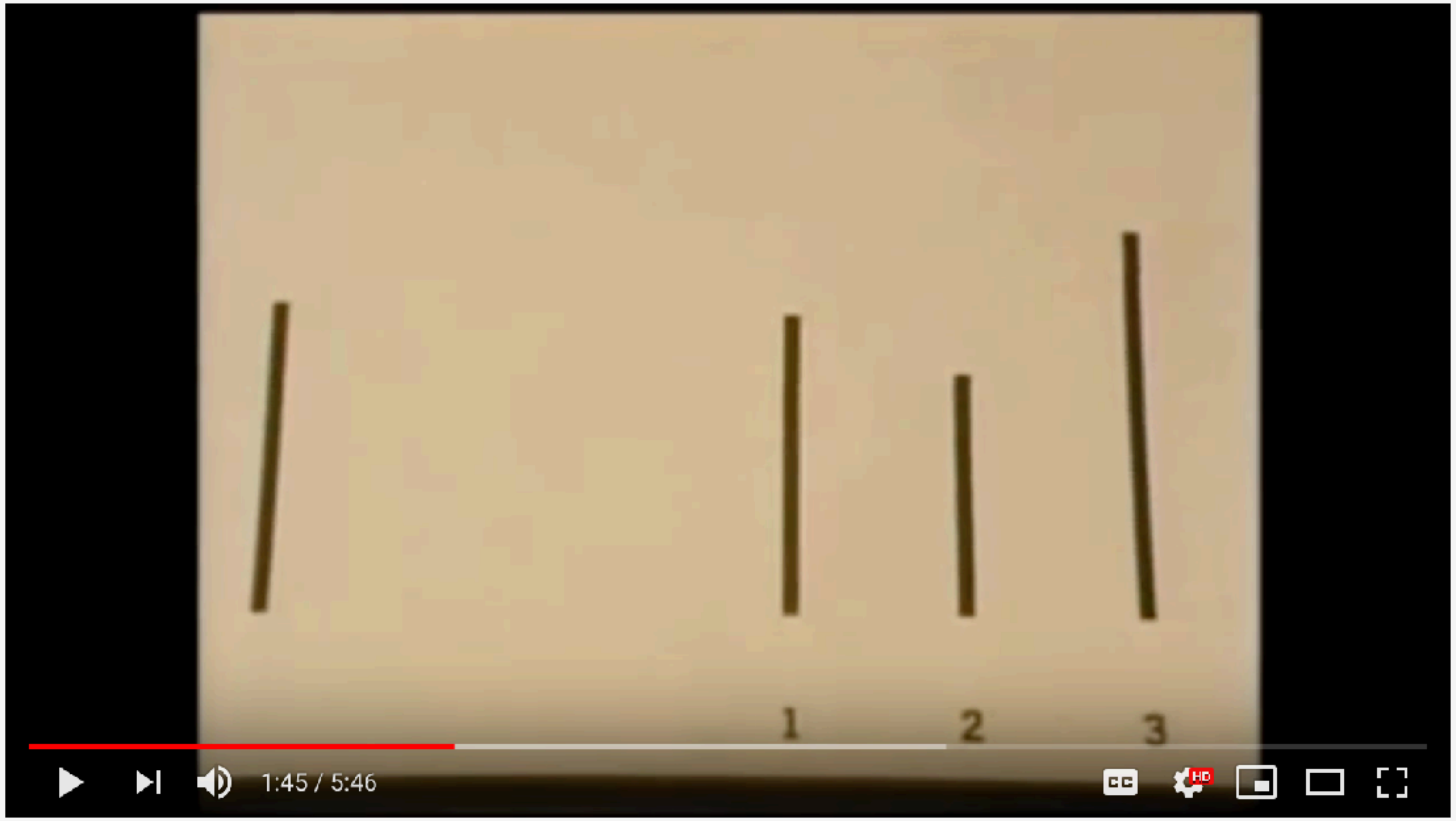
Social contagion

Conformity experiment and group influence



Asch Conformity Experiment

https://www.youtube.com/watch?v=NyDDyT1lDhA

Different kinds of contagion

- **Epidemics**: a pathogen is transmitted by infected individuals
- **Social Contagion**: diffusion and adoption of ideas, opinions, innovations, behaviors, …

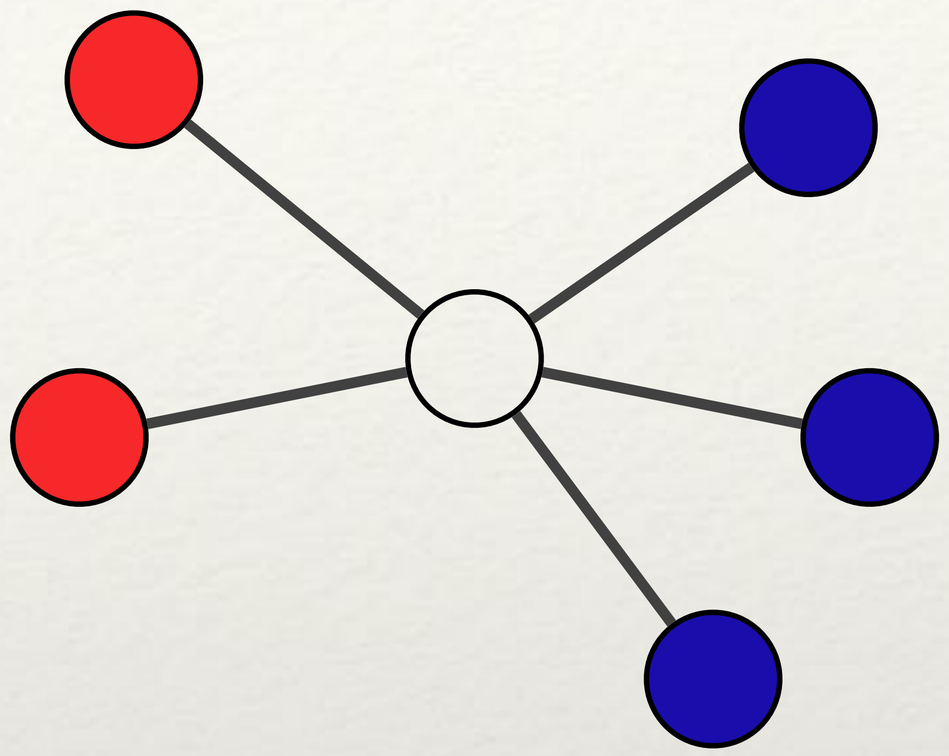
A diffusion of a new behavior

- Assumption: individuals make *decisions based* on the choices of *their neighbors*
  - focus on links
- Natural model introduced by Stephen Morris in 2000

Stephen Morris. Contagion. Review of Economic Studies, 67:57–78, 2000.

A simple (linear) threshold model

- It is natural to use a **coordination game**
  - each node has a choice between two possible behaviors, A and B
  - players have an incentive to adopt the same behavior



