

Digital epidemiology

Lesson 15

Michele Tizzoni

Dipartimento di Sociologia e Ricerca Sociale
Via Verdi 26, Trento
Ufficio 6, 3 piano



UNIVERSITÀ
DI TRENTO



FONDAZIONE
BRUNO KESSLER

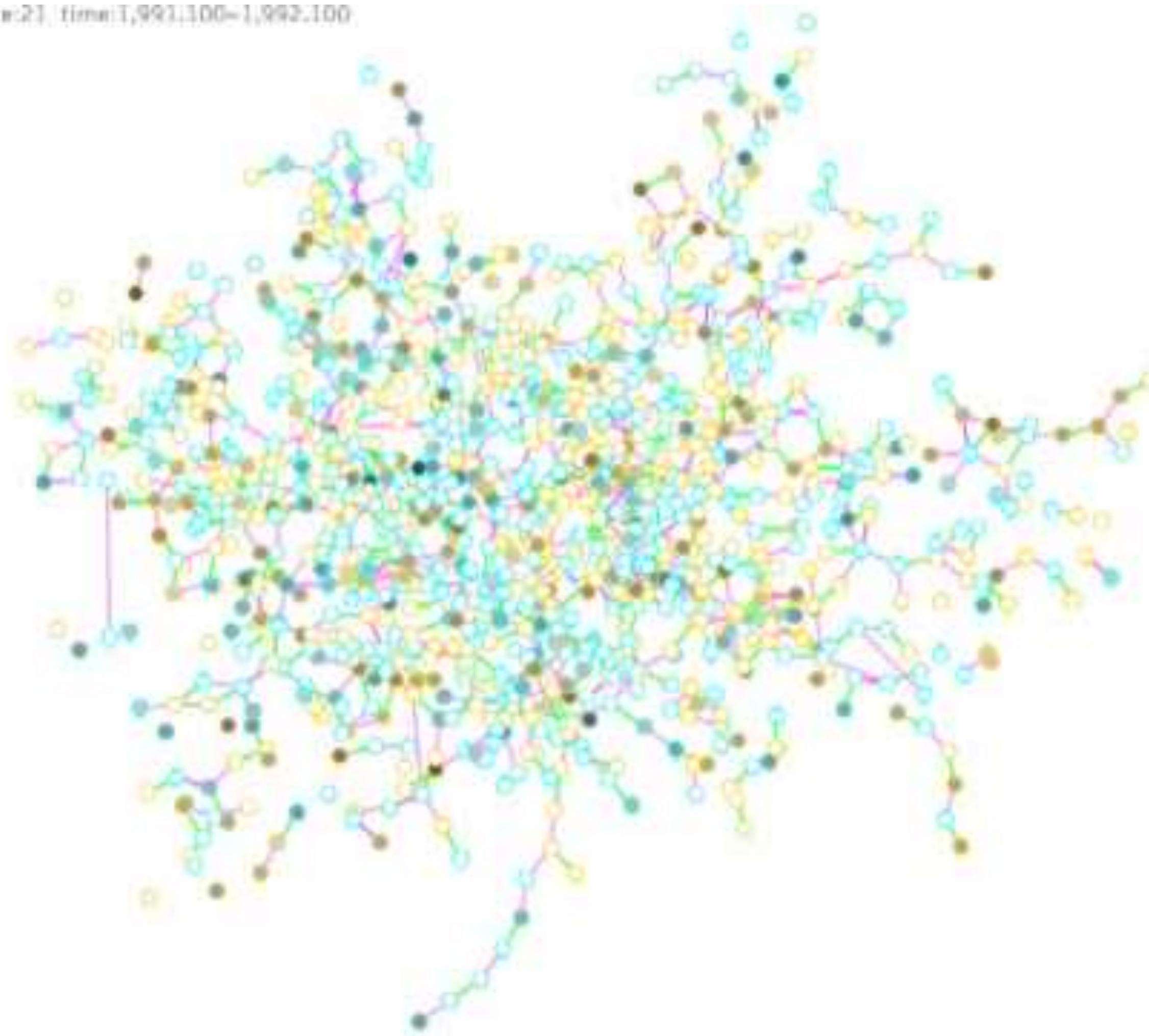


C2S2 Center for
Computational Social Science
and Human Dynamics

Social contagion

Social contagion

slice 23, time 1,991,100 - 1,992,100

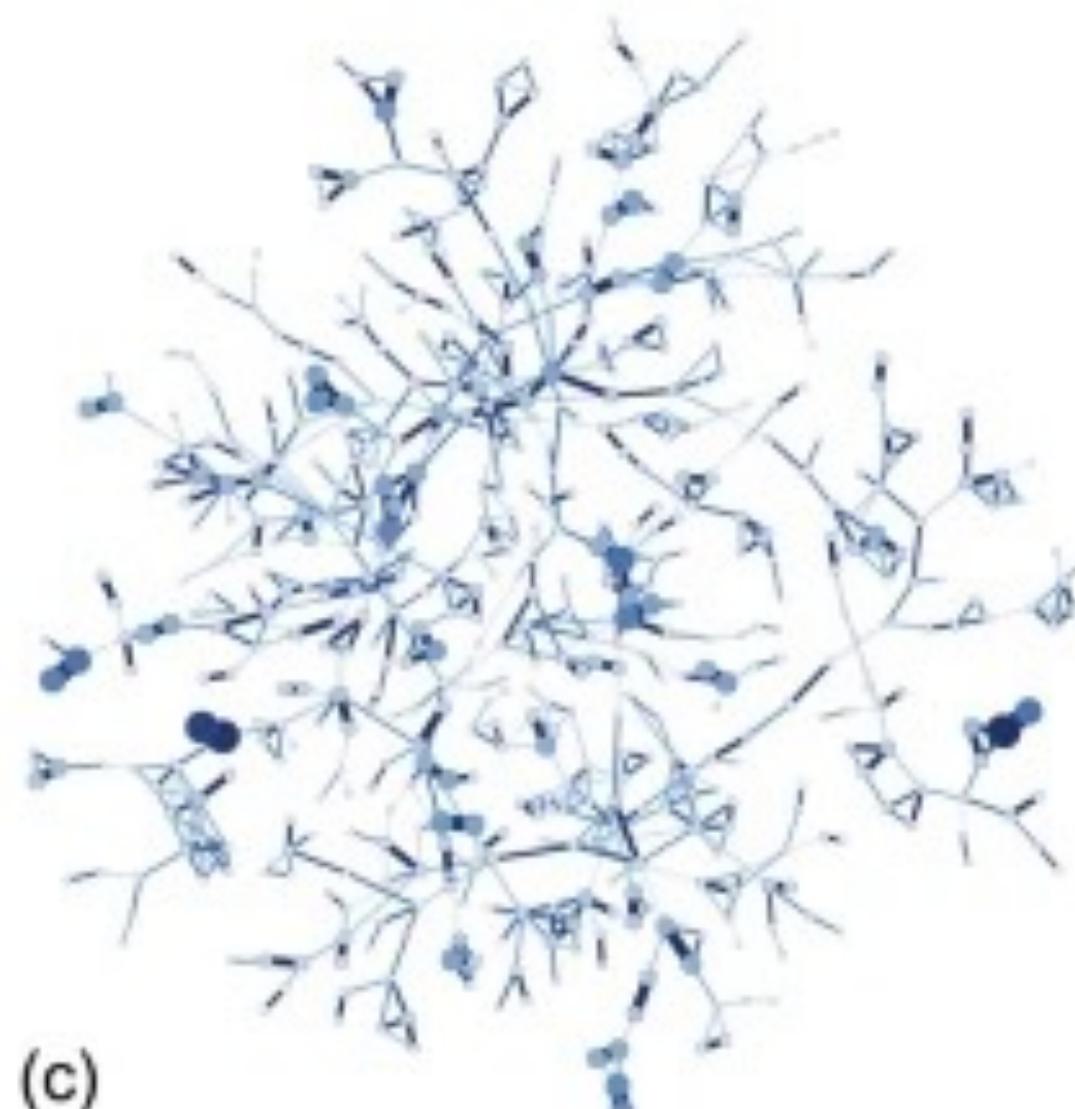


The Collective Dynamics of Smoking in a Large Social Network
Christakis and Fowler, NEJM 2008

Social contagion

Social networks are the support of different dynamical processes

- ▶ (Infectious disease epidemics)
- ▶ Social influence
- ▶ Rumor propagation
- ▶ Opinion/consensus formation
- ▶ Cooperative phenomena



Social influence important for:
▶ innovation adoption,
▶ decision making,
▶ rumor spreading
▶ group problem solving
which affect economics, political science,
anthropology and **health**



Information spreading

- ▶ Rumors and information spreading phenomena are the prototypical examples of social contagion processes in which the infection mechanism can be considered of psychological origin.
- ▶ Social contagion phenomena refer to different processes that depend on the individual propensity to adopt and diffuse knowledge, ideas or simply a habit.
- ▶ The similarity between social contagion processes and epidemiological models was recognized quite a long ago.

Information spreading

- ▶ Rumors and information spreading phenomena are the prototypical examples of social contagion processes in which the infection mechanism can be considered of psychological origin.
- ▶ Social contagion phenomena refer to different processes that depend on the individual propensity to adopt and diffuse knowledge, ideas or simply a habit.
- ▶ The similarity between social contagion processes and epidemiological models was recognized quite a long ago.

Social and physiological contagion processes **differ in some important features:**

- ▶ spread of information is an intentional act, unlike a pathogen contamination.
- ▶ it is usually advantageous to access a new idea or information, so being infected is no longer just a passive process.
- ▶ acquiring a new idea or information may need **time and exposure to more than one source of information**, thus the importance of models in which memory has an important role.

Social contagion models

Historical perspective

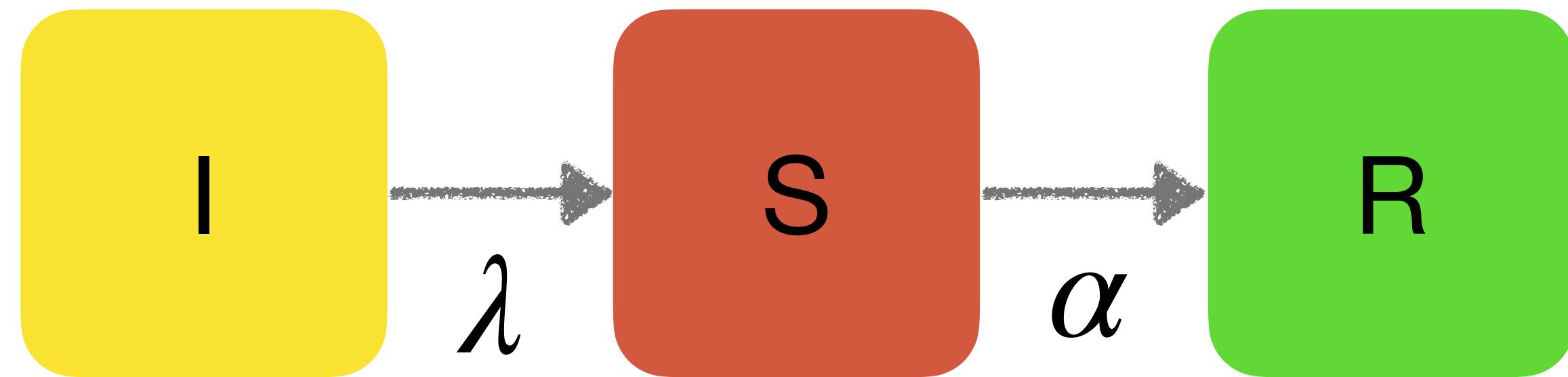
- ▶ Rumor model
- ▶ Opinion dynamics
- ▶ Axelrod model
- ▶ Naming game

