The moment we move away from fully Bayesian setting, things change!

Same problem with resource constraints: pseudo-Bayesian updating +belief sampling

- **Limited cognitive power**: We consider a non-Bayesian update rule with imperfect recall of the past history, motivated by *Jadbabaie et al. 2012*
  - [Hazla, Jadbabaie, Mossel, & Rahimian `2020] suggest that fully Bayesian learning in groups is computationally intractable.
  - Use behavioral updates!

PMLR Proceedings of Machine Learning Research

Volume 99 JMLR MLOSS FAQ Submission Format RSS

[edit]

Reasoning in Bayesian Opinion Exchange Networks Is PSPACE-Hard

Jan Hązła, Ali Jadbabaie, Elchanan Mossel, M. Amin Rahimian ; Proceedings of the Thirty-Second Conference on Learning Theory, PMLR 99:1614-1648, 2019.

informs
http://pubsonline.informs.org/journal/opre

OPERATIONS RESEARCH
Articles in Advance, pp. 1–23
ISSN 0030-364X (print), ISSN 1526-5463 (online)

Methods

Bayesian Decision Making in Groups is Hard

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Received: August 13, 2018
Revised: July 26, 2019
Accepted: January 2, 2020
Published Online in Articles in Advance: ■■ ■■, 2020

Area of Review: Decision Analysis

https://doi.org/10.1287/opre.2020.2000

Abstract. We study the computations that Bayesian agents undertake when exchanging opinions over a network. The agents act repeatedly on their private information and take myopic actions that maximize their expected utility according to a fully rational posterior belief. We show that such computations are NP-hard for two natural utility functions: one with binary actions and another where agents reveal their posterior beliefs. In fact, we show that distinguishing between posteriors that are concentrated on different states of the world is NP-hard. Therefore, even approximating the Bayesian posterior beliefs is hard. We also describe a natural search algorithm to compute agents' actions, which we call *elimination of impossible signals*, and show that if the network is transitive, the algorithm can be modified to run in polynomial time.

Funding: This work was supported by the Office of the Secretary of Defense, Vannevar Bush Fellowship, and the Army Research Office [Grants W911NF-12-1-0509, W911NF-19-0217]. This work was partially supported by the Office of Naval Resarch (ONR) [Grant ONR N00014-16-1-2227] and the National Science Foundation (NSF) [Grant NSF CCF-1665252].

Keywords: observational learning • Bayesian decision theory • computational complexity • group decision making • computational social choice • inference over graphs

Research question and findings

- **Research question:**
  - Conditions on the network structure and private sources of information for learning and mislearning to occur in pseudo-Bayesian social learning
- **Main findings:**
  - Learning occurs with probability one if
    - network is strongly connected, and
    - the population includes a group of *self-confident experts* in different states:
      - Self-confident: trusts her private source of information.
      - Expert in state x: can solely learn whether x is the true state or not.
  - Mislearning occurs with positive probability as long as agents trust their neighbors' experience more than their private sources of information
  - The probability of learning improves as agents with high quality sources of information become influential in the network.

Literature review

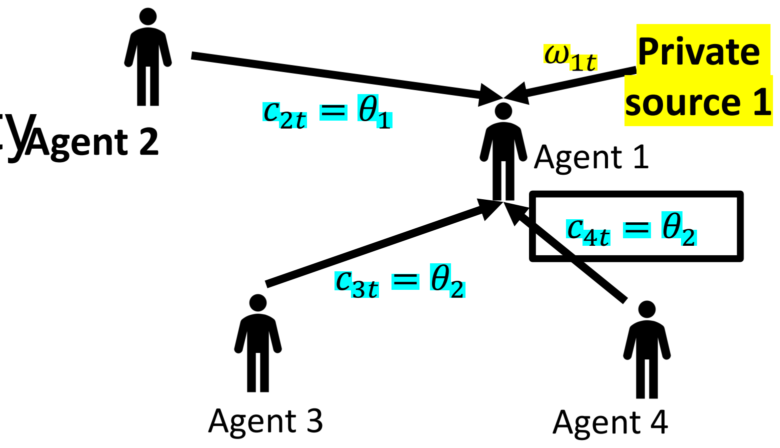
- **[Molavi, Tahbaz-Salehi, & Jadbabaie `2018]:**
  - General family of social learning rules that are non-Bayesian with imperfect recall and history neglect
  - Agents repeatedly receive private signals
  - Agents share **full beliefs**.
- **[Arieli, Babichenko, & Mueller-Frank `2019; Golub & Jackson `2010; DeMarzo, Vayanos, & Zwiebel `2003, Tamuz and Mossel 2012, Jadbabaie et al. 2012, Rahimian et al. 2014-8]:**
  - DeGroot-like model.
  - Agents receive private signals **once**.
  - Learning is studied in the limit of an **infinite number of agents**.
- **[Mossel, Olsman & Tamuz `2016]:** Bayesian learning in Gaussian setting with full belief sharing
- **[Hare, Uribe, Kaplan &Jadbabaie `2020 (I,II)]** Non-Bayesian social learning with uncertain likelihoods (probabilities over likelihood models)

Model

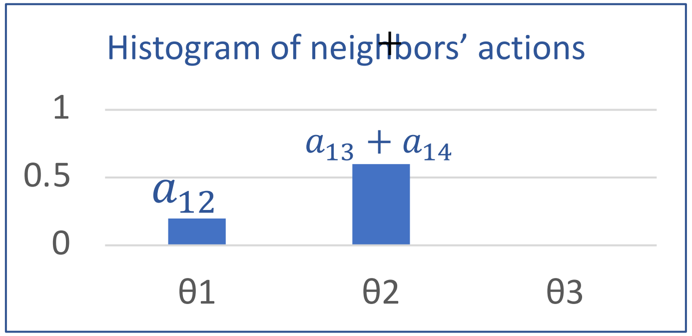
- Agents communicate through a network $A = (a_{ij})$, where $a_{ij} > 0$ means that agent i can observe a sample of agent j's belief distribution

- The belief of agent i at time t is μ_{it} which is a probability distribution on Θ

Example $\boldsymbol{\Theta} = \{\boldsymbol{\theta_1}, \boldsymbol{\theta_2}, \boldsymbol{\theta_3}\}$:



- At each time period t, agent i receives:
  - a private signal ω_{it} according to a likelihood function $l_i(\omega|\theta)$
  - a sample c_{jt} from her neighbor j, c_{jt} is sampled from Θ according to the distribution μ_{jt}.



