Modeling epidemics on networks

Epidemic spreading

the Black Death

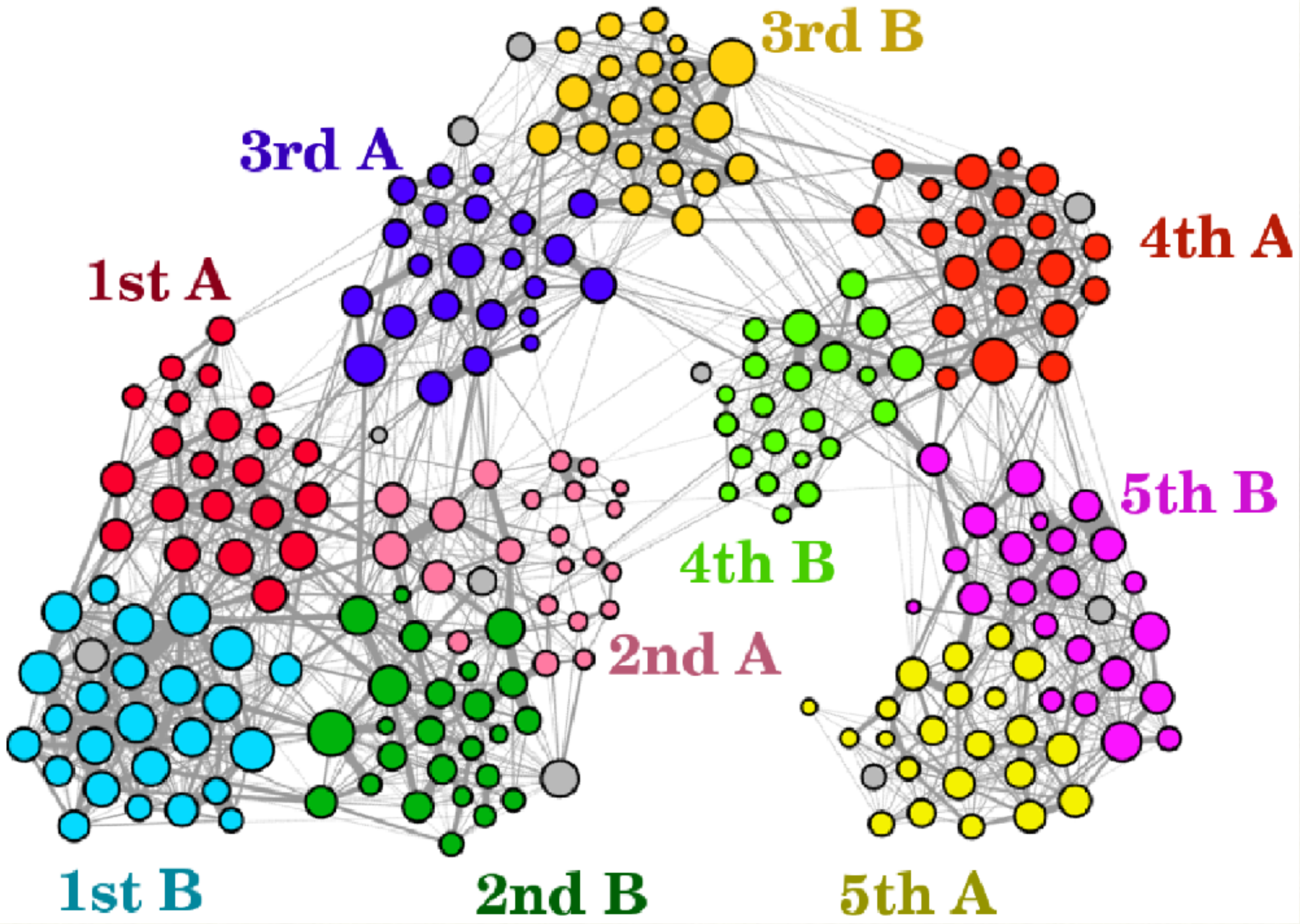
Probably originated in Central Asia, it spread throughout all of Europe between 1346 and 1353. The Black Death is estimated to have killed 30-60% of Europe's population

Epidemic spreading

- Problems:
  - Nowadays the speed of epidemic spreading has increased enormously due to advances in transportation: someone contracting Ebola in Africa can travel to Europe, America and Asia and spread the disease before being aware of it
  - Technology has created new types of epidemics: computer viruses & malware spread over the Internet. Mobile phone viruses spread via Bluetooth or MMS. Misinformation spreads through social media, etc.

Contact networks

- Epidemics spread on contact networks, such as networks of physical contacts, transportation, the Internet, email, online social networks, and mobile phone communication



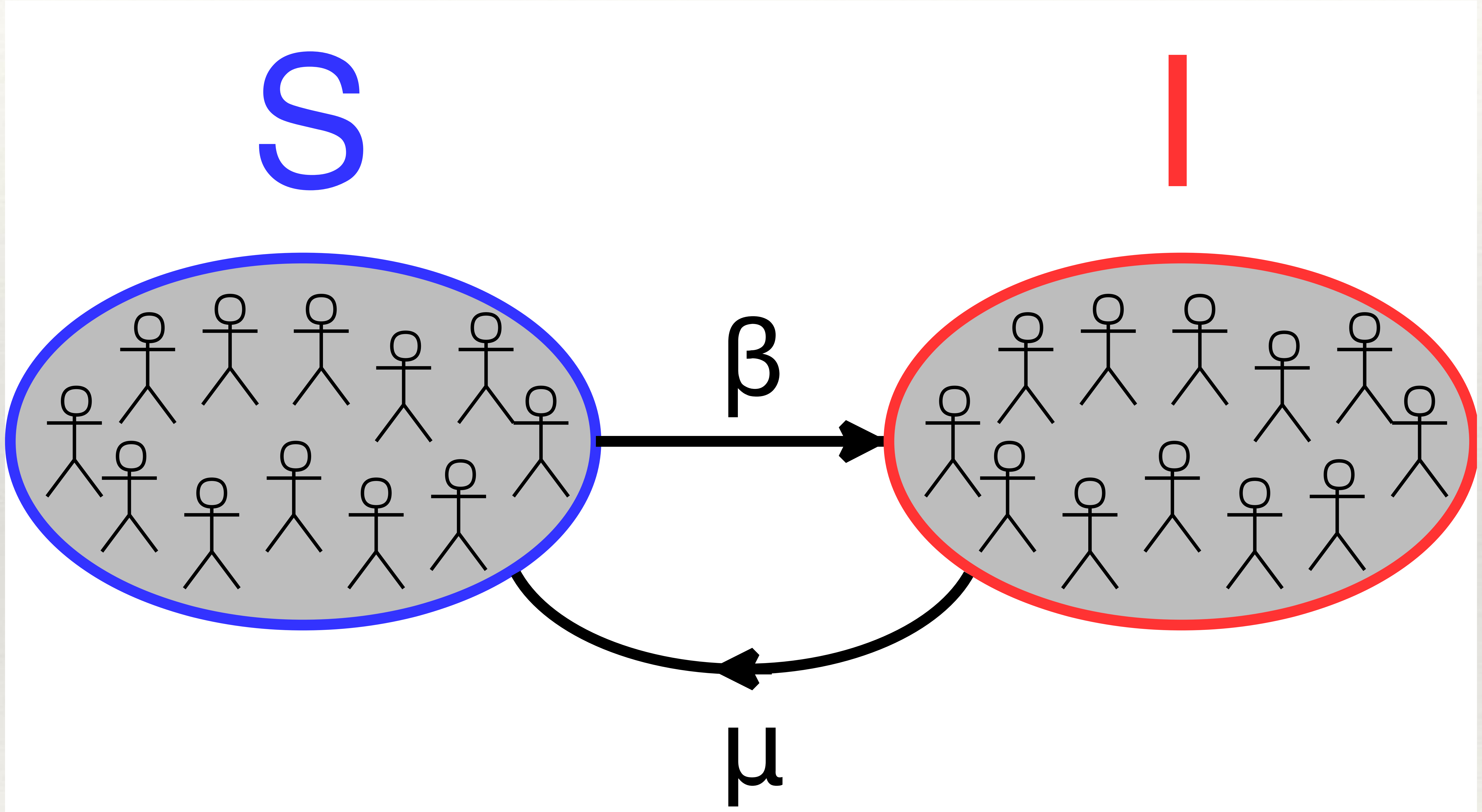
Epidemic models

- Classic epidemic models divide the population into **compartments**, corresponding to different stages of the disease
  - **Key compartments**:
    - **Susceptible (S)**: individuals who can contract the disease
    - **Infected (I)**: individuals who have contracted the disease and can transmit it to susceptible individuals
    - **Recovered (R)**: individuals who recovered from the disease and cannot be infected anymore

The SIS model

- Just two compartments: **Susceptible (S)** and **Infected (I)**
- Dynamics:
  - A susceptible individual gets infected with a probability β (**infection rate**)
  - An infected individual recovers and becomes susceptible again with a probability μ (**recovery rate**)
  - The model applies to diseases that do not confer long-lasting immunity (e.g., common cold)

The SIS model

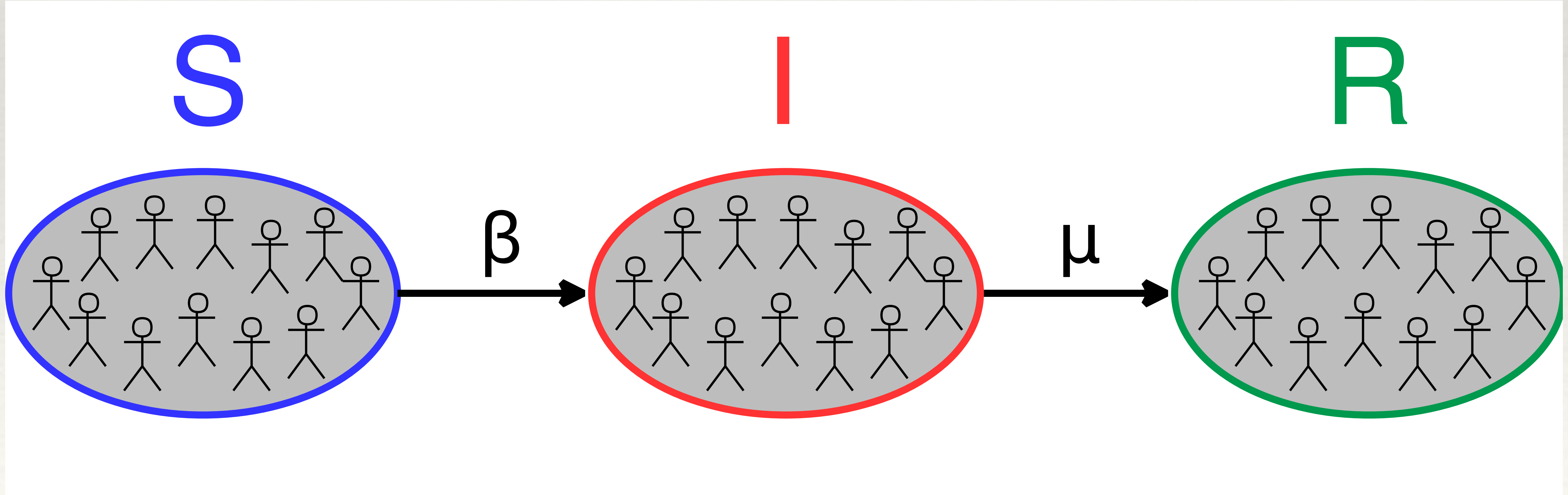


The SIS model

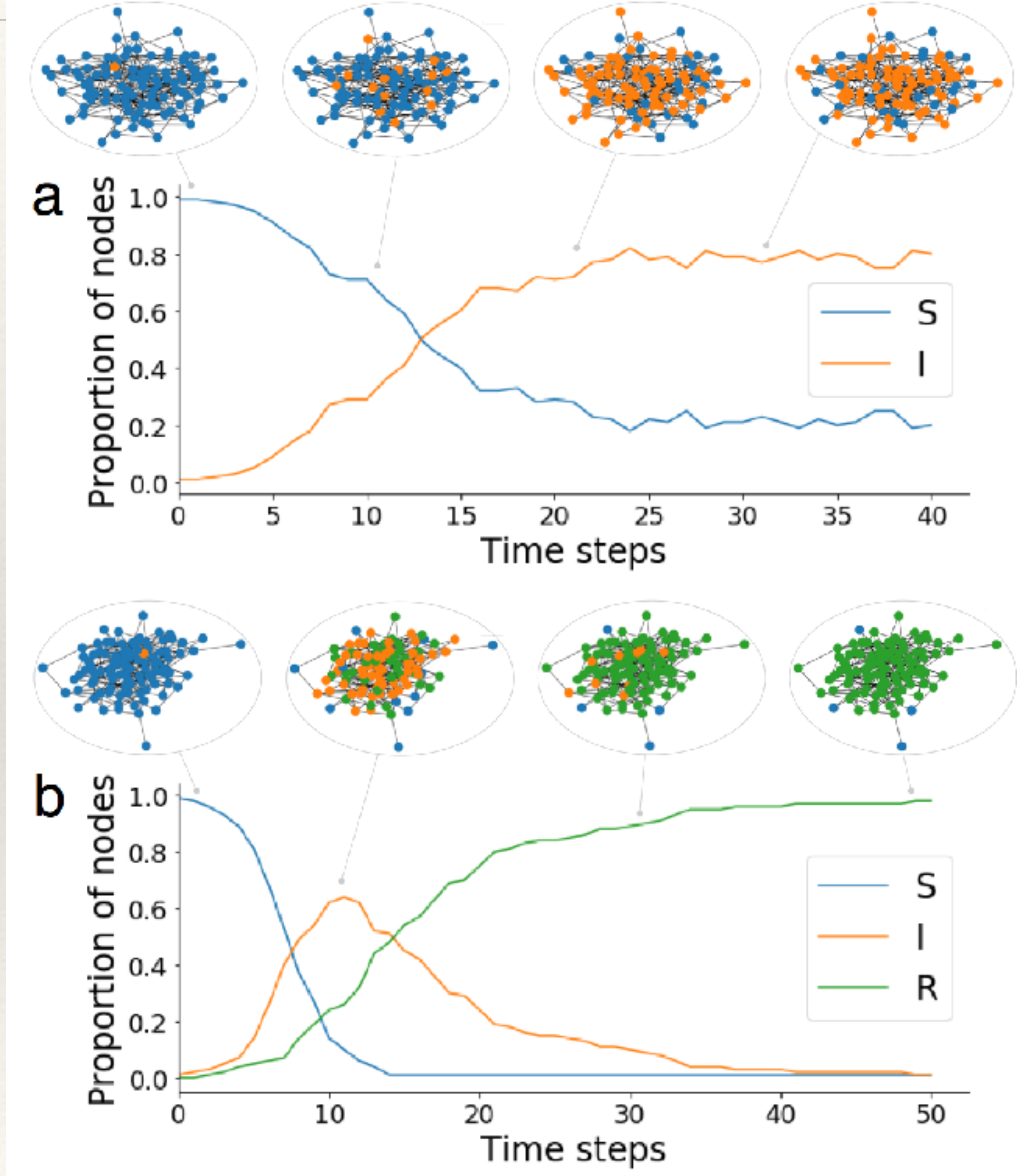
- Simulation of SIS dynamics on networks:
  - Take a network (e.g., a random network or a real contact network)
  - A number (fraction) of the nodes are infected (e.g., at random), all others are susceptible
  - All nodes are visited in sequence
  - For each node i:
    - If i is susceptible, loop over its neighbors: for each infected neighbor, i becomes infected with probability β
    - If i is infected, it becomes susceptible with probability μ

The SIR model

- **Difference from SIS model**: when infected individuals recover, they do not become susceptible again, but they are moved to the compartment R and play no further role in the dynamics
- The model applies to diseases that confer long-lasting immunity (e.g., measles, mumps, rubella, etc.)