Rumor model

Epidemics	Rumor
Susceptible	Ignorant
Infected	Spreader
Recovered	Stifler



Rumor model



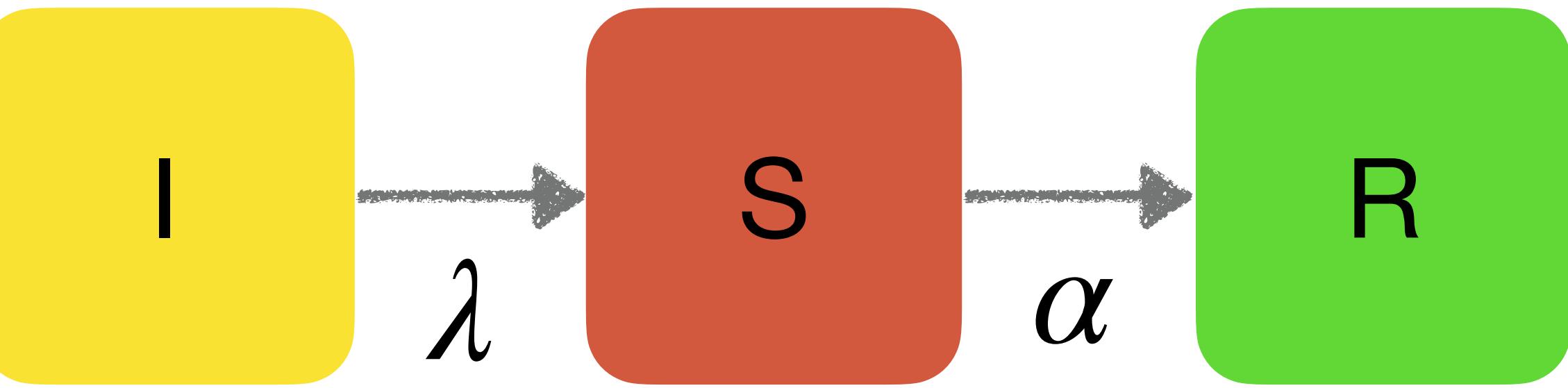
Ignorant + Spreader \rightarrow 2 Spreaders

Spreader + Spreader \rightarrow Stifler + Spreader

Spreader + Stifler \rightarrow 2 Stiflers

Rumor model

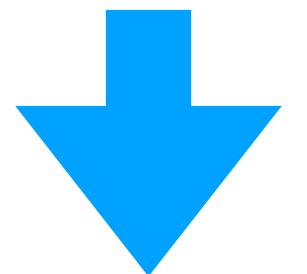
$$\left\{ \begin{array}{l} \frac{di}{dt} = -\lambda si \\ \frac{ds}{dt} = \lambda si - \alpha s(s+r) \\ \frac{dr}{dt} = \alpha s(s+r) \end{array} \right.$$



Rumor model

$$\frac{ds}{dt} = \lambda si - \alpha s^2 - \alpha s(1 - s - i)$$

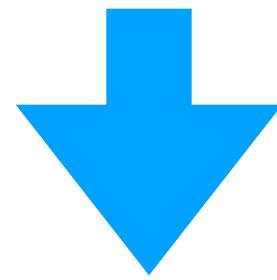
$$\frac{ds}{dt} = (\lambda + \alpha)si - \alpha s$$



Equivalent to the epidemic SIR
With $\lambda + \alpha = \beta$ and $\alpha = \mu$

Rumor model

$$\frac{ds}{dt} = (\lambda + \alpha)si - \alpha s$$



Equivalent to the epidemic SIR

With $\lambda + \alpha = \beta$ and $\alpha = \mu$

Early stage approximation

$$R_0 = \frac{\lambda + \alpha}{\alpha} > 1$$

No threshold in
homogeneous systems

$$\frac{\lambda}{\alpha} > 0$$

Social contagion models

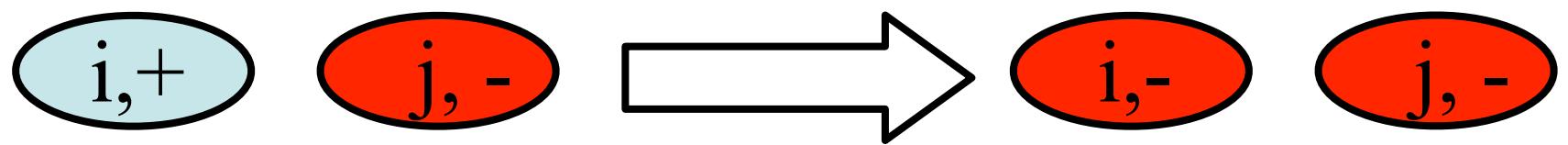
Historical perspective

- ▶ Rumor model
- ▶ **Opinion dynamics**
- ▶ Axelrod model
- ▶ Naming game

Opinion dynamics: voter model

Voter model on a lattice

- ▶ N agents ($k = 1, \dots, N$)
- ▶ Opinion: $s = +1, -1$



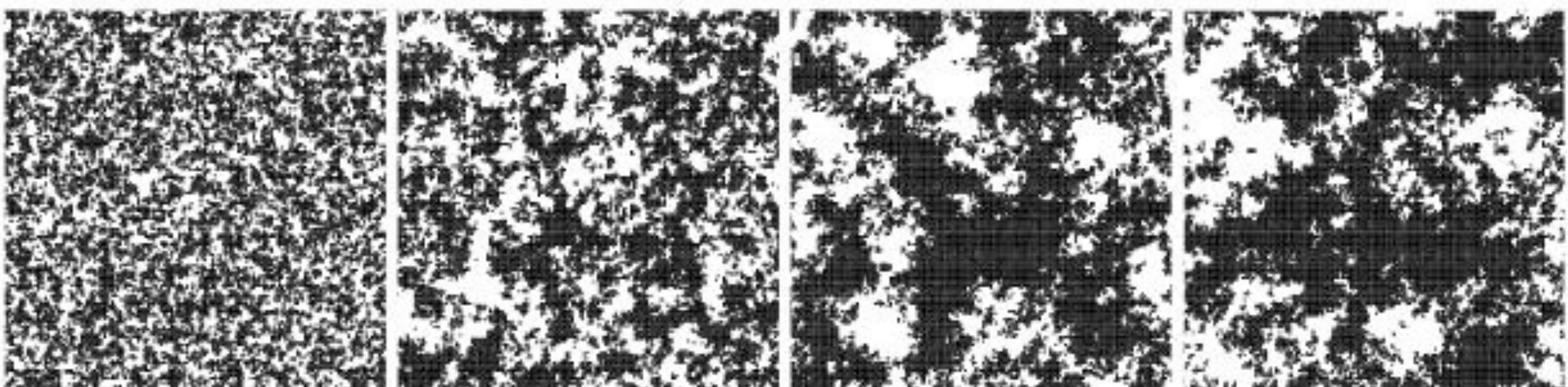
At each time step:

- ▶ Choose one agent k
- ▶ K chooses at random one of his neighbours j
- ▶ Agent k adopts the opinion of agent j

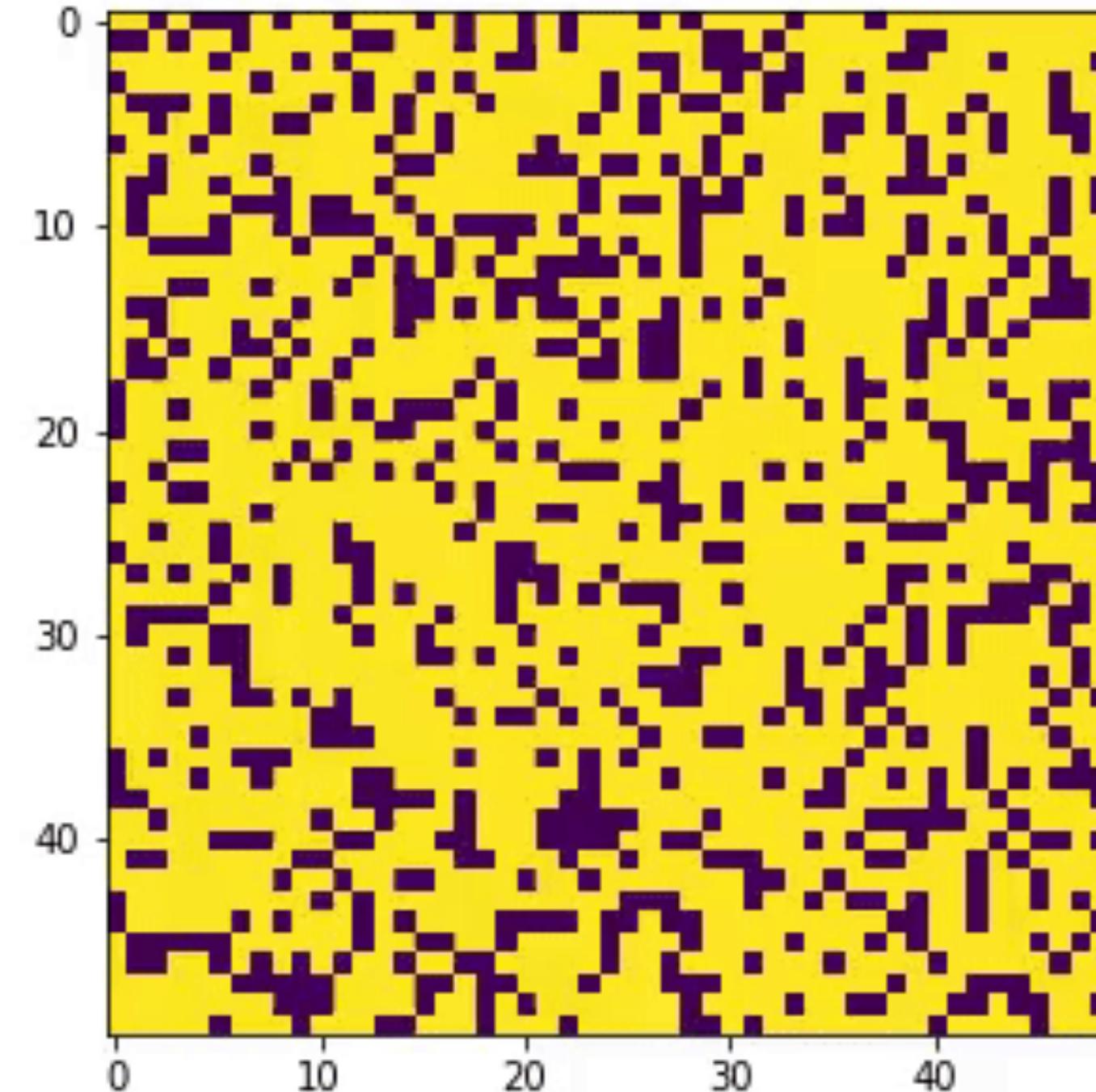
“Coarsening” of domains of similar opinion agents

Questions:

- ▶ Convergence to consensus?
- ▶ How? In how much time?



Opinion dynamics: voter model



- ▶ It is possible to show that for dimensionality $D>2$, the system does not reach consensus and domains of different opinions coexist indefinitely in time.
- ▶ **On scale-free networks, consensus is achieved quickly.** This rapid consensus is facilitated by “hubs- nodes of the largest degrees that influence their very many neighbours.

Social contagion models

Historical perspective

- ▶ Rumor model
- ▶ Opinion dynamics
- ▶ **Axelrod model**
- ▶ Naming game

Opinion dynamics: Axelrod model

- ▶ Robert Axelrod. The dissemination of culture. A Model with Local Convergence and Global Polarization.
- ▶ “If people tend to become more alike in their beliefs, attitudes and behaviour when they interact, why do not such differences eventually all disappear?”
- ▶ **Why don't we become all alike?**