- Agent i updates her belief as follows:

$$\mu_{it+1} = a_{ii} \times Bayes(\mu_{it}, \omega_{it}) + \sum_{j \in N_i} a_{ij} \times Dirac(c_{jt}),$$

Definitions

- **Learning and mis-learning:** Agent i learns (mis-learns) the true state θ^* along a sample path of signals if her belief converges to one (to zero) along this path

- **Individual and collective distinguishability:**
  - Individually distinguishable states: Every agent can distinguish between the states, i.e. $\forall i, \forall \theta \neq \theta', l_i(.|\theta) \neq l_i(.|\theta') \rightarrow$ each agent can learn on her **own** the true state, for example, using Bayes rule

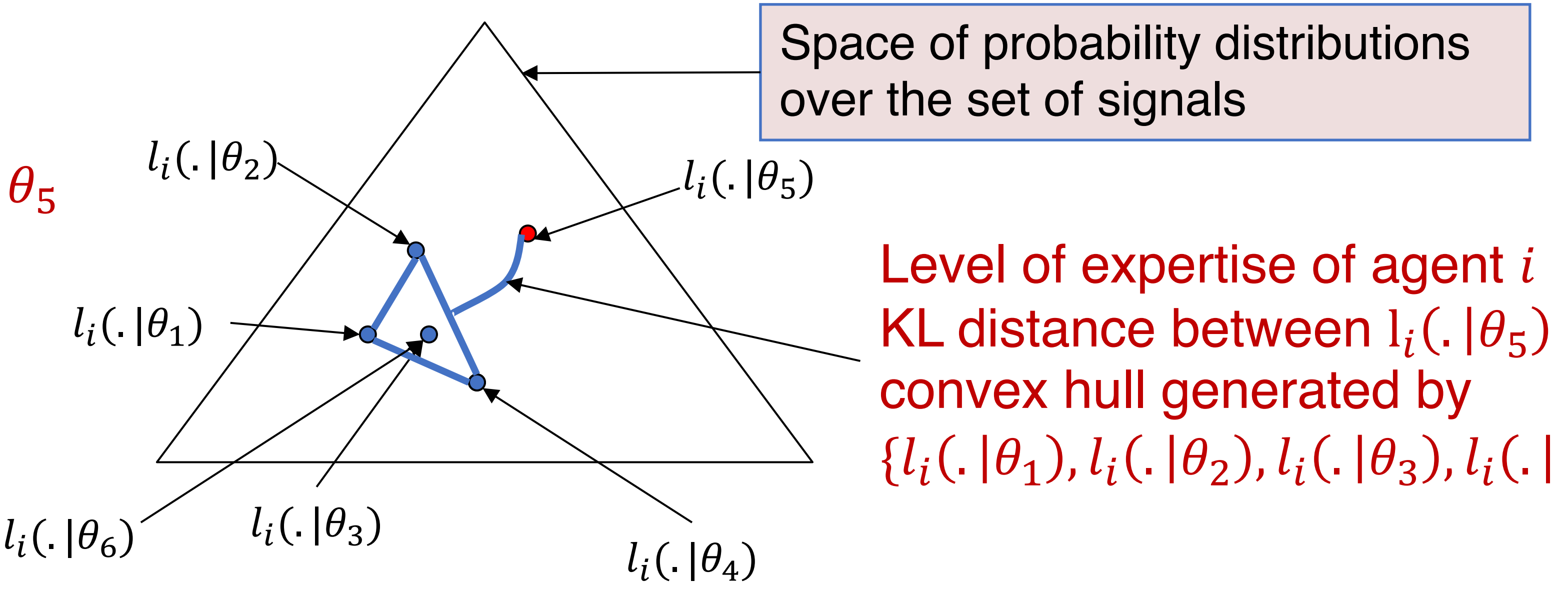
  - **Collectively distinguishable st**ates: For every states $\theta \neq \theta'$, there exists an agent i that can distinguish between the two of them, i.e. $l_i(.|\theta) \neq l_i(.|\theta') \rightarrow$
  - Jadbabaie *et al.* [2012], Molavi *et al.* [2018], Rahimian and Jadbabaie [2019]:

  If agents share their **full beliefs** and there is enough information in the network, learning occurs with probability 1

What happens when samples are shared?

- Need a stronger notion of distinguishability
  - Agent i is a **self-confident expert** in state θ if $l_i(.|\theta)$ is not in the convex hull generated by the rest of likelihood functions and $a_{ii} > \exp(-i's\ level\ of\ expertise\ in\ \theta)$, where i's level of expertise is the KL distance between $l_i(.|\theta)$ and this convex hull.

Agent i is expert in state θ_5 but cannot distinguish between θ_3 and θ_6.



Level of expertise of agent i in θ_5 = KL distance between $l_i(.|\theta_5)$ and the convex hull generated by $\{l_i(.|\theta_1), l_i(.|\theta_2), l_i(.|\theta_3), l_i(.|\theta_4), l_i(.|\theta_6)\}$

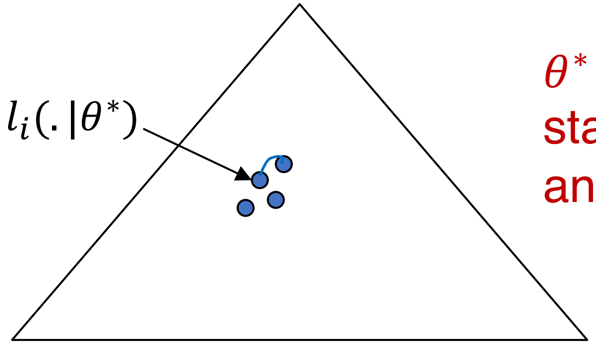
Low self confidence results in msilearning

Theorem (mislearning): Suppose that the network is connected and for all agent i the self-confidence coefficient a_{ii} is less than

$\exp(-KL\,[\,l_i(.\,|\theta^*)\,||l_i(.\,|\theta)])$, for any state θ. Then, all agents mis-learn the true state θ^* with positive probability.

The probability of learning is bounded below by:

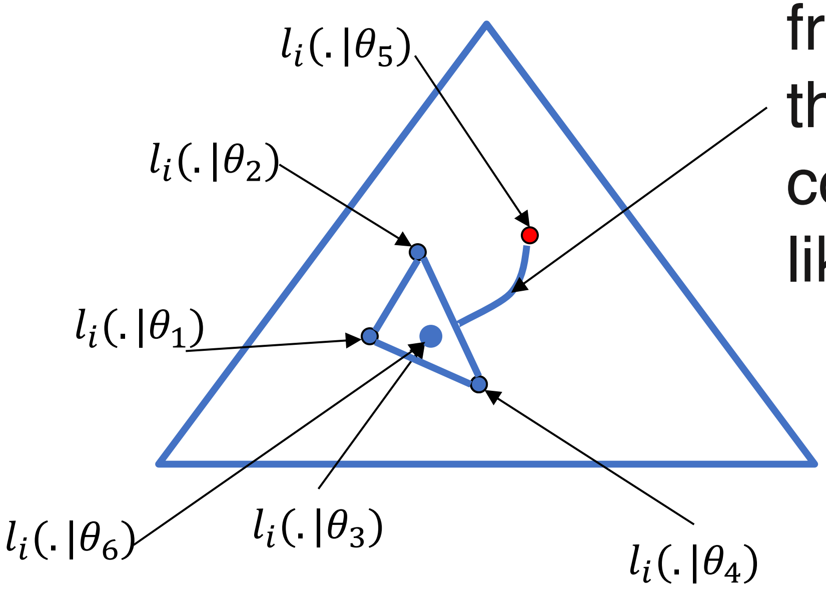
$$\sum_{i=1}^{n}(centrality\ of\ i)\times(1+a_{ii})\times\mu_{i0}(\theta^*)\times(Quality\ of\ signal\ \omega_{it}).$$



θ^* barely distinguishable from the rest of states: KL distance between $l_i(.\,|\theta^*)$ and any other $l_i(.\,|\theta)$ is less than $-\log a_{ii}$

Learning with self-confident experts

Theorem (learning): Suppose that the network is connected and for each state θ there exists a self-confident expert in θ. Then, all the agents learn the true state with probability one.