Epidemic spreading



- Three characteristic stages of the **dynamics**:
  - **Initial stage**: just a few people are infected, and the diffusion of the epidemic is irregular and slow
  - **Ramp-up phase of exponential growth**, that can quickly affect a large number of people
  - **Stationary state**, in which the disease is either endemic, i.e. it affects a stable fraction of the population over time, or eradicated

Homogeneous mixing

- **Hypothesis**: every individual is in contact with every other
- **Consequence**: all individuals in the same compartment have identical behavior and only the relative proportions of people in the various compartments matter for the model dynamics
- Justified for a small population, e.g., the inhabitants of a little village where all people are in touch with each other.
- In real large-scale epidemics, individuals can only be infected by the people they come in contact with. In this case it is **necessary to reconstruct the actual network of contacts**

SIS & SIR models on networks

- **Start**: homogeneous contact network, with all nodes having degree approximately equal to $\langle k \rangle$
- **Early stage**: few people are infected, so we can assume that every infected individual is in contact with mostly susceptible individuals
- Each infected individual can transmit the disease to about $\langle k \rangle$ people at each iteration —> the expected number of people infected by a single person after one iteration is $\beta\langle k \rangle$
- If there are I infected individuals, we expect to have $I_{sec} = \beta\langle k \rangle I$ new infected people after one iteration and $I_{rec} = \mu I$ recovered people

SIS & SIR models on networks

- **Threshold condition** for epidemic spreading: $I_{sec} > I_{rec}$

$$\beta \langle k \rangle I > \mu I \implies R_0 = \frac{\beta}{\mu} \langle k \rangle > 1$$

- $R_0 = \beta\langle k\rangle/\mu$ is the **basic reproduction number**
- If $R_0 < 1$, the initial outbreak **dies out in a short time**, affecting only a few individuals
- If $R_0 > 1$, the epidemic keeps spreading

SIS & SIR models on networks

- **Problem**: real contact networks are not homogeneous
- **Hubs drastically change the scenario.** On contact networks with hubs there is effectively no epidemic threshold —> even diseases with low infection rate and/or high recovery rate may end up affecting a sizable fraction of the population!
- **Reason**: even if the infection rate is low, the process is likely to eventually infect a hub, via one of its many contacts; the hub can in turn infect a large number of susceptible individuals, including possibly other hubs, and so on
- Effective disease containment strategies should aim at isolating/vaccinating individuals with many contacts. The latter can be identified by picking the endpoints of randomly selected links, as this increases the chance to bump into hubs. So, don't vaccinate a random sample of the population: **vaccinate their friends**!

Modeling the spread of misinformation

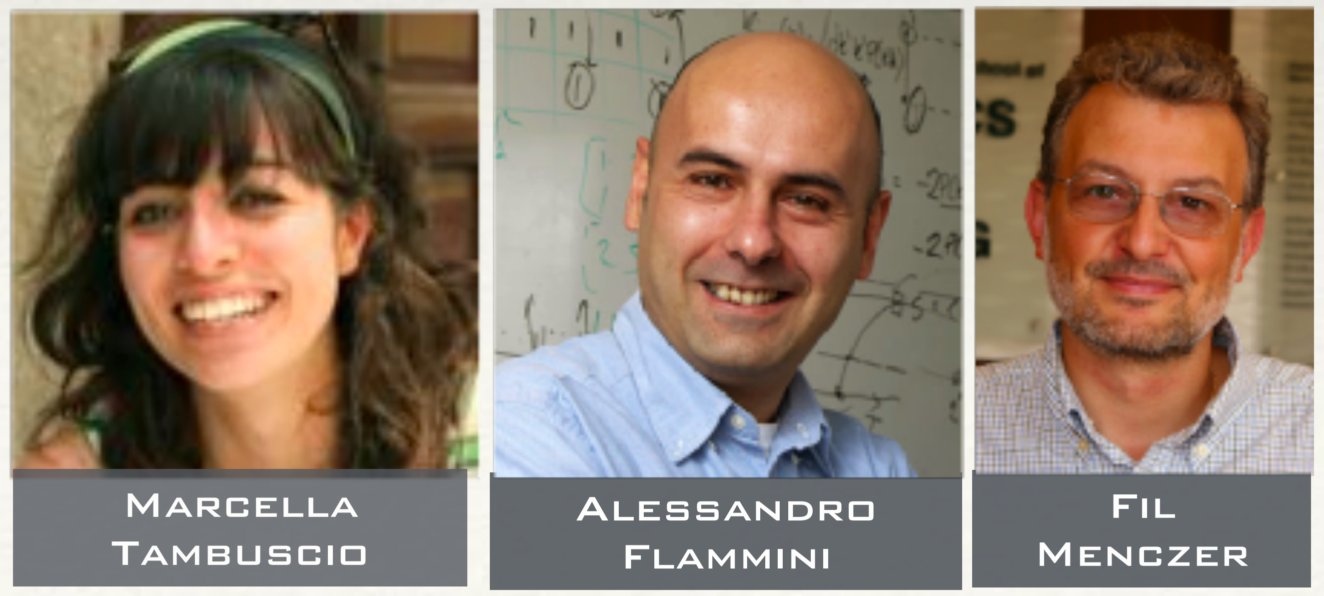
Questions

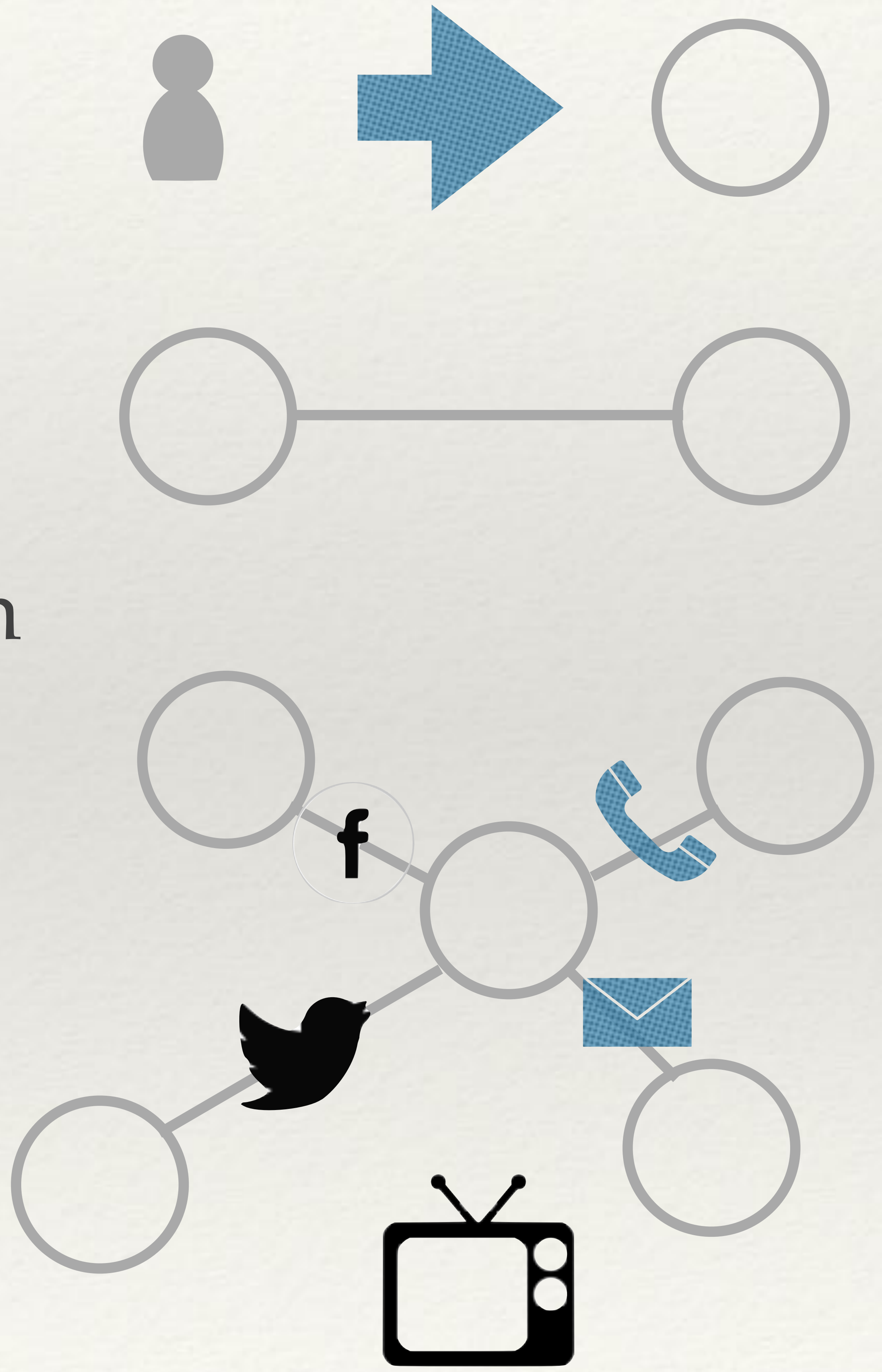
- Is fact-checking effective against the diffusion of fake-news?

- Do “echo-chambers” play a role as inhibitors or facilitators of fake-news spreading?

Networks and their context

- nodes are **actors** involved in a **generic** social network (no assumption is given)
- links are **social relationships**
- nodes can be exposed to news from both **internal and external sources** and via different communication devices

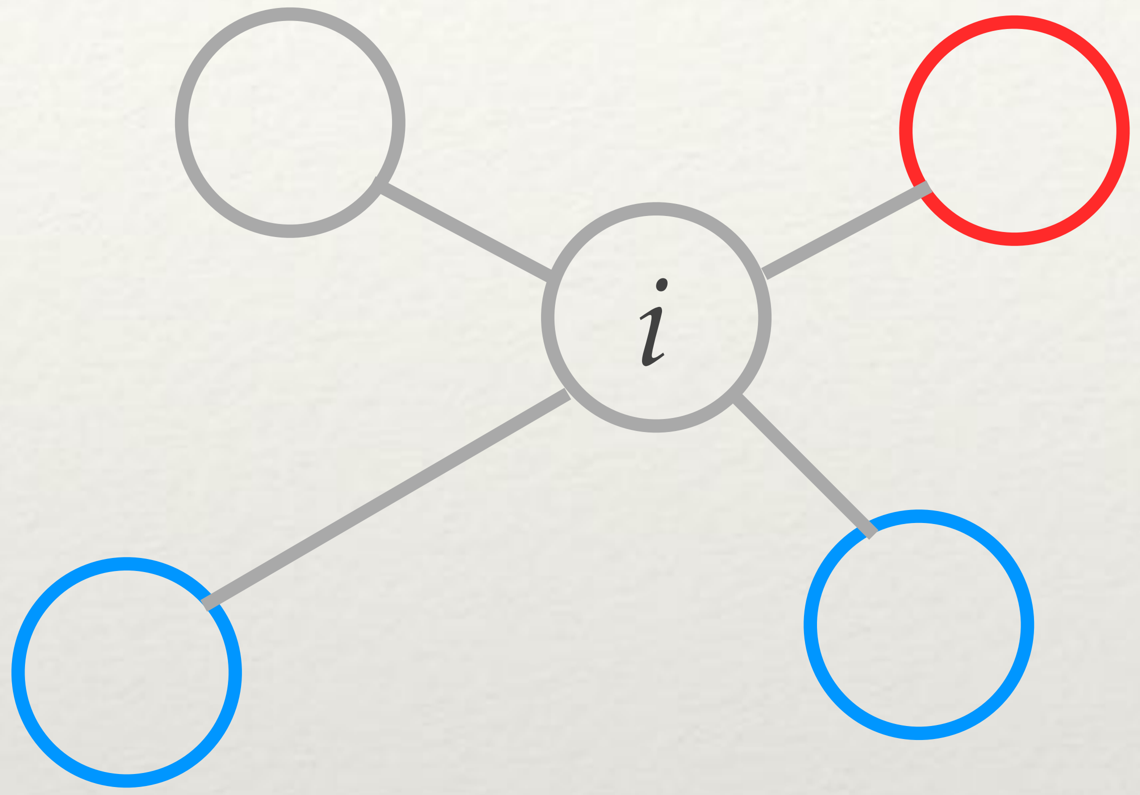




- **network topologies** can be created artificially or built from real data
- The **news is factually false** (can be debunked or someone else has already debunked it)
- We need a **model** for predictions and what-if analysis; data for validation and tuning only

