NETWORK SCIENCE OF ONLINE INTERACTIONS

Polarization Dynamics on Networks

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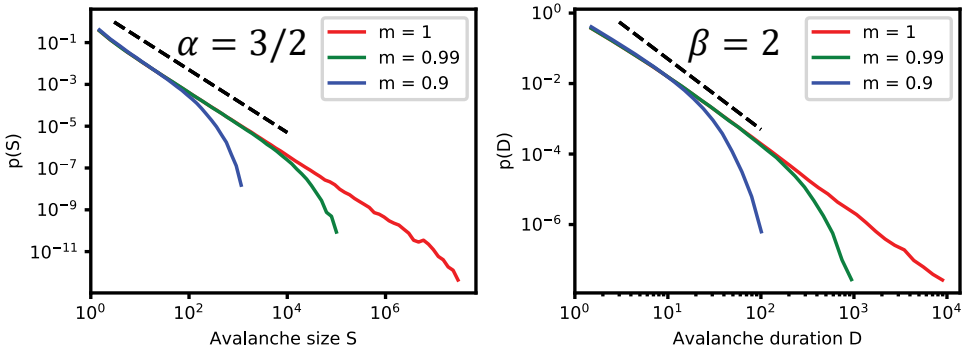
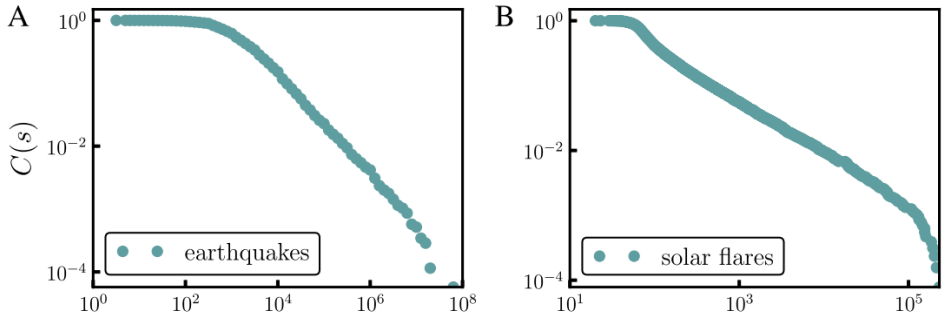
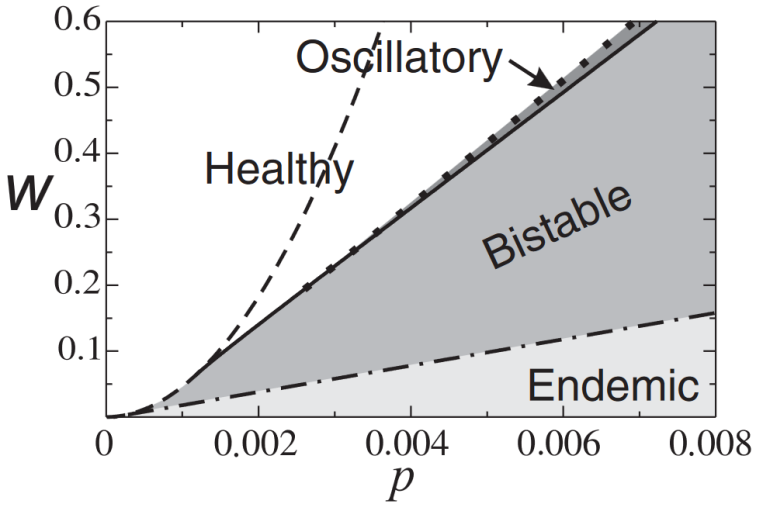
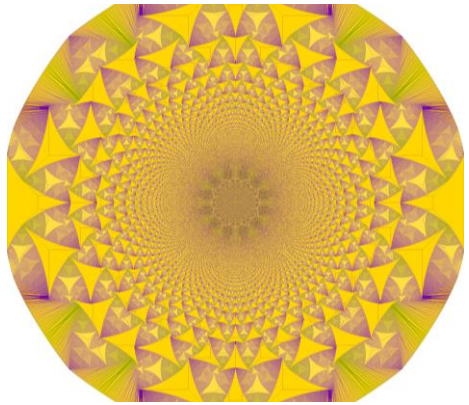
SUMMARY

- Adaptive networks can have much richer dynamics
  - They can reach states and topologies not possible in the static networks
- Branching processes can easily create many of the power-laws we've seen in the course
- Mechanisms like self-organized criticality can also explain those power-laws without fine-tuning



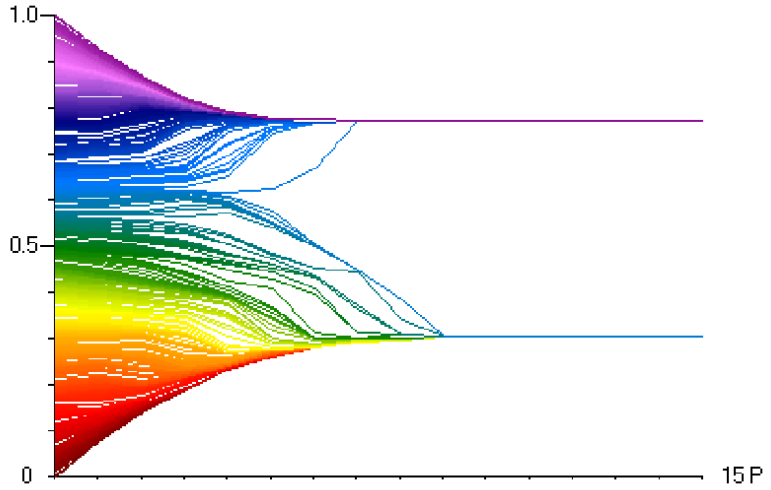






INTRODUCTION

- A vast literature of opinion models exist
  - Polarization focuses on the conditions for a bimodal opinion distribution
  - Example: bounded confidence model



- However
  - Rarely considering network structure
  - Rarely considering more than one opinion
  - Rarely considering social media dynamics

MODELS

- Two models
  - 1D polarization in social networks
  - Extension to multidimensional opinion space

PHYSICAL REVIEW LETTERS **124,** 048301 (2020)

Modeling Echo Chambers and Polarization Dynamics in Social Networks

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PHYSICAL REVIEW X **11,** 011012 (2021)

Emergence of Polarized Ideological Opinions in Multidimensional Topic Spaces

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1D POLARIZATION DYNAMICS

- Social media aspects
  - Few users are hyper-active
  - Activity and extreme opinions are likely correlated
  - Algorithms tend to create echo chambers
- The model
  - N agents, opinions $x_i \in [-\infty, \infty]$
  - $\dot{x}_i = -x_i + K \sum_j A_{ij}(t) \tanh(\alpha x_j)$
  - A_{ij} is 0 or 1
  - Network is temporal, switching completely every timestep
  - Parameters:
    - K: influence parameter strength
    - α: shape parameter