Self-confident expert in θ_5: $\mathrm{l}_i(.|\theta_5)$ is far from the rest of likelihood functions, where the KL distance between $\mathrm{l}_i(.|\theta_5)$ and the convex hull generated by the rest of likelihood functions is greater than $-\log a_{ii}$.

Future work

- ▶Gap between the learning and mis-learning ?
- ▶Tighter conditions for learning for more general updates
- ▶General sampling strategies and social learning rules
- ▶Rates of convergence
- ▶ Group polarization?

Persuasion, Polarization and Misinformation

- II. Persuasive campaigns and curse of dimensionality

[Hazla, Jin, Ramnayaran, Mossel 2020]

- III. Persuasion, news sharing, and spread of misinformation

[Hsu, Ajorlou, Jadbabaie 2020, Hsu, Ajorlou, Jadbabaie, Yildiz 2020]

Mathematics of Opinion Exchange Dynamics

- Huge body of work modeling opinion dynamics.
- Main questions: convergence, agreement, learning.
- The more elegant models satisfy convergence and agreement.
- E.G.: DeGroot Model, Bayesian Learning.
- Learning depends on finer properties of network / model.

Probability Surveys
Vol. 14 (2017) 155–204
ISSN: 1549-5787
DOI: 10.1214/14-PS230

Opinion exchange dynamics

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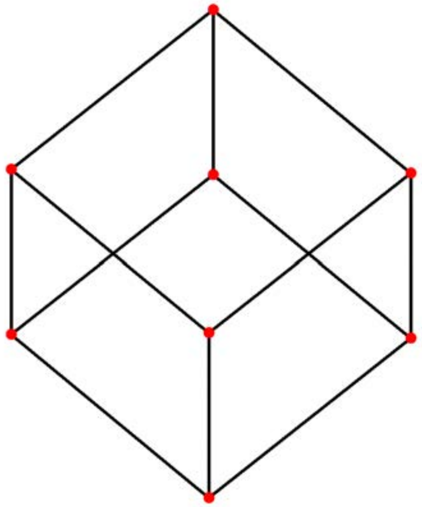
Mossel and Tamuz, *Probability Surveys*, 2017

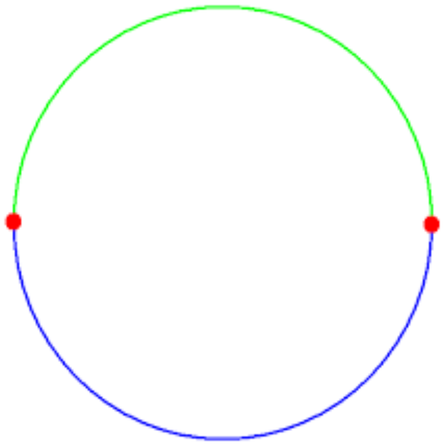
But people do not agree …

- Aumann 76: “The results of this paper might be considered evidence against this view, as there are in fact people who respect each other’s opinions and nevertheless disagree heartily”.
- Many mathematical models to explain polarization:
- dishonesty / Peer interaction / homophily of social network / echo chamber.
- Bias Assimilation (Lord, Ross, Lepper 79 ...):
- Social media users who are assigned to follow accounts that share opposing opinions, hold their old political opinions and often to a more extreme degree (Bail et. al. 18).

Polarization, Alignment, Radicalization

- Models above explain why opinions are polarized on each topic, but do not explain alignment.



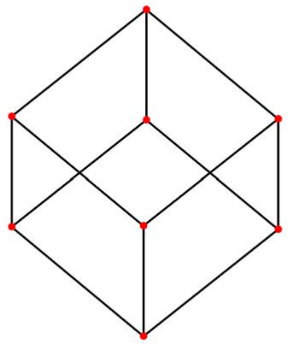


Polarization, Alignment, Radicalization

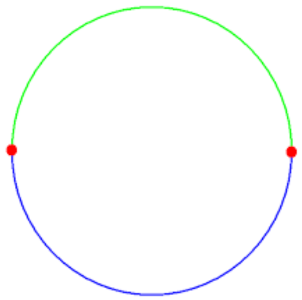
- Polarization on topic i: $\rho_i(S) = \frac{1}{|S|^2} \max_{U \subset S} \sum_{x \in U, y \in S \setminus \mathrm{U}} (x_i - y_i)^2$,

- Overall polarization: $\rho(S) = \frac{1}{|S|^2} \max_{U \subset S} \sum_{x \in U, y \in S \setminus \mathrm{U}} ||x - y||^2$.