Node states in the SBFC model

- Susceptible
- Believer
- Fact-Checker

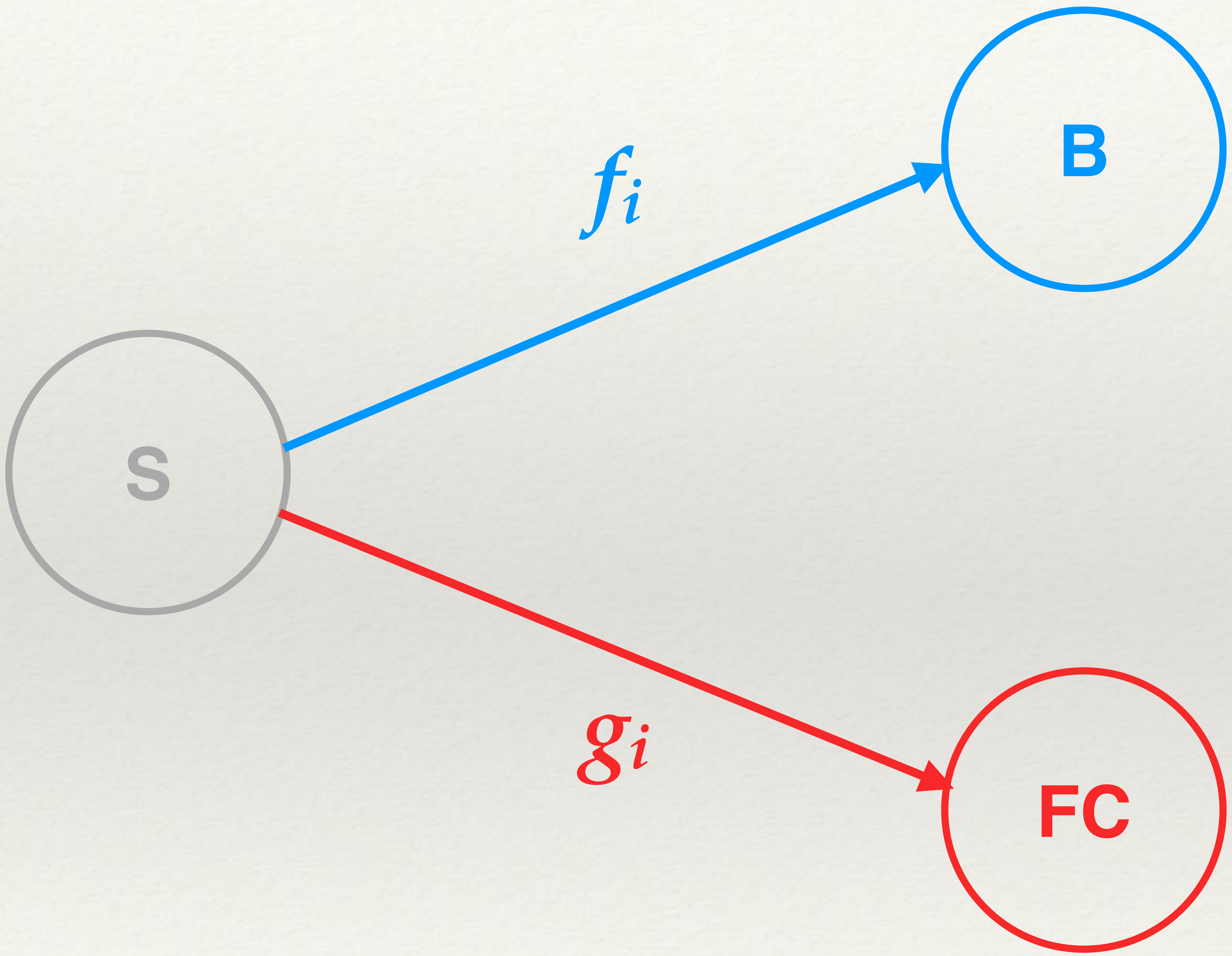


neighbors of i: $\boldsymbol{n_i}$

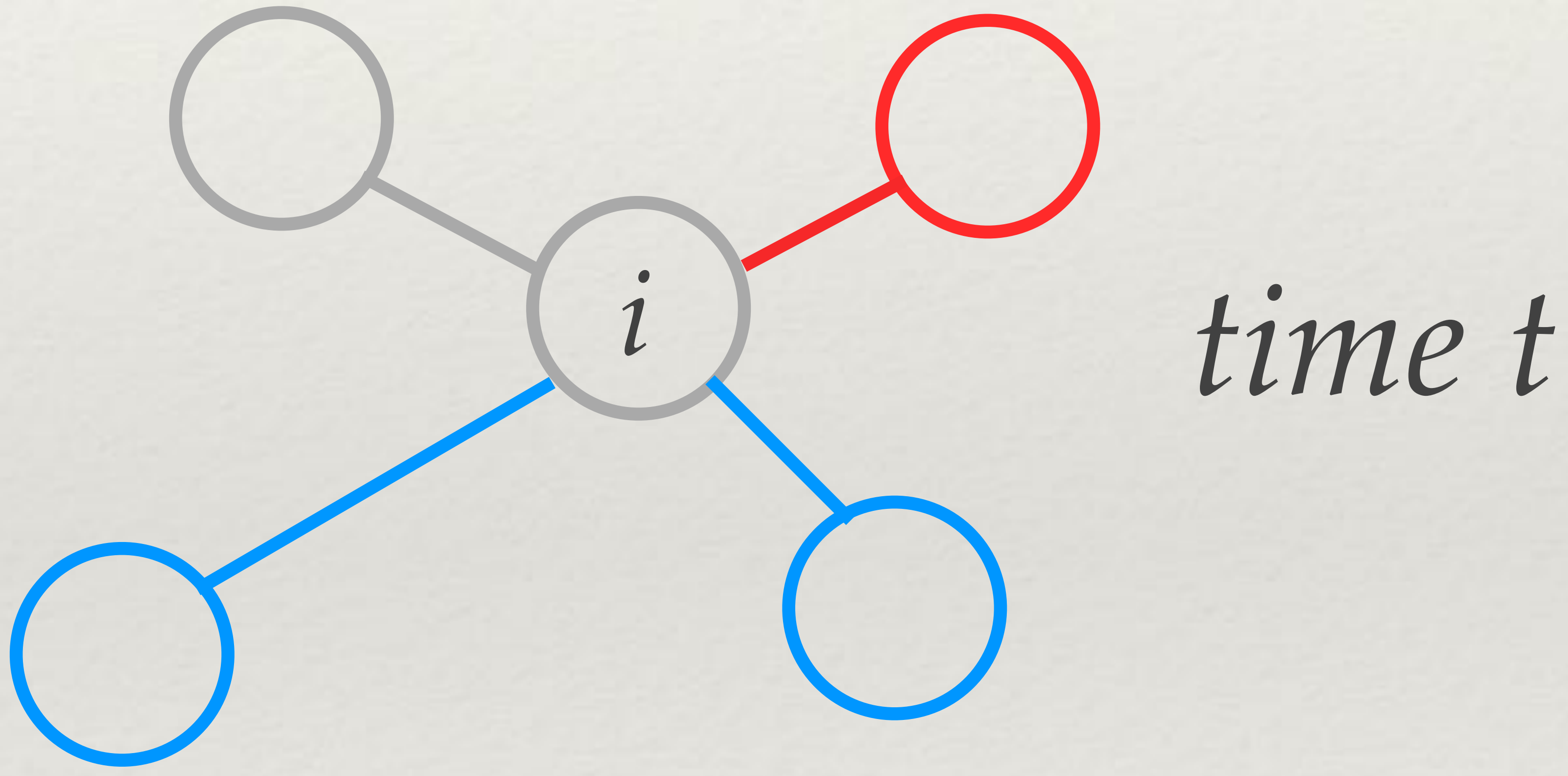
credibility of the hoax: $\boldsymbol{\alpha}$

spreading rate: $\boldsymbol{\beta}$

From Susceptible to Believer/Fact-Checker

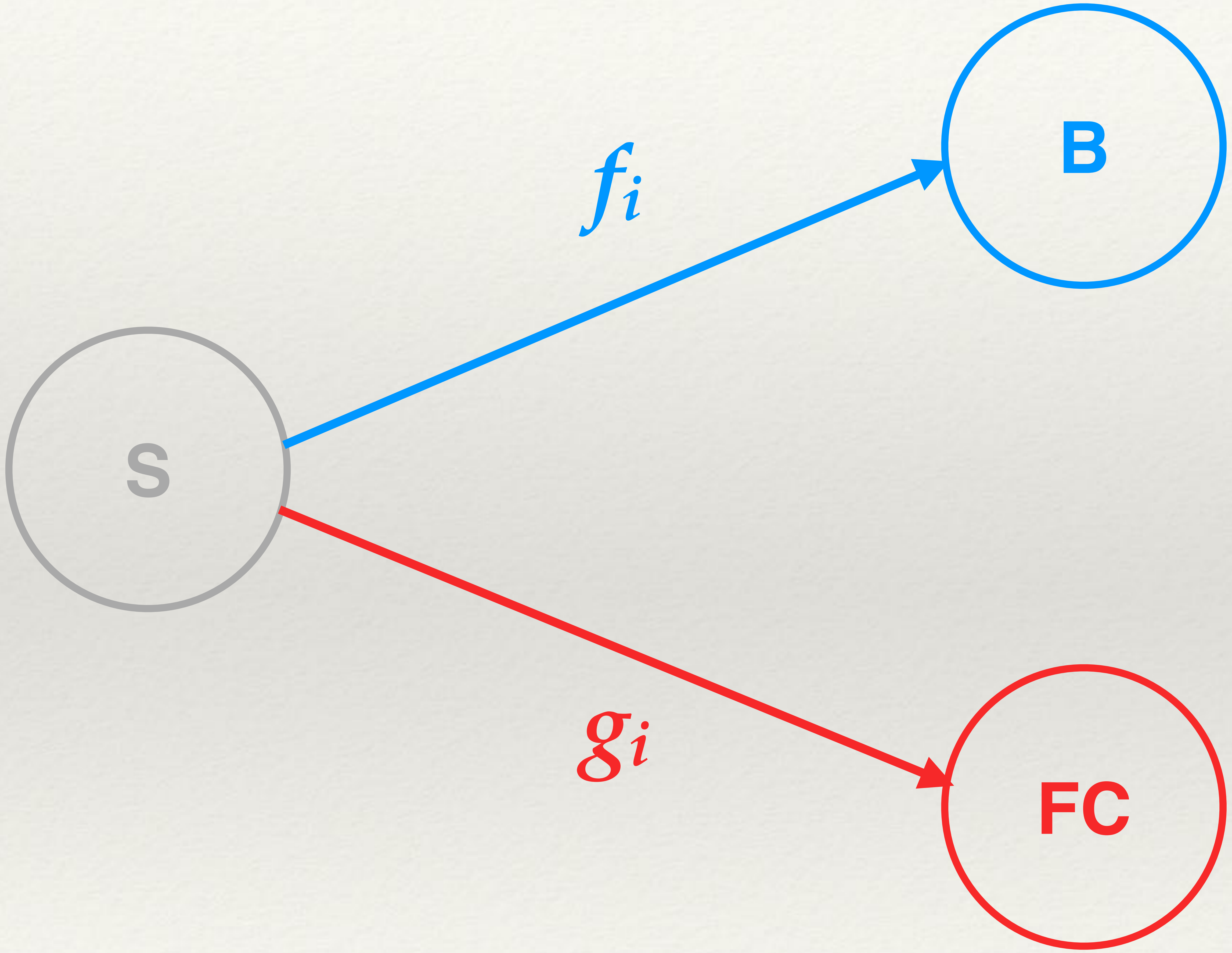


$$f_i(t) = \beta \frac{n_i^B(t)(1+\alpha)}{n_i^B(t)(1+\alpha) + n_i^F(t)(1-\alpha)}$$

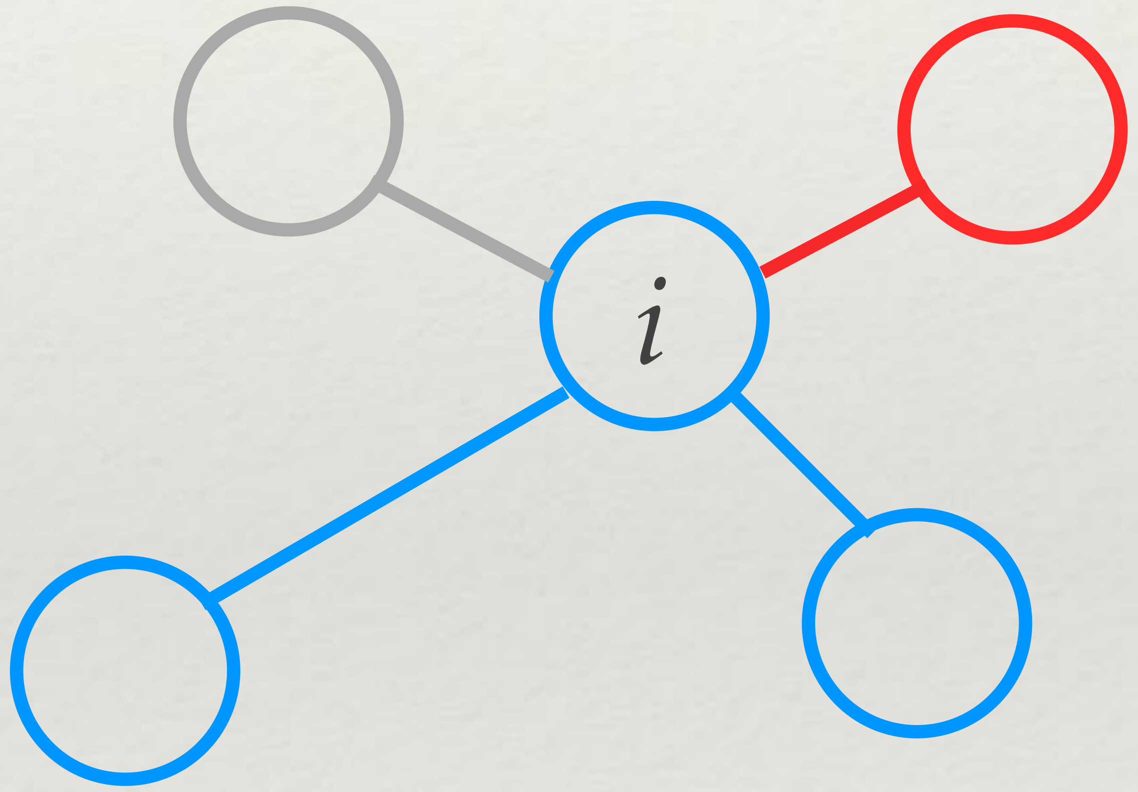


$$g_i(t) = \beta \frac{n_i^F(t)(1-\alpha)}{n_i^B(t)(1+\alpha) + n_i^F(t)(1-\alpha)}$$