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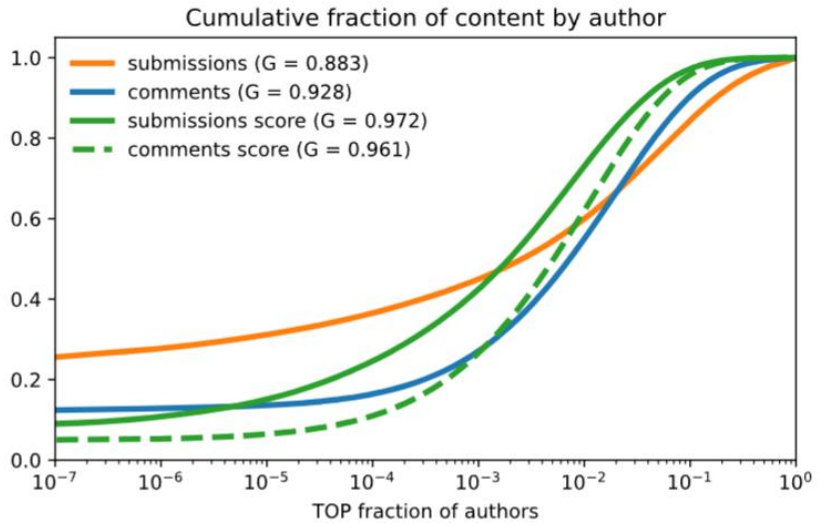
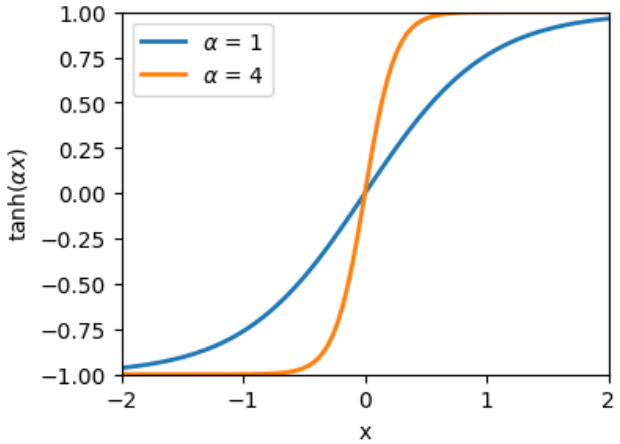
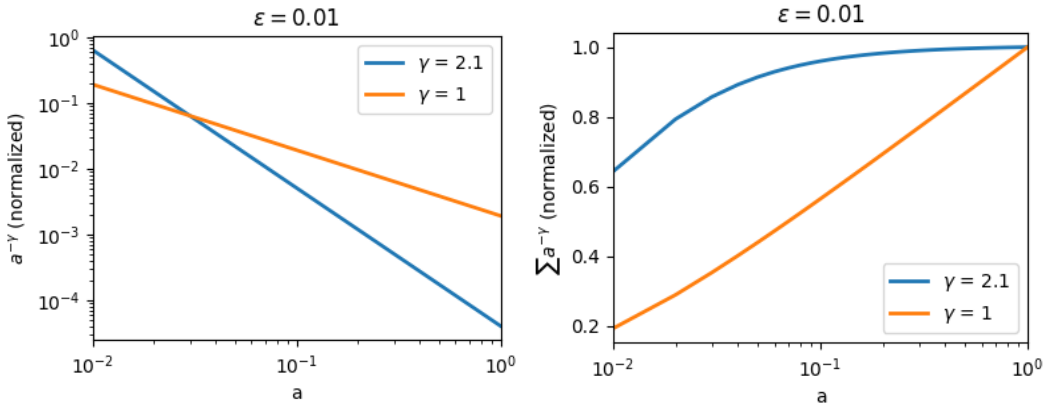


1D POLARIZATION DYNAMICS

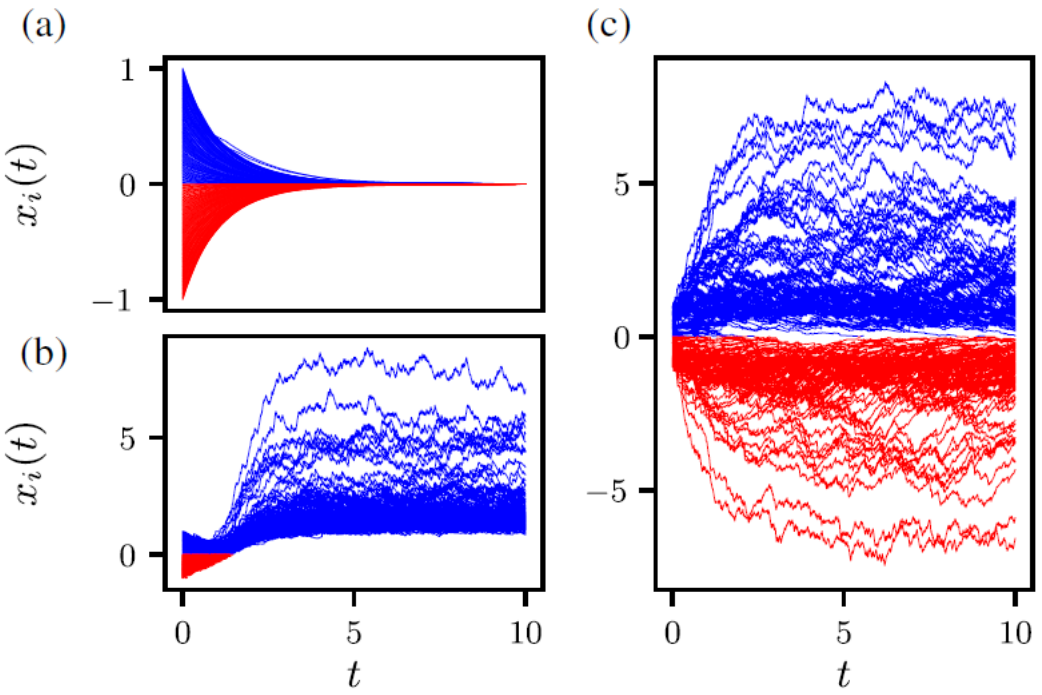
- Opinion dynamics
  - $\dot{x_i} = -x_i + K \sum_j A_{ij}(t) \tanh(\alpha x_j)$
  - $K = 0 \rightarrow x_i = 0$ (opinions only from interactions)
  - Larger K means larger global influence of opinions
  - Larger α means larger influence of extreme ($|x| \gg 0$) opinions
- Network dynamics
  - Nodes have activity rates $a_i \in [\epsilon, 1]$ (probability of being active)
  - a_i is drawn from $F(a) \sim a^{-\gamma}$
  - Larger γ means activity is more distributed
  - An active node will contact m nodes
  - Contact probability is $p_{ij} \sim |x_i - x_j|^{-\beta}$
  - Larger β means larger homophily
  - Network is directed, with reciprocity parameter r