$$\max_i \rho_i(S) \leq \rho(S) \leq \sum_i \rho_i(S).$$

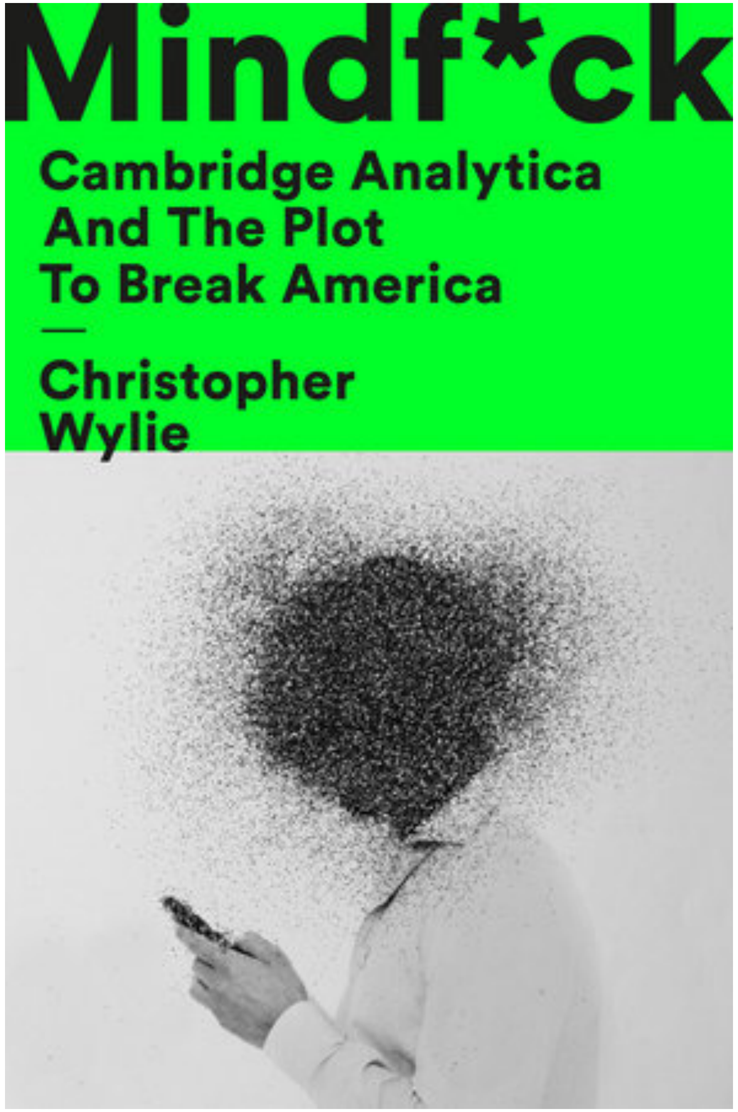


(a) In cube: $\rho \sim \frac{1}{2} \sum_i \rho_i$

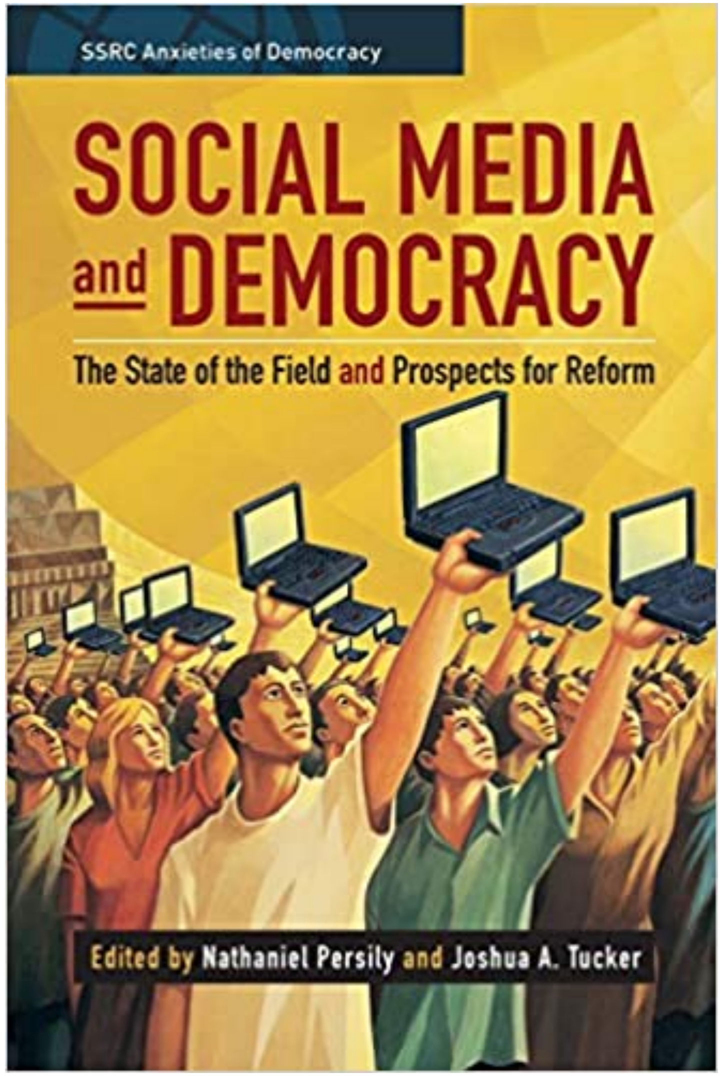


(b) $\rho = \sum_i \rho_i$ for antipodal points

Campaigns are High Dimensional



Campaigns are High Dimensional



The High Dimensional Nature of Campaigns

Donald E. Vinson, Jerome E. Scott and Lawrence M. Lamont

The Role of Personal Values in Marketing and Consumer Behavior

Can Personal Values be used to assist marketers in determining consumer choice behavior?

MARKETERS have long acknowledged the importance of attitudes and attitude change in the study of marketing and consumer behavior, but the role of values has received relatively little attention. Even though the marketing literature reflects an emerging interest in the topic,[1] personal values have not been widely used to investigate the underlying dimensions of consumer behavior. This is surprising considering the importance typically assigned to values by a wide variety of social observers and businessmen alike.[2]

While it seems that personal values have important implications for marketing practitioners and researchers, values and the ways in which they influence the behavior of consumers who look at and choose brands, product classes, and product attributes is not clear. In order to investigate these relationships, it is necessary to operationally define what values are, and to indicate empirical methods available for examining the connections between personal values and consumer behavior.

The purpose of this article is to address these issues. Specifically, attention will be focused on:

1. A discussion of the meaning of values and their relationship to behavior.
2. Presentation of an operational value paradigm suitable for studying consumer behavior.
3. Results of an empirical investigation of the impact of value orientations on the importance of product attributes, the appeal of various consumer products, and a number of social issues.
4. The implications of value analysis for the practice of marketing.

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Personal Values

Conceptualization of the term "value" reflects the interest of several disciplines:

- Anthropology, with its interest in life styles and cultural patterns. (For example, Thomas and Zaraniecki define values as ". . . objective, social elements which impose themselves upon the individual as a given and provoke his reaction.")[3]
- Sociology, focusing on ideologies and customs. (For example, Bronowski suggests that "a value is a concept which groups together some modes of behavior in our society.")[4]
- Psychology, which examines values from the standpoint of attitudes and personal motives. (For example, Rokeach views ". . . a value as a centrally held, enduring belief which guides actions and judgments across specific situations and beyond immediate goals to more ultimate end-states of existence.")[5]

In this article, and in the study reported herein, we follow mostly the psychological definition, and in particular Rokeach's view.

From Nyhan, Reifler (2010)

- However, individuals who receive unwelcome information may not simply resist challenges to their views. Instead, they may come to support their original opinion even more strongly: what we call a "backfire effect".
- From *When Corrections Fail: The persistence of political misperceptions* (Nyhan, Reifler, 2010).

Model

- Opinions u are d dimensional unit vectors $\in \; S^{d-1}$
- After intervention v, u updates to a vector proportional to :

$$w = u + \eta \cdot \langle u, v \rangle \cdot v, \qquad \eta > 0,$$

- Main results: Campaigns lead to polarization.

- No peer effect, network structure, etc.