w

		A	**B**
v	**A**	a, a	0, 0
	B	0, 0	b, b

p fraction of neighbors adopting A

1-p fraction of neighbors adopting B

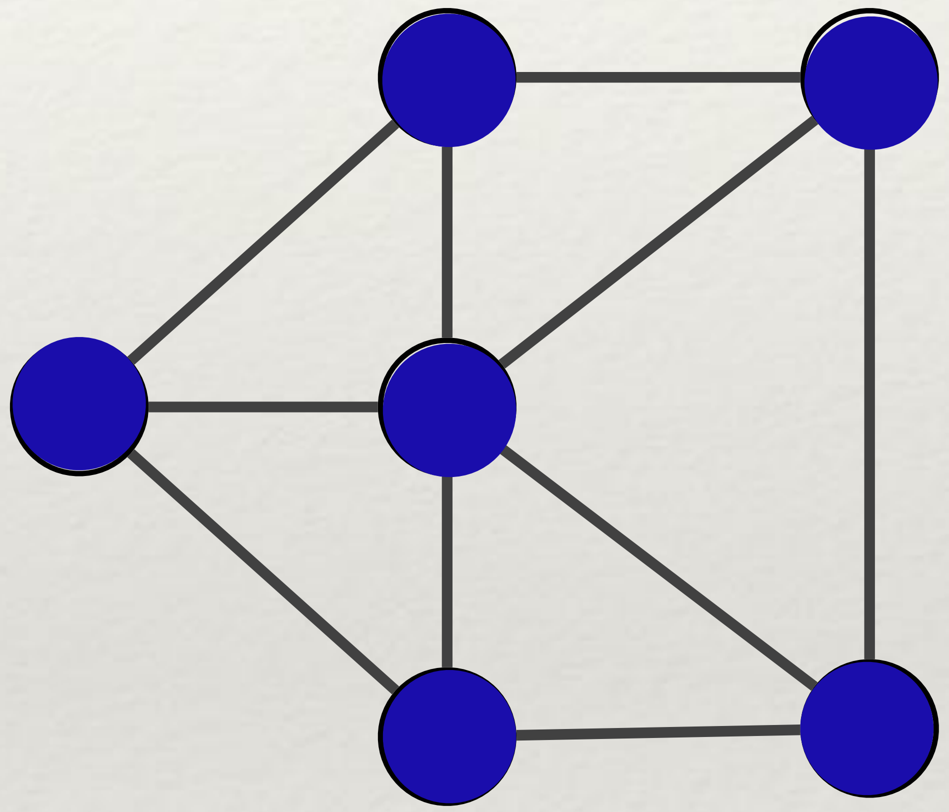
d is the number of neighbors

the node chooses A if $pda \geq (1-p)db$

$$\Rightarrow p \geq \frac{b}{a+b} = q$$

Example

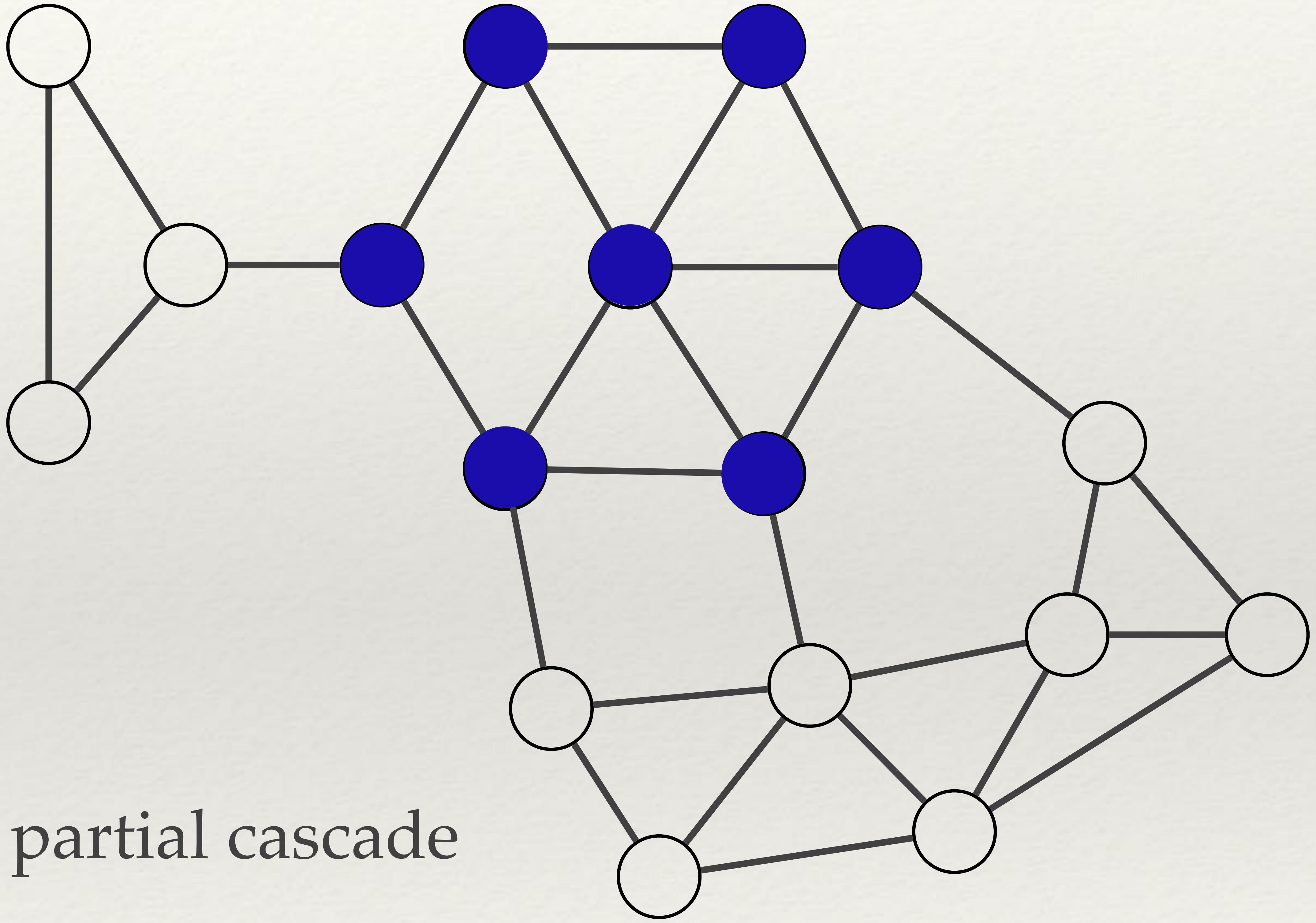
- $q = \dfrac{2}{5}$
- $S = \{u, v\}$



Chain reaction: complete cascade

Another example

- $q = \dfrac{2}{5}$
- $S = \{u, v\}$

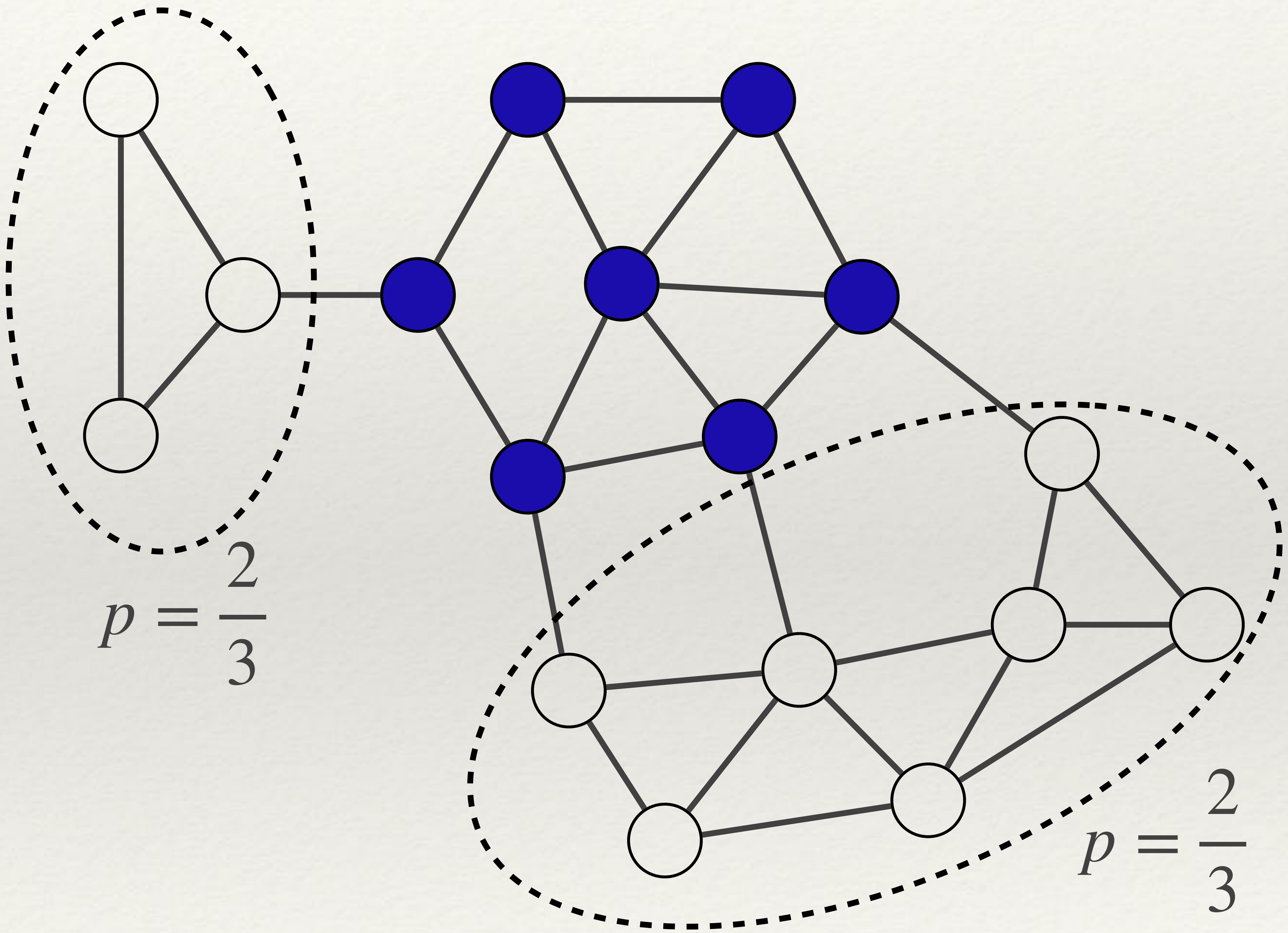


The diffusion of A stops here: partial cascade

Clusters are **barriers** to diffusion!

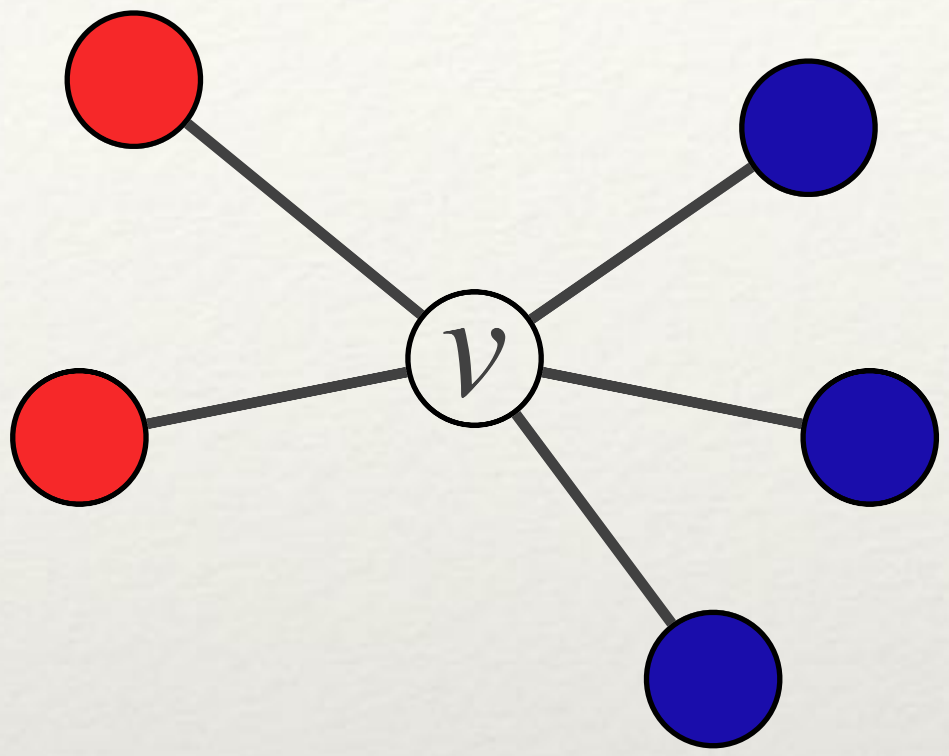
Stopping cascades

- What prevents cascades from spreading?
    - *Homophily* can serve as a barrier to diffusion: it is hard for innovation to arrive from outside densely connected communities
- Let's try to quantify this intuition:
    - <u>def</u>. *cluster of density p is a set of nodes C where* ***each node*** *in the set has at least p fraction of edges in C*



Heterogeneous thresholds

- Let's suppose each person gives values to A and B subjectively



w

v		**A**	**B**
	A	a_v, a_w	0, 0
	B	0, 0	b_v, b_w

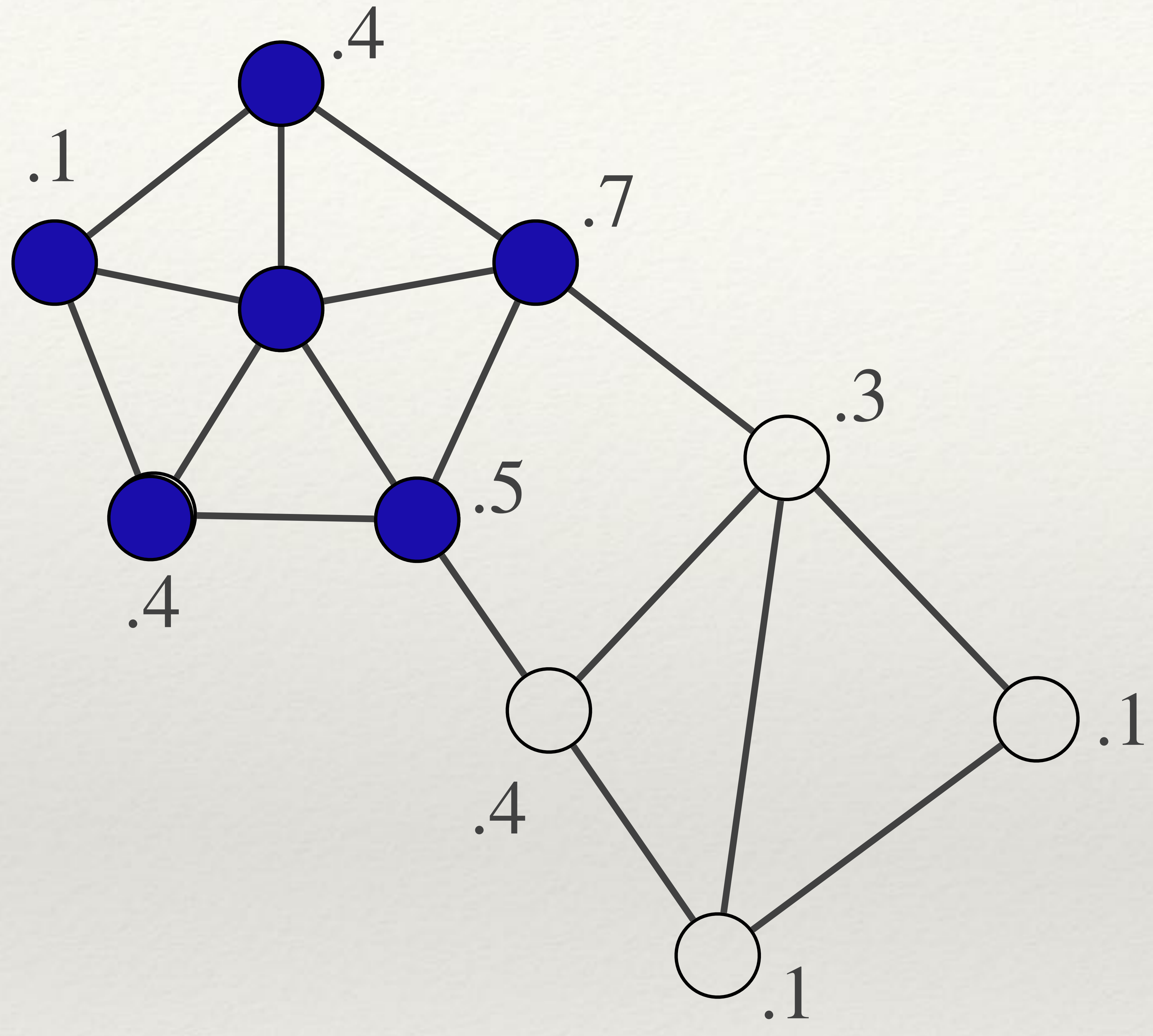
p fraction of neighbors adopting A

$1\text{-}p$ fraction of neighbors adopting B

d is the number of neighbors

the node chooses A if $pda_v \geq (1-p)db_v$

$$\Rightarrow p \geq \frac{b_v}{a_v + b_v} = q_v$$



Watts and Dodds: we need to take into account not just the power of influential nodes, but also the extent to which these influential nodes have access to easily **influenceable** people.

Reformulating the notion of **blocking clusters**: set of nodes for which each node v has a fraction $> (1 - q_v)$ of its friends inside the set.

The notion of density becomes **heterogeneous** as well: each node has a different requirement for the fraction of friends it needs to have in the cluster.

Duncan J. Watts and Peter S. Dodds. Networks, influence, and public opinion formation. Journal of Consumer Research, 34(4):441–458, 2007.

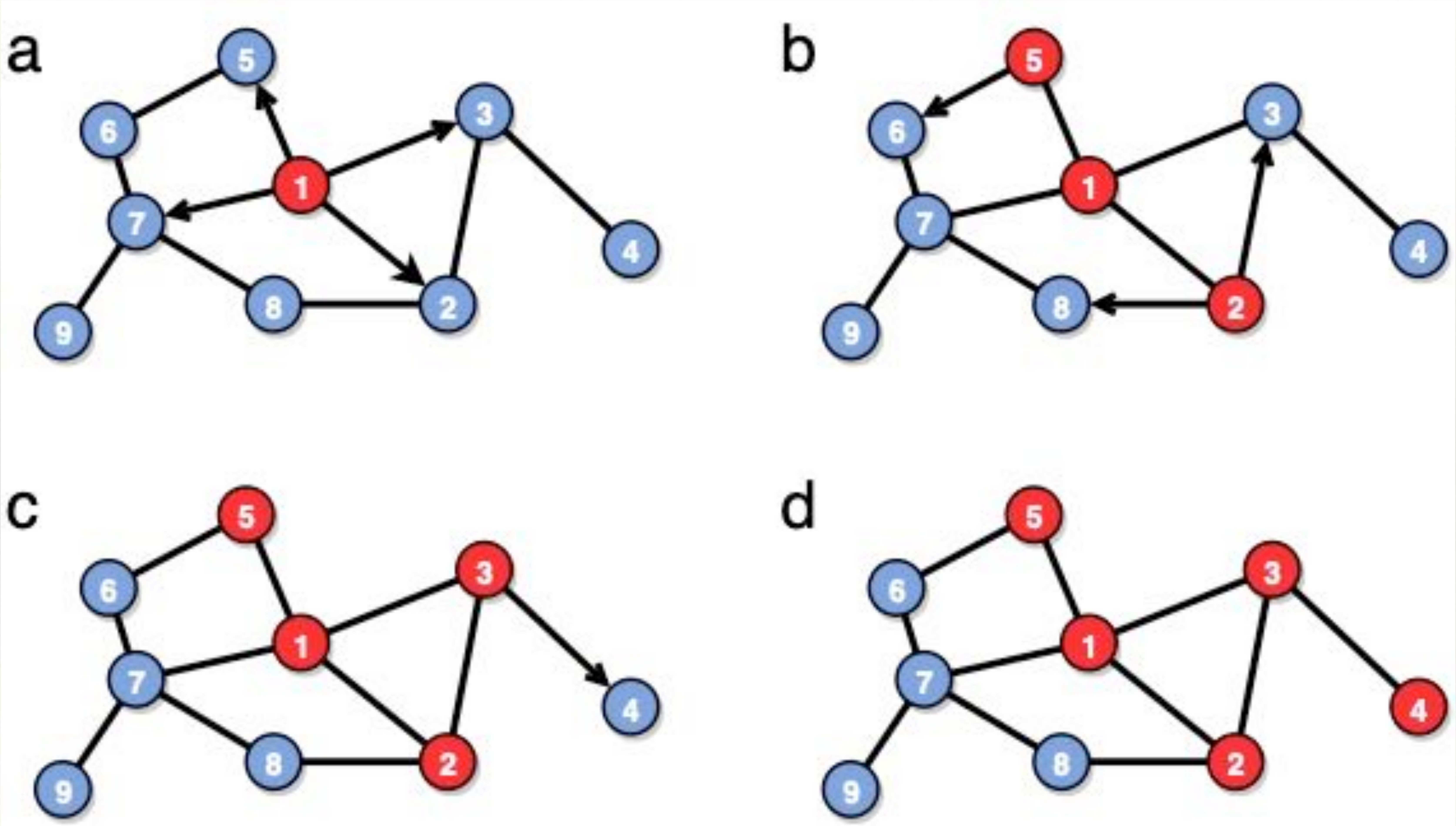
Independent cascade models

- Principle of threshold models: **peer pressure**, the more people try to persuade you, the more likely they will succeed
- **Remark:** social influence often works **one-to-one**, we may be persuaded by a single passionate individual
- **Alternative principle:** each of our contacts has their own influence
- **Independent cascade models** are based on node-node interactions!