Opinion dynamics: Axelrod model

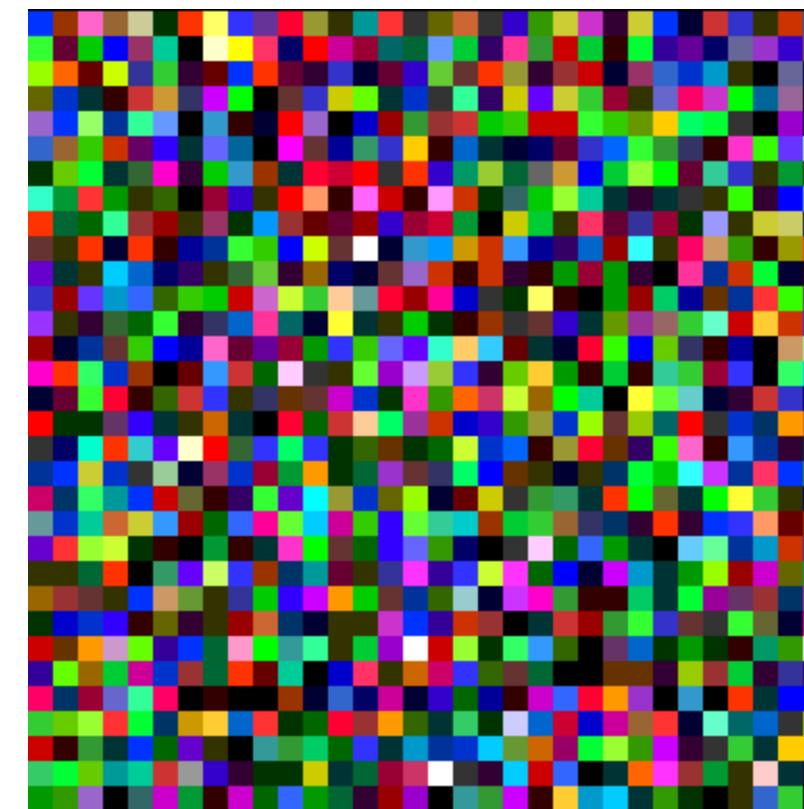
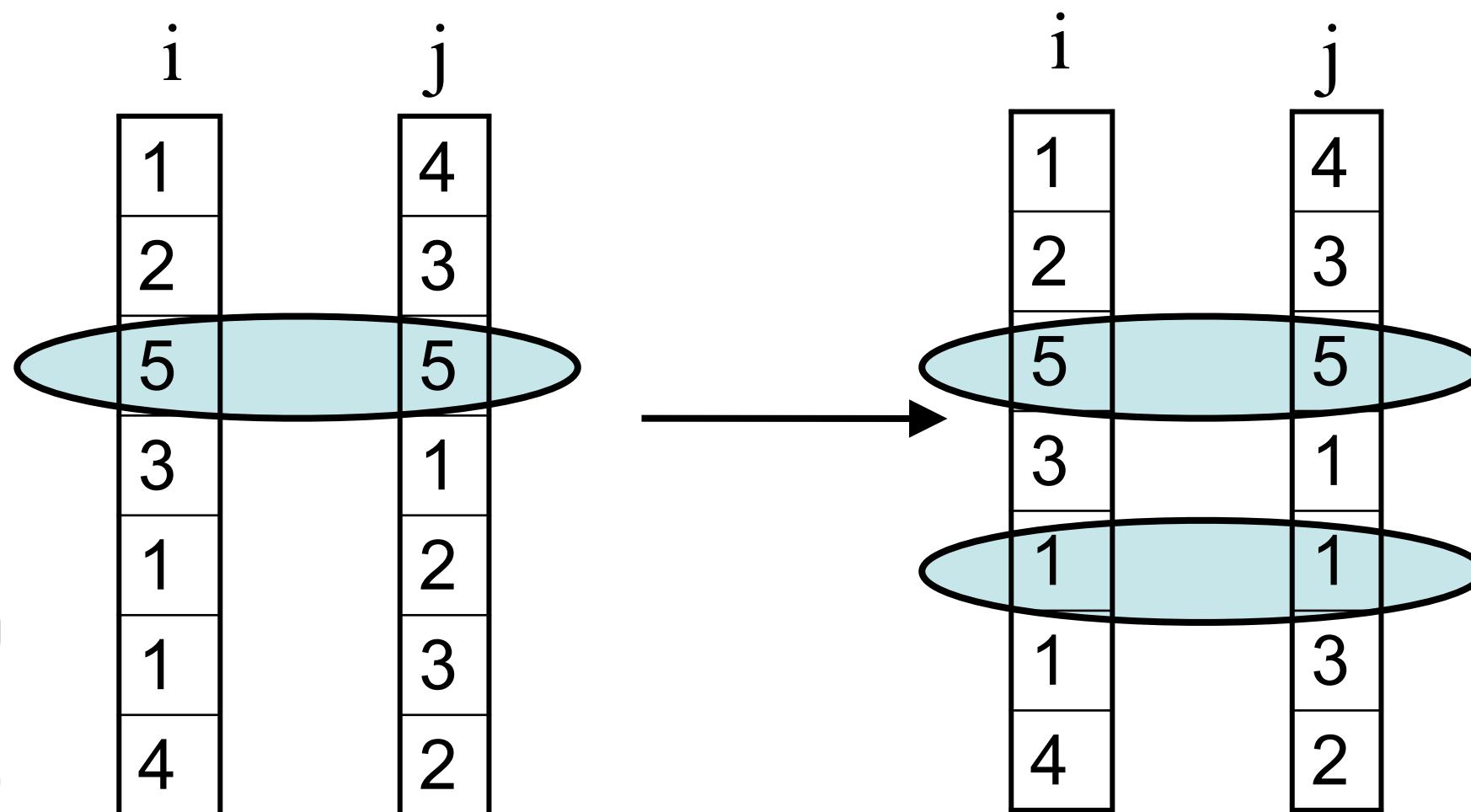
N agents $i=1,\dots,N$ on a lattice

- Each agent has F attributes
- Each attribute can take q values

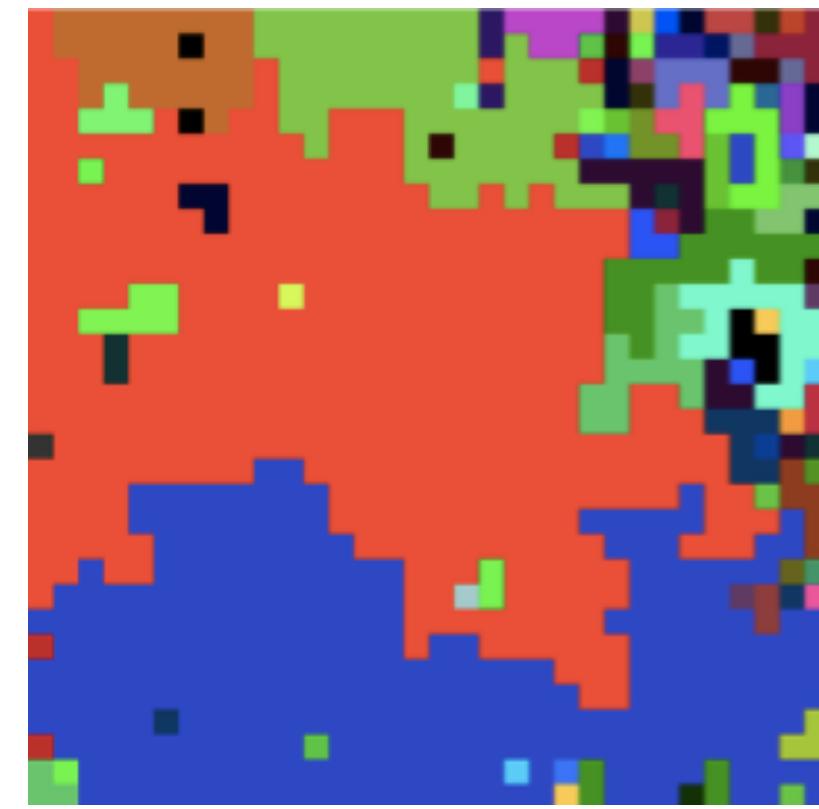
i	j
1	4
2	2
5	3
3	5
1	1
2	2
1	3
4	2

Dynamical interaction:

- If i and j have no common attribute:
No interaction possible
- If i and j have at least one common attribute:
 i chooses one of the other attributes and adopt j 's value