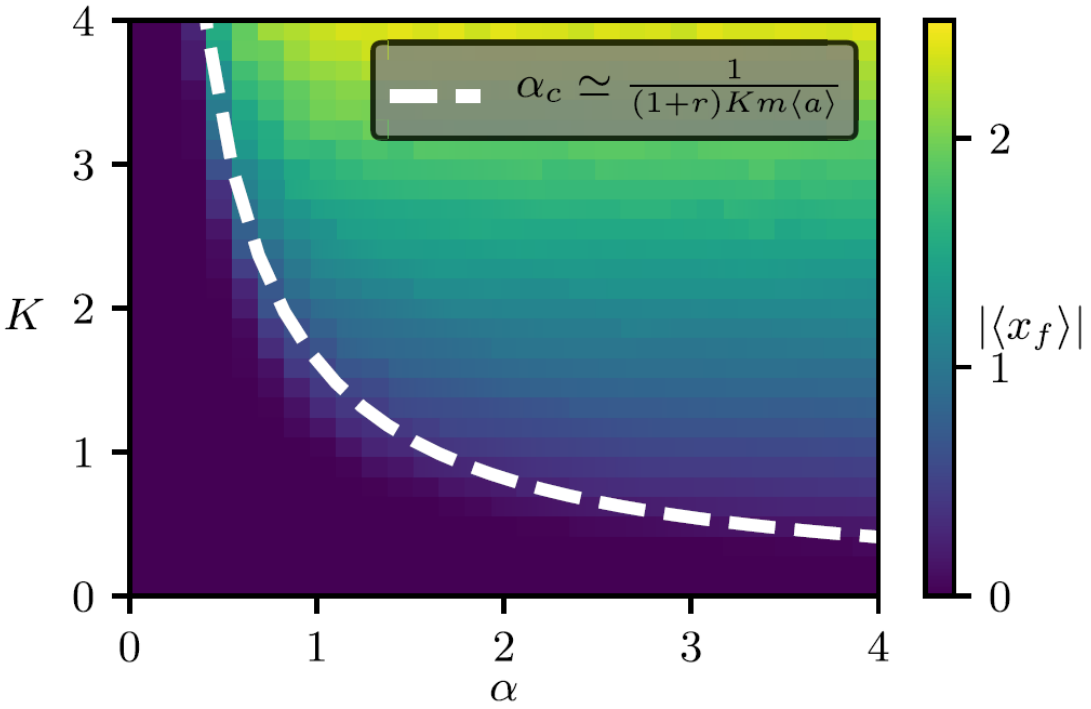
1D POLARIZATION DYNAMICS

- Important parts
  - Dynamics: $\dot{x}_i = -x_i + K \sum_j A_{ij}(t) \tanh(\alpha x_j)$
  - Activity distribution: $F(a) \sim a^{-\gamma}$
  - Connection probability: $p_{ij} \sim |x_i - x_j|^{-\beta}$
  - Reciprocity r
- Results:
  - Fixed: $K = 3, r = 0.5$
  - (a): $\alpha = 0.05, \beta = 2$: Low influence of extreme opinions, high homophily
    - Consensus
  - (b): $\alpha = 3, \beta = 0$: High influence of extreme opinions, no homophily
    - Radicalization (one-sided)
  - (c): $\alpha = 3, \beta = 3$: High influence of extreme opinions and homophily
    - Polarization



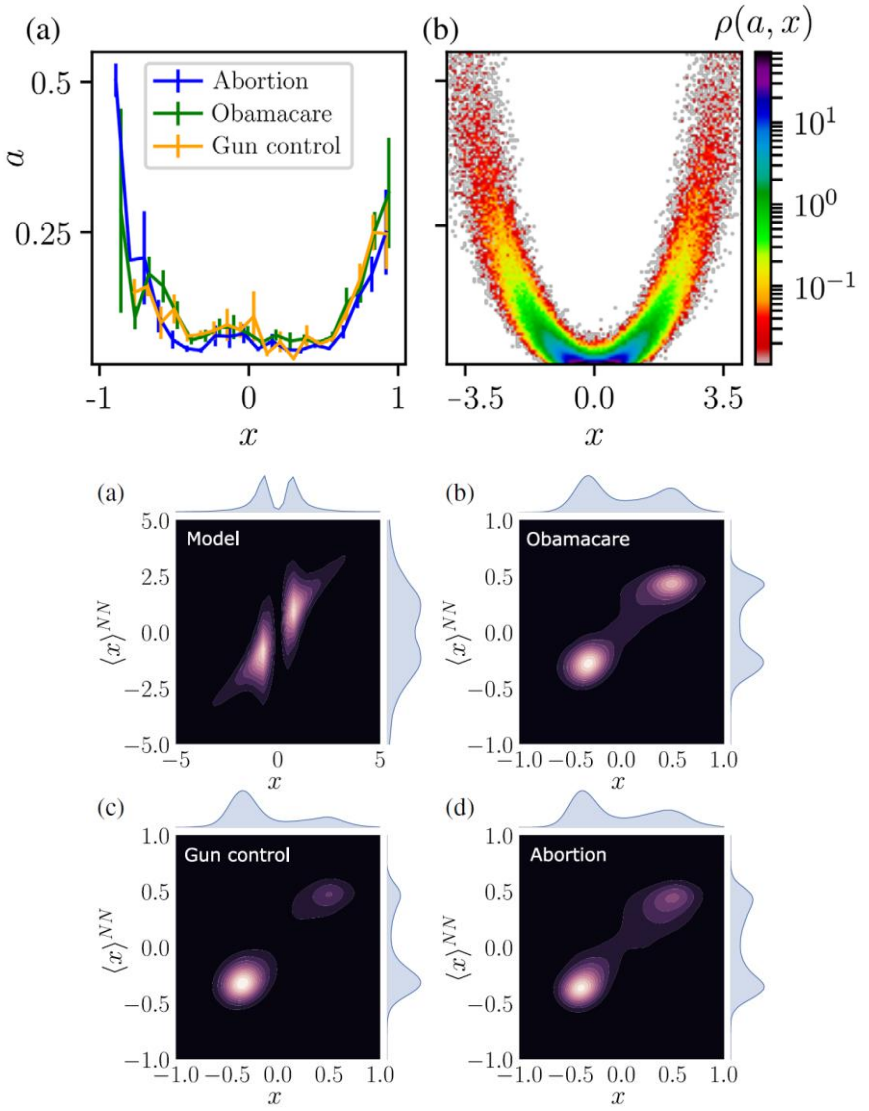
1D POLARIZATION DYNAMICS

- The $K - \alpha$ phase space
  - Changing both the overall effect of opinions (K) and the relative impact of extreme opinions (α)
  - Critical value $\alpha_c \approx 1/[(1+r)Km\langle a\rangle]$
    - Ignores effects of homophily $(\beta = 0)$
  - Below the white line opinions converge to consensus $(\beta = 0.5, \mathrm{r} = 0.5)$



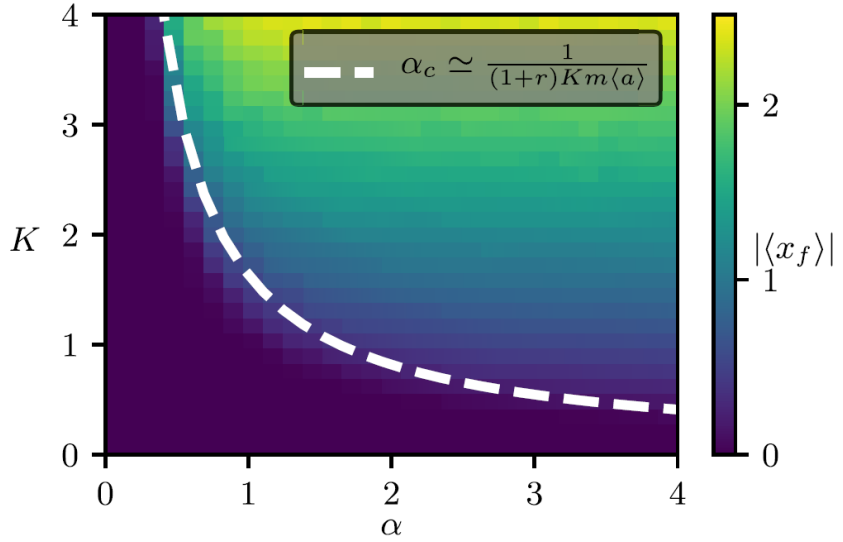
1D POLARIZATION DYNAMICS

- Comparing with Twitter data
  - Three topics: abortion, gun control, Obamacare
  - Users tagged $x_i \in [-1,1], r = 0.65$
  - Contacts from following network
  - Activity from tweets
- Results
  - Model with $K = 2, \alpha = 3, \beta = 1$
  - Opinion-activity correlation resembles model
  - Echo chamber: x vs $\langle x \rangle^{NN}$
    - Model results resemble empirical data to some extent