Polarization under Random Interventions

Theorem (Hazla-Jin-M-Ramnarayan-19)

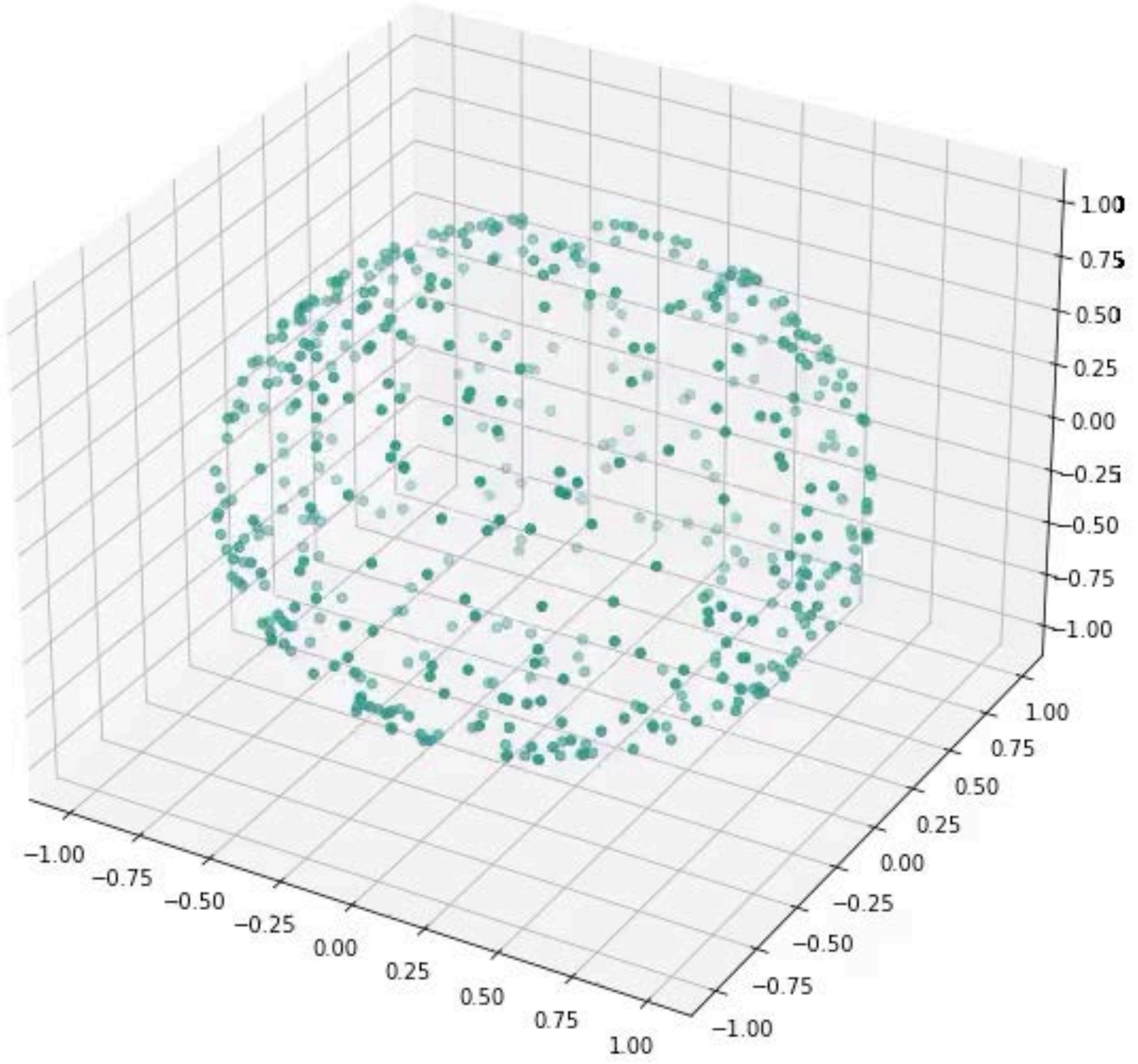
For any two fixed initial opinions u, v, and a sequence of random interventions, the updated opinions $u^{(t)}, v^{(t)}$ satisfy

- *with probability* $\alpha(u, v)$: $\lim_{t\to\infty} u^{(t)} - v^{(t)} = 0$,
- *with probability* $1 - \alpha(u, v)$: $\lim_{t\to\infty} u^{(t)} + v^{(t)} = 0$,

where $\alpha(u, v) = \arccos\langle u, v\rangle$.

- See movie

Polarization under Random Interventions



Optimal Long Time Strategy for a Single Advertiser

- Suppose there is a single advertiser who can apply a large number of iterations of campaigns (e.g. Bannon, Putin).
- Advertiser's goal: get as many people as possible to have opinion v^*.
- **Thm [HJMR19]:** Optimal strategy is
  - 1. Find densest hemisphere centered at w.
  - 2 Apply w repeatedly.
  - 3 Slowly flow from w to v^* .
- Optimal Strategy leads to polarization.
- **Thm [HJMR19]:** Finding densest hemisphere is computational hard: even deciding if density is $1 - \varepsilon$ or $1/2 + \varepsilon$ is NP hard.

One Step Intervention with a Threshold

- Consider agents that do not have an opinion about a topic, $u_{d+1} = 0$.
- Advertiser who wants to maximize the number of agents such as $\mathrm{u}_{\mathrm{d+1}}^{(1)} > t$, after a single intervention.

- **Thm[HJMR19]:** Optimal campaigns reduce to finding densest cap, i.e., maximizing the number of i's such that $\langle u_i, v\rangle > c$.

Variations of the Model and Future Work

- Some natural variations of the model include:
- Targeting: Influencers can target different subsets and apply different interventions.
- Peer effects in social networks.
- Strategic competing influencers.

Two Important Questions and Future Work

- Q1: The model seems to suggest that communication leads to polarization. Is there a way to avoid it?
- Q2: What is the meaning of $u_1 = 0$?
  - **1** No opinion on the topic.
  - **2** Well thought of research on the topic, recognizing advantages and disadvantages of each approach and deciding that on balance they are both reasonable.
- A2: Our model assumes the first definition.
- Future work: finer models of individual opinions.
- Hope to answer Q1: Mechanisms for consensus building (education, exchanges, etc)

Information Sharing and Subscription on Social Media

Many people around the world get their news from social media

- Q (I): Why do people forward information on social media?

- Q (II): How do people allocate their limited attention span among the many available news outlets?

What if Persuasion plays a key role in both?

Paper on SSRN, ID: 3391585

Information Sharing on Social Media

- **Approach:**
  - Framework of perspectives and opinions in [Sethi & Yildiz, *Econometrica* (2016)
  - News-sharing as a mechanism for persuasion: "*I share in order to change your information set, hence your perspective, so your views are closer to mine*"
  - Sharing Cascade emerges from micro-level sharing behaviors

- **Main results:**
  - Affirmation and surprise emerge from persuasive motive :
  - Connections between likelihood of a sharing cascades, the diversity [heterogeneity] of perspectives and collective wisdom of crowds
    - As individual perspectives become more diverse, a wider range of news credibility levels cause a cascade
    - In a widely-diverse society, even news with low credibility are quite likely to go viral
    - high-precision news will not spread in homogeneous populations whose opinions concentrate around truth

Related literature

- Vosoughi et al. (2018) show that users on Twitter are more likely to retweet the false rumors than the truth, hypothesizing that the novelty of fake news might be a major factor.
- Pennycook and Rand (2018)’s experiments indicate that people are susceptible to fake news because they are lazy to think.
- Kranton and McAdams (2020) study how expanding social connectedness impacts producers’ incentive to publish the true news which the consumers prefer to share and act on.