Independent cascade models

- **Model dynamics:**
  - An active node *i* has a probability p_{ij} to convince its inactive neighbor *j* ($p_{ij} \neq p_{ji}$, in general)
  - All active nodes are considered in sequence: the inactive neighbor *j* of the active node *i* is activated with probability p_{ij}. All inactive neighbors of *i* have one chance to be persuaded by *i*
  - If a node *j* is activated, it has only one chance to activate its inactive neighbors

Independent cascade models



Independent cascade models

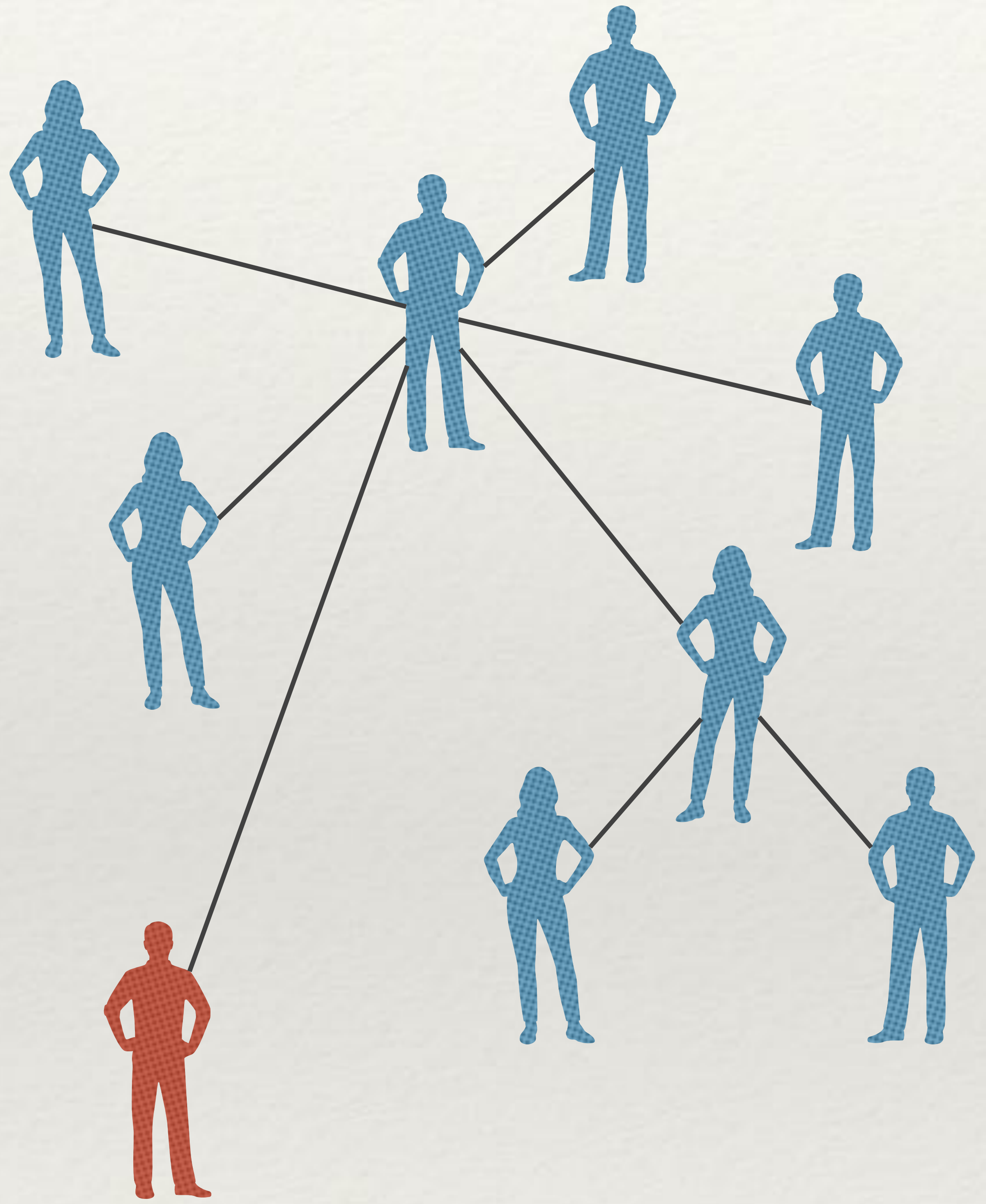
- **Remark**: the more active neighbors, the more likely a node will be activated
- **Independent cascade versus threshold models**:
    - Threshold models focus on the inactive nodes, independent cascade models on the active ones
    - Threshold models are (usually) **deterministic**: the dynamics depends on whether the threshold condition is satisfied or not
    - Independent cascade models are **probabilistic**: nodes are activated with a given probability —> it is more **difficult to control a cascade!**

Information diffusion

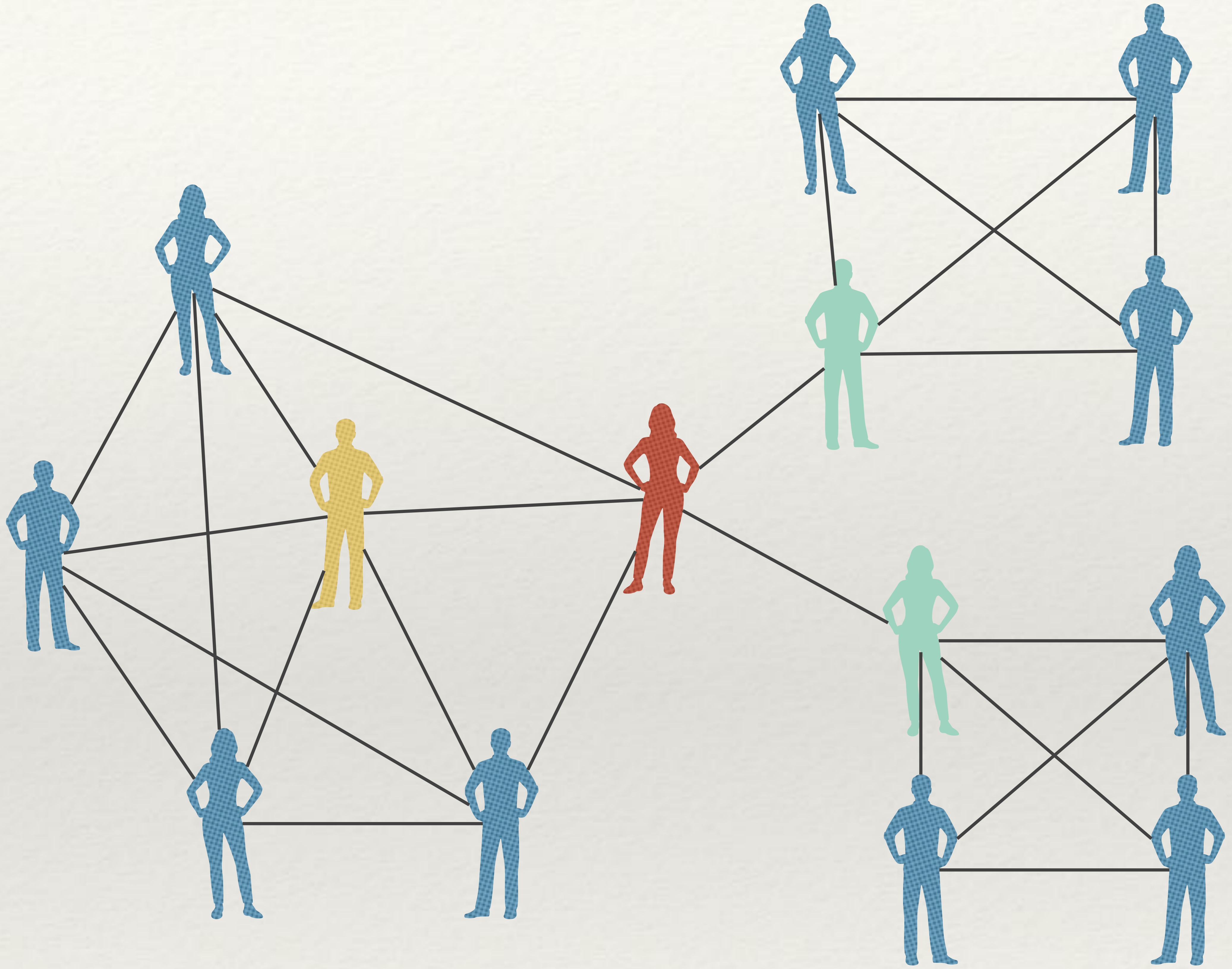
- **Problem**: models are too simple to be realistic
- **Solution**: more sophisticated variants!
- **Example**:
  - Probabilistic version of threshold model, in which the chance of being activated grows with the number of active neighbors (instead of the usual yes/no dynamics)
  - Similar to independent cascade model, except that the active neighbors **do not exert influence independently of each other!**
- **Complex contagion:** each new person exposing us to a new idea or product has greater influence than the previous ones!

Adrien Guille, Hakim Hacid, Cecile Favre, and Djamel A. Zighed. 2013. Information diffusion in online social networks: a survey. SIGMOD Rec. 42, 2 (May 2013), 17–28. DOI:https://doi.org/10.1145/2503792.2503797

Recall: real networks are heterogeneous



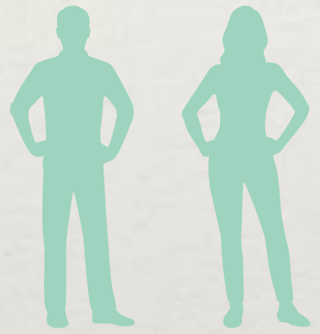
Rich-get-richer dynamics
(aka preferential attachment)



weak/strong ties, betweenness,
homophily, clusters

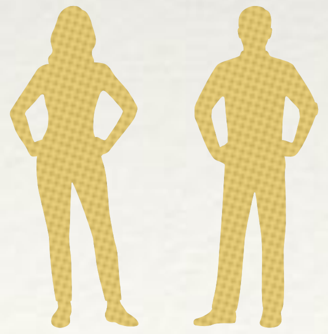
The role of weak ties

Threshold models highlight some important implications of 'the strength of weak ties' theory