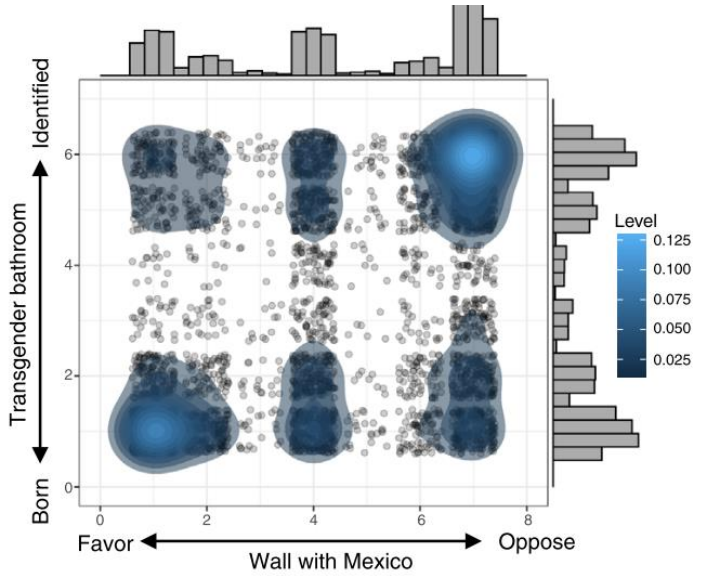
1D POLARIZATION DYNAMICS

- Model conclusions
  - Mimics the unbalanced activity of social media
  - Relative impact of extreme opinions shapes dynamics
  - Homophily can create polarization
- Model limitations
  - Many parameters
  - Unclear if all mechanisms (e.g. $F(a) \sim a^{-\gamma}$) are important
  - Assumes a base state $x \to 0$
  - **Only one opinion**



MULTIDIMENSION POLARIZATION DYNAMICS

- Extension of the previous model
- Core idea: Issue alignment:
  - certain combinations of opinions are more likely
  - May be due to common sets of arguments
  - But seemly different opinions are correlated



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Emergence of Polarized Ideological Opinions in Multidimensional Topic Spaces

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Opinion polarization is on the rise, causing concerns for the openness of public debates. Additionally, extreme opinions on different topics often show significant correlations. The dynamics leading to these polarized ideological opinions pose a challenge: How can such correlations emerge, without assuming them *a priori* in individual preferences or in a preexisting social structure? Here, we propose a simple model that qualitatively reproduces ideological opinion states found in survey data, even between rather unrelated, but sufficiently controversial, topics. Inspired by skew coordinate systems recently proposed in natural language processing models, we solidify these intuitions in a formalism of opinions unfolding in a multidimensional space where topics form a nonorthogonal basis. Opinions evolve according to the social interactions among the agents, which are ruled by homophily: Two agents sharing similar opinions are more likely to interact. The model features phase transitions between a global consensus, opinion polarization, and ideological states. Interestingly, the ideological phase emerges by relaxing the assumption of an orthogonal basis of the topic space, i.e., if topics thematically overlap. Furthermore, we analytically and numerically show that these transitions are driven by the controversialness of the topics discussed; the more controversial the topics, the more likely are opinions to be correlated. Our findings shed light upon the mechanisms driving the emergence of ideology in the formation of opinions.

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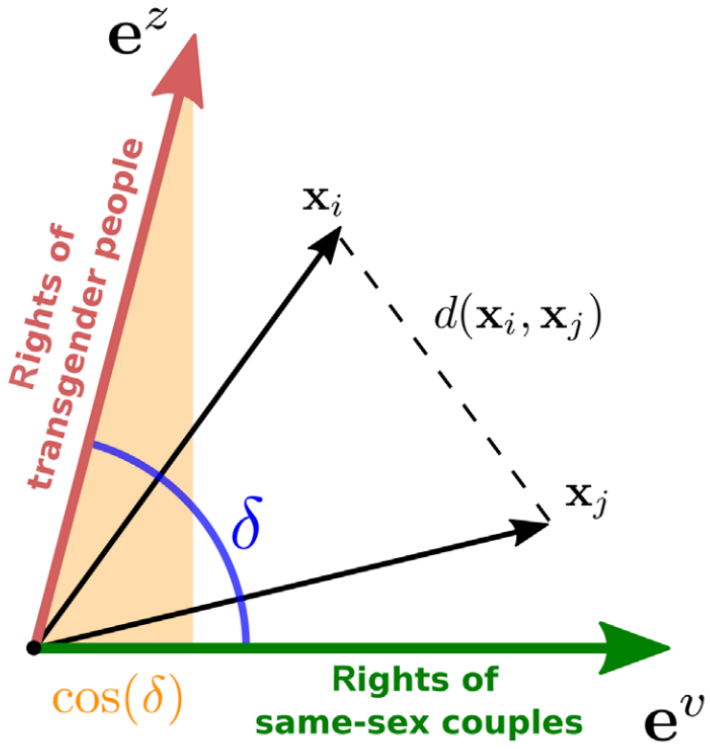
MULTIDIMENSION POLARIZATION DYNAMICS

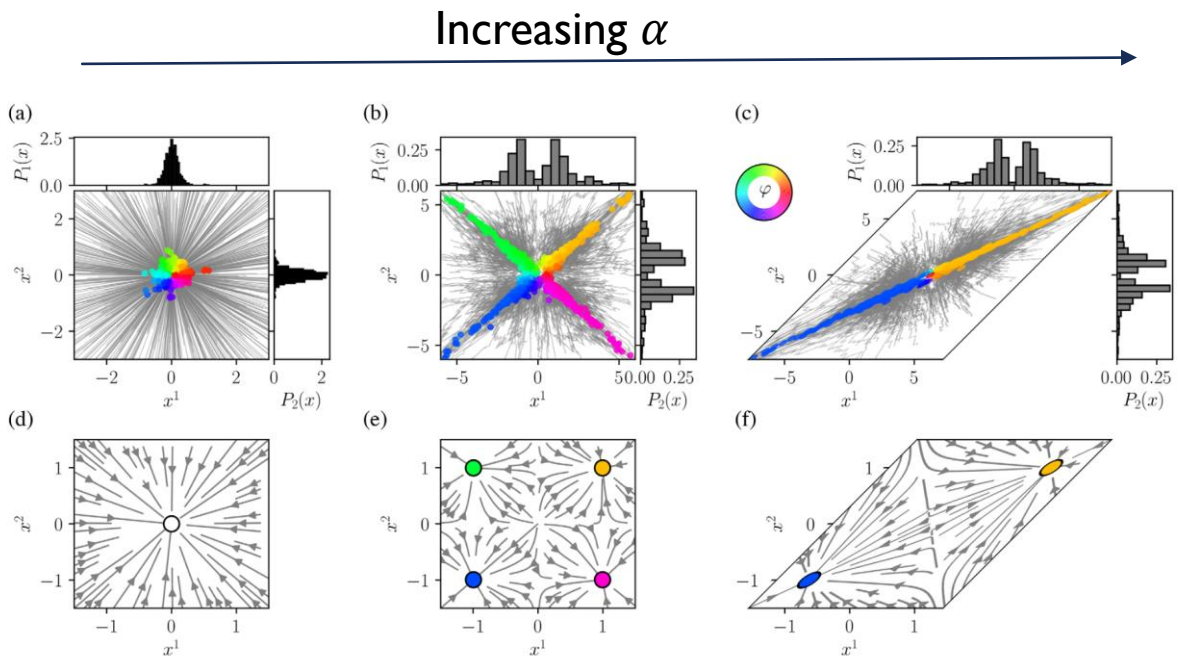
- The model:
  - Agents have an opinion vector $\boldsymbol{x}_i = \left\{x_i^{(1)}, \dots, x_i^{(T)}\right\} = \sum_v x_i^v \, \boldsymbol{e}^{(v)}$
  - Dynamics evolves with
    - $\dot{x}_i^v = -x_i^v + K \sum_j A_{ij}\,(t) \tanh\left(\alpha\left[\boldsymbol{\Phi} x_j\right]^v\right)$
  - With
    - Strength of interactions K
    - Time-evolving binary adjacency matrix A_{ij}
    - Matrix $\boldsymbol{\Phi}$ of $\cos\delta$
    - Relative strength of opinions α
- The network: activity driven (AD) model
  - Nodes get activated and send m links with rate $a_i \in [\epsilon, 1]$, drawn from $F(a) \sim a^{-\gamma}$
  - Homophily: $p_{ij} \sim d\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)^{-\beta}$