From Susceptible to Believer/Fact-Checker



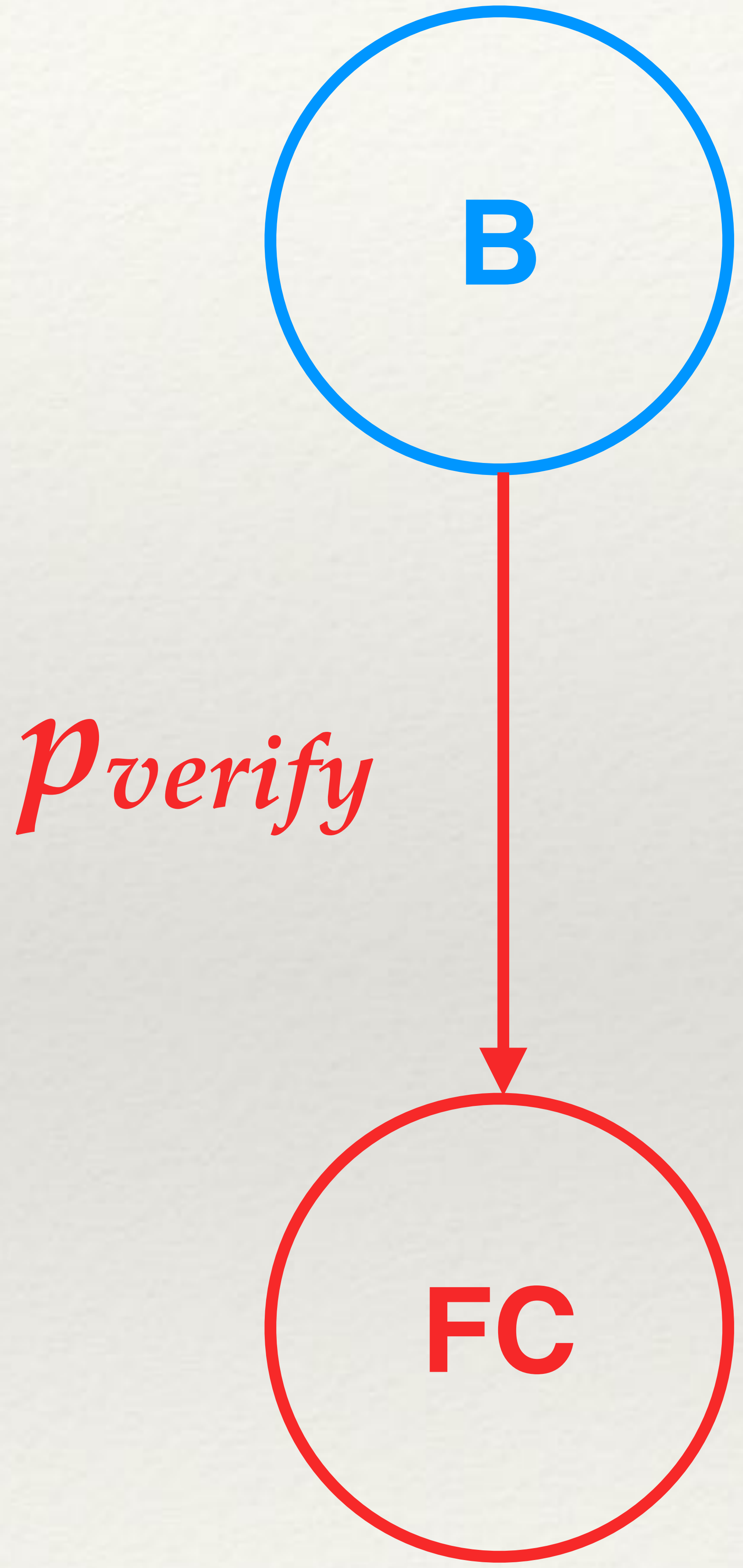
$$f_i(t) = \beta \frac{n_i^B(t)(1+\alpha)}{n_i^B(t)(1+\alpha) + n_i^F(t)(1-\alpha)}$$



time t+1

$$g_i(t) = \beta \frac{n_i^F(t)(1-\alpha)}{n_i^B(t)(1+\alpha) + n_i^F(t)(1-\alpha)}$$

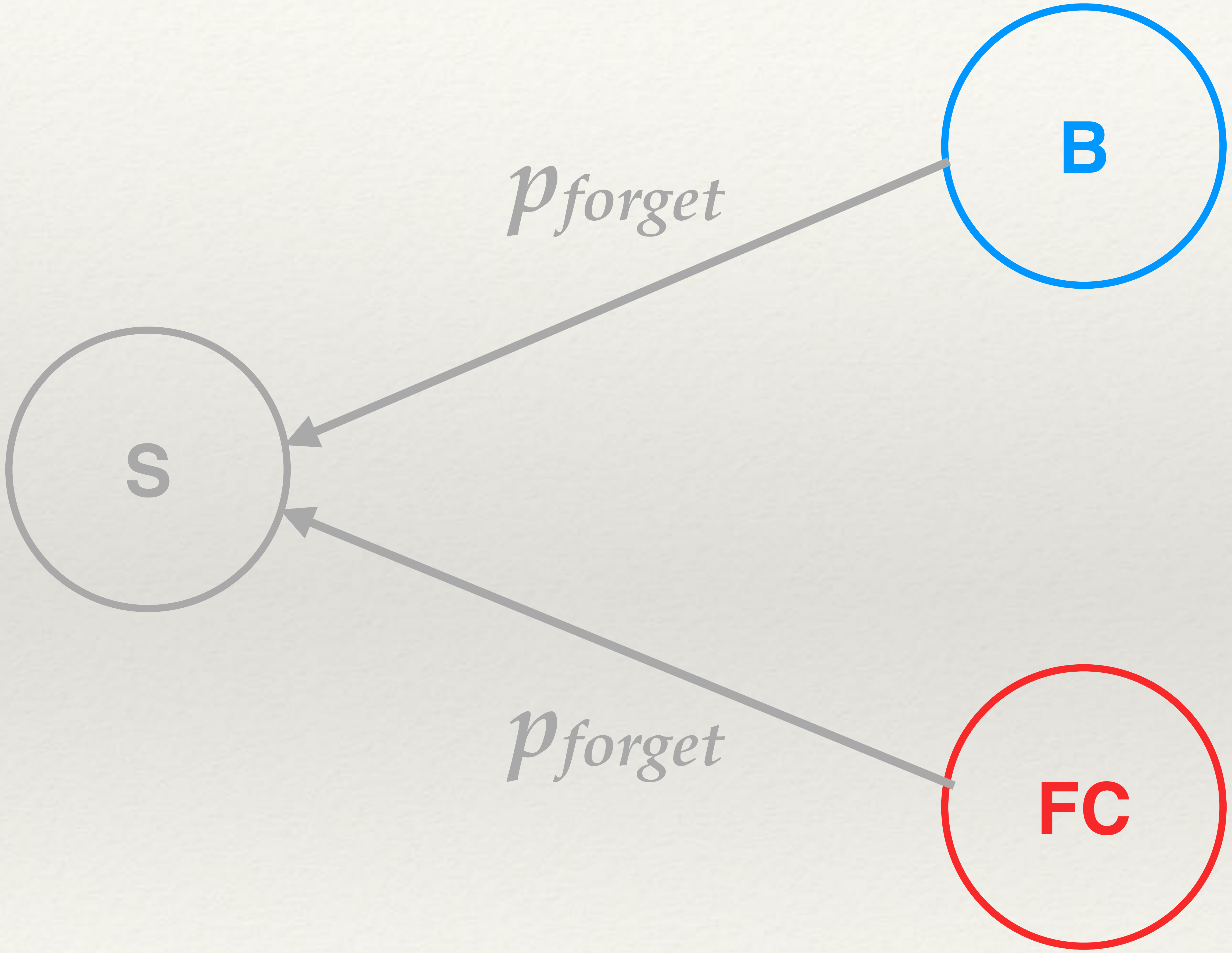
From Believer to Fact-Checker



VERIFYING

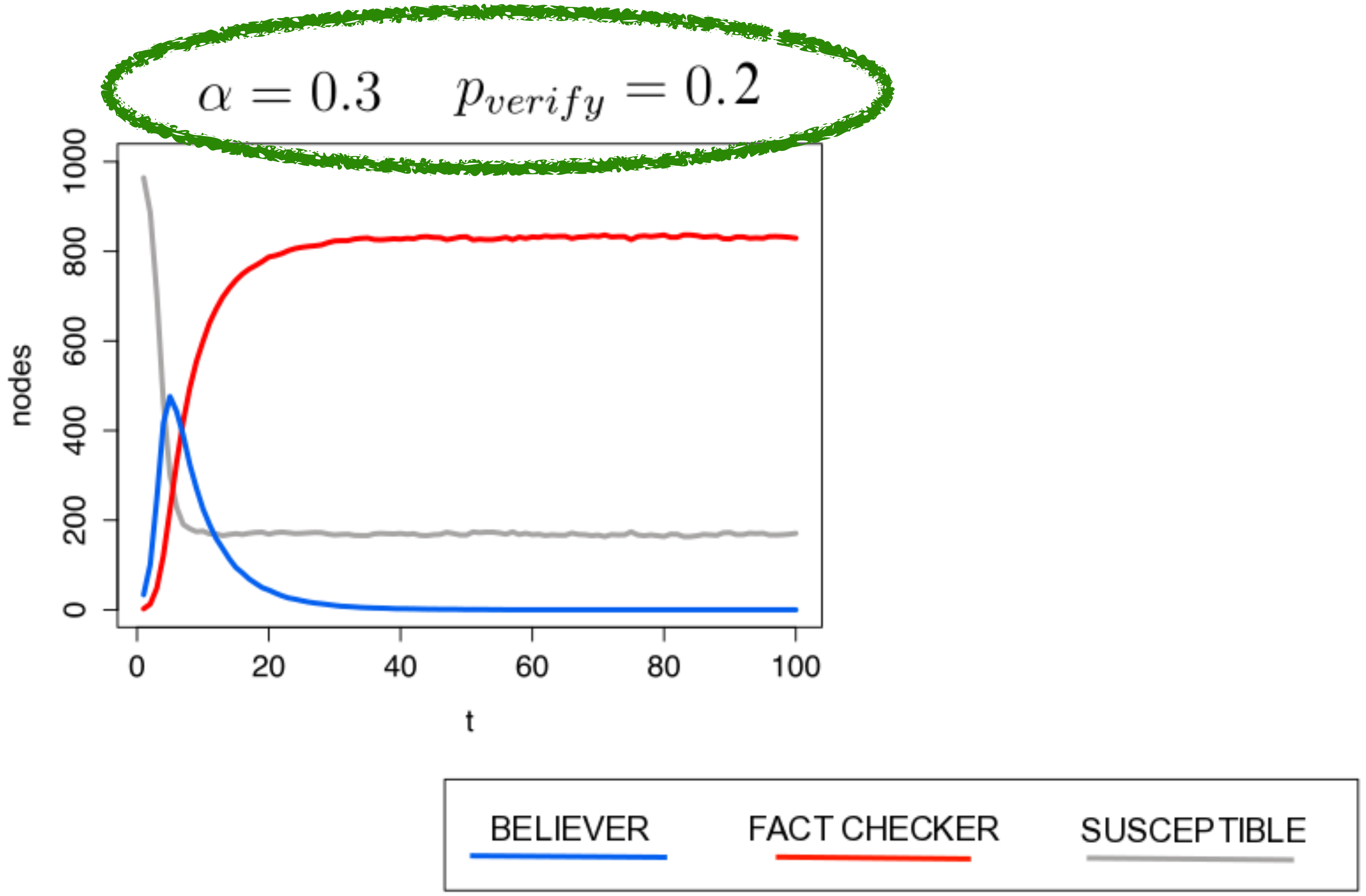
probability of fact-checking (or just deciding not to believe)