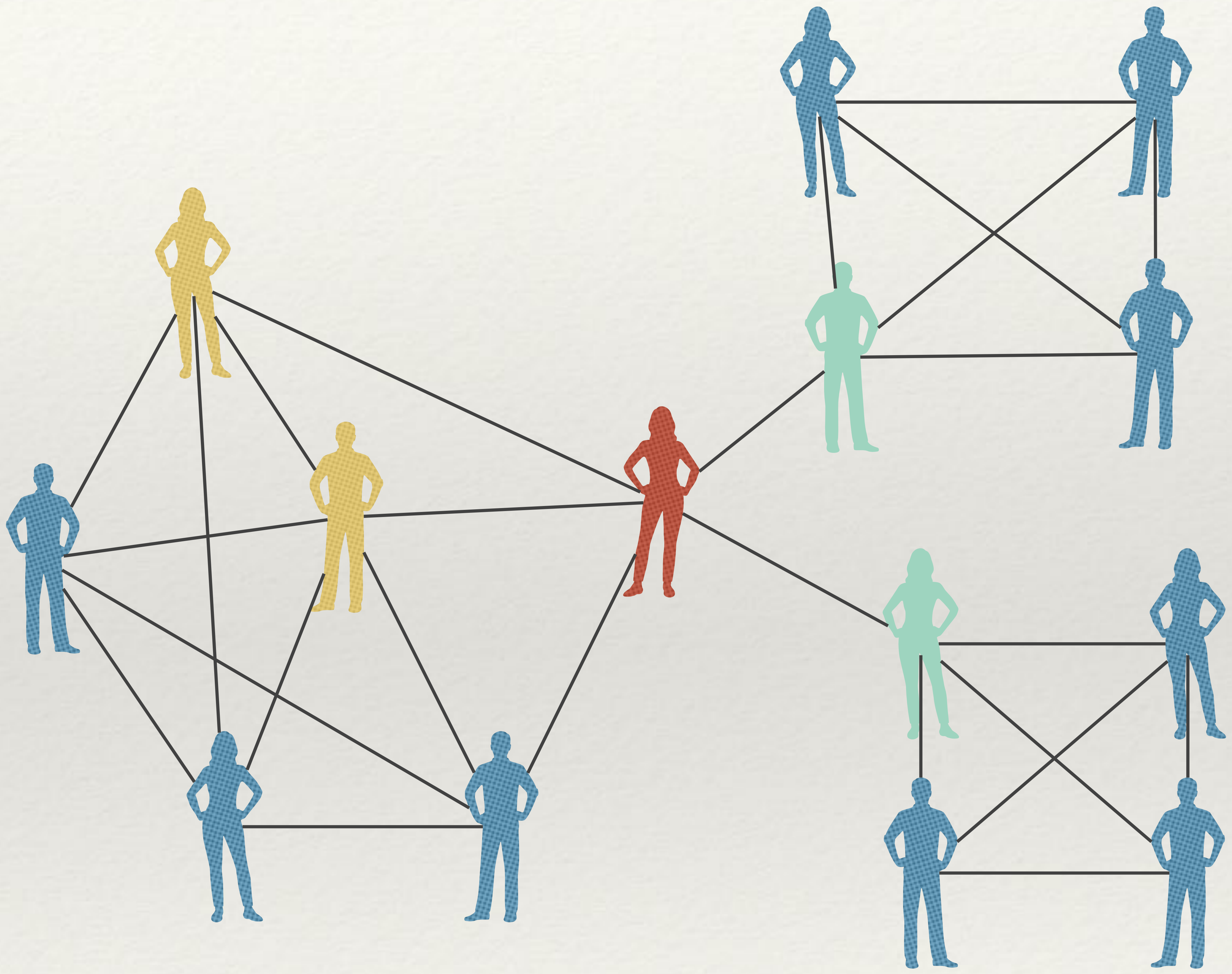


They receive very **fresh ideas** from other communities; not enough for adoption and spread (try threshold model with with $q = \frac{1}{2}$)

Bridges and weak ties are great for **spreading rumors** or jokes across the network, but **not for diffusion of innovation or social mobilization**



Strong ties can have more significant role for others in the community to take actions



Damon Centola and Michael Macy. Complex contagions and the weakness of long ties. American Journal of Sociology, 113:702–734, 2007.

Complex contagion

Simple contagion: a single contact with an "infected" individual is usually sufficient to transmit the behavior.

Complex contagion: when behaviors require **social reinforcement**, a network with more clustering may be more advantageous, even if the network has a larger diameter.

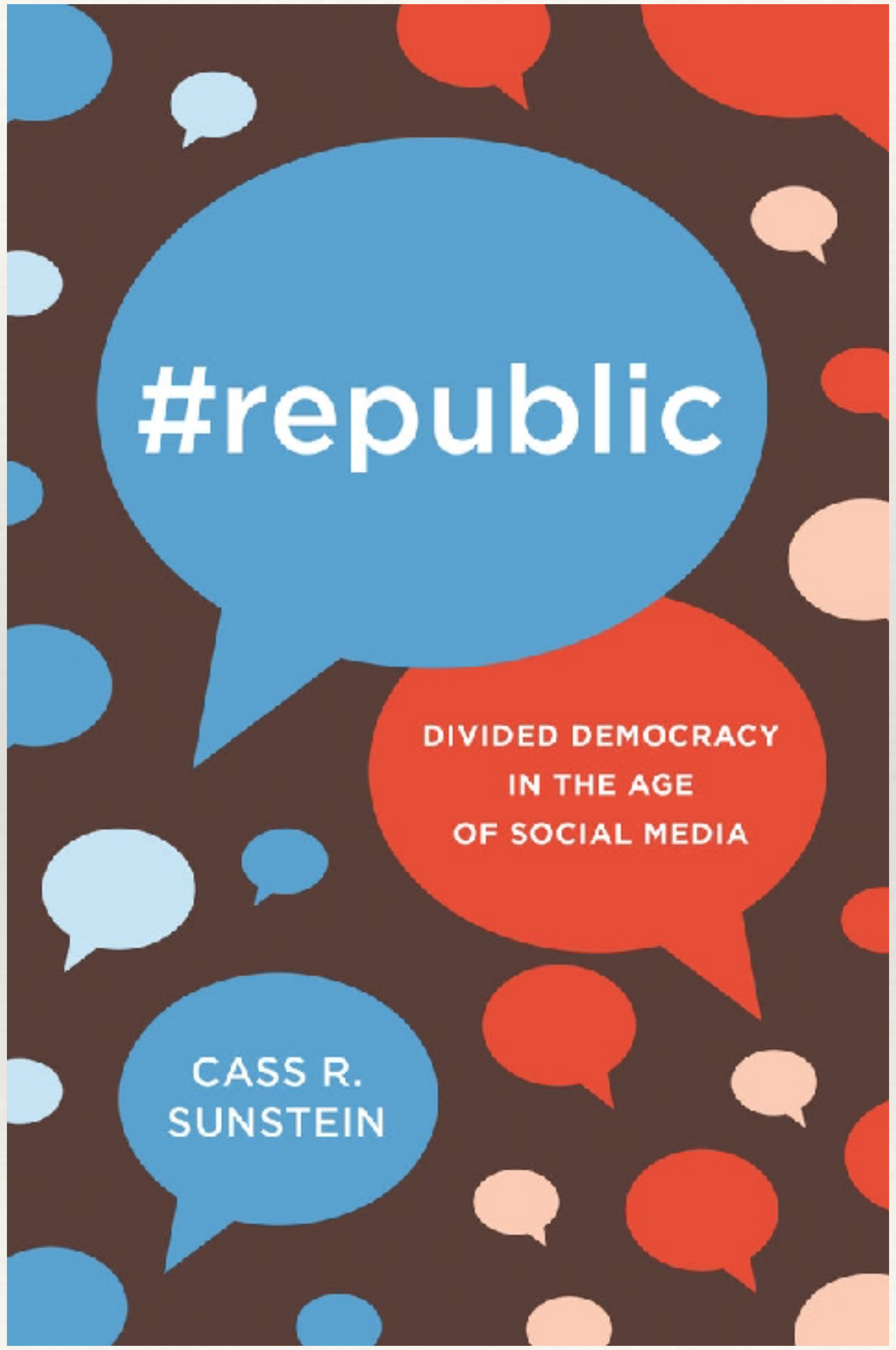
Centola investigated the effects of network structure on diffusion by studying t*he spread of health behavior through artificially structured online communities*

D. Centola, The Spread of Behavior in an Online Social Network Experiment, Science 03 Sep 2010: 1194-1197

Echo-chambers

Echo-chambers

- "Echo-chambers" metaphor superbly explained by Cass Sunstein
- Group of like-minded people amplifies their's members view
- Many factors:
    - Homophily (selection & influence)
    - Confirmation bias
    - Back-fire effect
    - Hypercorrection effect
    - Bandwagon effect