<u>Disclosure, cheap talk & persuasion games</u>:
Milgrom (1981, 2008);
Grossman (1981);
Crawford and Sobel (1982);
Milgrom and Roberts (1986);
Banerjee and Somanathan (2001);
Che and Kartik (2009)

<u>Communications</u>

Cialdini (2001,…)

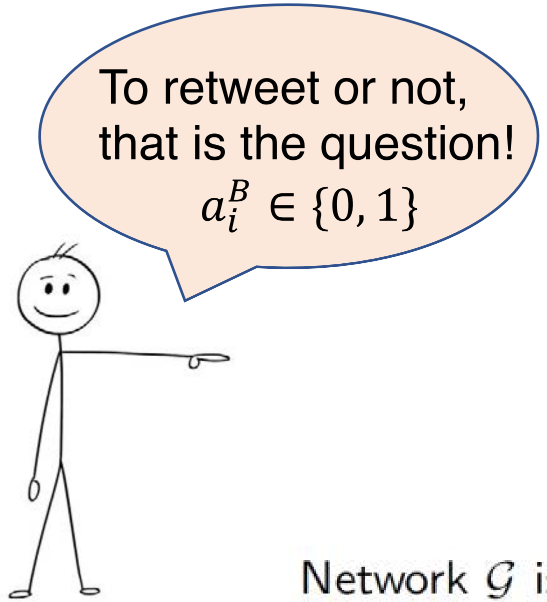
<u>Psychology</u>

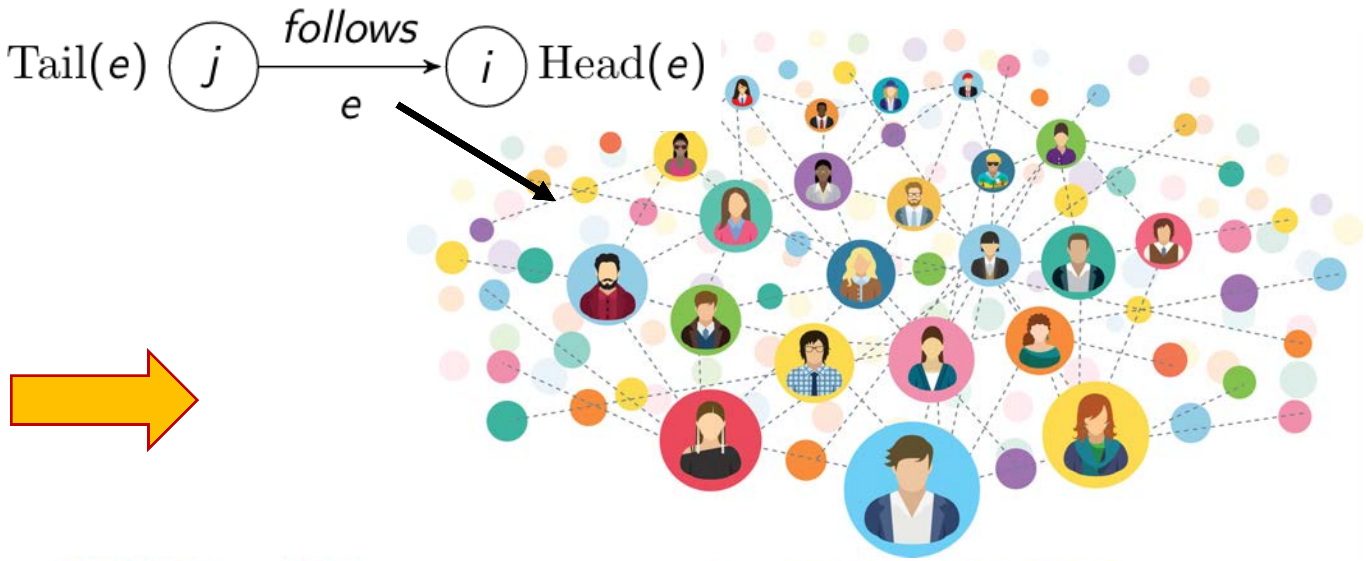
Falk and Scholz (2018)

<u>Controlling the information spread on networks & agents’ engagement</u>:
Campbell et al. (2017);
Ajorlou et al. (2018);
Candogan and Drakopoulos (2020)

<u>Information design & Bayesian persuasion</u>:
Rayo and Segal (2010);
Kamenica and Gentzkow (2011)

News-sharing on Twitter-like networks





Network $\mathcal{G}$ is formed (random network model)

News $x = \theta + \epsilon$ is realized & released

users who receive the news make sharing decision

Timeline:

θ is realized (unobservable)

0 1 2 3 $\cdots$ t

Prior beliefs/perspectives:

$$\forall i: \quad \theta \sim_i \mathcal{N}(\underbrace{\mu_i}_{\text{perspective of user } i}, \underbrace{\sigma_\theta^2}_{\text{uncertainty of beliefs}}) \qquad \mu_i \sim \mathcal{N}(\underbrace{\bar{\mu}}_{\text{aggregate perspective}}, \underbrace{\sigma_\mu^2}_{\text{diversity of perspectives}})$$

News-sharing decision making

Desire for persuading others

Beliefs: state of the mind

Sharing news if it reduces distance between beliefs

Sharing criteria for agent i and news x:

Prior beliefs

Bayesian Update

$$\mathbb{E}_i[d(\mathrm{BU}(P_i;x),P_k)\,|\,k\in N^{in}(i)] - \mathbb{E}_i[d(\mathrm{BU}(P_i;x),\mathrm{BU}(P_k;x))\,|\,k\in N^{in}(i)] > \frac{C}{1-q}$$

$$2\underbrace{(1-\beta)(\mu_i-\bar{\mu})}_{\text{interim bias of user } i}\underbrace{\beta(x-\bar{\mu})}_{\text{credible surprise}}+\underbrace{\beta^2(x-\bar{\mu})^2}_{\text{magnitude of surprise}}+\underbrace{(1-(1-\beta)^2)\sigma^2}_{\text{reduction in variance of perspectives}} > \frac{C}{1-q}$$

Likelihood that a follower of agent i has already heard the news

Expected distance if a follower does not get the news!

Followers of agent i

Expected distance if a follower gets the news!

Credibility of news

$\beta = \dfrac{\sigma^2}{\sigma^2+\sigma_\varepsilon^2} \in [0,1]$

$\beta = 1$ News is the true state

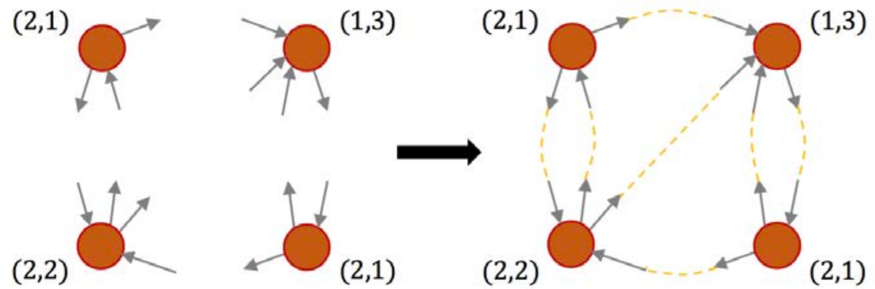
$\beta = 0$ Pure noise

- Affirmative news supports user's bias and incentivizes sharing
- Surprising news incentivizes sharing if news is affirmative, or so surprising that flips the sign of user's bias
- Reduction in the variance of perspectives as incentivizing force for sharing
- Sharing also gets less likely as followers get more likely to have already heard the news (larger q)