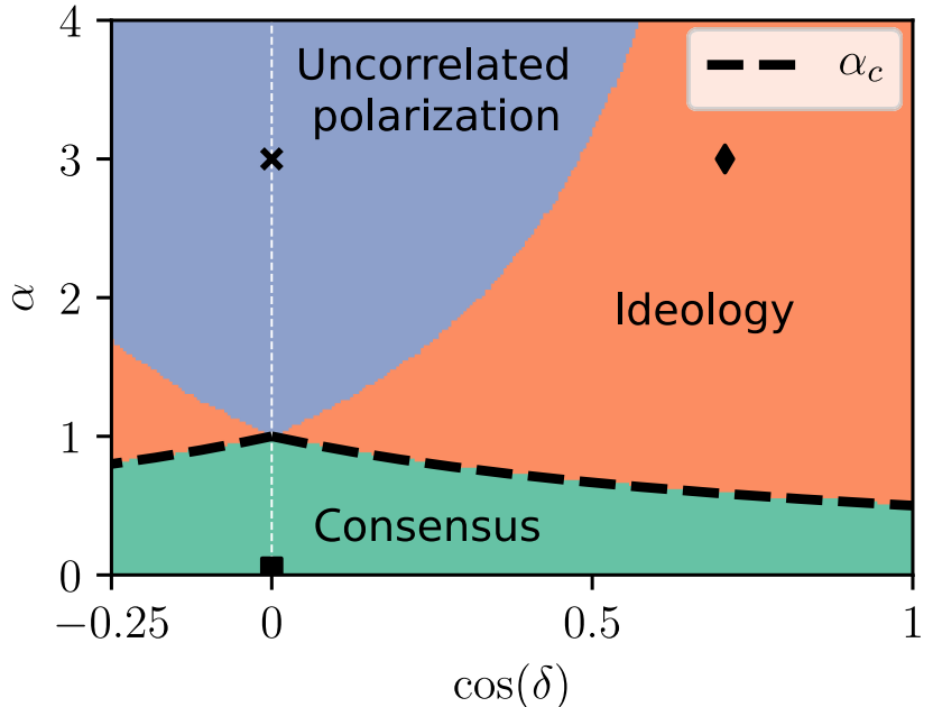


MULTIDIMENSION POLARIZATION DYNAMICS

- Complicated.
- Two opinions mean-field
  - Critical $\alpha_c = \frac{1}{2Km\langle a\rangle[1+\cos\delta]}$

$$\dot{x}_i^v = -x_i^v + K\sum_j A_{ij}(t)\tanh\left(\alpha\left[\mathbf{\Phi}x_j\right]^v\right)$$

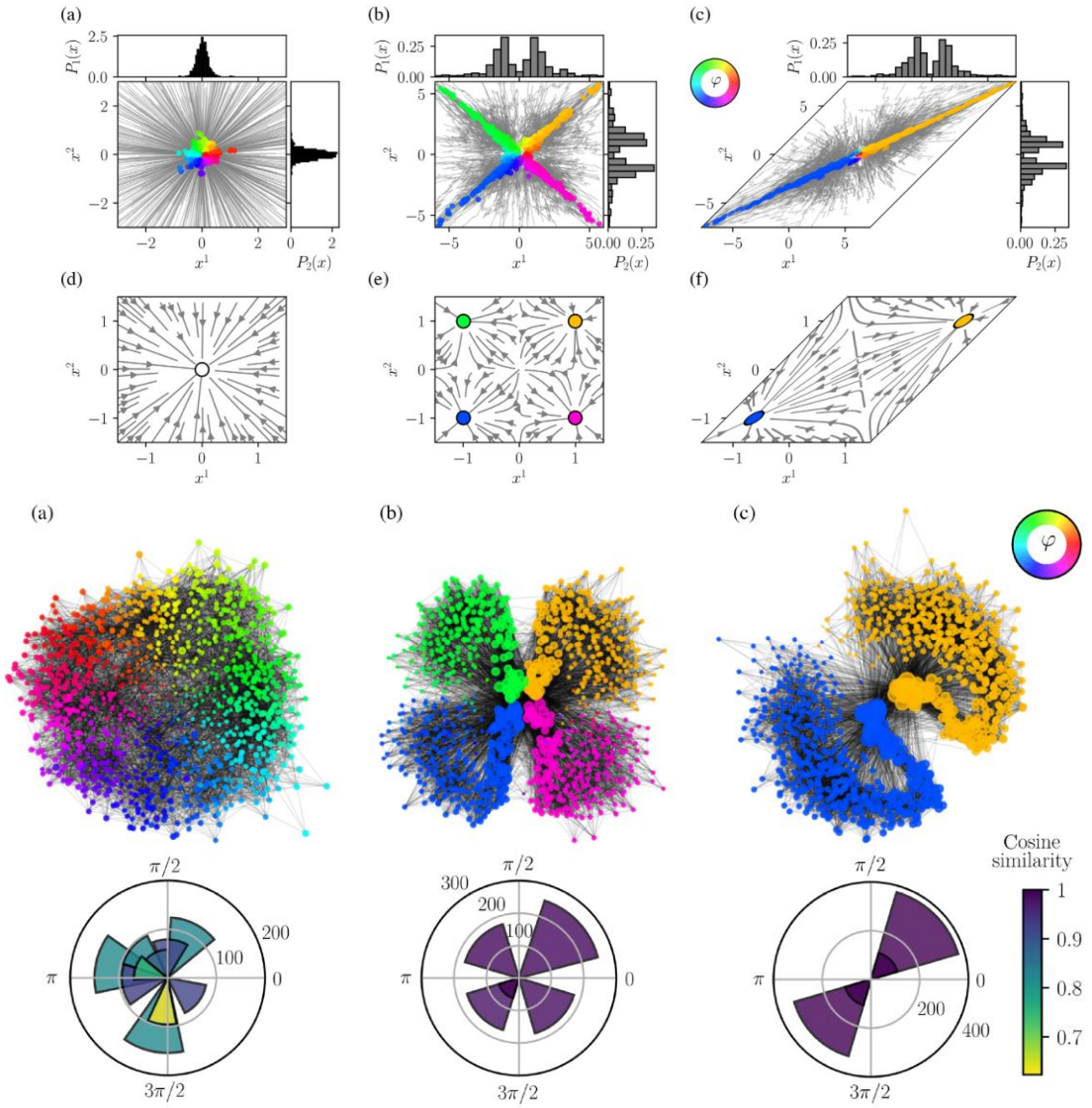




MULTIDIMENSION POLARIZATION DYNAMICS

- (Temporal) Network structure
  - (a): $\alpha = 0.05, \delta = \pi/2$
  - (b): $\alpha = 3, \delta = \pi/2$
  - (c): $\alpha = 3, \delta = \pi/4$