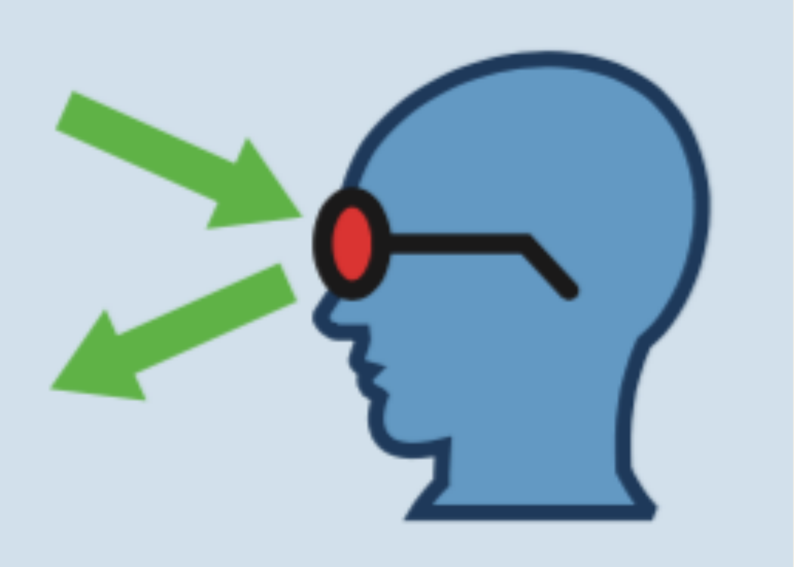


Psychological issues

Confirmation Bias

Hypercorrection Effect

Backfire effect



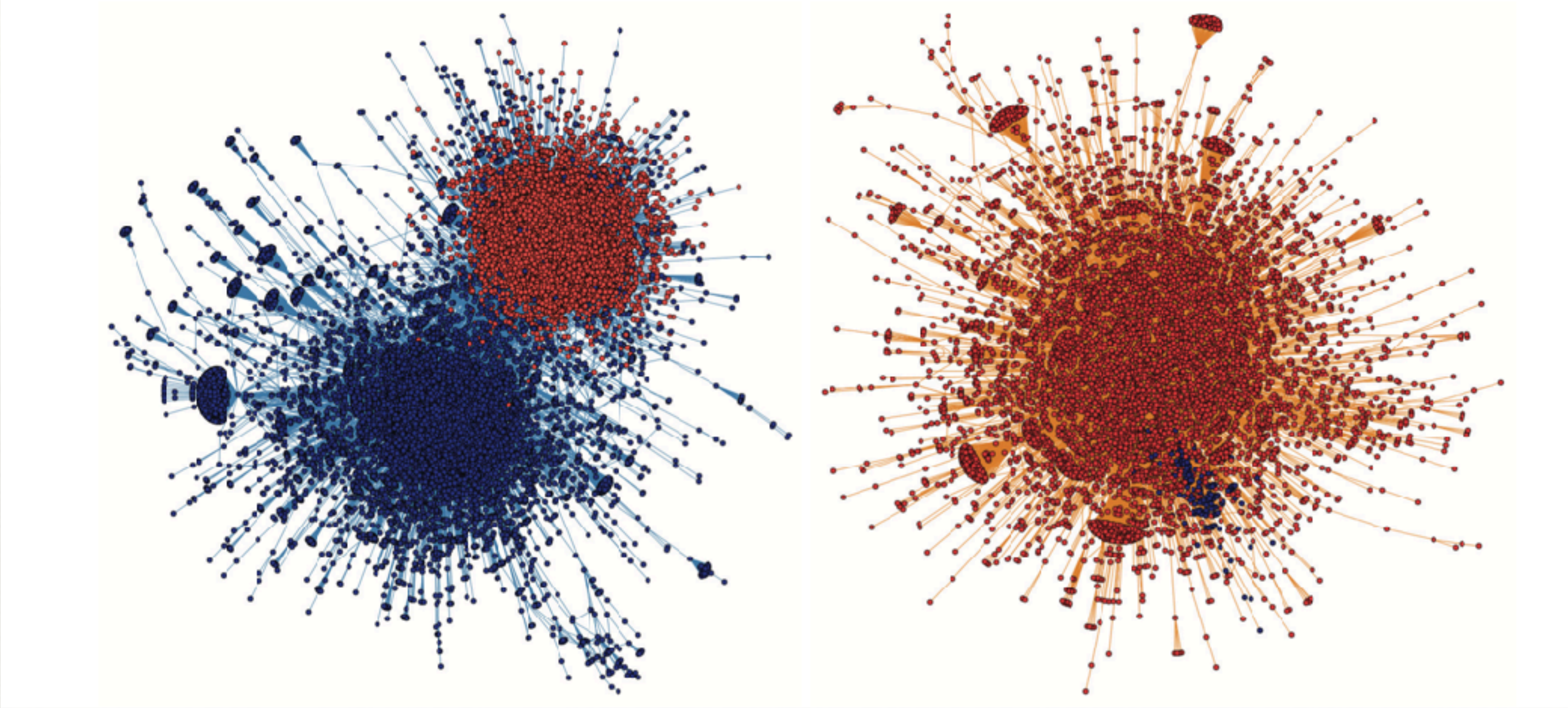
Bandwagon effect

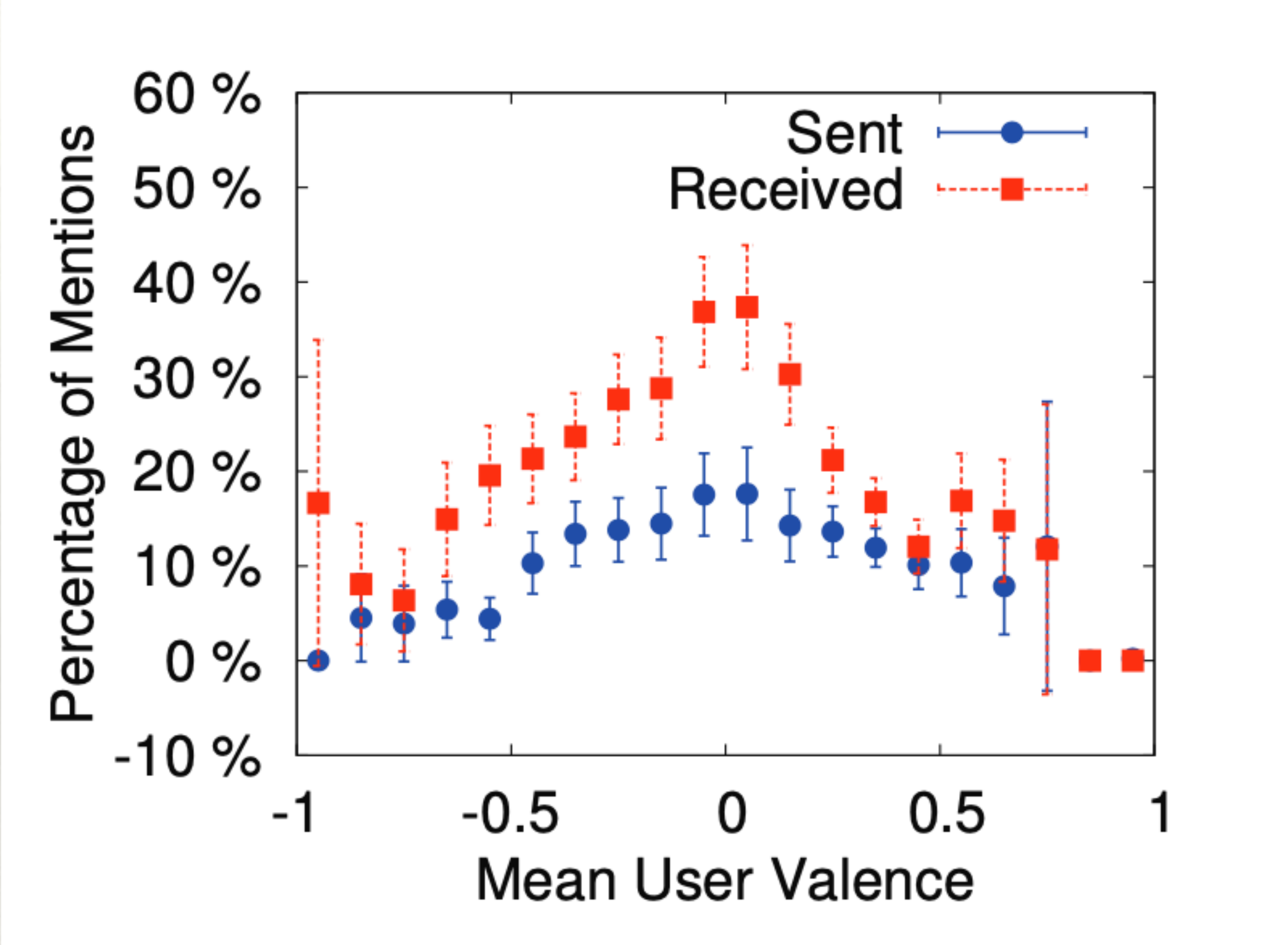
Butler AC, Fazio LK, Marsh EJ. The hypercorrection effect persists over a week, but high-confidence errors return. Psychon Bull Rev. 2011 Dec;18(6):1238-44. doi: 10.3758/s13423-011-0173-y. PMID: 21989771.

Lewandowsky, S. et al. (2012) Misinformation and Its Correction: Continued Influence and Successful Debiasing, Psychological Science in the Public Interest, 13(3), pp. 106–131. doi: 10.1177/1529100612451018.

Polarization emerges from radicalized segregation, but not necessarily a segregated network is also polarized.
However, some topics are strongly divisive (echo-chambers), others are not.

Political polarization on Twitter

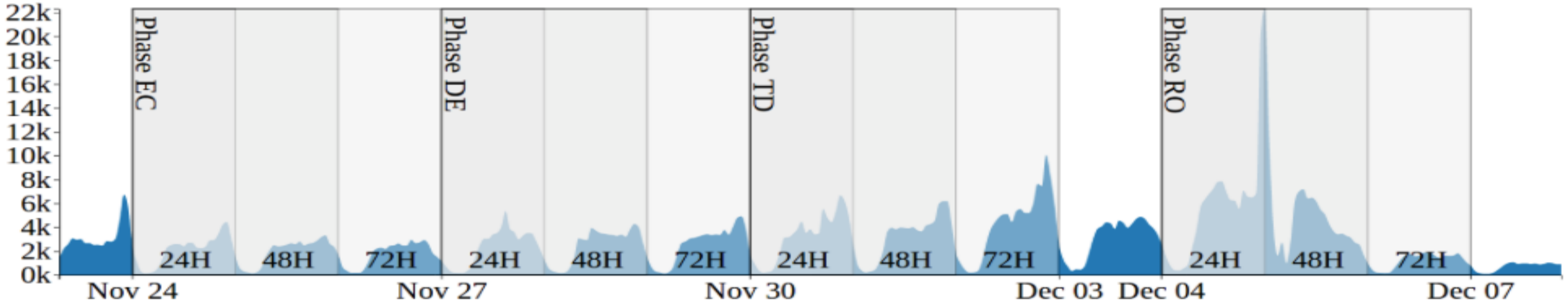




Conover, M., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., & Flammini, A. (2011, July). Political polarization on twitter. In *Proc. of the Intern. AAAI Conference on Web and Social Media* (Vol. 5, No. 1) - ICWSM 2011.

Italian 2016 Constitutional Referendum

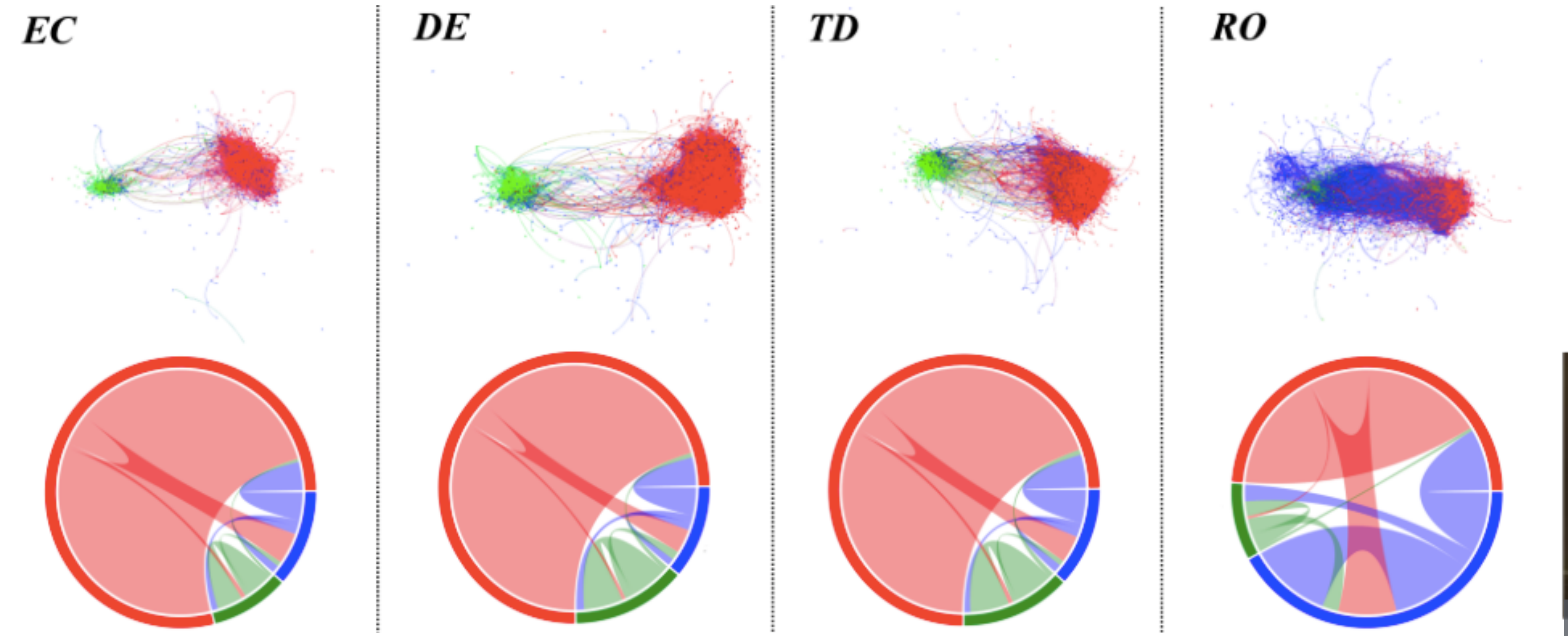
Collected Tweets



stance detected as **AGAINST**

stance detected as **IN FAVOR**

stance detected as **NONE**



Retweet Network

strong signal of **homophily**

M Lai, M Tambuscio, V Patti, P Rosso, G. Ruffo, Stance Polarity in Political Debates: a Diachronic Perspective of Network Homophily and Conversations on Twitter, Data & Knowledge Engineering Journal, online: September 2019

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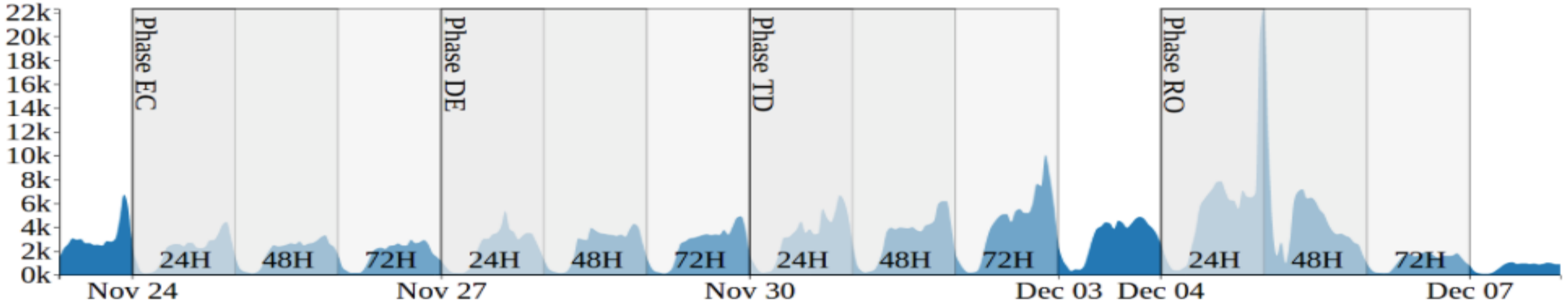
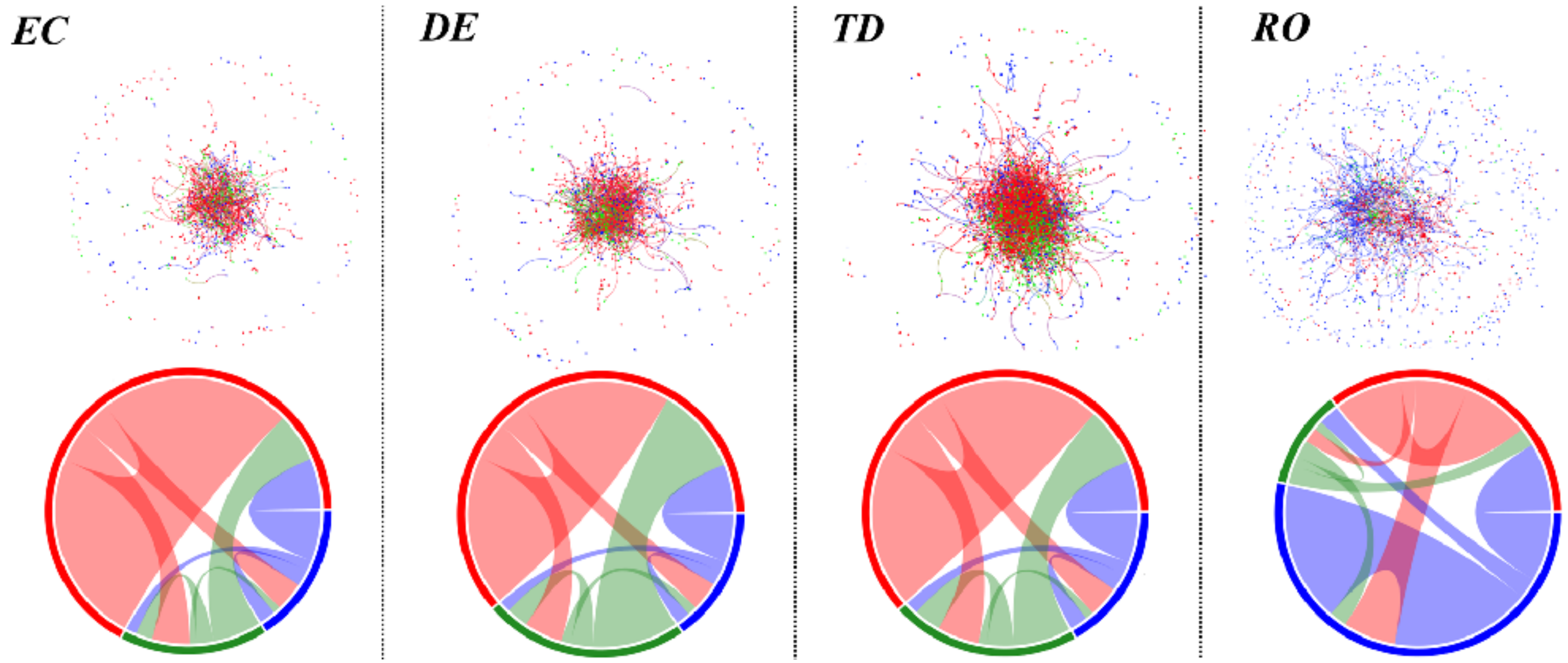