From Believer/Fact-Checker to Susceptible

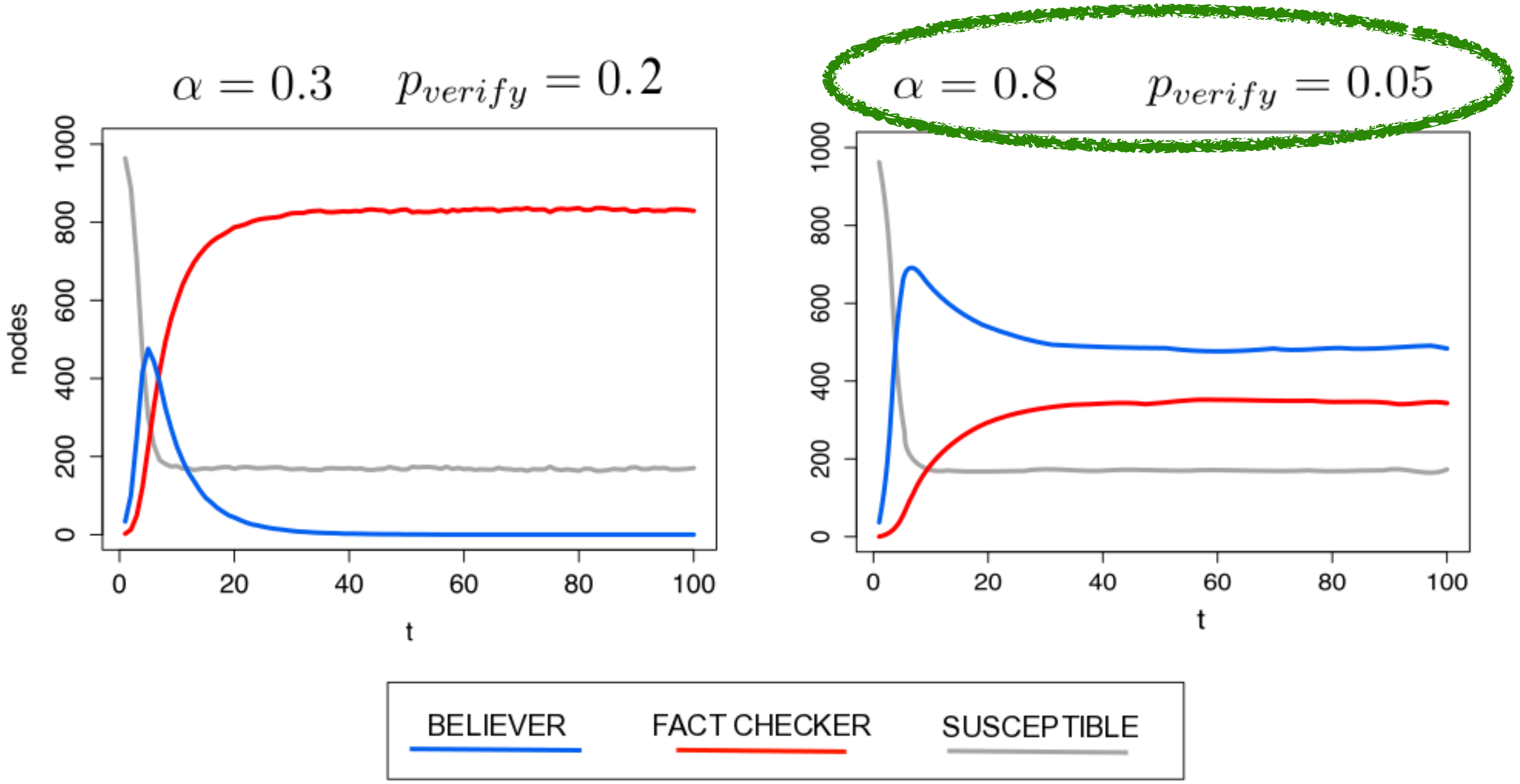


FORGETTING

Dynamics (agent-based simulations)



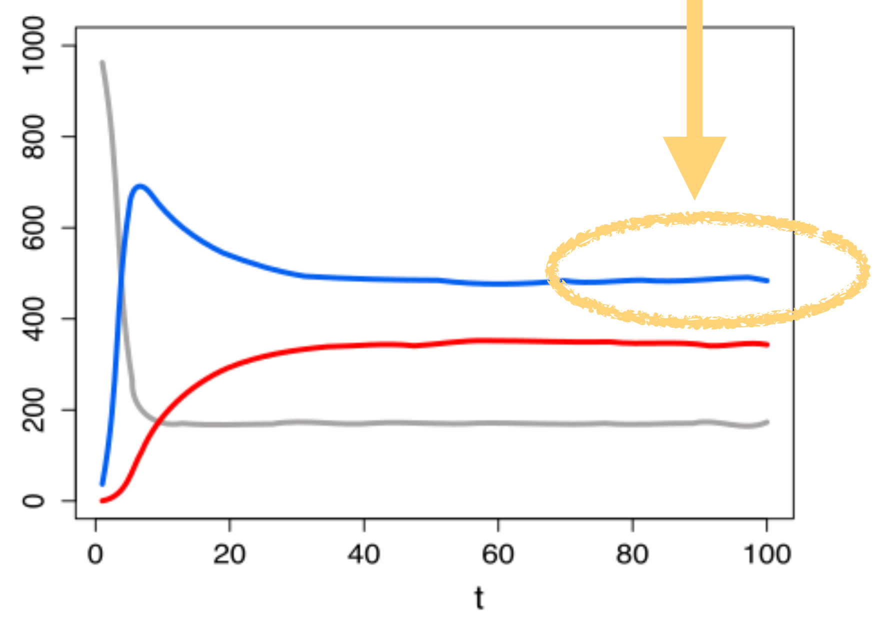
Dynamics (agent-based simulations)

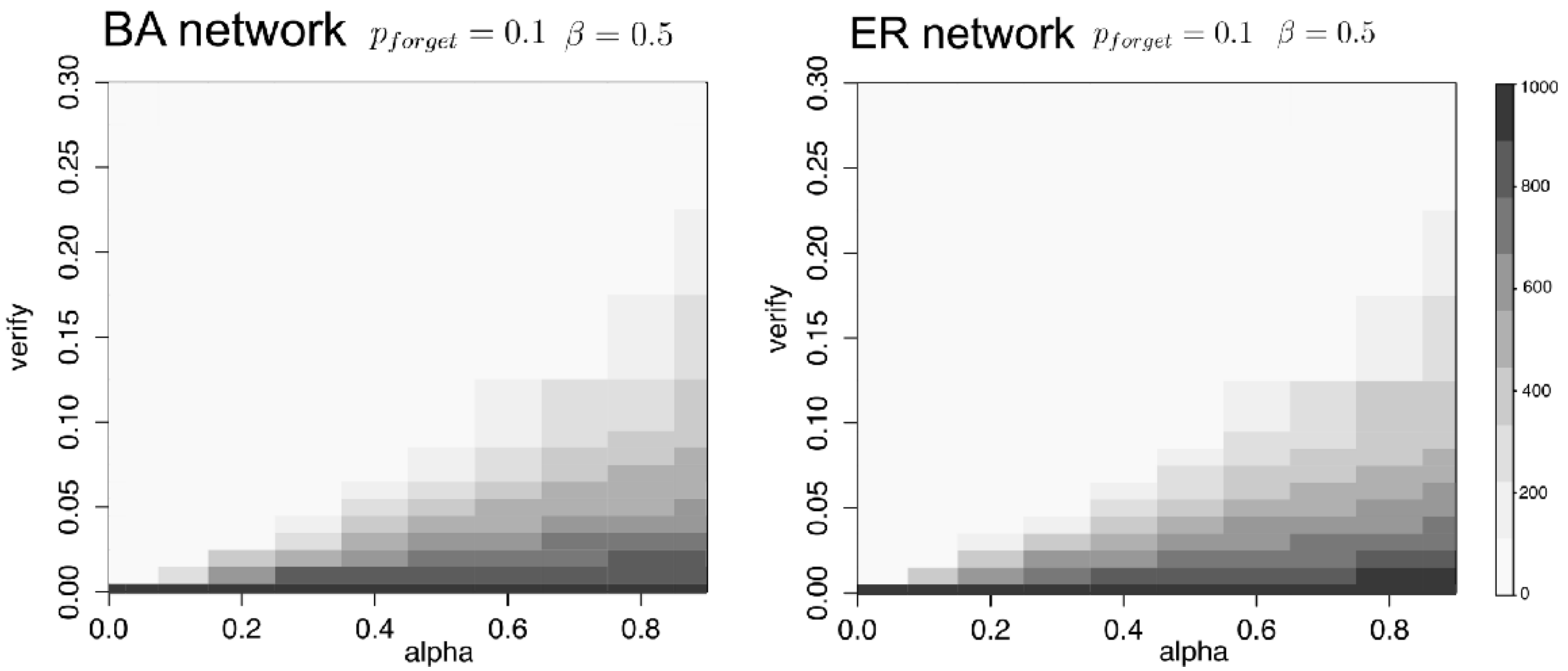


hoax **credibility** and **fact-checking probability** rule hoax persistence in the network

Dynamics (agent-based simulations)

number of 'believers' at the equilibrium





First step toward "good practices" understanding

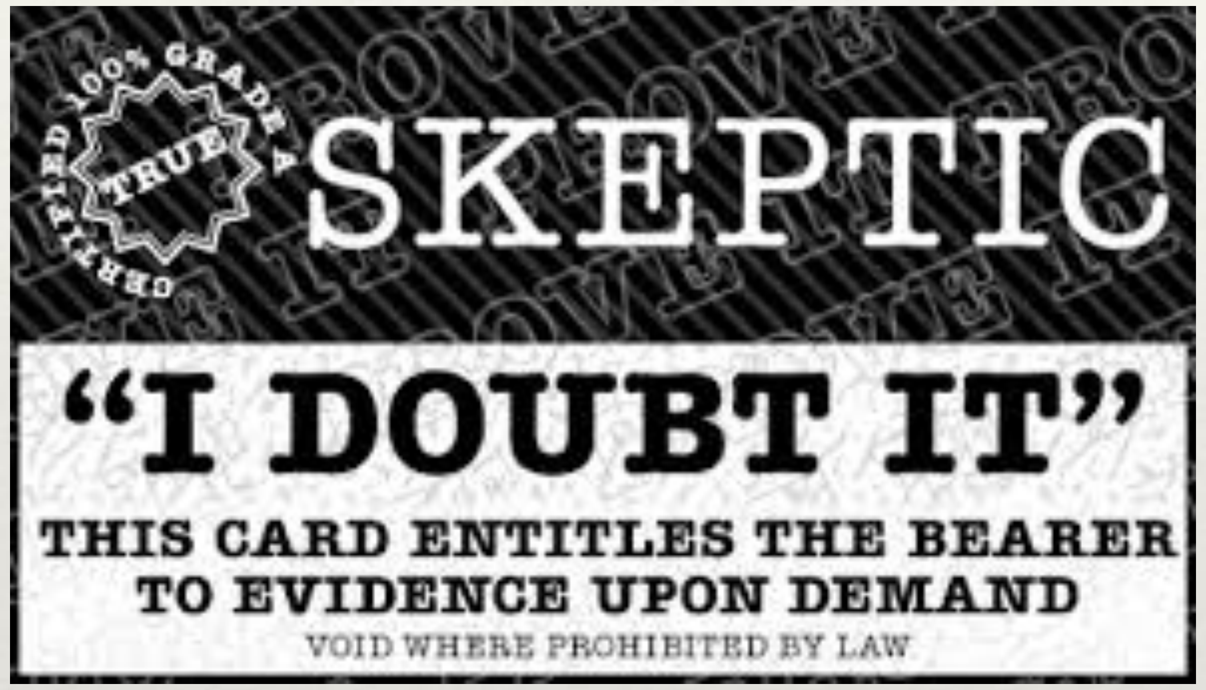
threshold on verifying probability: our model provides an idea of how many believers we need to convince to guarantee the removal of the hoax

M Tambuscio, G Ruffo, A Flammini, and F Menczer. 2015. Fact-checking Effect on Viral Hoaxes: A Model of Misinformation Spread in Social Networks. In Proc. of the 24th Int. Conf. on World Wide Web (WWW '15 Companion)

The role of segregation

Skeptical and gullible agents

let's tune **credibility** accordingly

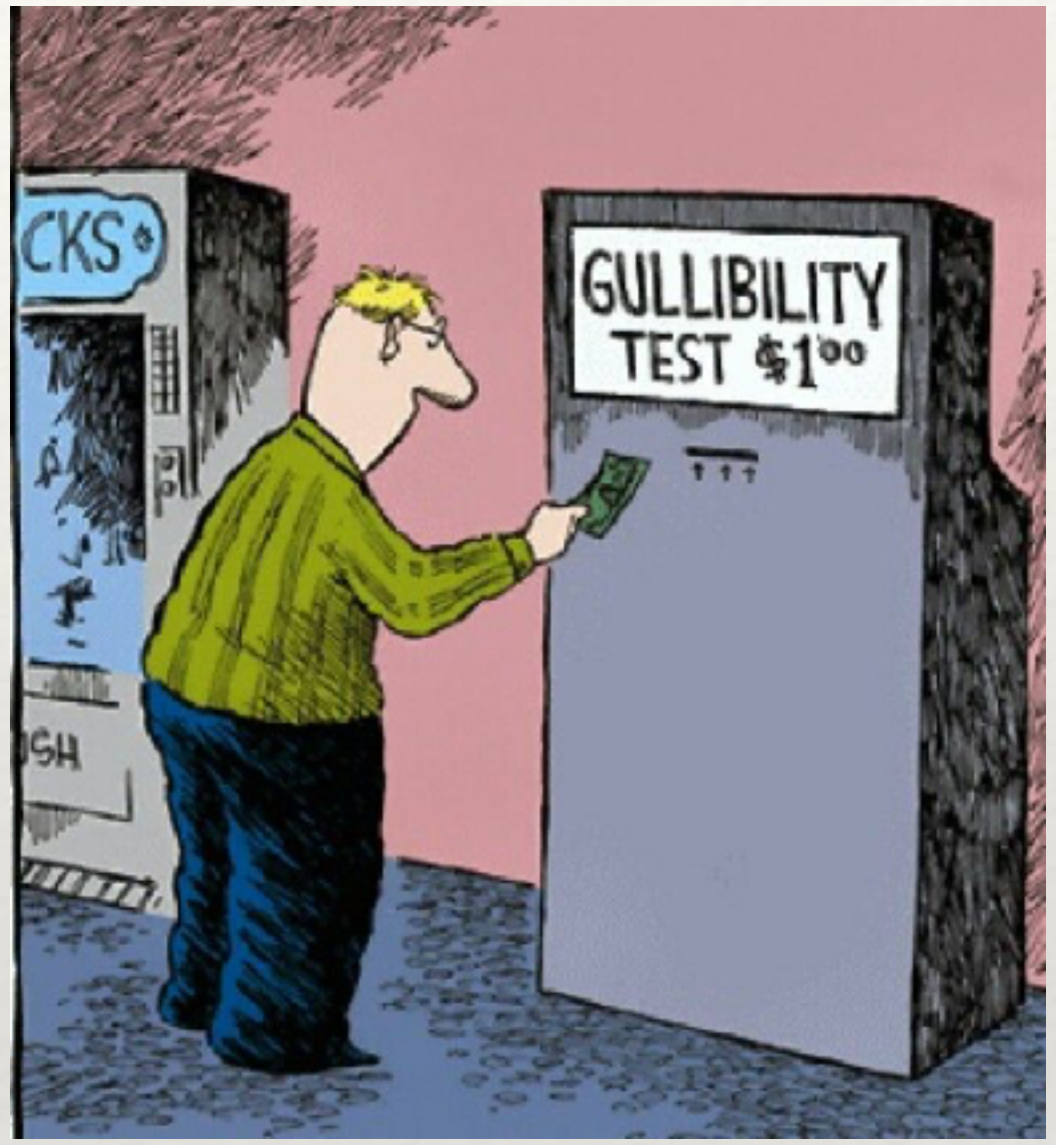


α

less credible — *more credible*

0 ⟷ 1

*more **skeptical*** — *more **gullible***



the propensity to believe is also a property of the node (**gullibility**)

What does it happen when skeptics and gullible agents are segregated?