- Polarization also creates emergent community structure

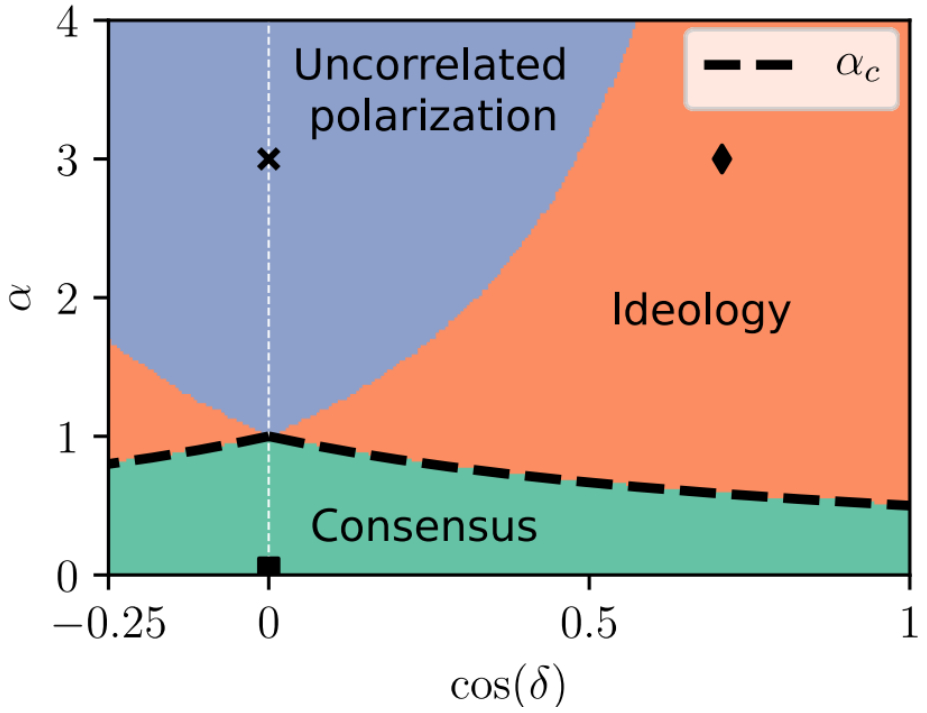


MULTIDIMENSION POLARIZATION DYNAMICS

- Results
  - Relative strength of opinions α is important
  - Ideology may emerge even from small correlations between opinions (small $\cos\delta$)
  - Ideology absent with non-correlated opinions (either consensus or uncorrelated polarization)

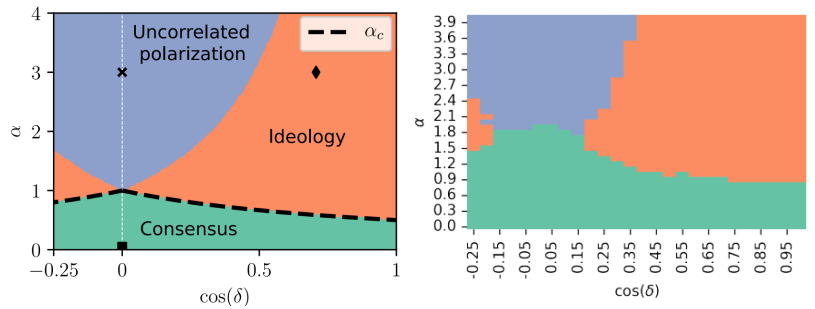
- Model limitations
  - "Influencers" are nodes with large activity in the temporal network, but they still only talk to (mostly the same) m nodes
  - Influencers likely have much more influence in social media
  - Still assumes $x \to 0$

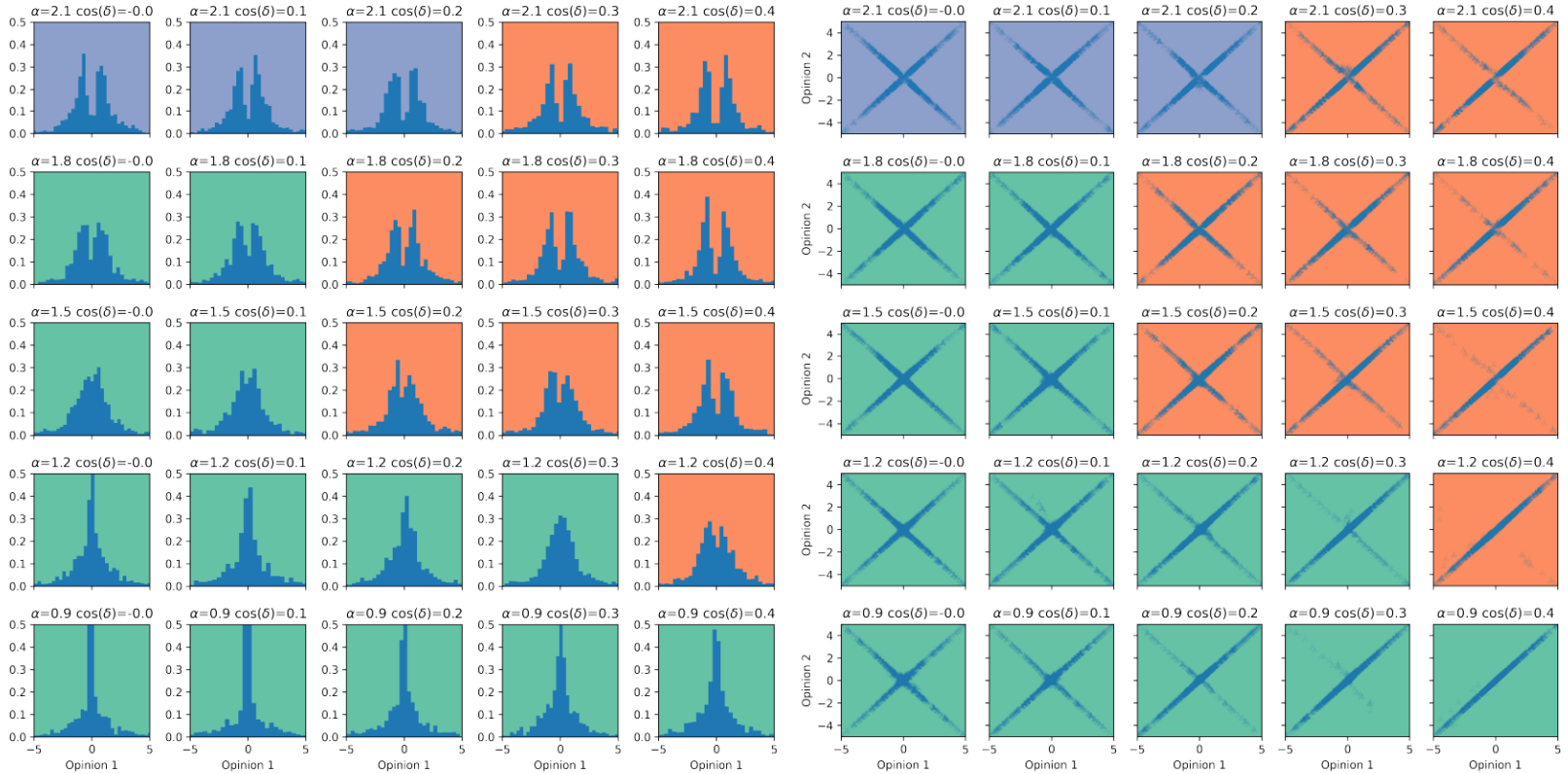
$$\dot{x}_i^v = -x_i^v + K \sum_j A_{ij}(t) \tanh\left(\alpha [\mathbf{\Phi} x_j]^v\right)$$