stance detected as **AGAINST**

stance detected as **IN FAVOR**

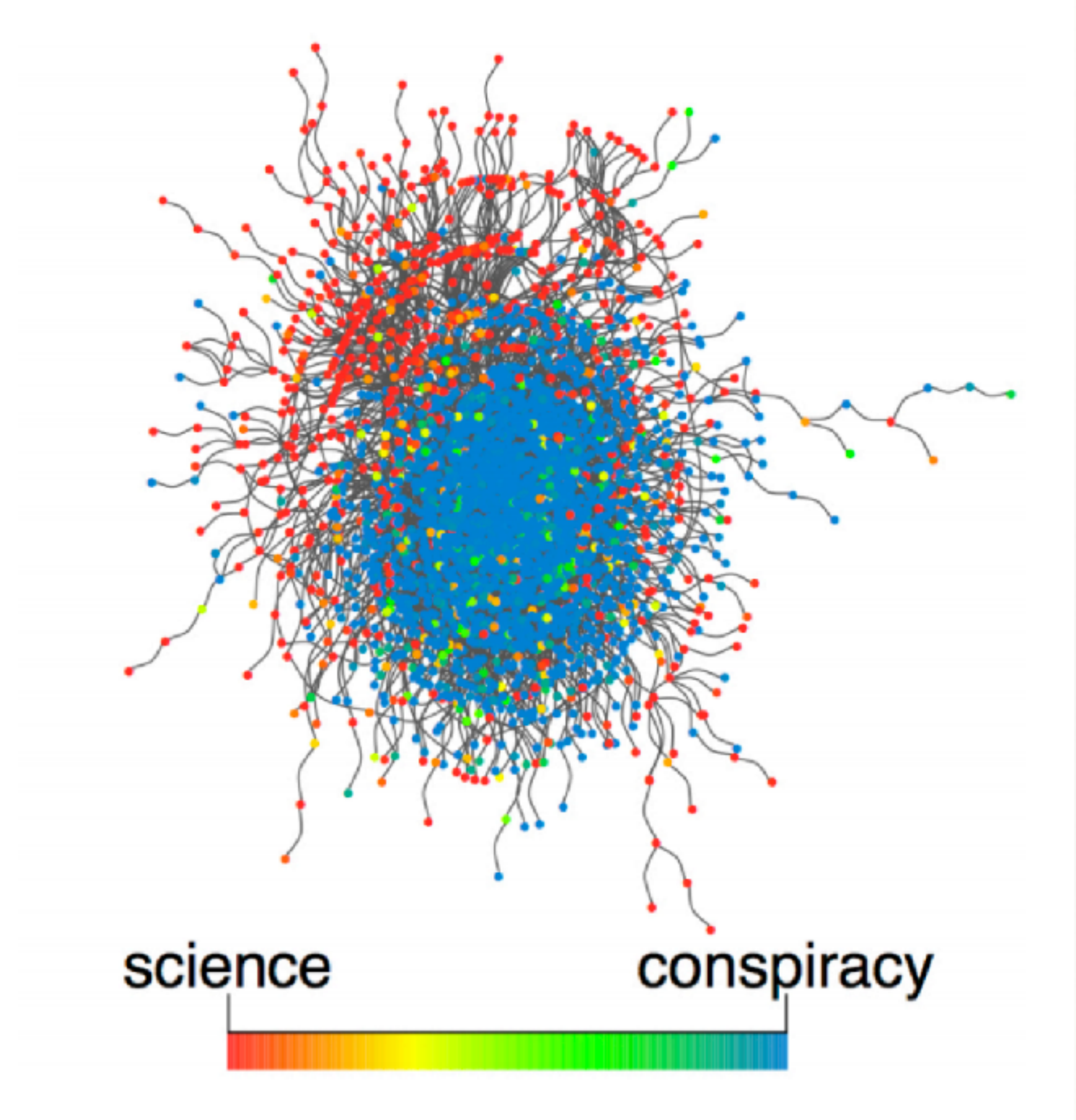
stance detected as **NONE**

Mention Network

signal of **inverse homophily**

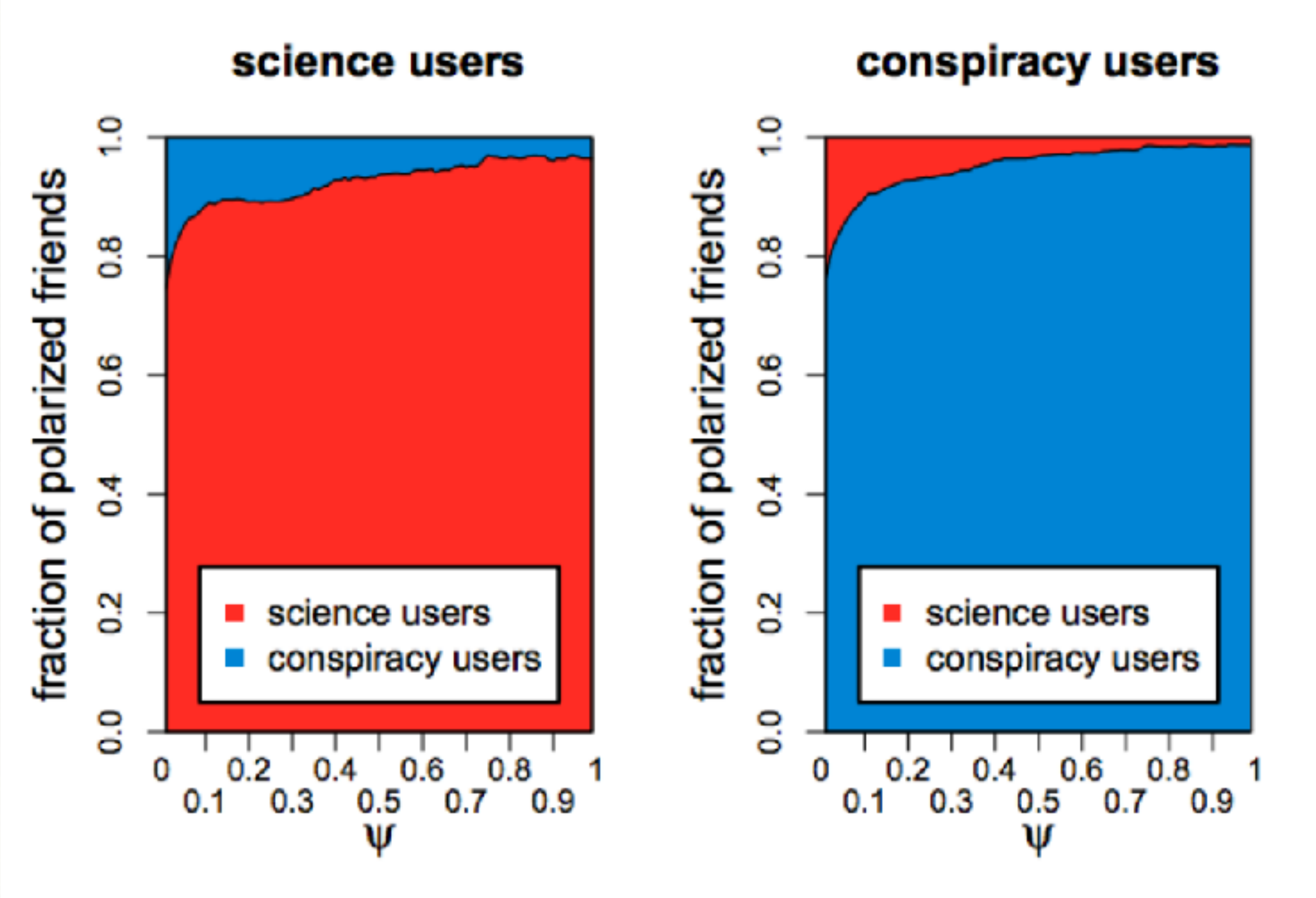
M Lai, M Tambuscio, V Patti, P Rosso, G. Ruffo, Stance Polarity in Political Debates: a Diachronic Perspective of Network Homophily and Conversations on Twitter, Data & Knowledge Engineering Journal, online: September 2019

Misinformation tends to polarize



Users engagement correlates with the number of friends having similar consumption patterns

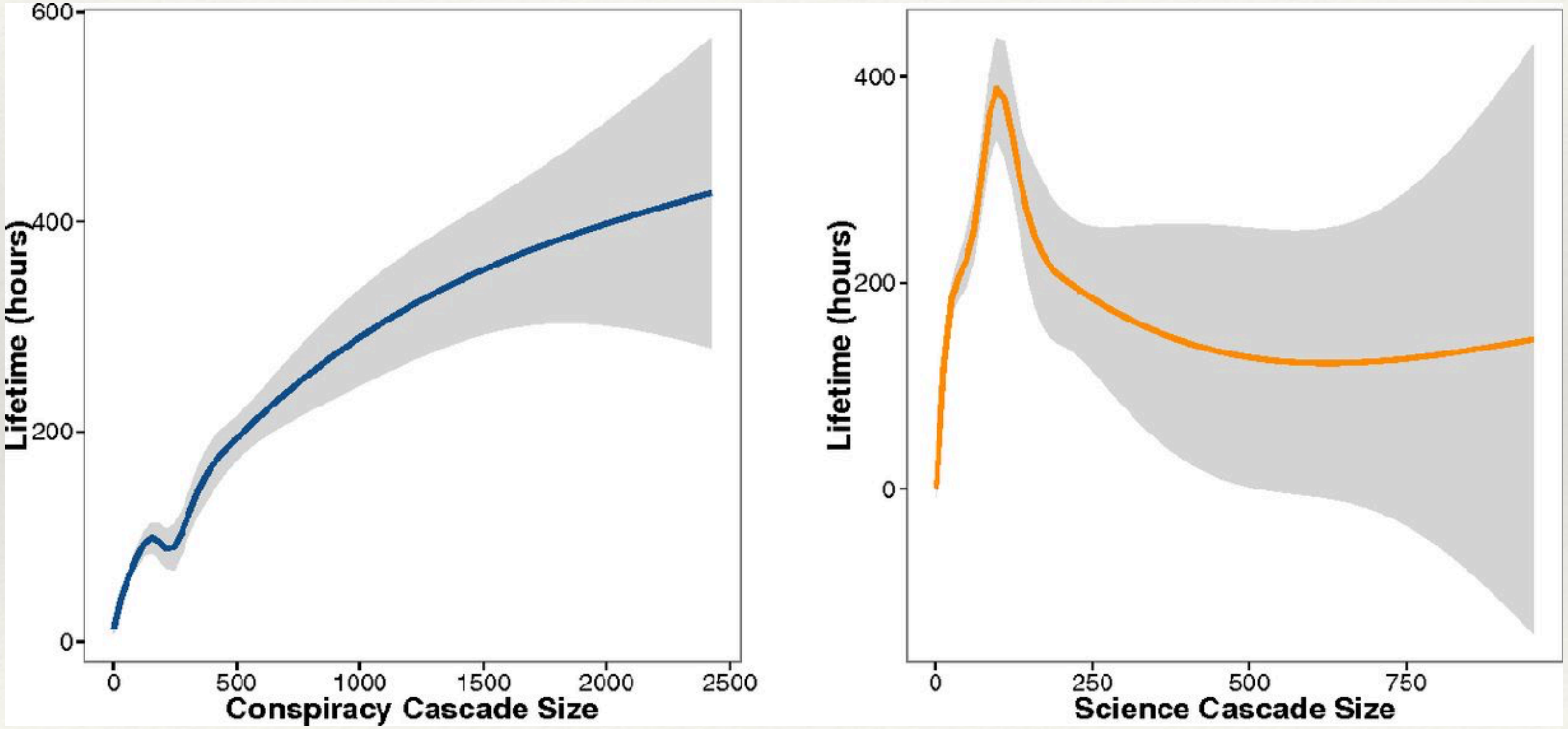
homophily!



A. Bessi, …., G. Caldarelli, W. Quattrociocchi, Viral Misinformation: The Role of Homophily and Polarization, WWW 2015 Companion, May 18–22, 2015, Florence, Italy.