***q* estimated from:** retweet count of original tweet, knowledge on network structure

News cascades on networks

- Random degree distribution-based network model (Configuration model):
  - Estimate local decision variables from public observations (q from number of retweets)
  - Characterize the dynamics of news spread
  - Necessary and sufficient conditions for cascades



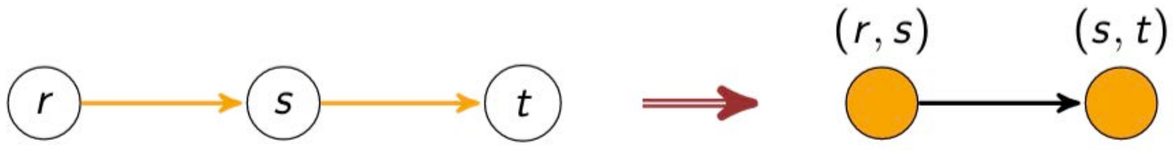
Random realization of network generated from joint degree distribution $P(d, \ell)$

- **News cascade:** news spreads to a non-zero fraction of a very large population in the steady state (i.e., a giant component of size $\Theta(n)$ emerges)
- News cascade happens if and only if:

$$\frac{\mathbb{E}[\ell d]}{\mathbb{E}[d]}\underbrace{\Phi(\eta_\beta(x) - K_\beta(x))} > 1$$

the average in-(out-)degree of the line graph $L(\mathcal{G})$, denoted as $\mu^{Line}(\mathcal{G})$

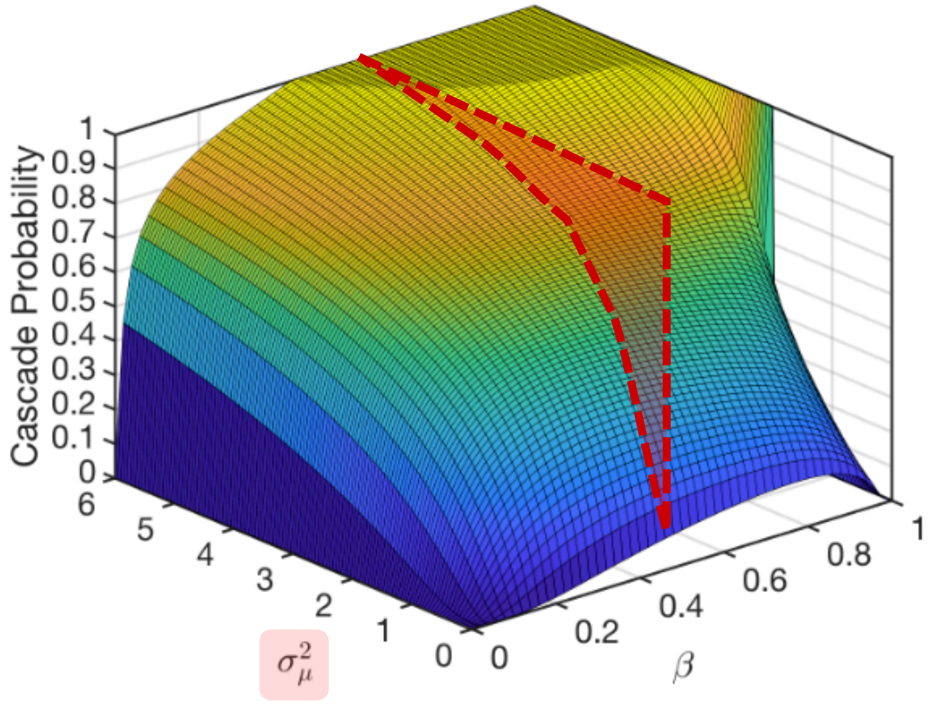
the fraction of informed users sharing early on (when spread size ≈ 0)



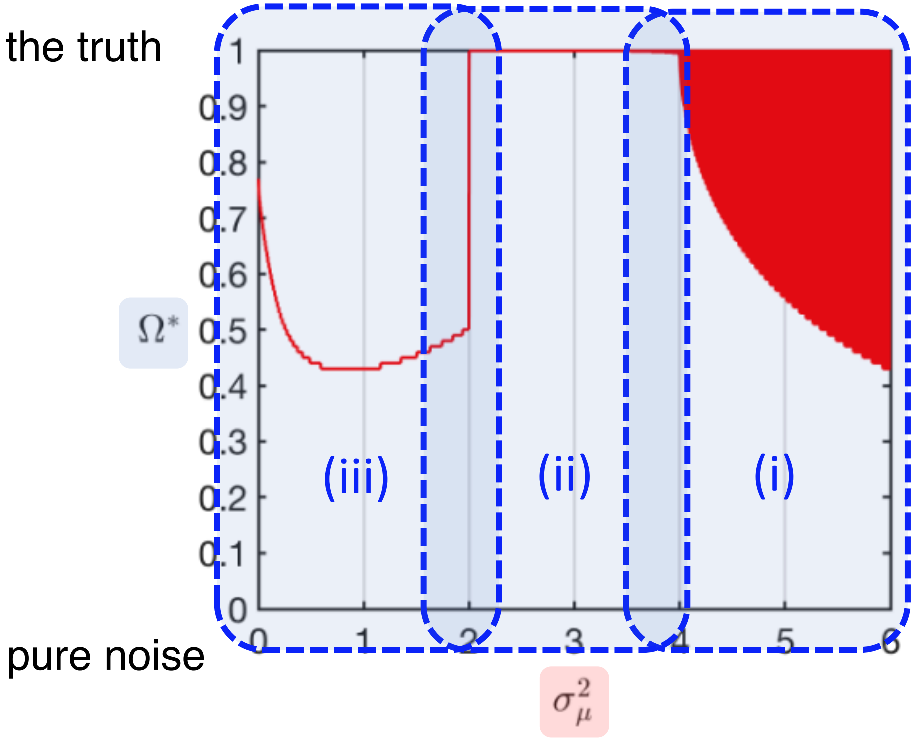
Cascade likelihood v.s news credibility and the diversity in the society

Well-connected networks ($\frac{\mathbb{E}[d\ell]}{\mathbb{E}[d]} = \mu^{Line}(\mathcal{G}) > 2$)

Example: $\bar{\mu} = 0, \sigma_\theta = 2, (\theta - \bar{\mu})^2 = 2, C = 4$, and $\mu^{\text{Line}}(\mathcal{G}) = 6350.3$



Cascade likelihood versus the credibility β and the diversity in perspectives σ_μ^2.



The set of optimal credibility Ω^* as the correspondence of the diversity in perspectives σ_μ^2

the cascade probability is **increasing in σ_μ^2** for all β

(i) **Diverse** perspectives: β^* close to 1 whereby the gain resulting from reducing the variance of followers' perspectives surpasses the cost of broadcasting

(ii) Perspectives are **not diverse**: β^*=1 when truth is surprising to a population with close perspectives

(iii) A **wise** population with **homogeneous** perspectives: The truth and highly imprecise news are filtered out; moderately imprecise news will cascade.