MULTIDIMENSION POLARIZATION DYNAMICS

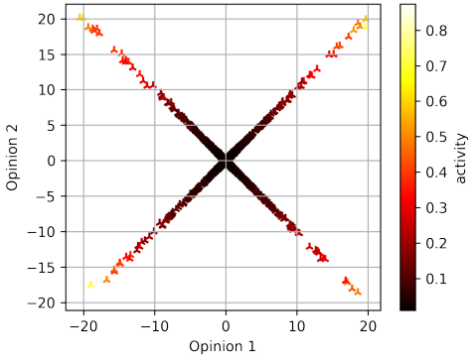
- Studying the model (Robin Danek)
- Simulation results
  - Simulations match mean-field
  - While classification changes, the behaviour changes smoothly with parameters

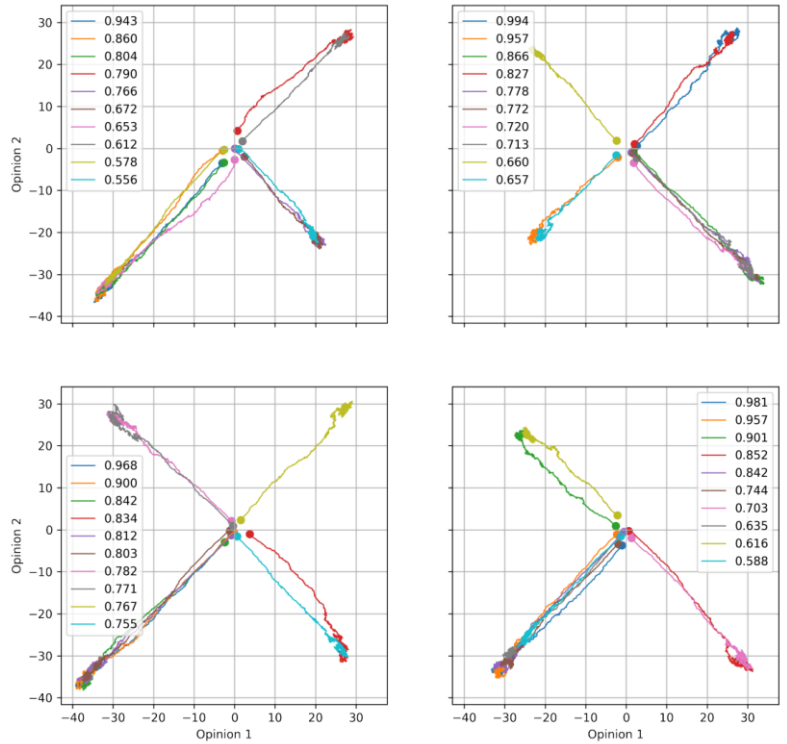




MULTIDIMENSION POLARIZATION DYNAMICS

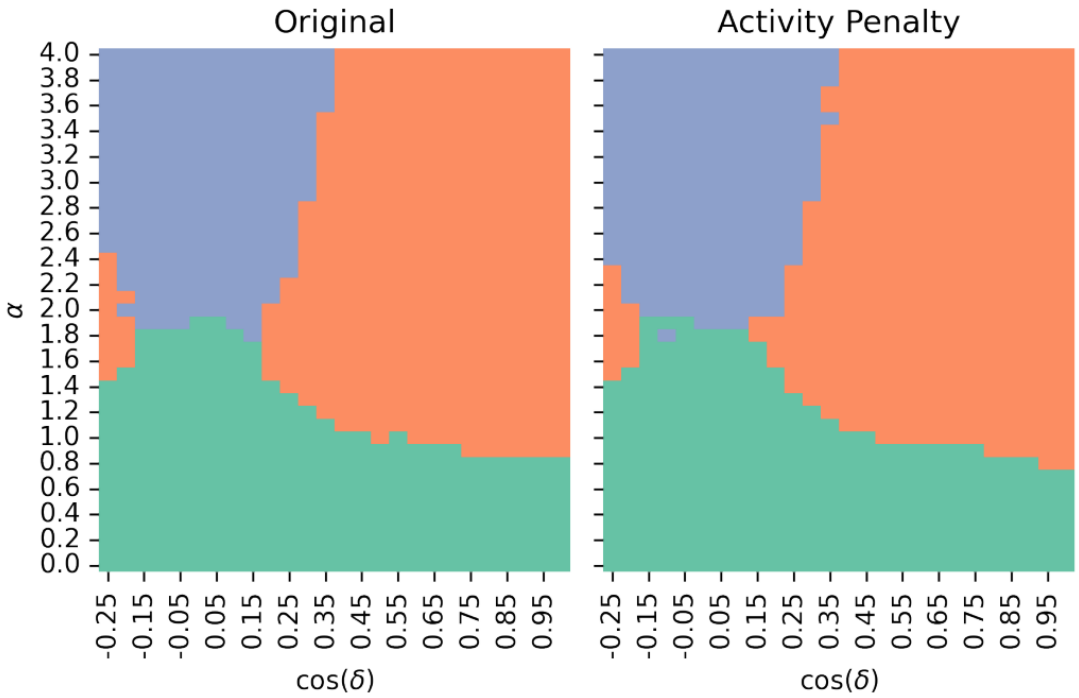
- Activity vs Opinion
  - $\alpha = 3, \delta = \pi/2$ (uncorrelated polarization)
  - Activity and opinion are still highly correlated
- How do the hyper-active users change their opinions?
  - Quickly, and smoothly towards the extremes
  - They are more hyper-influenced than influencers
  - **Removing them has no effect**