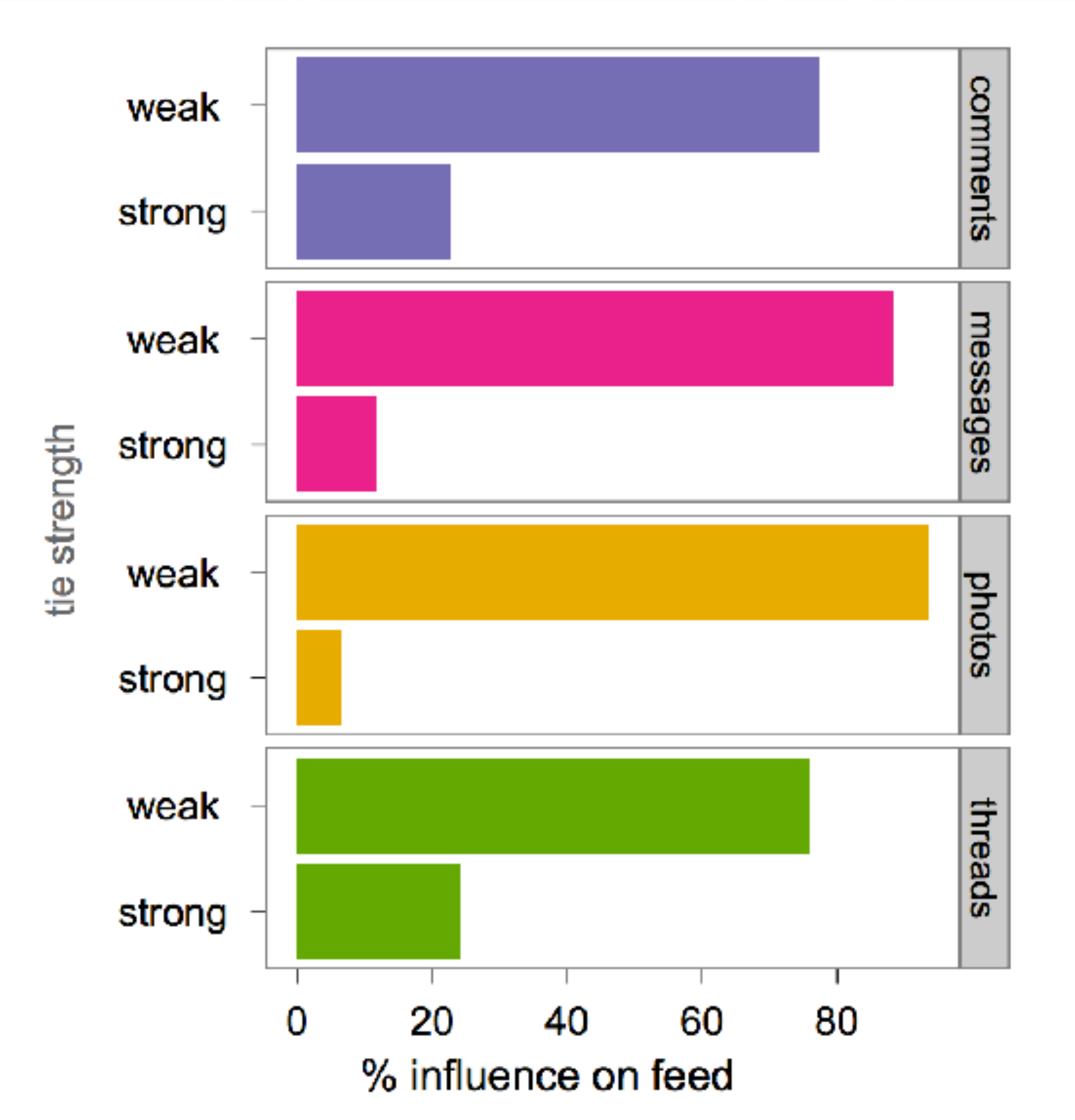
… and polarization fuels misinformation spread

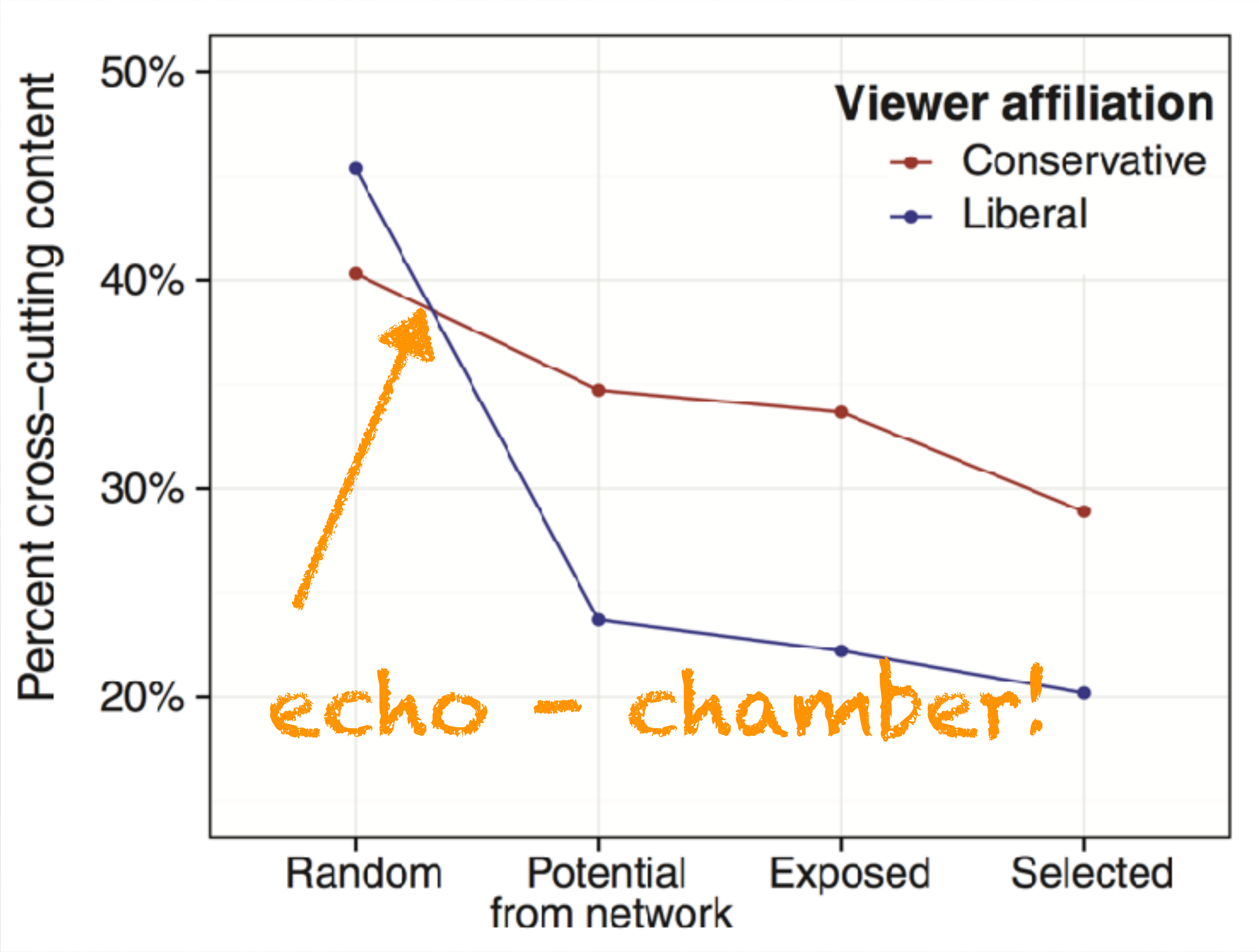
A data-driven percolation model of rumor spreading that demonstrates that homogeneity and polarization are the main determinants for predicting cascades' size



M. Del Vicario, A. Bessi, F. Zollo, F. Petroni, A. Scala, G. Caldarelli, H. E. Stanley, W. Quattrociocchi, Echo chambers in the age of misinformation, PNAS, Jan 2016, 113 (3) 554-559; DOI: 10.1073/pnas.1517441113

"Weak ties" are important, too





E. Bakshy, I. Rosenn, C. Marlow, and L. Adamic. 2012. The role of social networks in information diffusion. In Proc of the 21st Int. Conf. on World Wide Web (WWW '12). ACM, New York, NY, USA, 519–528. DOI:https://doi.org/10.1145/2187836.2187907

E. Bakshy, S. Messing, L. Adamic, Exposure to ideologically diverse news and opinion on Facebook, Science 05 Jun 2015: Vol. 348, Issue 6239, p. 1130-1132, DOI: 10.1126/science.aaa1160(Bakshy et al. 2015)

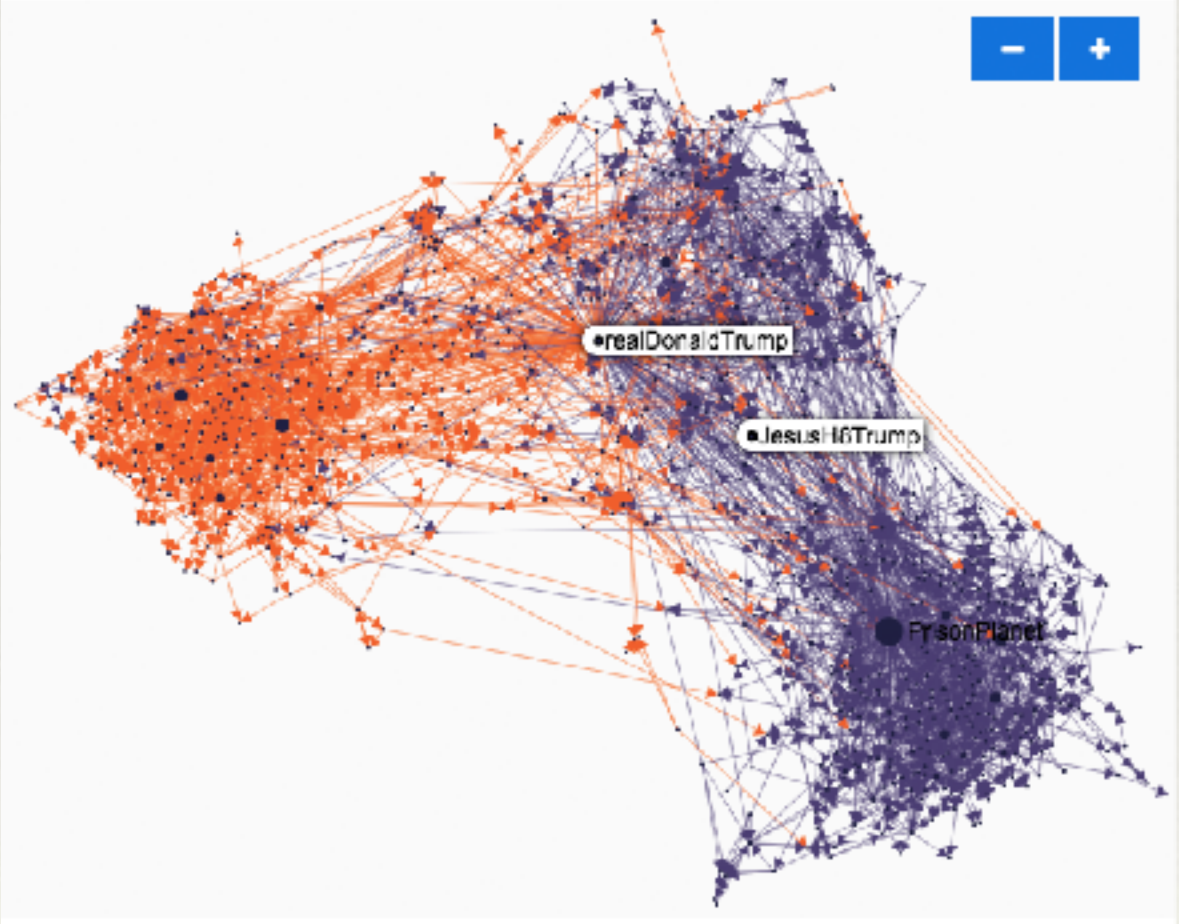
Analyzing the structure of a misinformation network

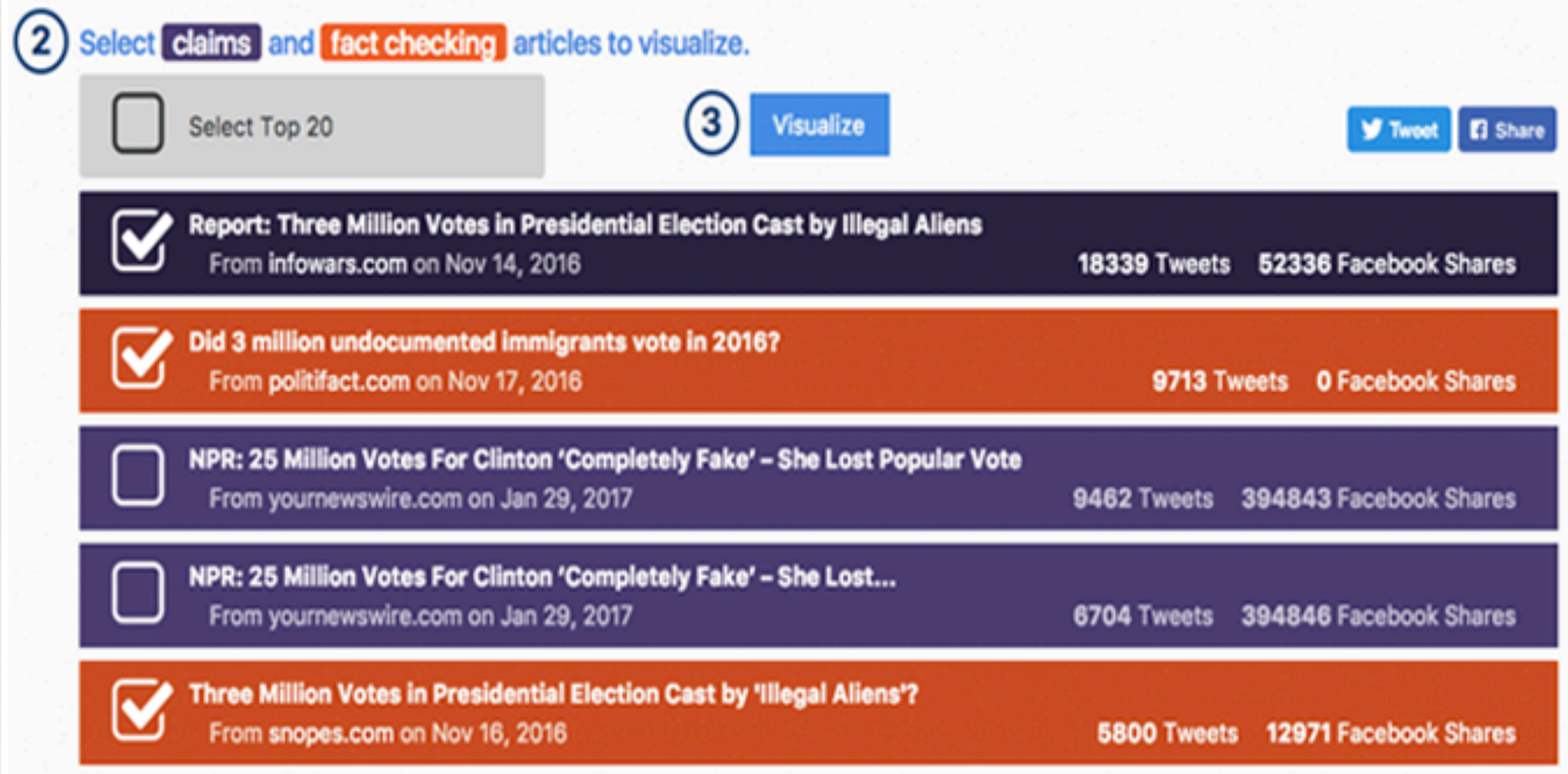
- *What are the structural and dynamic characteristics of the core of the misinformation diffusion network, and who are its main purveyors?*
- "As we move from the periphery to the core of the network, fact-checking nearly disappears, while social bots proliferate."