$t=0$: initial disordered state

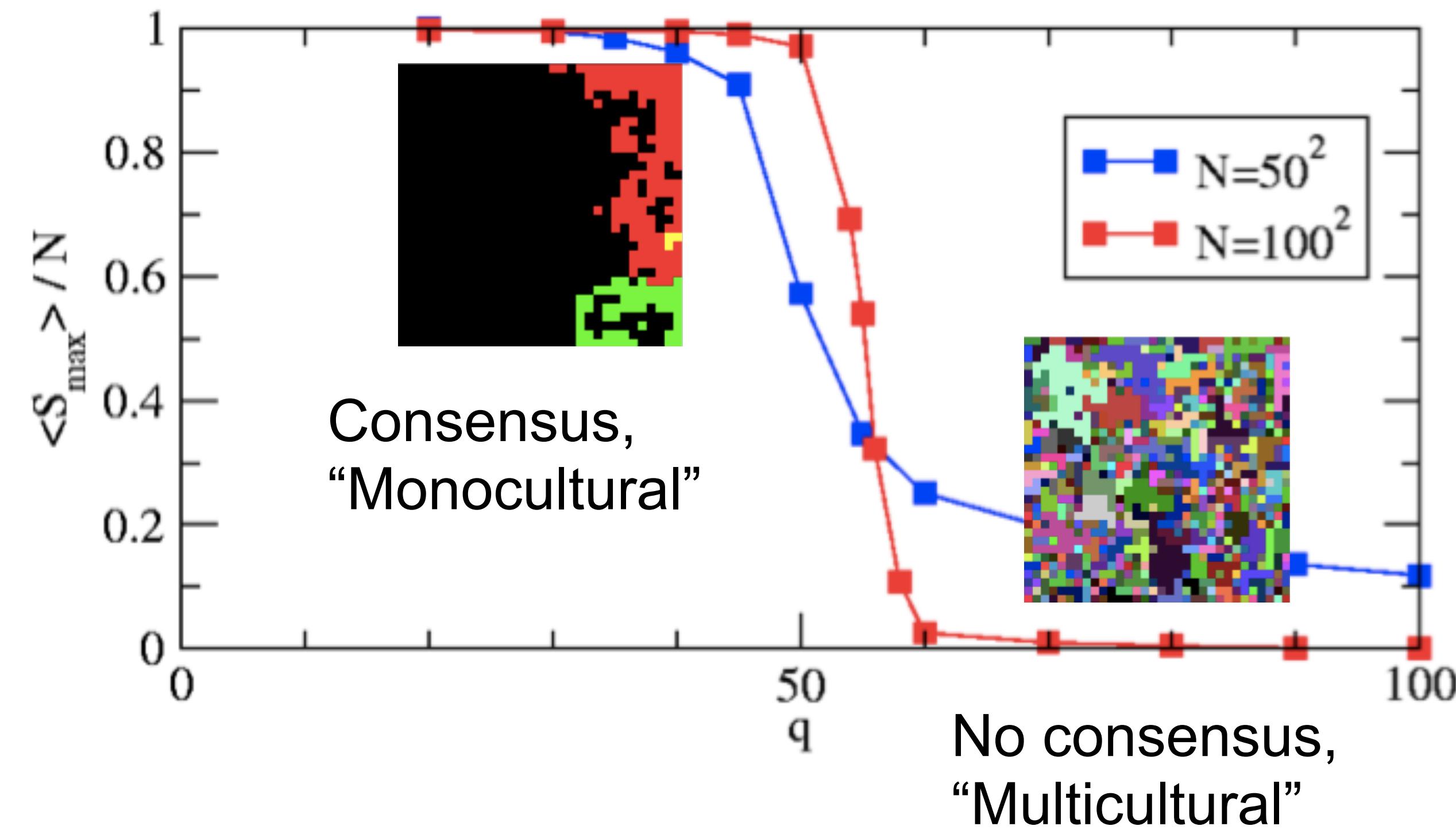


Large t : freezing

Opinion dynamics: Axelrod model

Dynamical interaction **favors convergence**

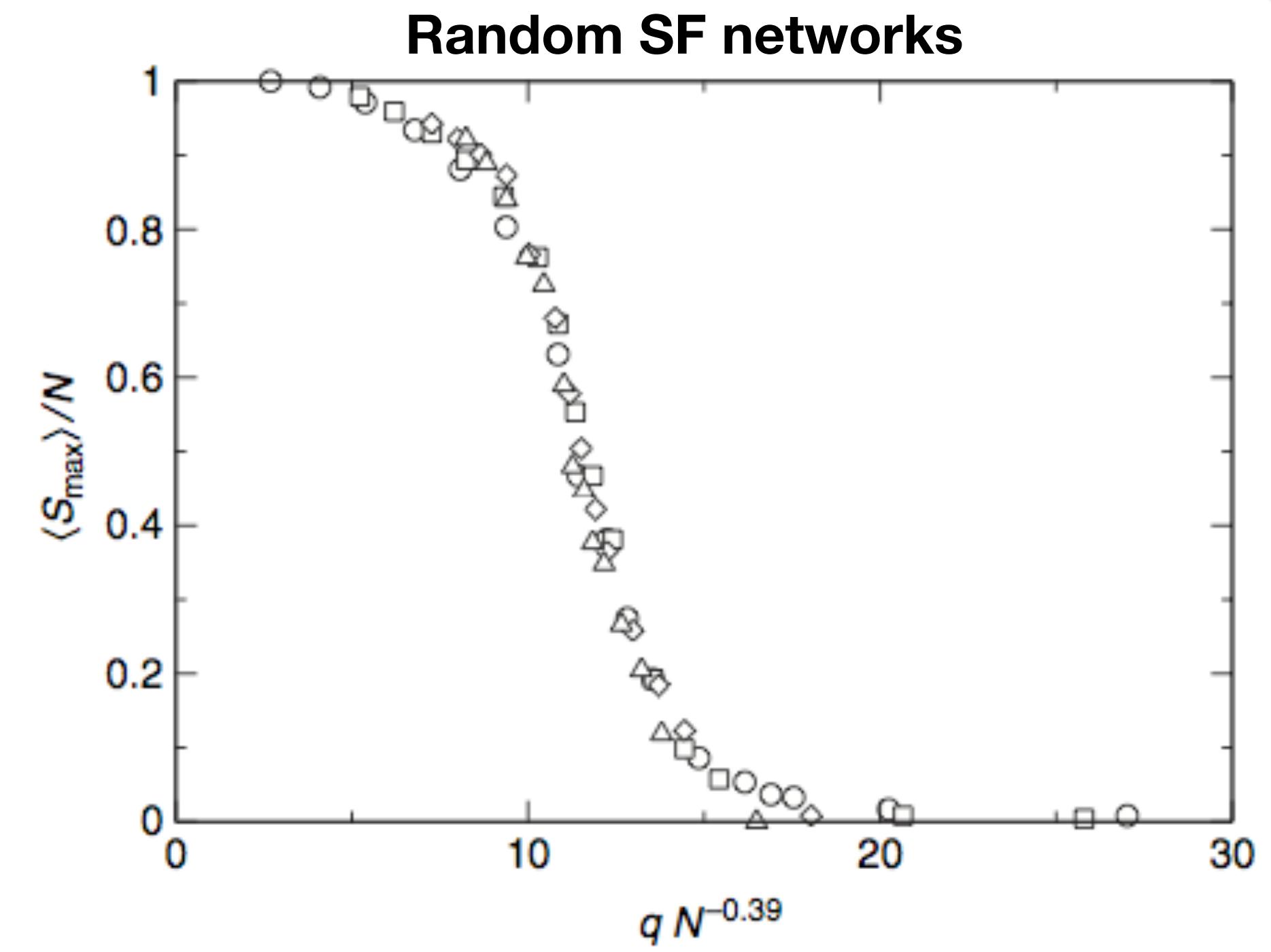
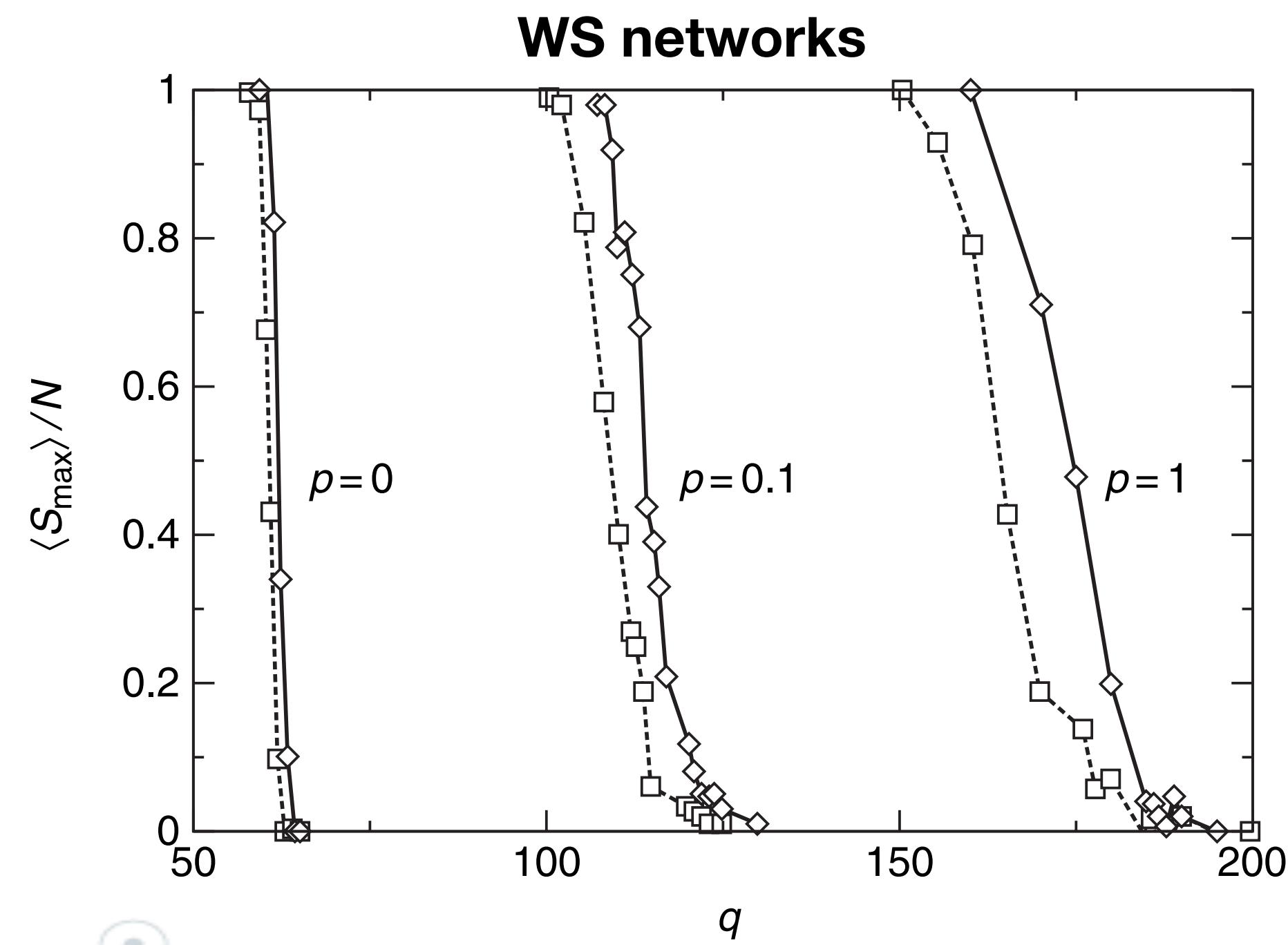
- Large F (number of attributes): large probability to have at least one common attribute.
- Large q: small probability to have at least one common attribute.



Transition from consensus to fragmented state as q increases

Axelrod model on networks

- q_c grows with disordering WS models
- q_c grows in SF networks: hubs hinder cultural fragmentation

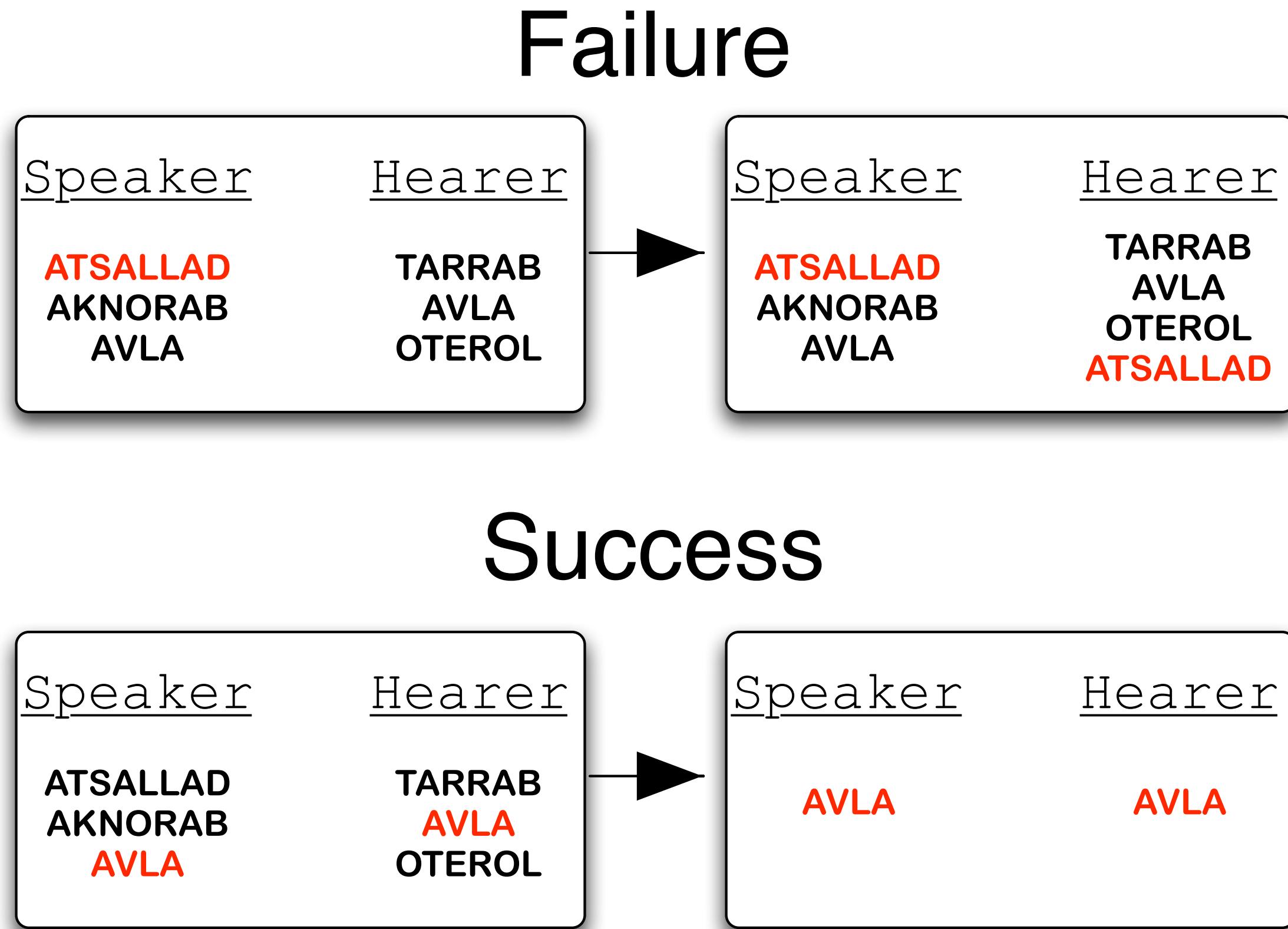


Social contagion models

Historical perspective

- ▶ Rumor model
- ▶ Opinion dynamics
- ▶ Axelrod model
- ▶ **Naming game**

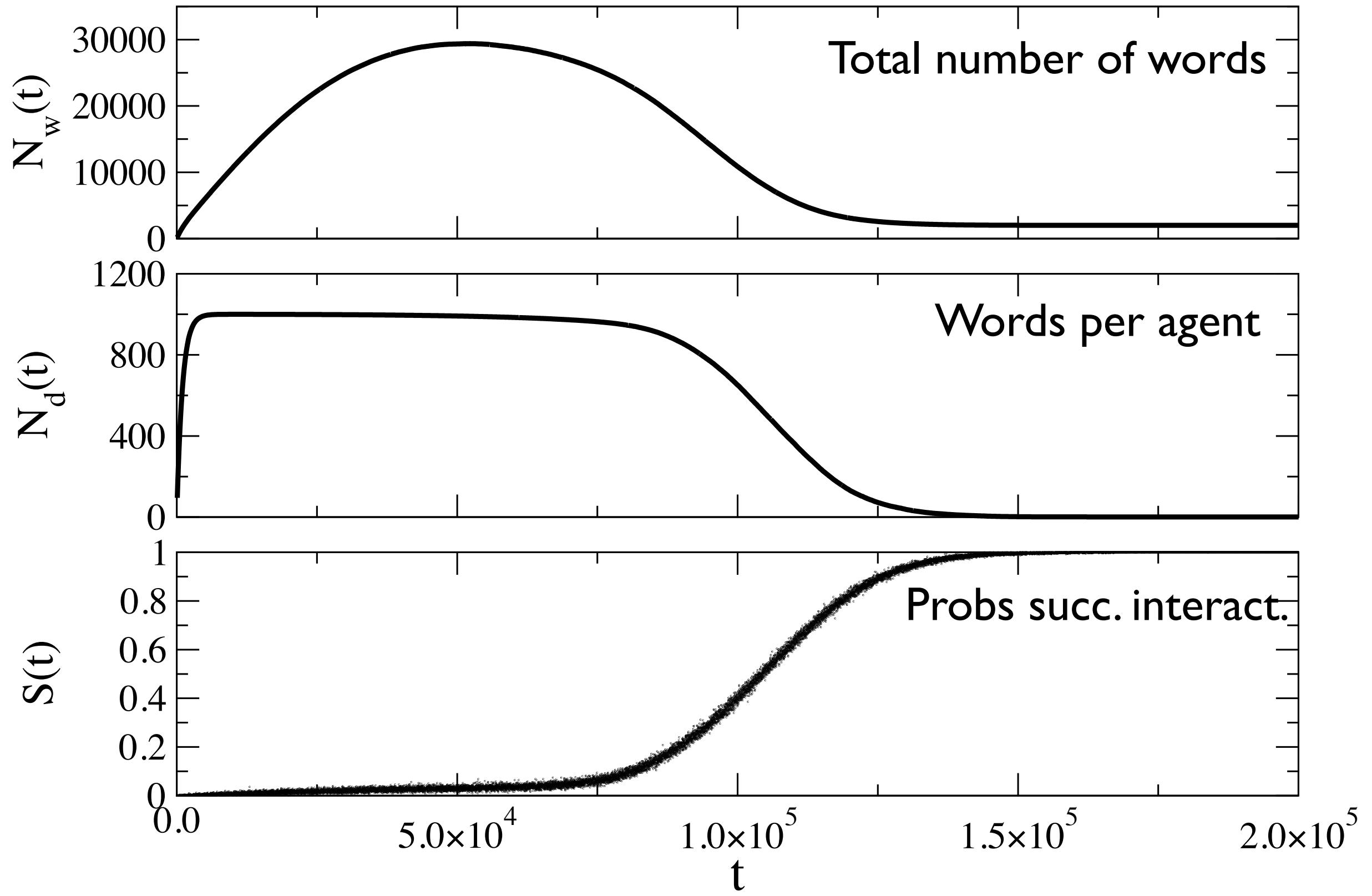
The naming game



- ▶ N agents ($k = 1, \dots, N$)
 - ▶ Each agent starts with an empty dictionary
- At each time step:
- ▶ One agent k (speaker) chooses at random one of his neighbours j (the hearer)
 - ▶ Speaker randomly selects one of its words and conveys it to the hearer;
 - ▶ if the hearer's inventory contains such a word, the two agents update their inventories so as to keep only the word involved in the interaction (success);
 - ▶ otherwise, the hearer adds the word to those already stored in its inventory (failure).