Modeling two segregated communities

Skeptic

α **small**

size $(0 < \gamma < N)$

\# **nodes** in the gullible community

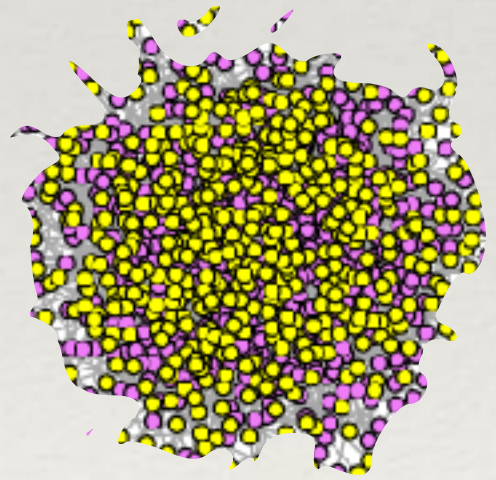
segregation $(0.5 < \mathbf{s} < 1)$

fraction of edges within same community

[Gu-Gu, Sk-Sk]

Gullible

α **large**

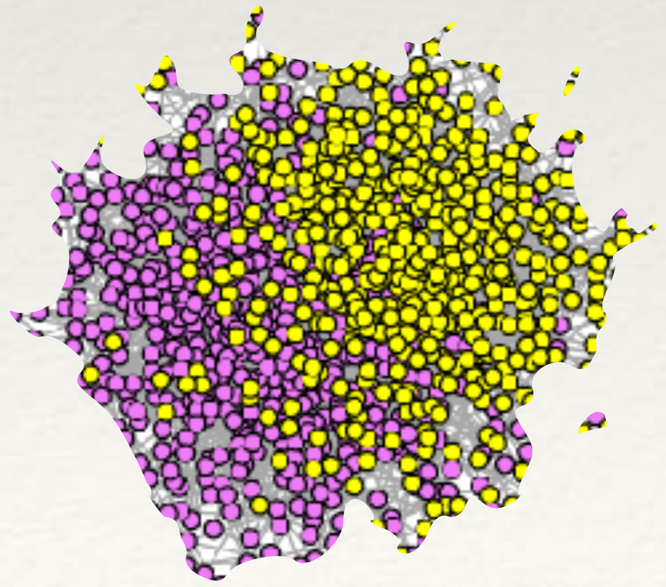


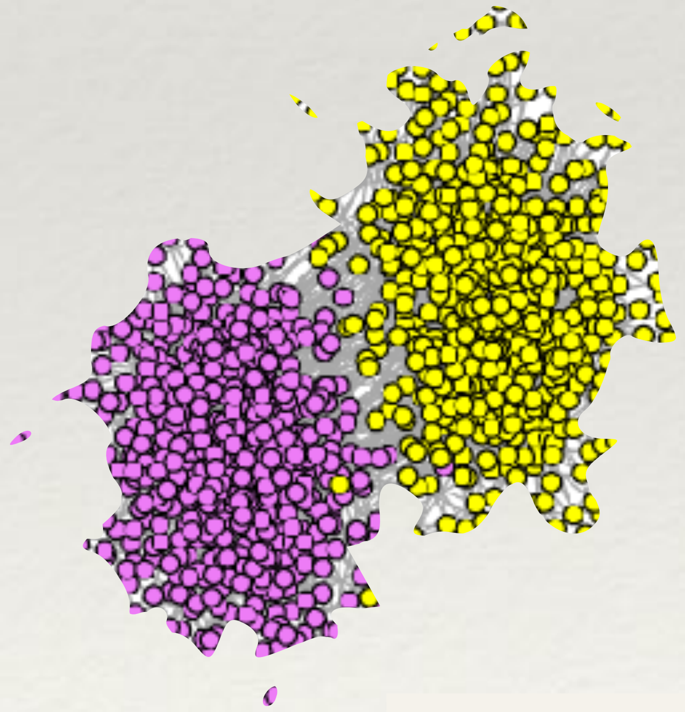
s=0.55

γ=500

s=0.8

γ=500



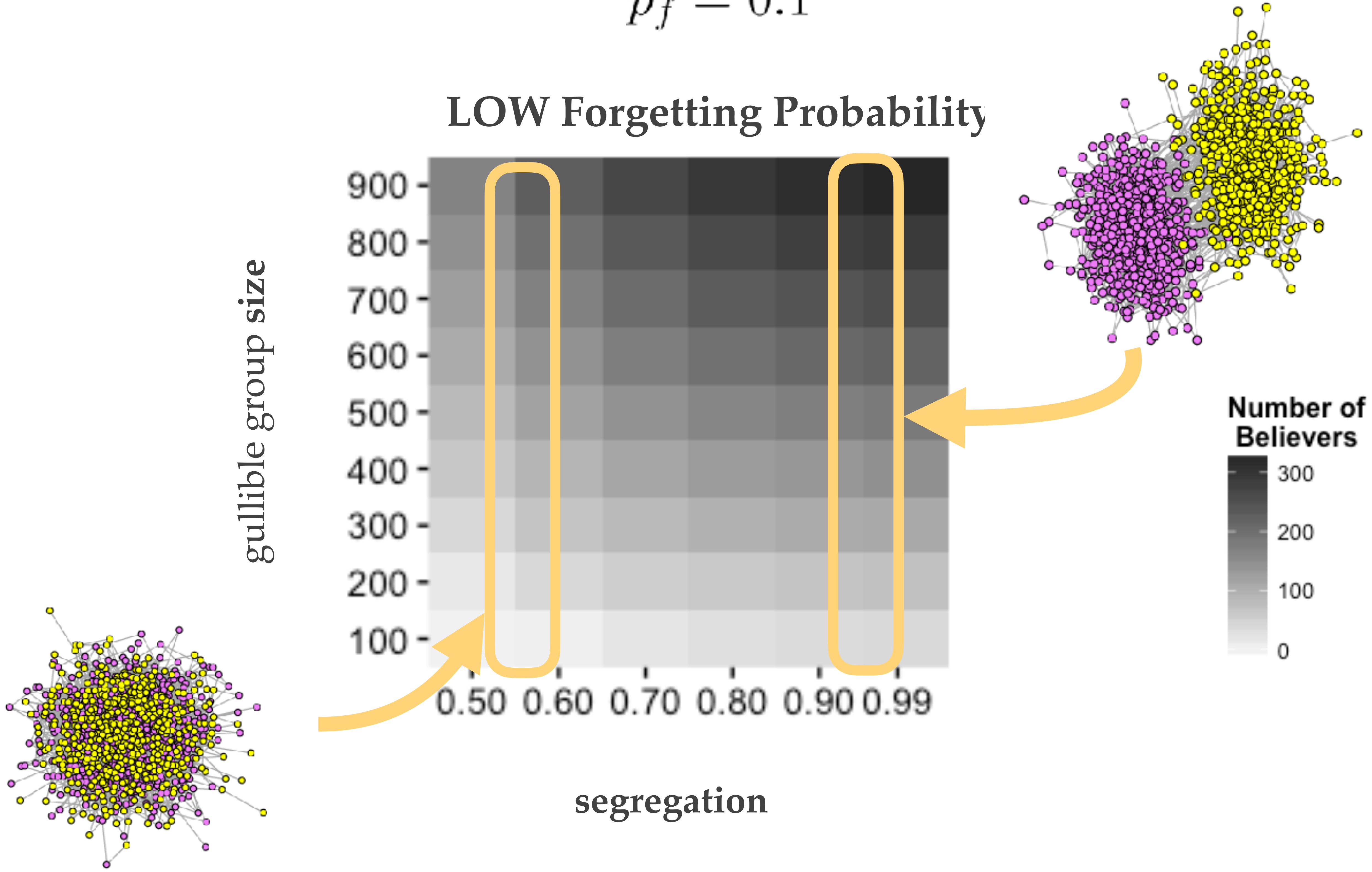


s=0.95

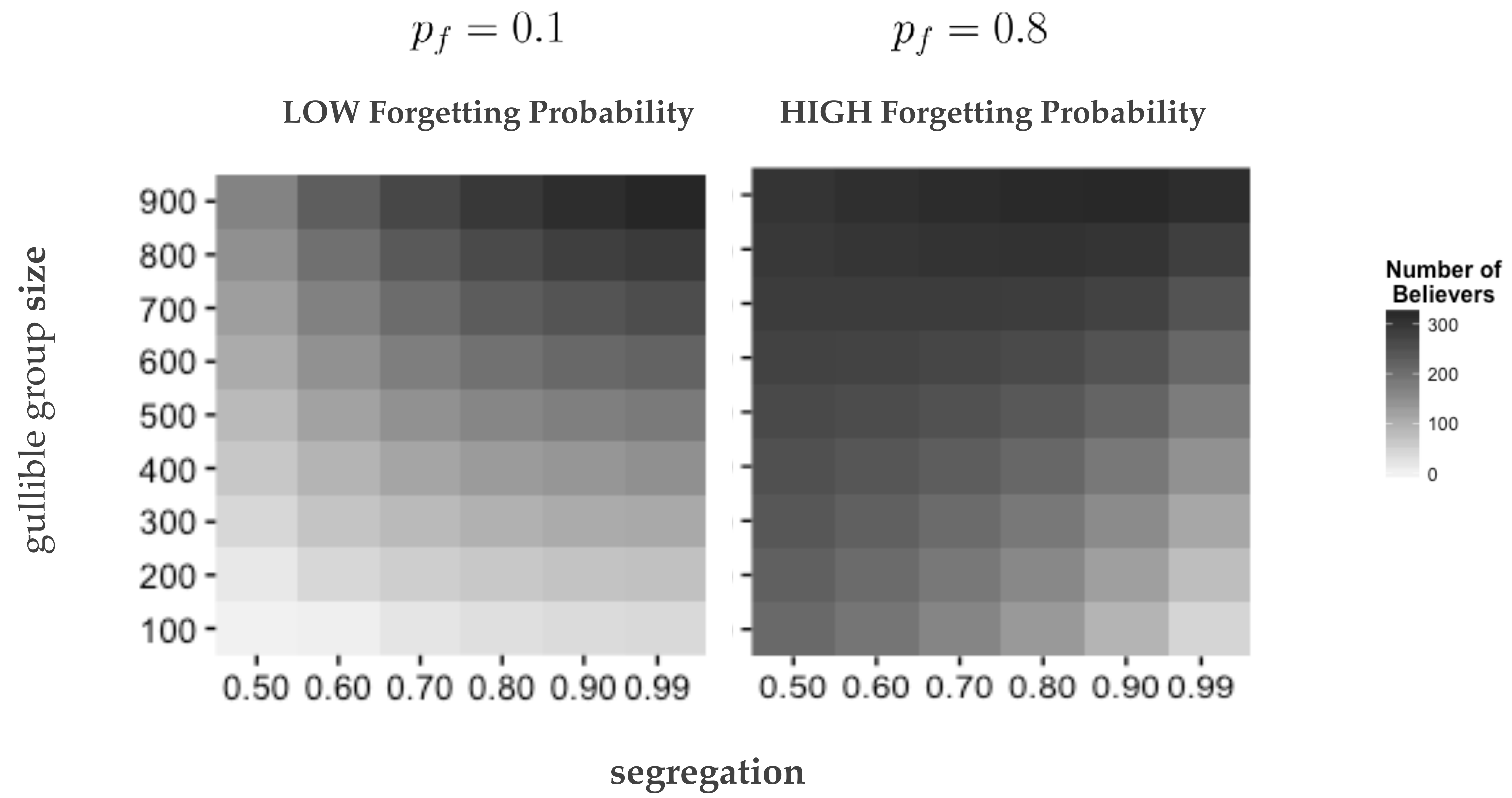
γ=500

Size vs segregation

$p_f = 0.1$



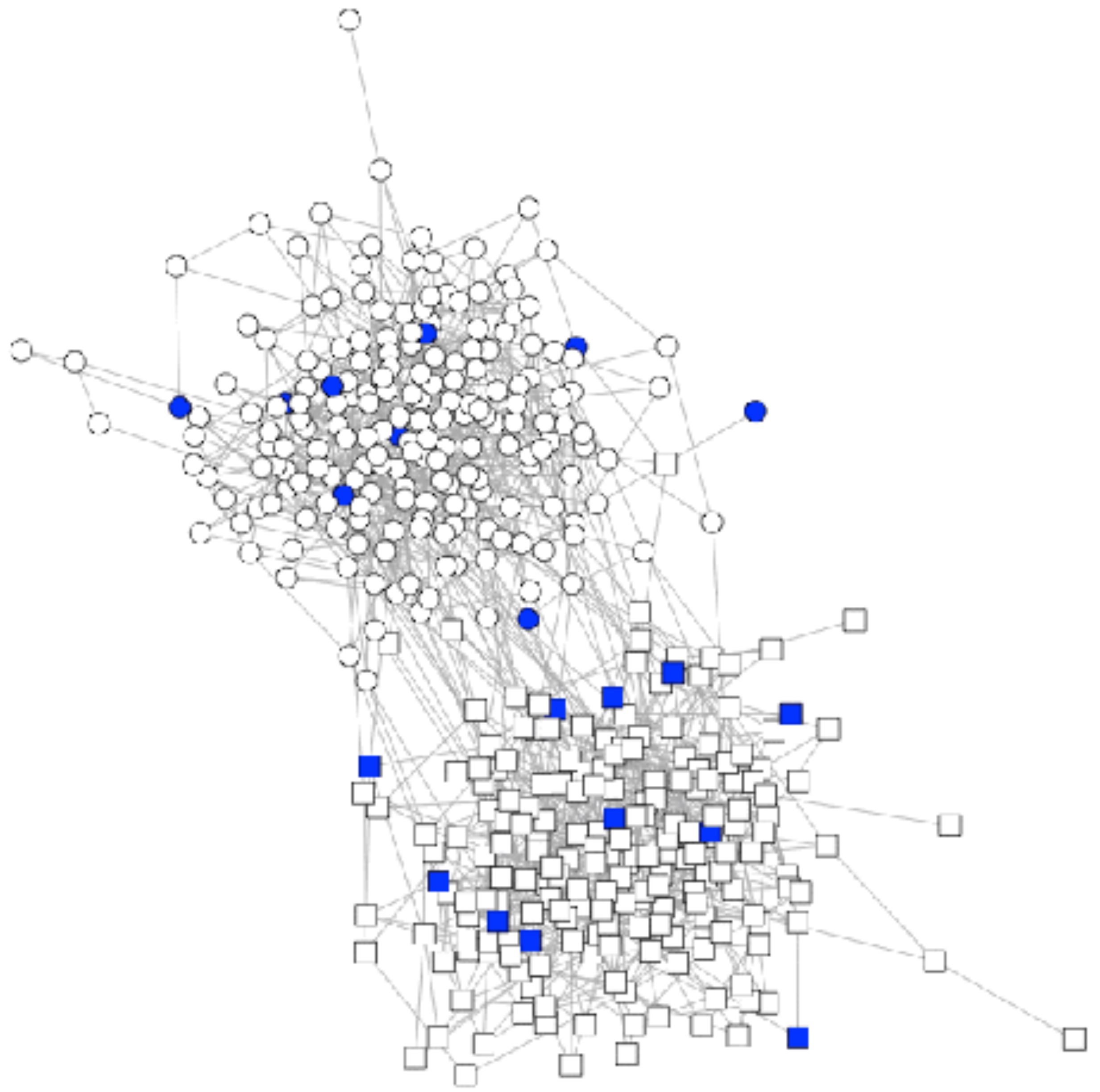
Size vs segregation



Role of forgetting

LOW Forgetting Rate

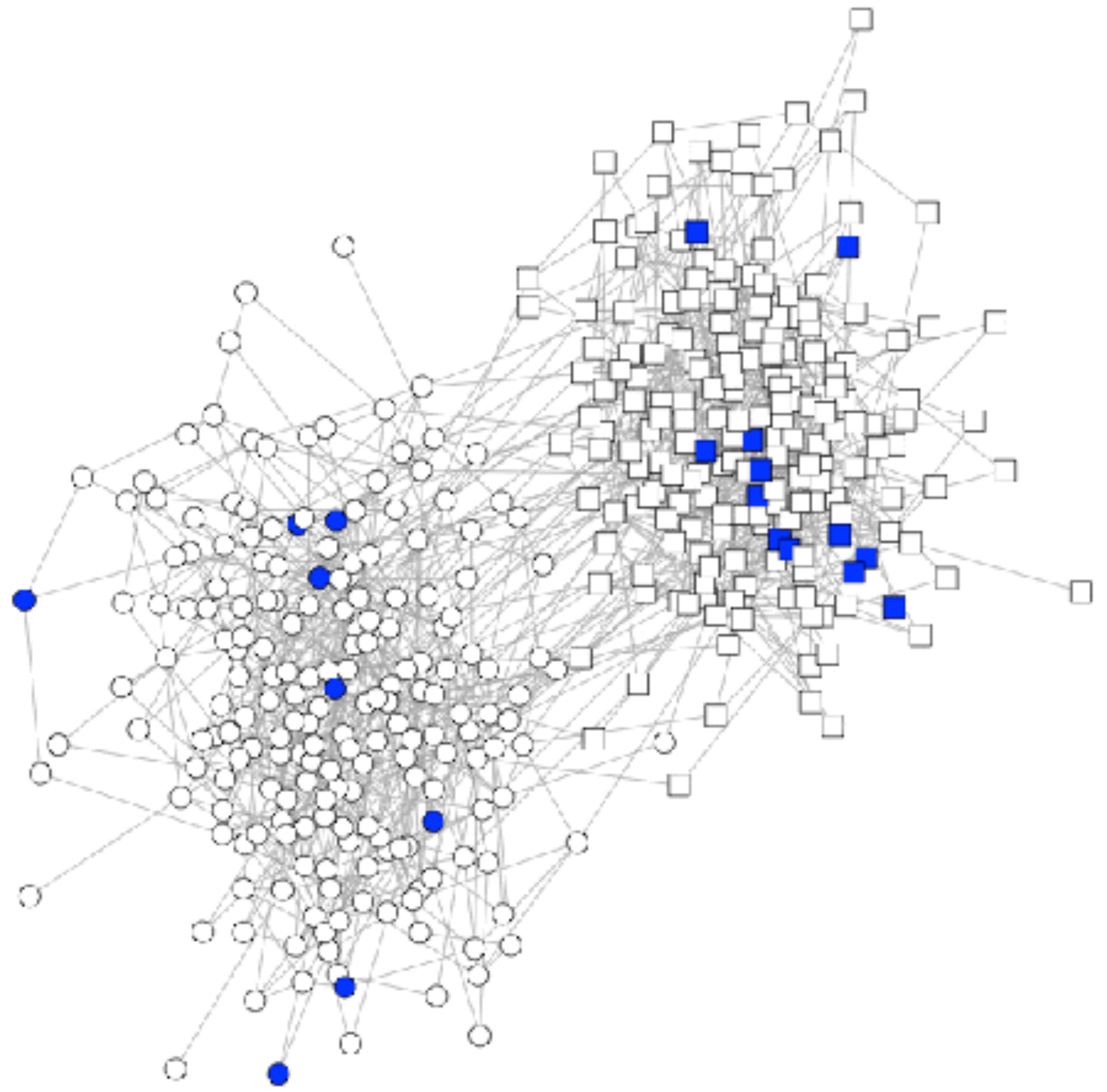
$p_f = 0.1$



Time = 1

HIGH Forgetting Rate

$p_f = 0.8$



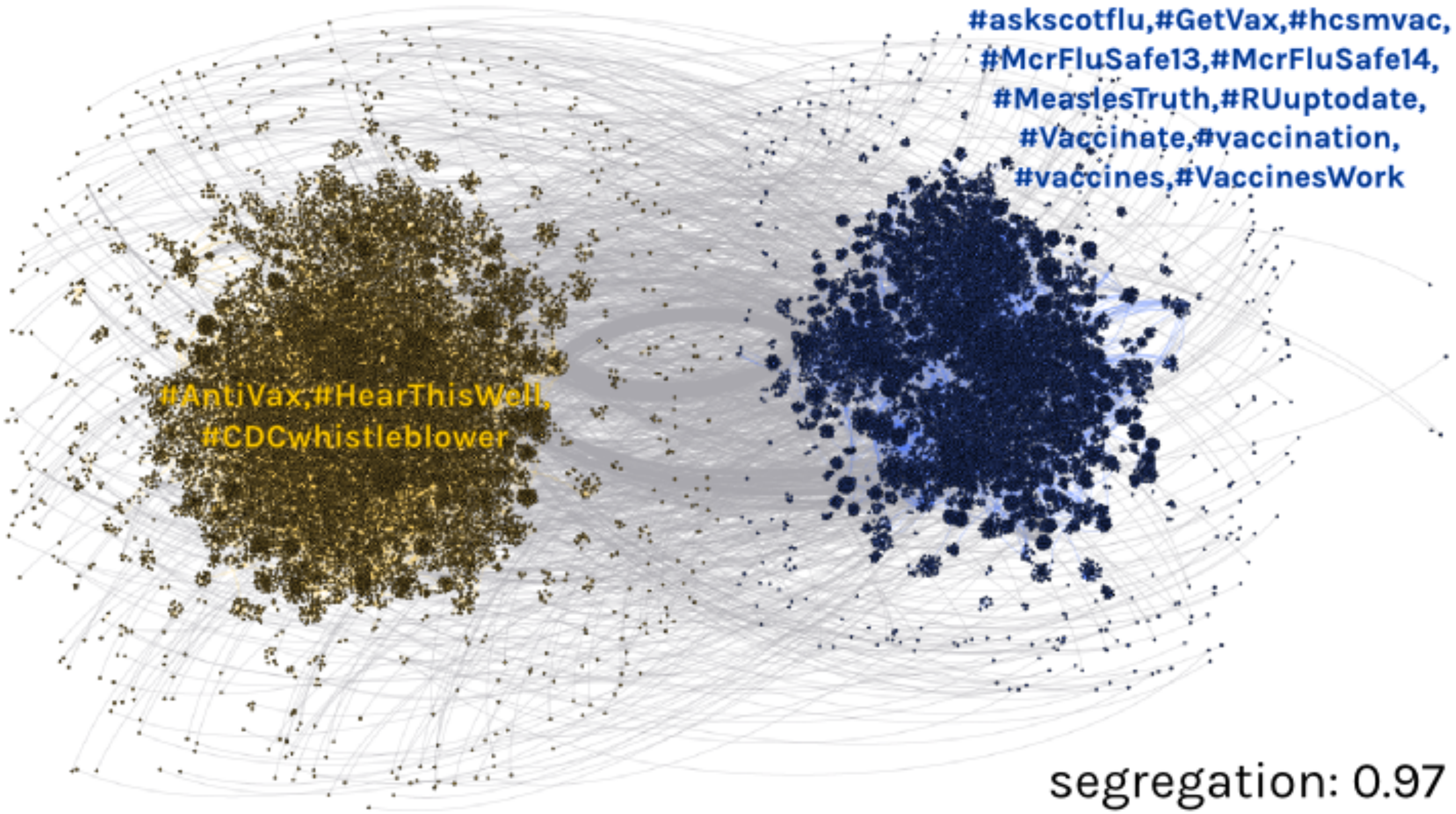
Time = 1

Lessons learned and observations

- We can use our model to study the fake-news diffusion process in **segregated community**
- **Complex contagion** is observed: interplay and not trivial outcomes
- **Forgetting** probability becomes relevant as well as the **level of segregation:**