HOAXY beta ®

Visualize the spread of claims and fact checking.

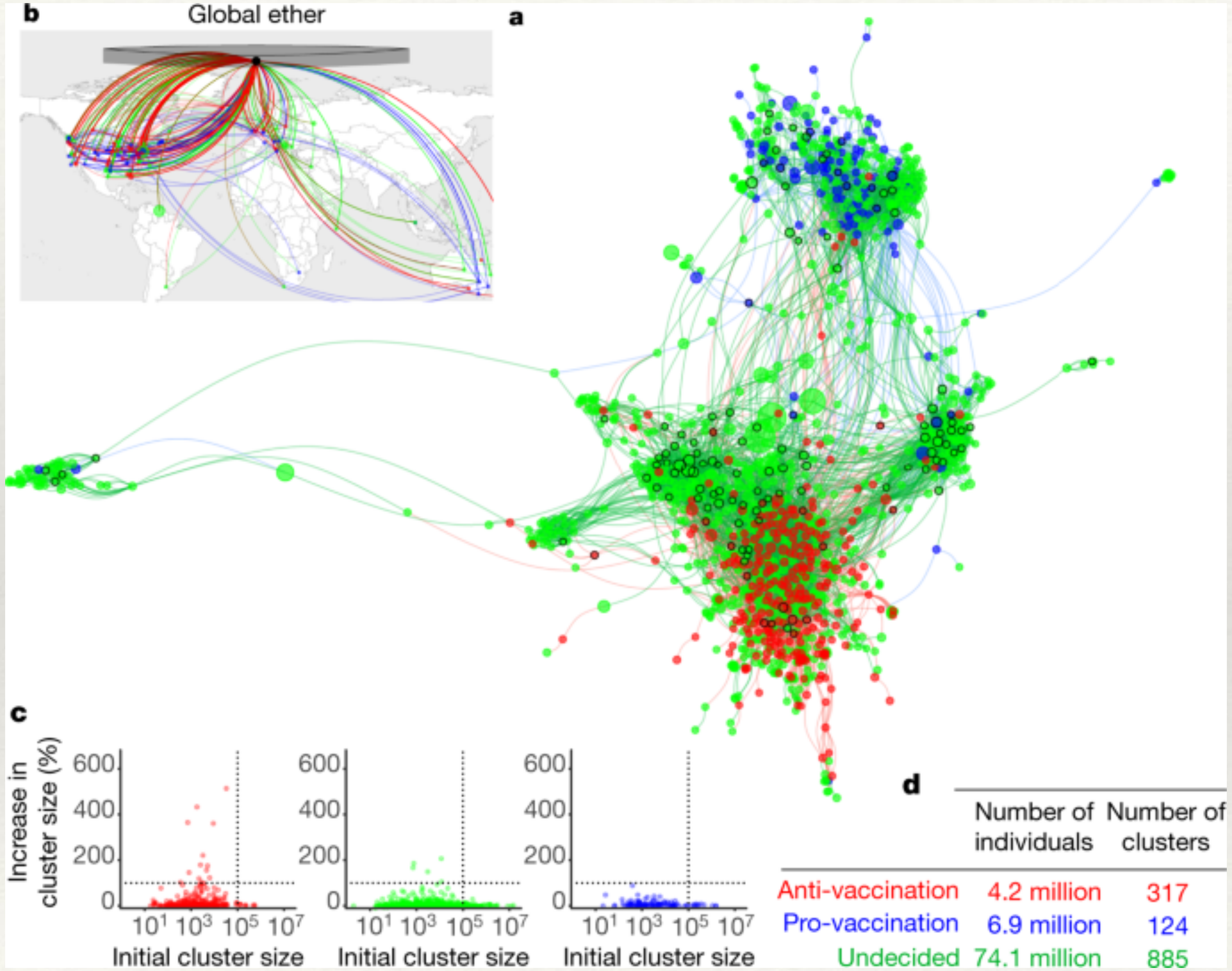
https://hoaxy.iuni.iu.edu



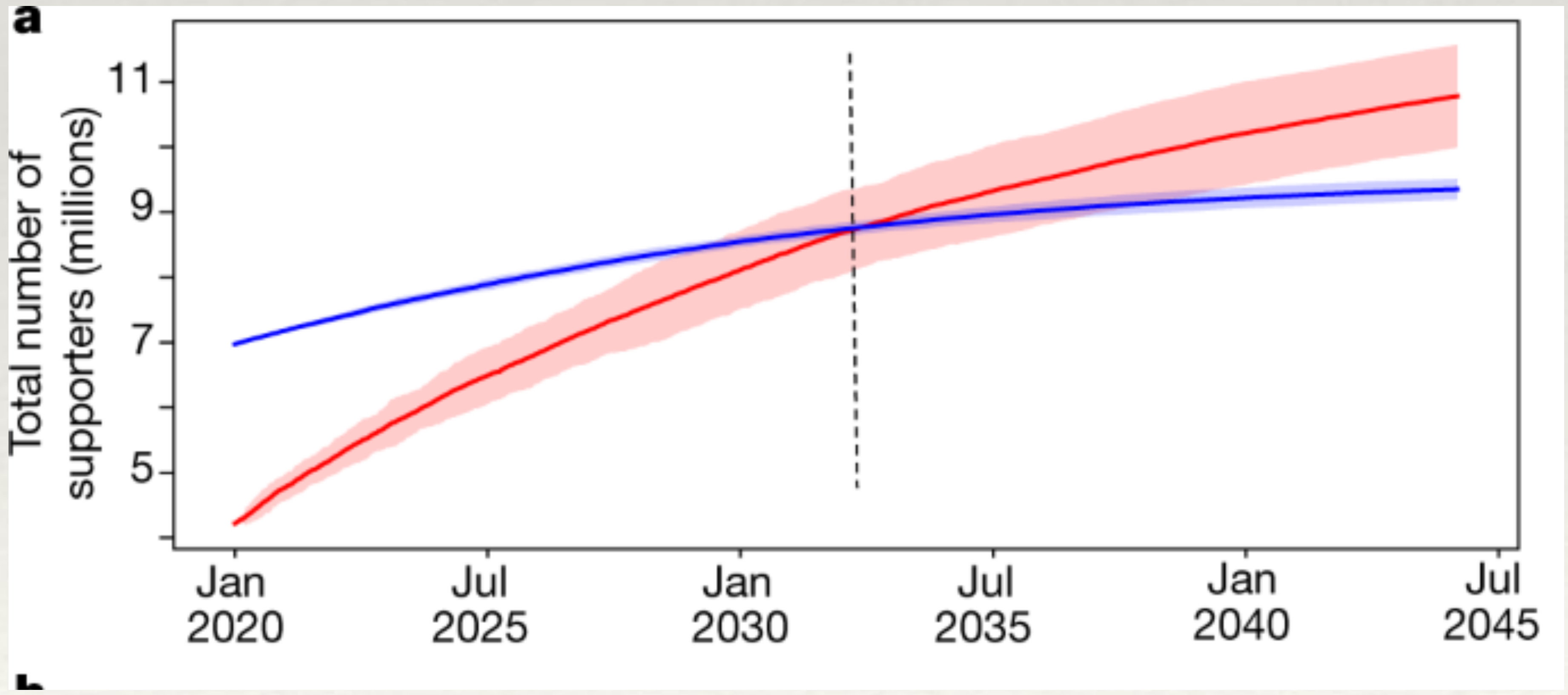


Shao C, Hui P-M, Wang L, Jiang X, Flammini A, Menczer F, et al. (2018) Anatomy of an online misinformation network. PLoS ONE 13(4):e0196087. https://doi.org/10.1371/journal.pone.0196087

The role of the undecided



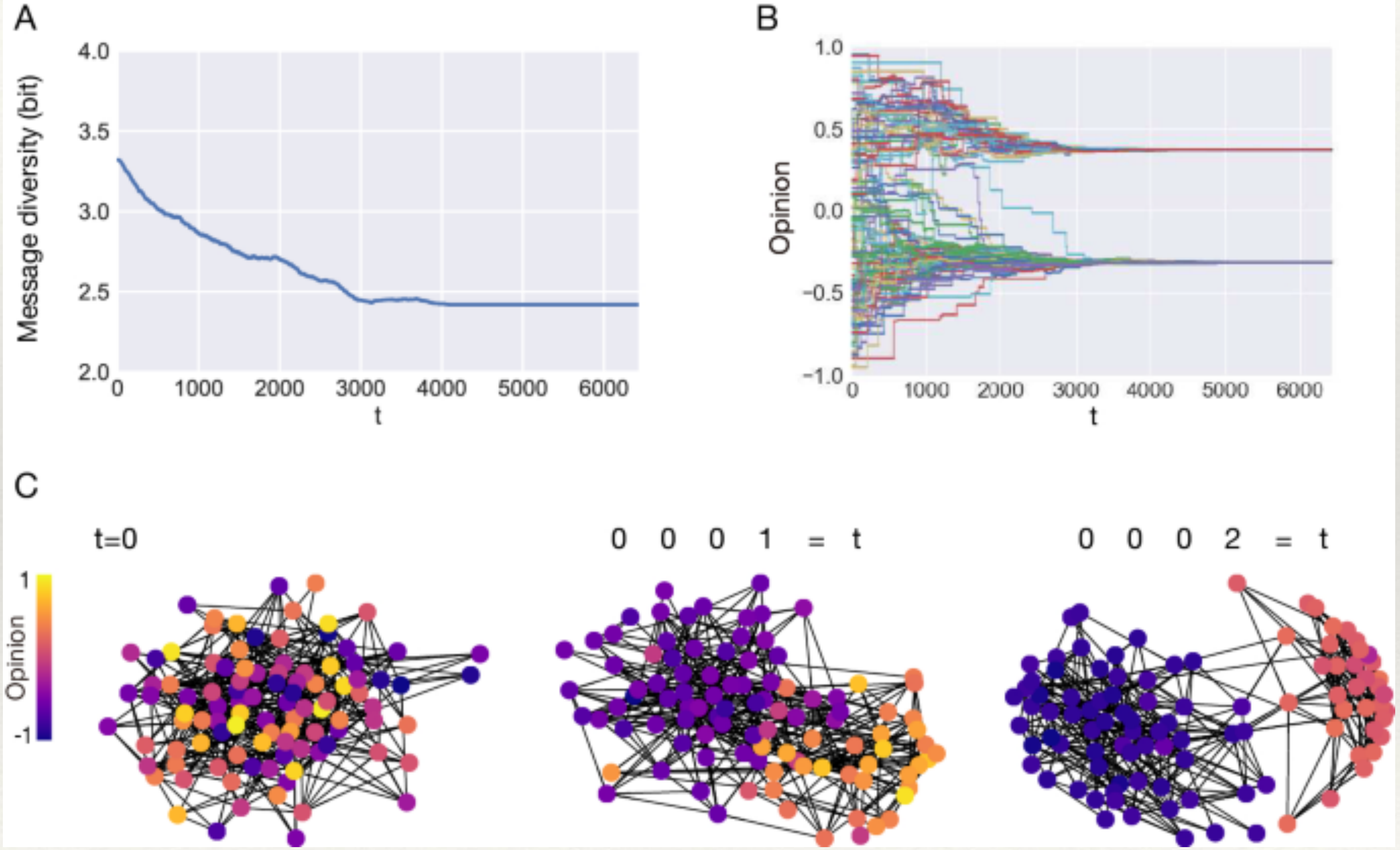
- Theoretical prediction for the future total size of anti-vaccination and pro-vaccination support
- Under the present conditions, it predicts that total anti-vaccination support reaches dominance in around 10 years



Johnson, N.F., Velásquez, N., Restrepo, N.J. *et al.* The online competition between pro- and anti-vaccination views. *Nature* **582,** 230–233 (2020).

The role of unfollowing

- The **model dynamics** show that even with minimal amounts of **influence** and **unfriending**, the social network rapidly devolves into polarized communities
- Predictions are consistent with **empirical data** from Twitter



Sasahara, K., Chen, W., Peng, H. Ciampaglia, G. L., Flammini, A., Menczer, F. Social influence and unfollowing accelerate the emergence of echo chambers. *J Comput Soc Sc* (2020). https://doi.org/10.1007/s42001-020-00084-7