The naming game

- ▶ Convergence is reached with a quite abrupt disorder/order transition that starts approximately just after the peak of the total number of words curve has disappeared.
- ▶ **Initially, agents hardly understand each others ($S(t)$ is very low); then the inventories start to present significant overlaps, so that $S(t)$ increases until it reaches 1.**



The naming game on networks

Main features of complex networks that affect the naming game:

- ▶ finite connectivity (agents have a finite number of neighbours)
- ▶ small-world property.

1. **Finite connectivity** implies finite memory requirements to the agents, disentangling the maximum inventory size from the number of individuals in the population.
2. The **small-world property** guarantees “fast” convergence, allowing the fast spreading of words created in otherwise far-apart regions of the underlying topology.

The committed minority

SOCIAL SCIENCE

Experimental evidence for tipping points in social convention

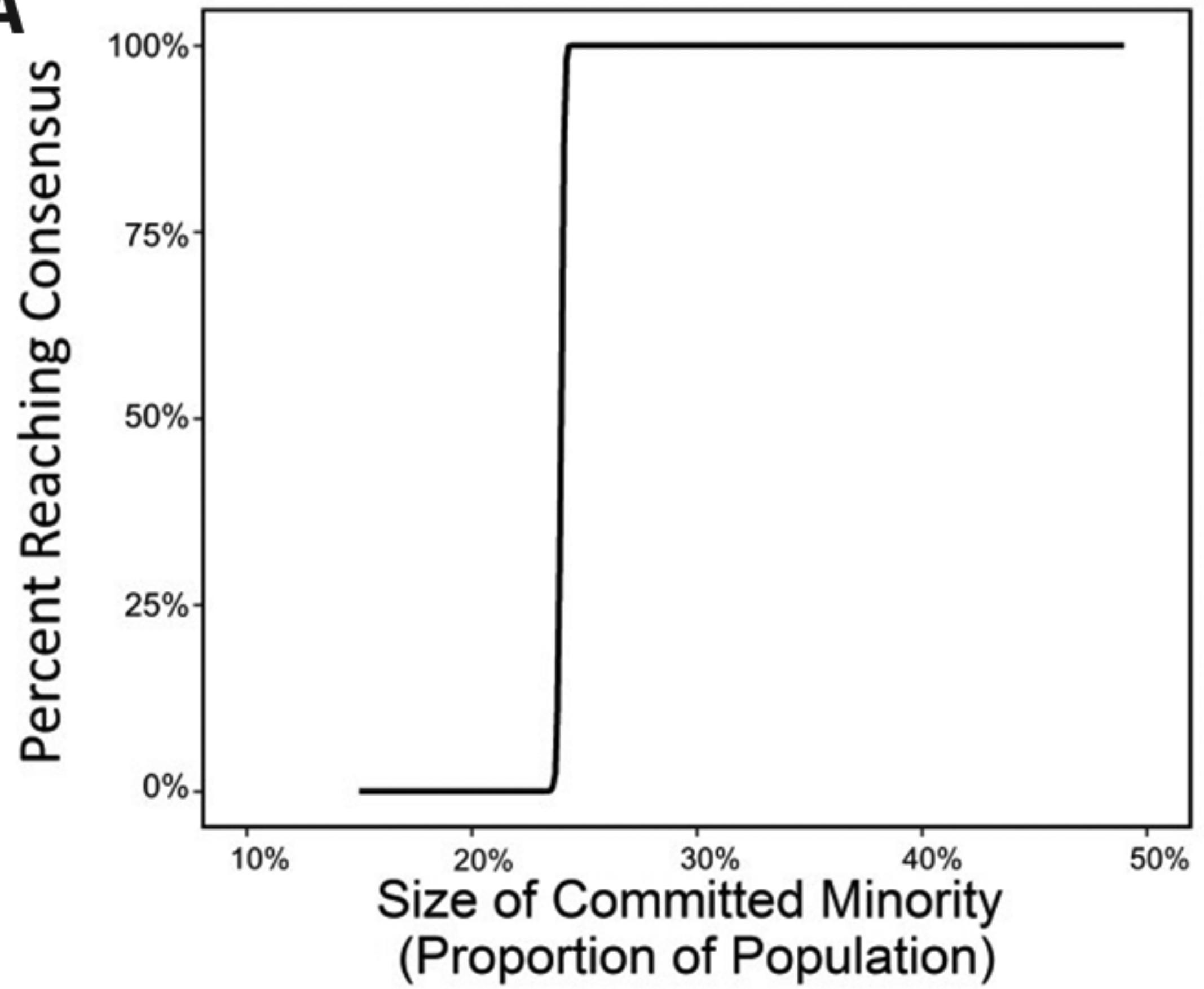
Damon Centola^{1,2*}, Joshua Becker¹, Devon Brackbill¹, Andrea Baronchelli³

Theoretical models of critical mass have shown how minority groups can initiate social change dynamics in the emergence of new social conventions. Here, we study an artificial system of social conventions in which human subjects interact to establish a new coordination equilibrium. The findings provide direct empirical demonstration of the existence of a tipping point in the dynamics of changing social conventions. When minority groups reached the critical mass—that is, the critical group size for initiating social change—they were consistently able to overturn the established behavior. The size of the required critical mass is expected to vary based on theoretically identifiable features of a social setting. Our results show that the theoretically predicted dynamics of critical mass do in fact emerge as expected within an empirical system of social coordination.

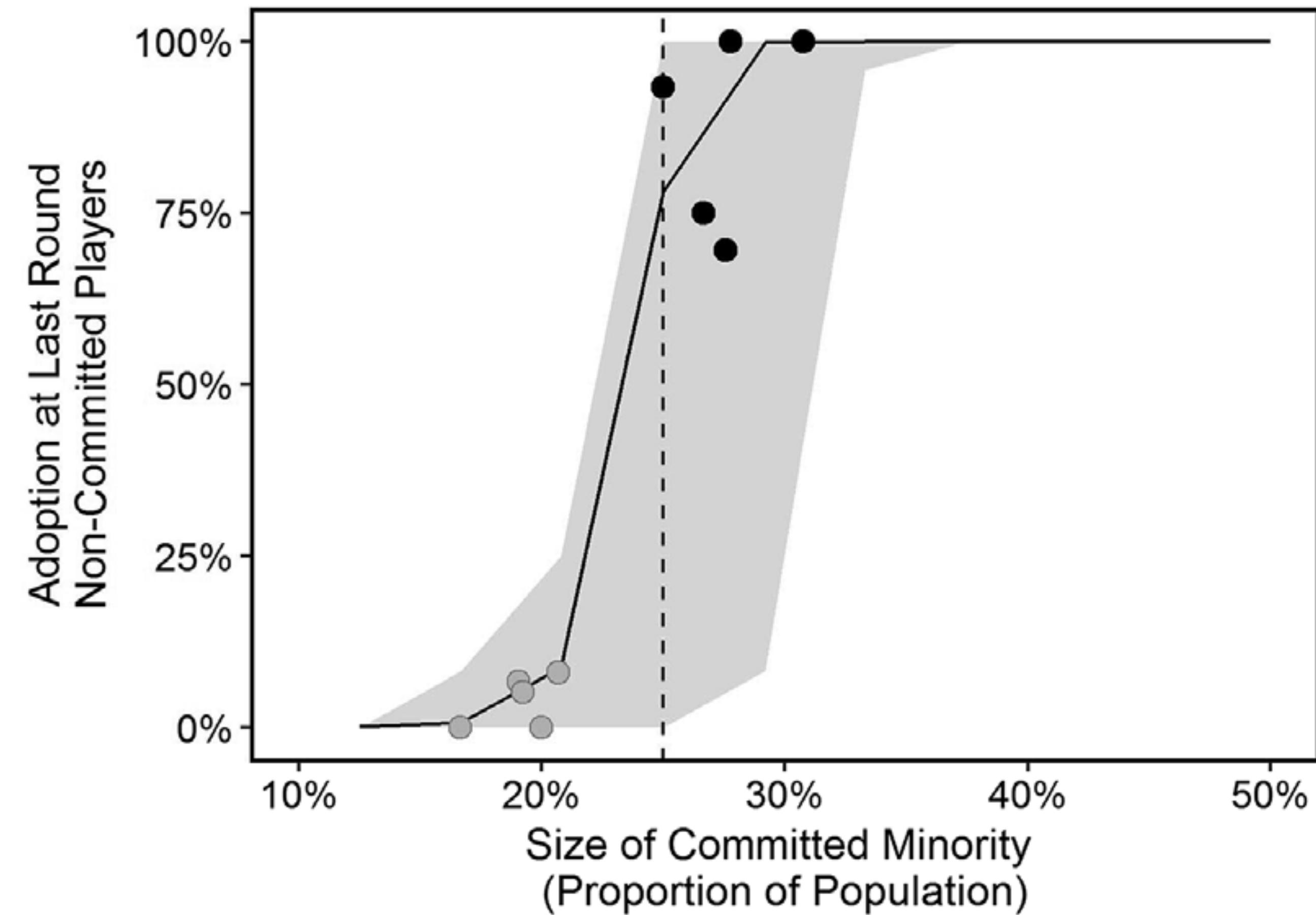
- ▶ Real world experiment
- ▶ Individuals are assigned to groups and coordinate online to name a given object (face)
- ▶ Once consensus is reached, a team of confederates (a committed minority) is introduced in the group with the goal of overturning the consensus.
- ▶ Results show that in all cases, the minority manages to change the convention.

The committed minority

A



Empirical Trials



Tipping points in social conventions



Market Summary > GameStop Corp.
NYSE: GME

347.51 USD **+199.53 (134.84%) ↑**

Closed: Jan. 27, 4:28 p.m. EST · Disclaimer
After hours 342.66 **-4.85 (1.40%)**

1 day 5 days 1 month 6 months YTD 1 year 5 years Max



Tipping points in social conventions



A screenshot of a Twitter profile for Elizabeth Warren. It features a circular profile picture of her smiling, a blue 'Following' button, and a bell icon with a plus sign indicating notifications. Her bio text includes her title as U.S. Senator, her family members, and her campaign account status.

Elizabeth Warren

@ewarren

U.S. Senator, former teacher, and candidate for president. Wife, mom (Amelia, Alex, Bailey, [@CFPB](#)), grandmother, and Okie. She/hers. Official campaign account.