  - **high forgetting** probability (e.g., just `normal' unfounded gossip) vanishes soon in **segregated communities**
  - **low forgetting** probability (e.g., conspiracy theories or partisanship beliefs) requires **low segregation**

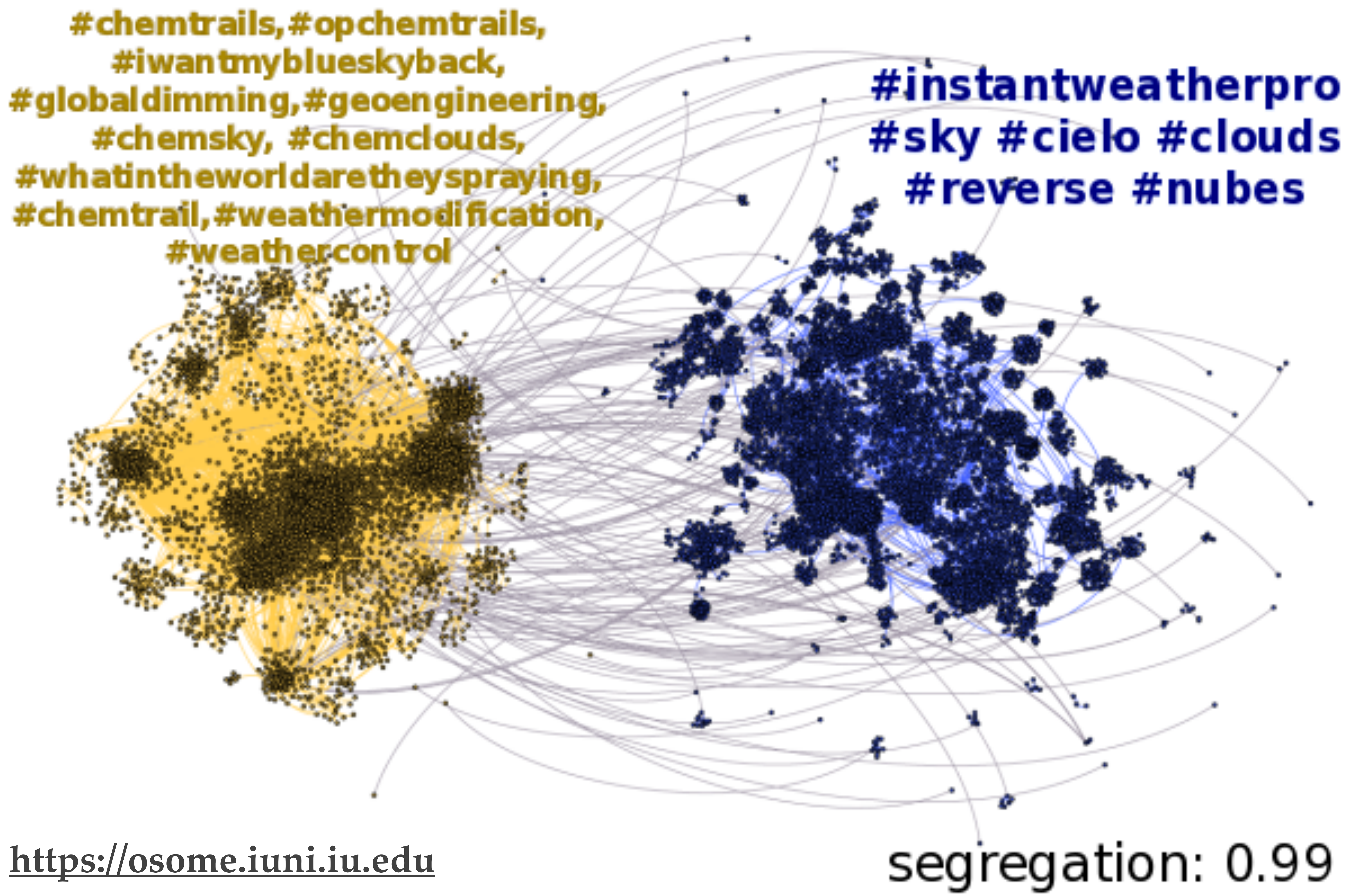
M Tambuscio, D F M Oliveira, G L Ciampaglia, G Ruffo, Network segregation in a model of misinformation and fact-checking, Journal of Computational Social Science (2018) 1: 261.

real data: vaccines



twitter data from IU https://osome.iuni.iu.edu

real data: chemtrails



twitter data from IU https://osome.iuni.iu.edu

Evaluating debunking strategies

What-if analysis

- We live in a **segregated** society: let's accept it!
- Misinformation can survive in the network for a long time: **low forgetting** probability
- **Computational epidemiology**: immunization works better if some node in the network (e.g., hubs, bridges) is vaccinated first
- **Where** to place fact-checkers?
- Stronger hypothesis: a believer do not verify ($\mathbf{p_{verify} = 0}$)
  - they can still forget
  - we can accept to leave half of the population in their own (false) beliefs, but we want at least to protect the skeptics!