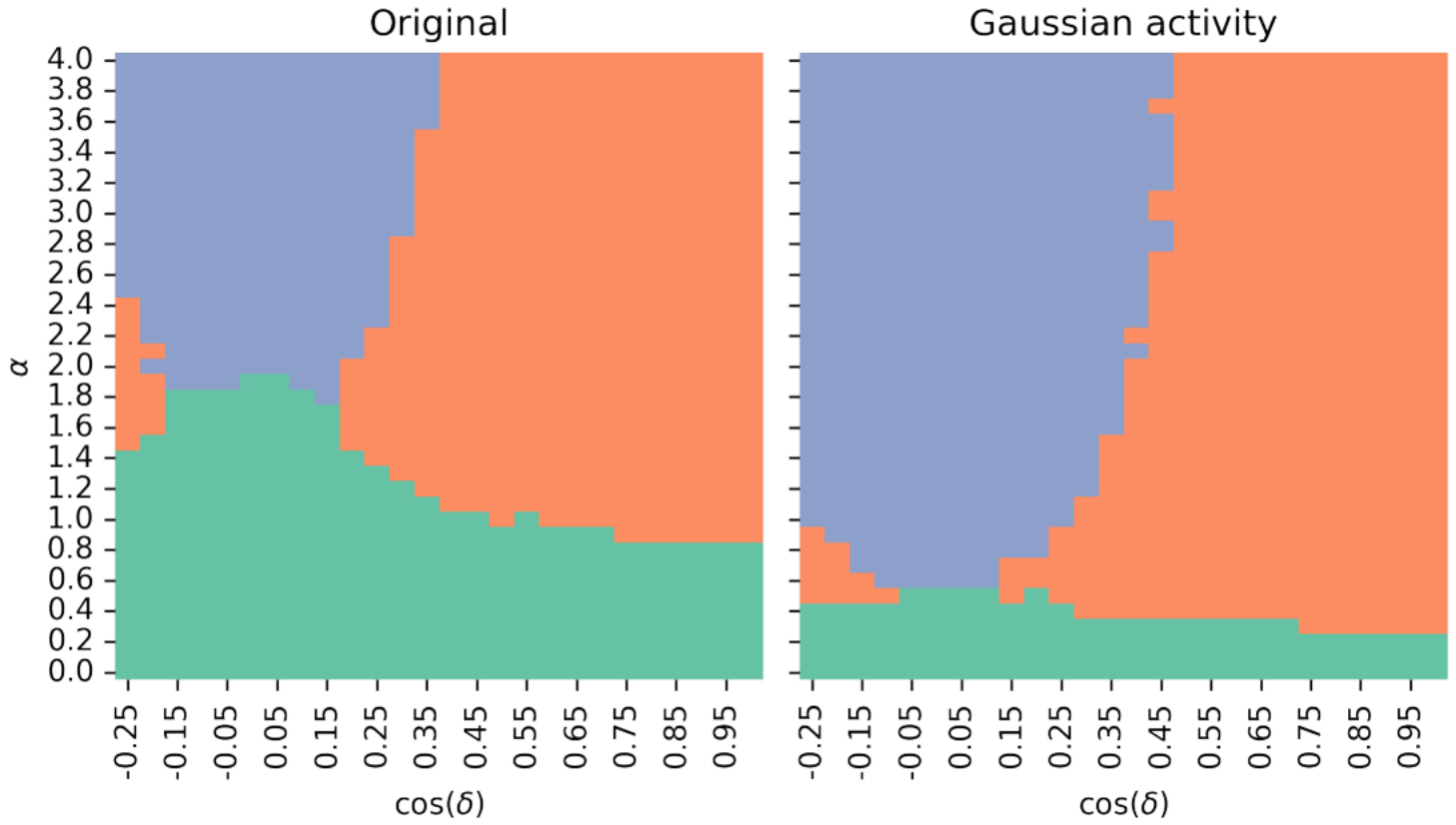


MULTIDIMENSION POLARIZATION DYNAMICS

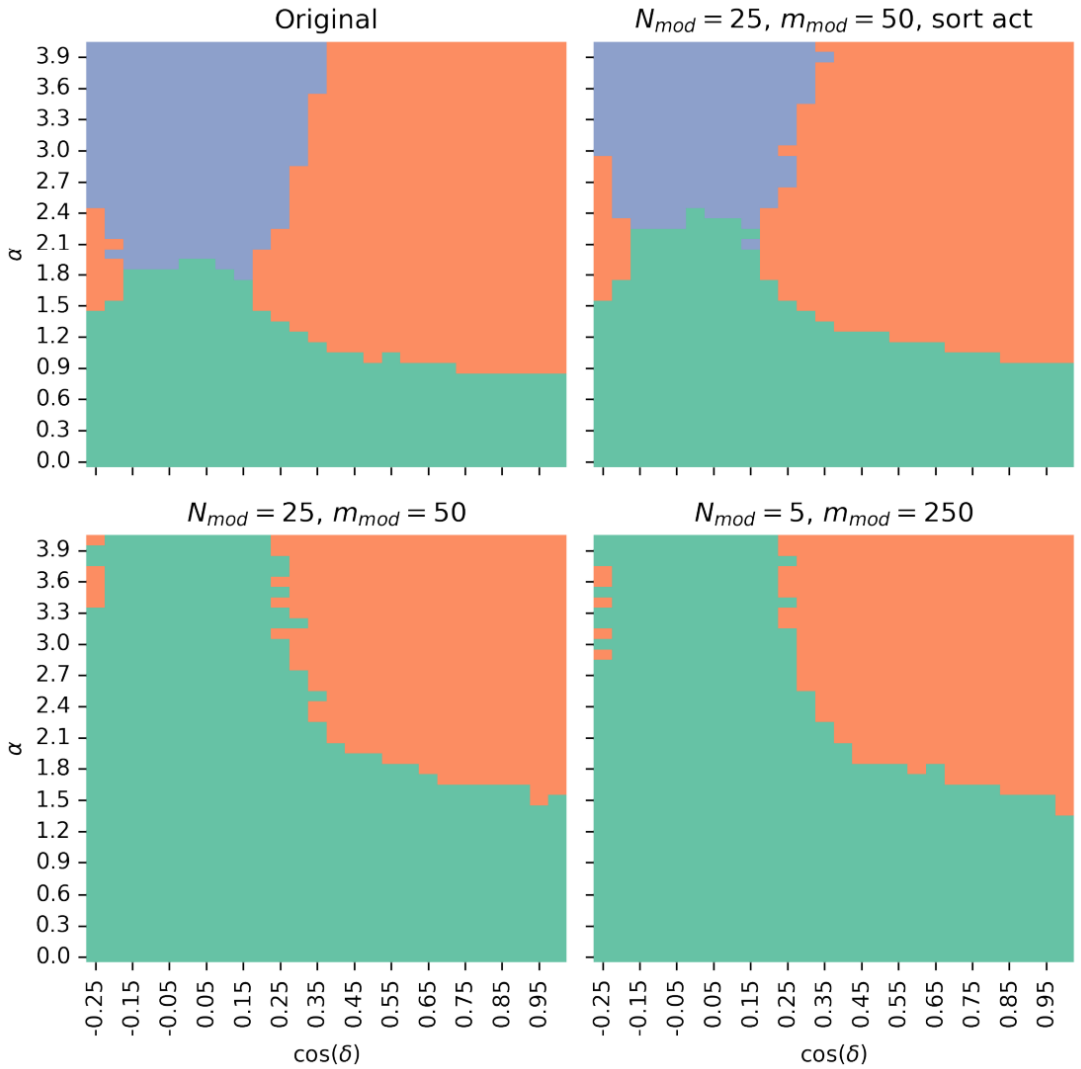
- How do we stop polarization?
- Mechanism #1: penalty to recent connections
  - Influence of an opinion is diminished with $p \sim e^{-\lambda(t-t_{ij})}$
- Results: no change to opinion space



- Mechanism #2: changing the activity distribution
  - Original: power-law
  - New: Gaussian
  - Total activity is kept constant
- Results: actually increases polarization



- Mechanism #3: Implementing moderators
  - Fraction of nodes with fixed $x = 0$ opinion
  - $N = 10^3$ users, N_{mod} moderators
  - Moderation stops polarization
  - Lesser effect on ideology
  - Even a small number of moderators have a large impact



CONCLUSION

- Polarization depends heavily on
  - Homophily
  - Relative impact of extreme opinions
- Opinion correlation may result in ideology
- Moderation can counter-balance polarization