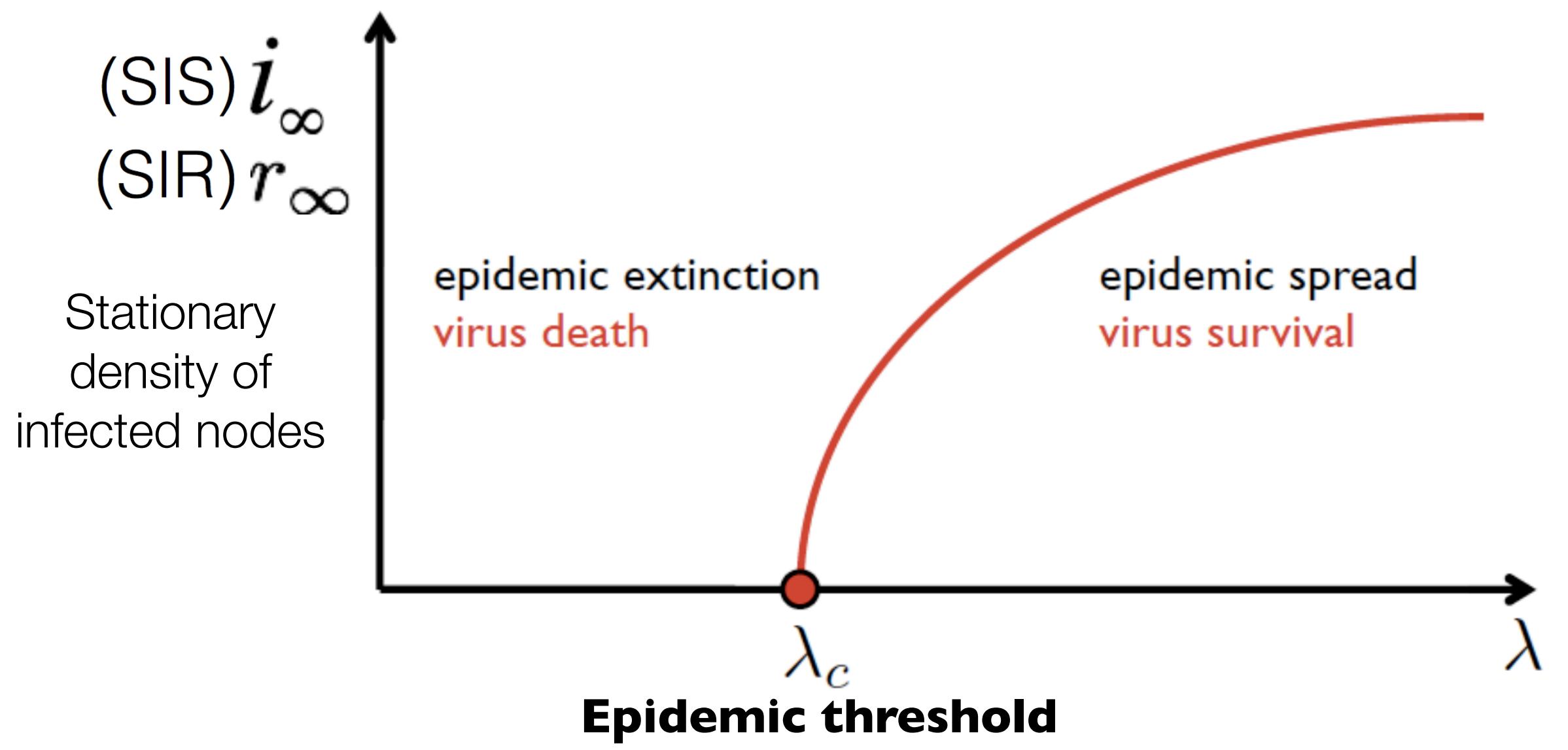
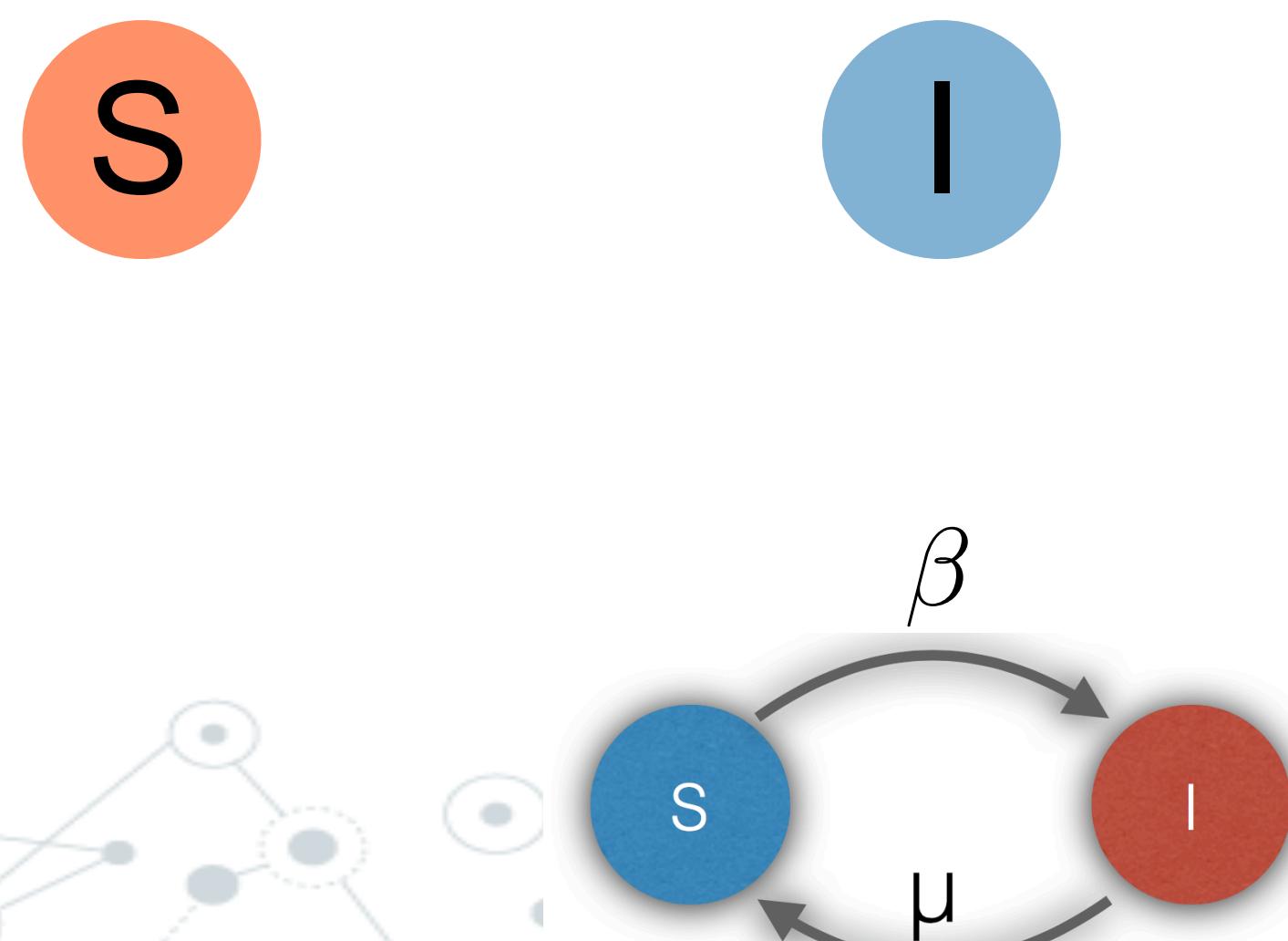
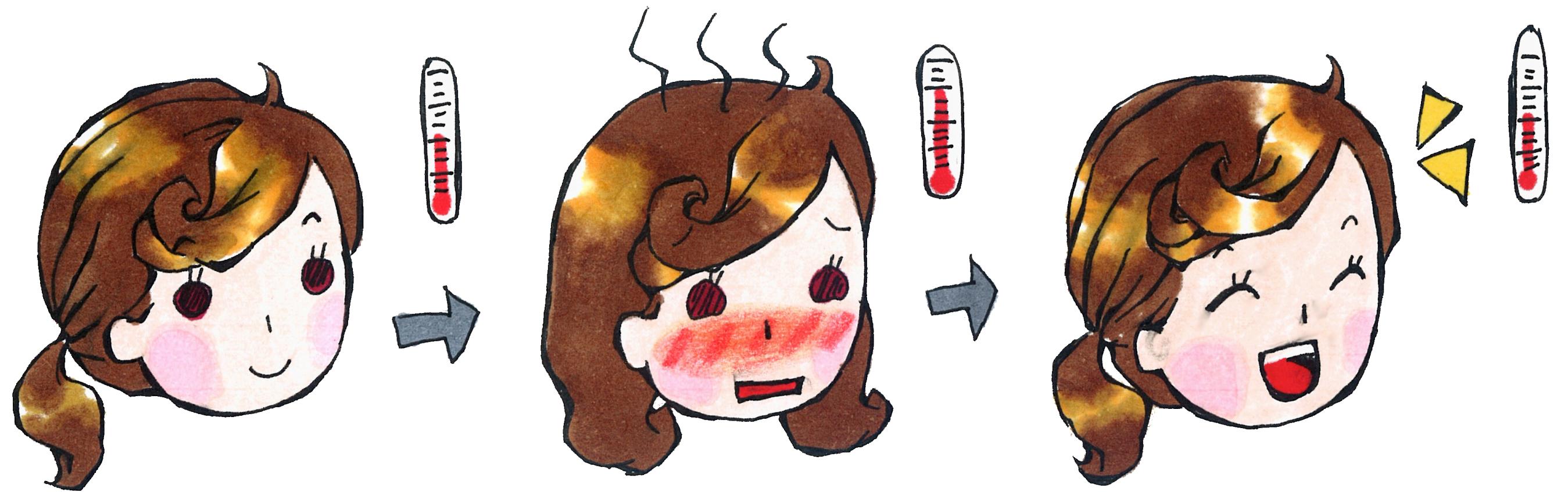
📍 Massachusetts [elizabethwarren.com](#)

Joined August 2011

341 Following 2.8M Followers

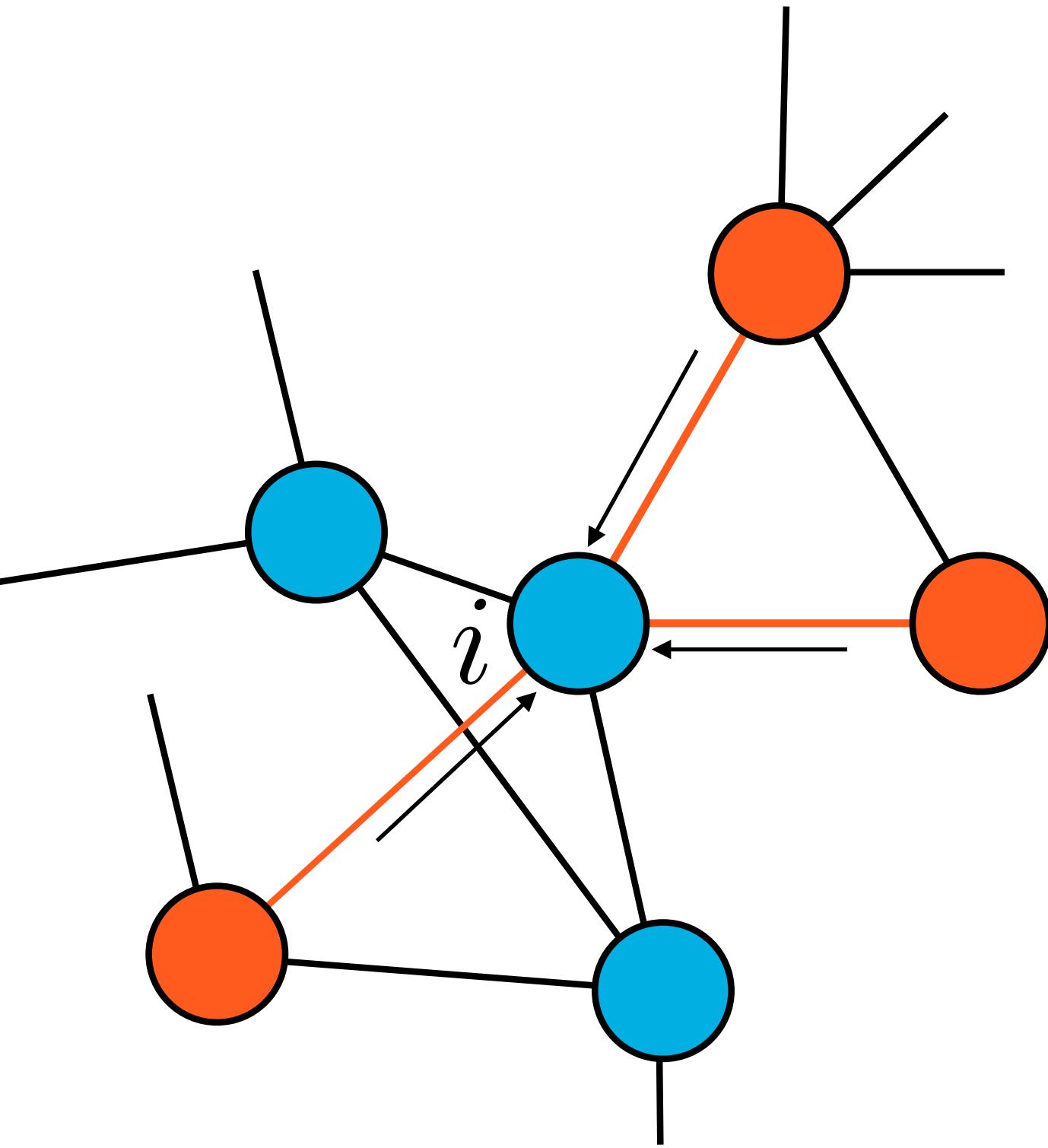


Simple contagion



Complex contagion

Multiple sources of activation are required for a transmission



Complex contagion process in spreading of online innovation

Márton Karsai^{1,2,3,4}, Gerardo Iñiguez², Kimmo Kaski^{2,5} and János Kertész^{2,6,7}

Structural diversity in social contagion

Johan Ugander, Lars Backstrom, Cameron Marlow, and Jon Kleinberg

PNAS April 17, 2012 109 (16) 5962-5966; <https://doi.org/10.1073/pnas.1116502109>

Edited by Ronald L. Graham, University of California at San Diego, La Jolla, CA, and approved February 21, 2012



RESEARCH ARTICLE

Evidence of complex contagion of information in social media: An experiment using Twitter bots

Bjarke Mønsted^{1*}, Piotr Sapieżyński^{1*}, Emilio Ferrara^{2,3*}, Sune Lehmann^{1*}

REPORT

The Spread of Behavior in an Online Social Network Experiment

Damon Centola

* See all authors and affiliations

Science 03 Sep 2010:
Vol. 329, Issue 5996, pp. 1194-1197
DOI: 10.1126/science.1185231

Social contagion and health

Social contagion and health

The Spread of Obesity in a Large Social Network over 32 Years

Nicholas A. Christakis, M.D., Ph.D., M.P.H., and James H. Fowler, Ph.D.