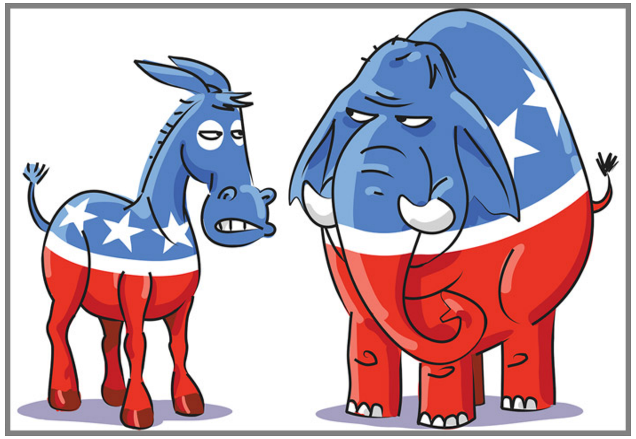
Summary of findings so far …

- Investigated new-sharing on social media through the lens of persuasion motives
- Affirmation-seeking sharing behavior and surprise arise from people's desire for persuading other

- Analyzed phenomena emerging at system-level from these micro-level sharing behaviors. In particular, the connections between likelihood of news cascades and its precision, diversity of perspectives and the collective wisdom.

Information Subscription on Social Media

- Countless sources of information/limited attention span
- Sources are **biased** and are motivated to persuade the public opinion:
  - promote news that can sway their subscribers towards their own political agenda or conceal the unfavorable one.
- Main questions:
  - How do people choose their news sources? what can they infer when their sources do not disclose?
  - Sources: what news to disclose or conceal?
- Joint work with Muhamet Yildiz



Credit: kbeis/Getty Images. Stanford News.

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Subscription-Disclosure game

$\theta \sim_2 N(\mu_2, \sigma_2^2) \quad \mu_2 < 0$

$\theta \sim_1 N(\mu_1, \sigma_1^2) \quad \mu_1 > 0$

$\theta \sim_j N(\mu_j, 1), \quad j \in \Lambda.$

Subscribers choose which leader to follow

Each leader decides whether to disclose or conceal the news, if received any

Subscribers update their beliefs, having observed action of leader they follow, then take actions

0 — 1 — 2 — t

News x is realized & passed to leaders independently w.p. $1 - p$

Leaders' persuasion motives

Subscriber j's utility

$$u_j(\theta, a_j) = a_j\theta \qquad a_j \in \{-1, +1\}$$

Leader i's utility

$$u_i(\theta, \{a_j\}) = \int_{j\in\Lambda} a_j\theta$$

Each leader is concerned with the total welfare of subscribers and desires to
Persuade followers to take the action that is optimal with resepect to their own perspective

Subscribers' strategic response to no disclosure

A fully Bayesian, strategic subscriber updates her belief on the state even when hearing no news, speculating on the possibility of the leader concealing the news from subscribers:

concealment set of the leader whom subscriber j follows

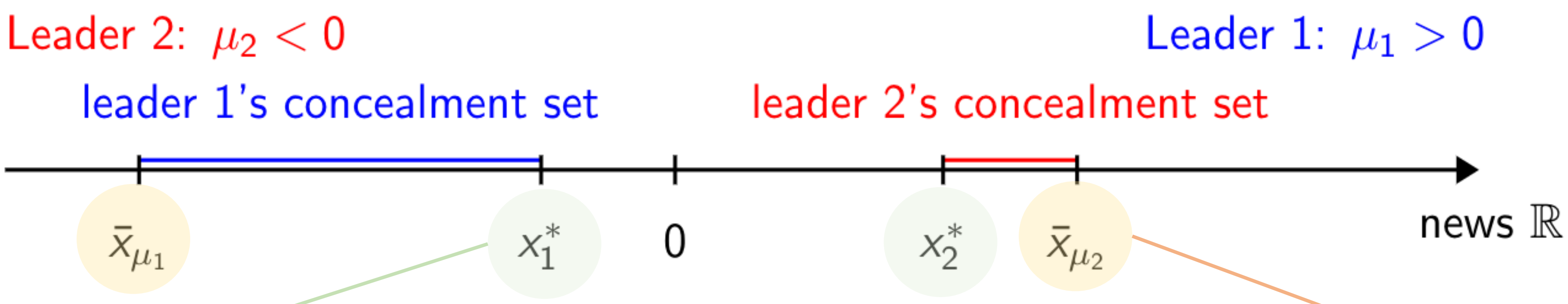
✔ $$y(\mu_j, \{x\}) = (1-\beta)\mu_j + \beta x,$$

✘ $$y(\mu_j, \emptyset) = \mu_j + \frac{(1-p)\mathbb{P}_j^0(C_{\lambda_j})}{p + (1-p)\mathbb{P}_j^0(C_{\lambda_j})}\mathbb{E}_j^0[\beta(x-\mu_j) \mid x \in C_{\lambda_j}].$$

ex-ante probability there is no news

compute w.r.t. subscriber j's prior belief on news

Equilibrium strategies

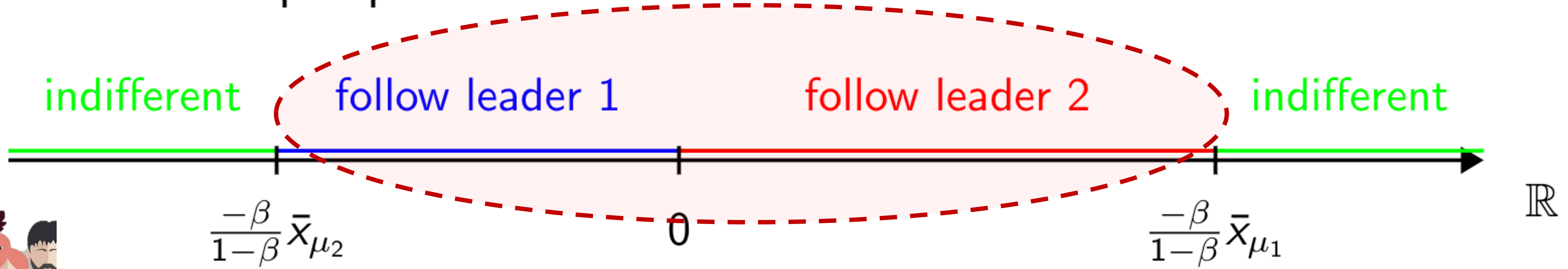


leader 1 feels indifferent between disclosing or not

When the news changes the sign of leader 2's perspective

Anti-homophily!!!

Subscribers' perspectives:



Concluding remarks and future work

- We investigated the information choices (news sharing and subscription) on social media through the lens of persuasion motives
- Future directions:
  - Identify more general settings for which anti-homophily result still holds.
  - Investigate the effect of the uncertainty in news precision on the topology of the subscription network, when news is a mixture of informative and uninformative signals
  - Investigating the effect of news verification, where the source, users, or both can verify the informativeness of news at a cost.
  - Future work: Experiments with Luke Hewitt and Josh Tenenbaum