“Network phenomena appear to be relevant to the biologic and behavioural trait of obesity, and obesity appears to spread through social ties. These findings have implications for clinical and public health interventions.”

ABSTRACT

BACKGROUND

The prevalence of obesity has increased substantially over the past 30 years. We performed a quantitative analysis of the nature and extent of the person-to-person spread of obesity as a possible factor contributing to the obesity epidemic.

METHODS

We evaluated a densely interconnected social network of 12,067 people assessed repeatedly from 1971 to 2003 as part of the Framingham Heart Study. The body-mass index was available for all subjects. We used longitudinal statistical models to examine whether weight gain in one person was associated with weight gain in his or her friends, siblings, spouse, and neighbors.

RESULTS

Discernible clusters of obese persons (body-mass index [the weight in kilograms divided by the square of the height in meters], ≥ 30) were present in the network at all time points, and the clusters extended to three degrees of separation. These clusters did not appear to be solely attributable to the selective formation of social ties among obese persons. A person’s chances of becoming obese increased by 57% (95% confidence interval [CI], 6 to 123) if he or she had a friend who became obese in a given interval. Among pairs of adult siblings, if one sibling became obese, the chance that the other would become obese increased by 40% (95% CI, 21 to 60). If one spouse became obese, the likelihood that the other spouse would become obese increased by 37% (95% CI, 7 to 73). These effects were not seen among neighbors in the immediate geographic location. Persons of the same sex had relatively greater influence on each other than those of the opposite sex. The spread of smoking cessation did not account for the spread of obesity in the network.

Is obesity contagious?

Fact: obese individuals are clustered

- ▶ Because of selection effects, in which people are choosing to form friendships with others of similar obesity status?
- ▶ Because of the confounding effects of homophily according to other characteristics, in which the network structure indicates existing patterns of similarity in other dimensions that correlate with obesity?
- ▶ Because changes in the obesity status of a person's friends was exerting a behavioural influence that affected his or her future obesity status?

Influence or homophily?

Major challenge

- ▶ Distinguish between **social influence** and **homophily**
- ▶ Social influence represents the actual change of behaviour due to social effects, peer pressure or similar.
- ▶ Homophily represents the natural tendency of individuals who share similar values, attitudes or behaviour, to form social connections.
- ▶ How can we separate the two effects?

Influence or homophily?

Major challenge

- ▶ Distinguish between **social influence** and **homophily**
- ▶ Social influence represents the actual change of behaviour due to social effects, peer pressure or similar.
- ▶ Homophily represents the natural tendency of individuals who share similar values, attitudes or behaviour, to form social connections.

Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks

Sinan Aral^{a,b,1}, Lev Muchnik^a, and Arun Sundararajan^a

^aInformation, Operations and Management Sciences Department, Stern School of Business, New York University, Kaufmann Management Center, 44 West 4th Street, New York, NY 10012; and ^bCenter for Digital Business, Sloan School of Management, Massachusetts Institute of Technology, 5 Cambridge Center–NE25, Cambridge, MA 02142

Edited by Matthew O. Jackson, Stanford University, Stanford, CA, and accepted by the Editorial Board October 6, 2009 (received for review August 4, 2009)

Influence or homophily?

Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks

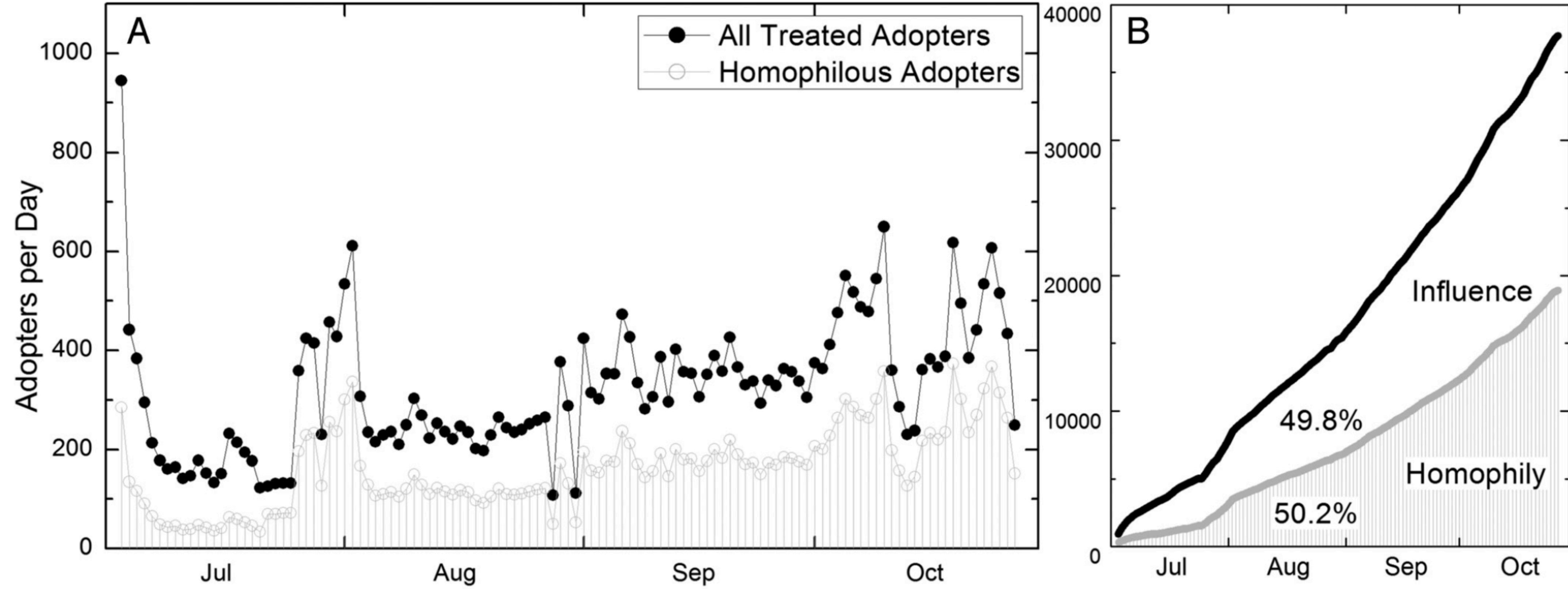
Sinan Aral^{a,b,1}, Lev Muchnik^a, and Arun Sundararajan^a

^aInformation, Operations and Management Sciences Department, Stern School of Business, New York University, Kaufmann Management Center, 44 West 4th Street, New York, NY 10012; and ^bCenter for Digital Business, Sloan School of Management, Massachusetts Institute of Technology, 5 Cambridge Center–NE25, Cambridge, MA 02142

Edited by Matthew O. Jackson, Stanford University, Stanford, CA, and accepted by the Editorial Board October 6, 2009 (received for review August 4, 2009)

- ▶ 27.4 million users of Yahoo.com
- ▶ day-by-day adoption of a mobile service application launched in July 2007
- ▶ matched sample estimation framework to distinguish influence and homophily effects in dynamic networks

Influence or homophily?



► Homophily can explain more than 50% of the adoptions

Exercise contagion

ARTICLE

Received 19 Jul 2016 | Accepted 27 Jan 2017 | Published 18 Apr 2017

DOI: [10.1038/ncomms14753](https://doi.org/10.1038/ncomms14753)

OPEN

Exercise contagion in a global social network

Sinan Aral¹ & Christos Nicolaides¹

We leveraged exogenous variation in weather patterns across geographies to identify social contagion in exercise behaviours across a global social network. We estimated these contagion effects by combining daily global weather data, which creates exogenous variation in running among friends, with data on the network ties and daily exercise patterns of ~1.1M individuals who ran over 350M km in a global social network over 5 years. Here we show that exercise is socially contagious and that its contagiousness varies with the relative activity of and gender relationships between friends. Less active runners influence more active runners, but not the reverse. Both men and women influence men, while only women influence other women. While the Embeddedness and Structural Diversity theories of social contagion explain the influence effects we observe, the Complex Contagion theory does not. These results suggest interventions that account for social contagion will spread behaviour change more effectively.

Exercise contagion



► Complex contagion? ✗

- Contagion occurs even with only one adopter friend and unconnected adopter friends, rather than connected adopter friends, are more likely to transmit exercise behaviours.

► Structural diversity? ✓

- the structural diversity of peer group activation (**the number of unconnected network components that exhibit running**) strongly predicts greater positive social contagion effects, even when we control for the number of distinct friends who run.

► Embeddedness? ✓

- the embeddedness of a relationship (**the number of mutual friends between contacts**) strongly moderates social influence and contagion in running behaviours.



ARTICLE

Received 19 Jul 2016 | Accepted 27 Jan 2017 | Published 18 Apr 2017

DOI: 10.1038/ncomms14753

OPEN

Exercise contagion in a global social network

Sinan Aral¹ & Christos Nicolaides¹

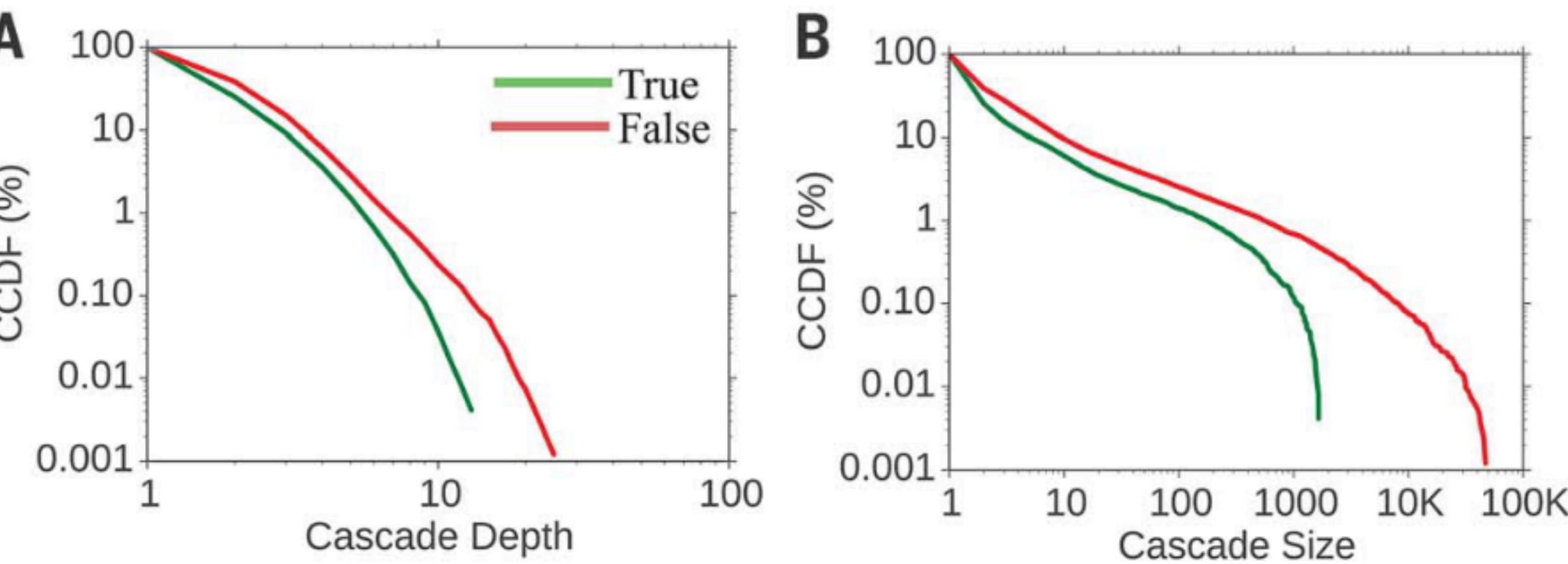
The spread of fake news

SOCIAL SCIENCE

The spread of true and false news online

Soroush Vosoughi,¹ Deb Roy,¹ Sinan Aral^{2*}

We investigated the differential diffusion of all of the verified true and false news stories distributed on Twitter from 2006 to 2017. The data comprise ~126,000 stories tweeted by ~3 million people more than 4.5 million times. We classified news as true or false using information from six independent fact-checking organizations that exhibited 95 to 98% agreement on the classifications. Falsehood diffused significantly farther, faster, deeper, and more broadly than the truth in all categories of information, and the effects were more pronounced for false political news than for false news about terrorism, natural disasters, science, urban legends, or financial information. We found that false news was more novel than true news, which suggests that people were more likely to share novel information. Whereas false stories inspired fear, disgust, and surprise in replies, true stories inspired anticipation, sadness, joy, and trust. Contrary to conventional wisdom, robots accelerated the spread of true and false news at the same rate, implying that false news spreads more than the truth because humans, not robots, are more likely to spread it.



The COVID-19 infodemic

Infodemic

Overview

An infodemic is too much information including false or misleading information in digital and physical environments during a disease outbreak. It causes confusion and risk-taking behaviours that can harm health. It also leads to mistrust in health authorities and undermines the public health response. An infodemic can intensify or lengthen outbreaks when people are unsure about what they need to do to protect their health and the health of people around them. With growing digitization – an expansion of social media and internet use – information can spread more rapidly. This can help to more quickly fill information voids but can also amplify harmful messages.

Infodemic management is the systematic use of risk- and evidence-based analysis and approaches to manage the infodemic and reduce its impact on health behaviours during health emergencies.

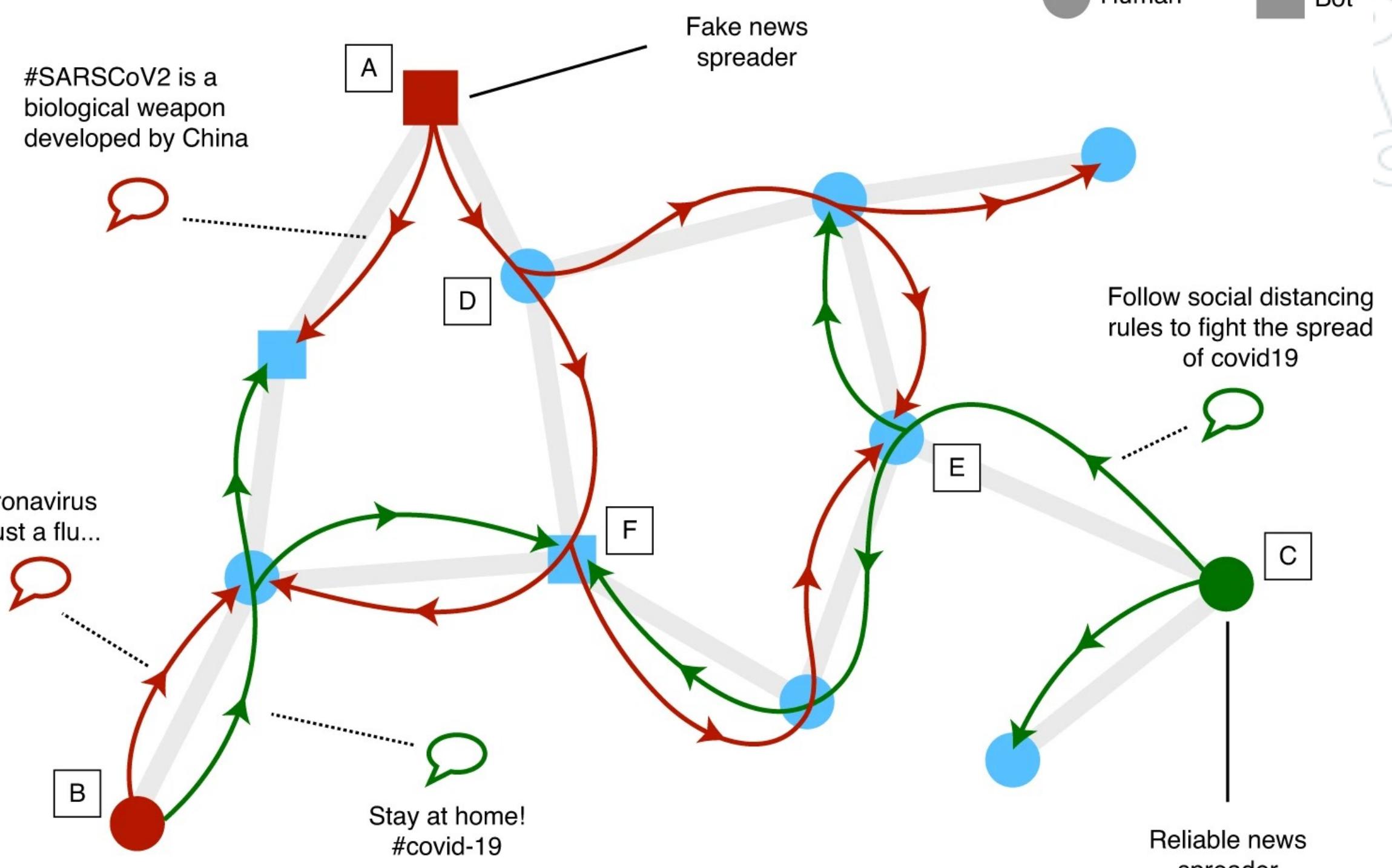


World Health Organization



Leadership

Research & innovation



Gallotti et al. Nature Human Behaviour 2020

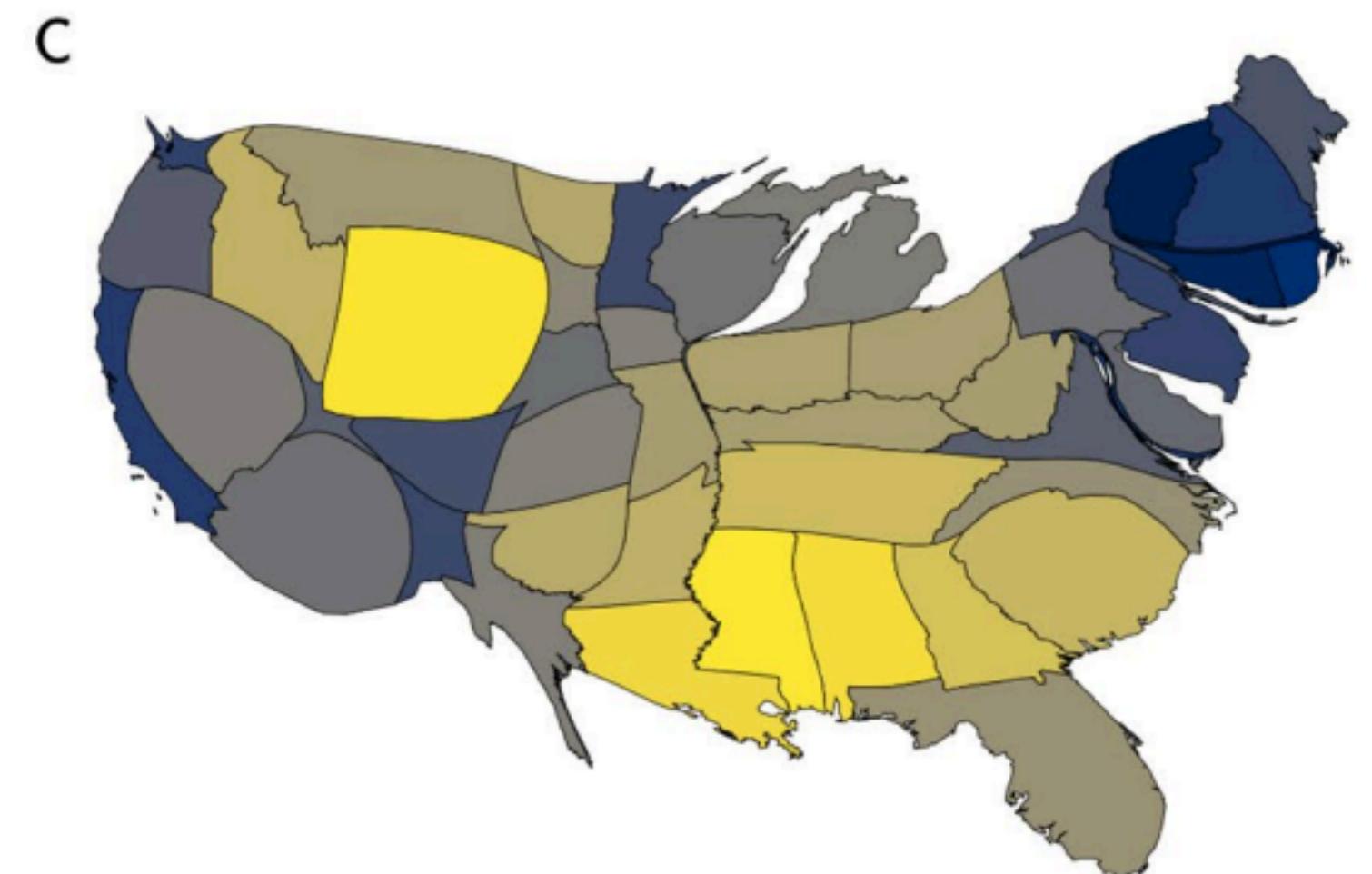
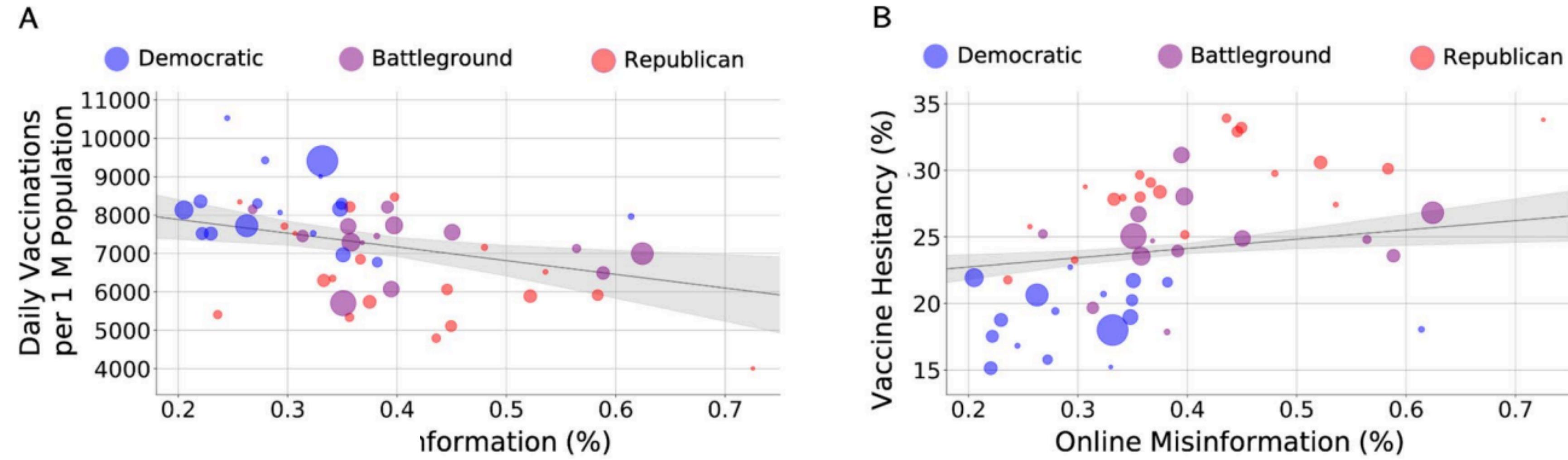
Vaccine hesitancy

scientific reports

OPEN

Online misinformation is linked
to early COVID-19 vaccination
hesitancy and refusal

Francesco Pierri^{1,3✉}, Brea L. Perry², Matthew R. DeVerna³, Kai-Cheng Yang³,
Alessandro Flammini³, Filippo Menczer³ & John Bryden³



Open questions and directions

- ▶ We can observe competing mechanisms of social contagion that do not apply to all settings.
No universal behaviour. Social contagion can happen in many ways, and it is important to distinguish influence from homophily.
- ▶ The interaction between epidemic and social contagion is hard to model. Empirically, it is very hard and sometimes impossible to distinguish between simple and complex contagions (Hébert-Dufresne et al. Nat. Physics 2020).
- ▶ How can we integrate the spread of information/misinformation into epidemic models?
- ▶ In general, how do we take into account the change of human behaviour during an epidemic?

Next... human behaviour and
epidemics