Basic settings with no verification

Setting

segregation: 0.92 (high)

forgetting: 0.1 (low)

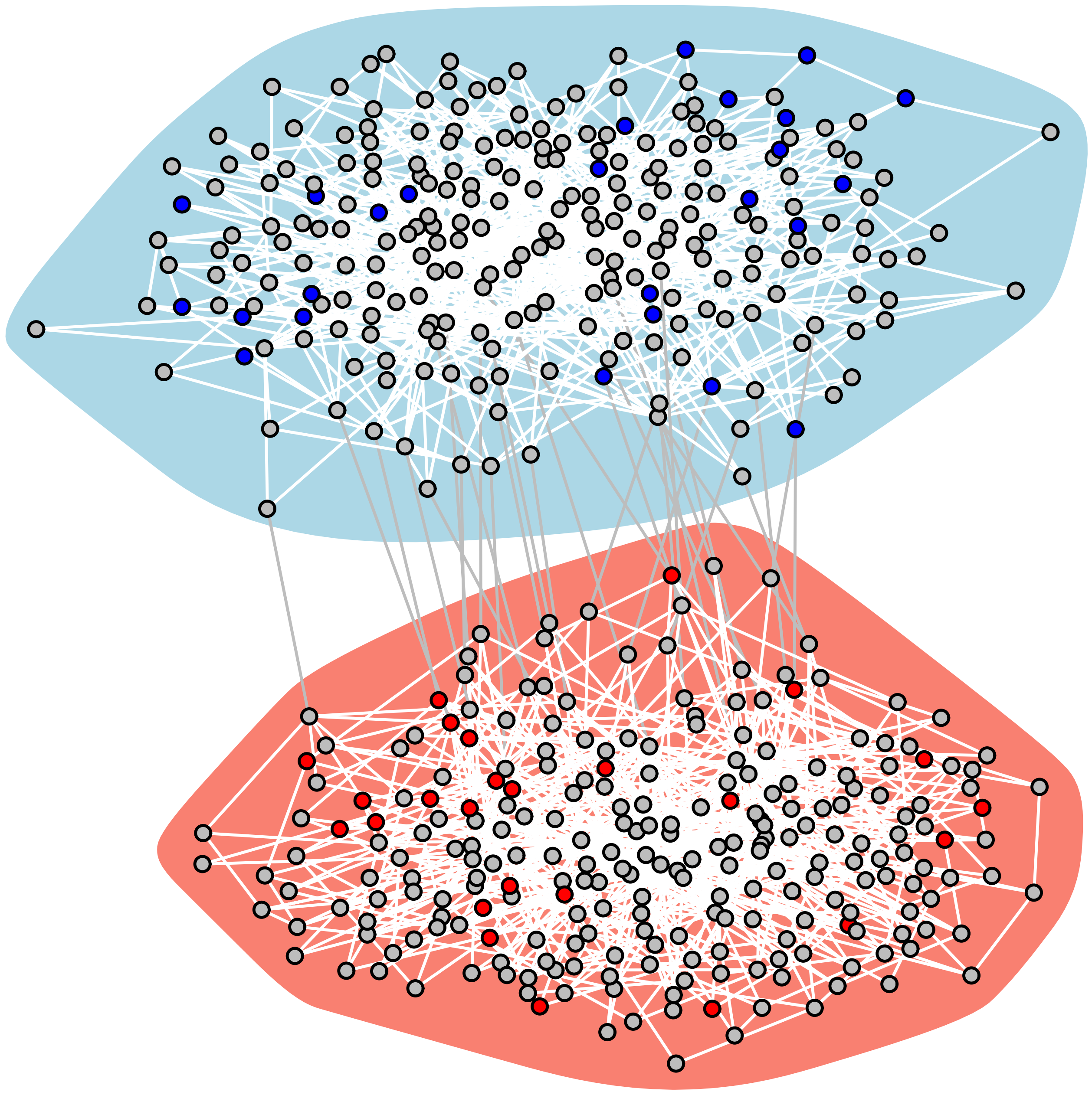
gullible group:

- α: 0.8
- seeders B: 10%

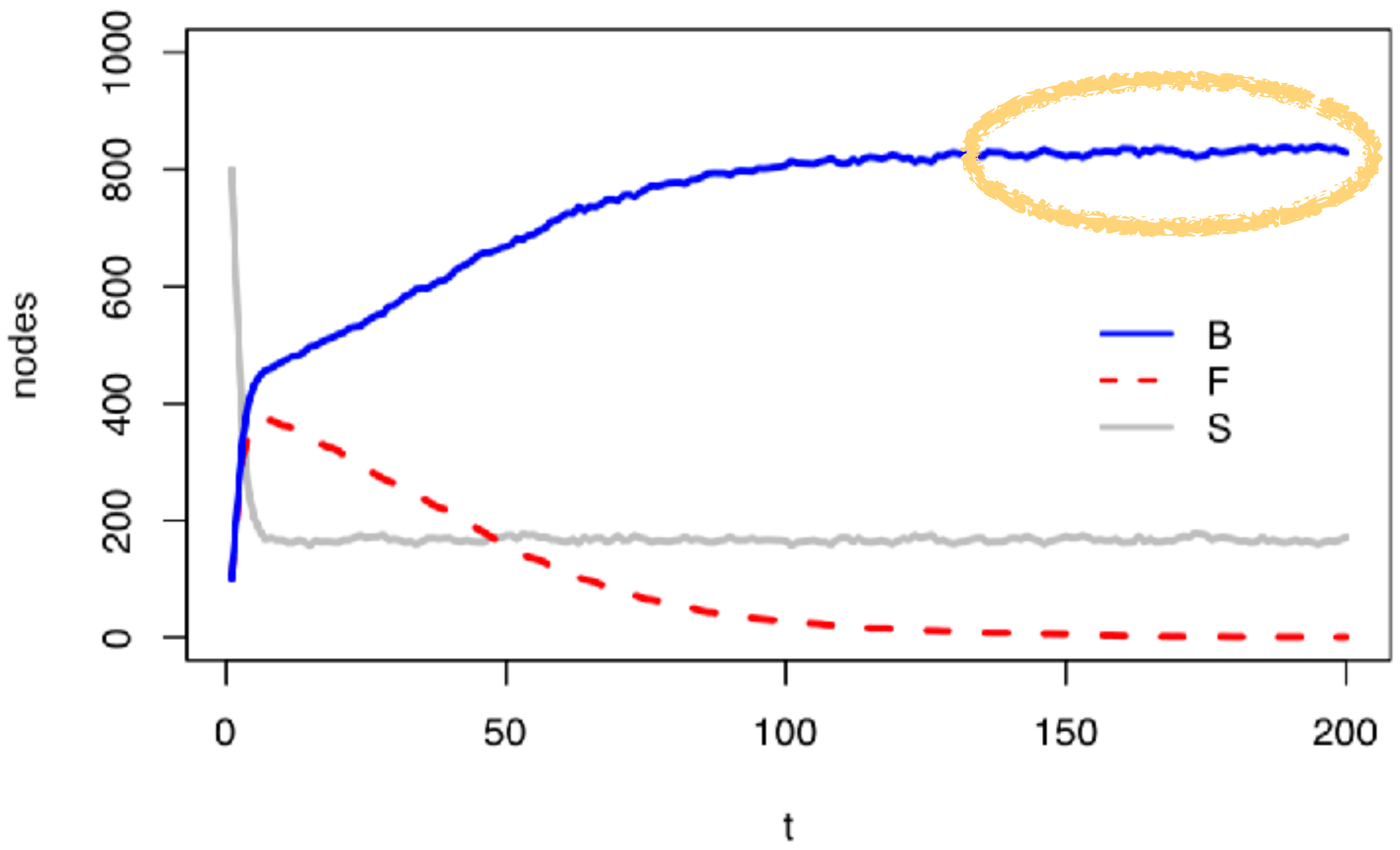
skeptical group:

- α: 0.3
- seeders FC: 10%

Simulation start



Simulation results



As expected: very **bad**!

Eternal fact-checkers placed at random

Setting

segregation: 0.92 (high)

forgetting: 0.1 (low)

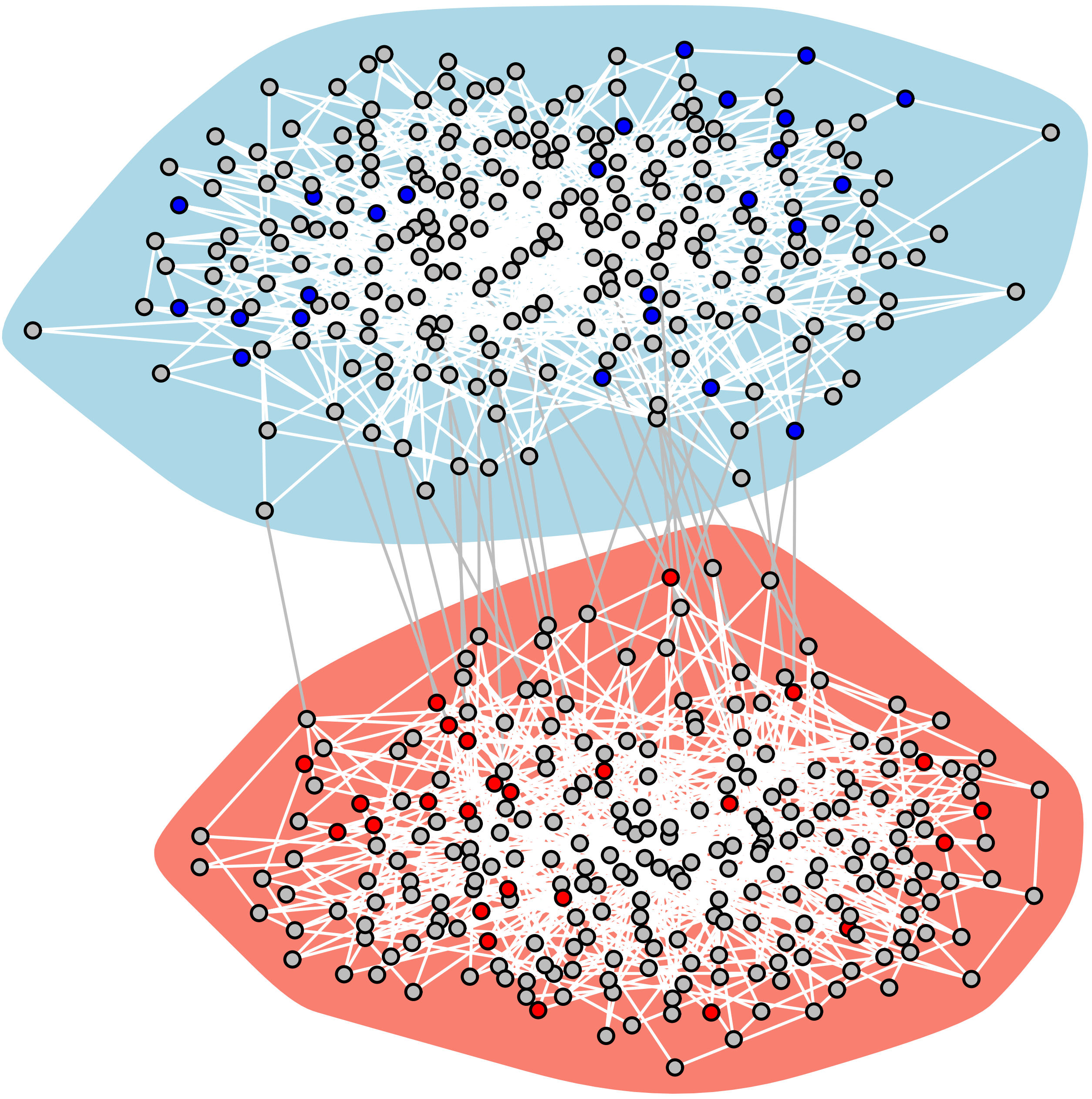
gullible group:

- α: 0.8
- seeders B: 10%

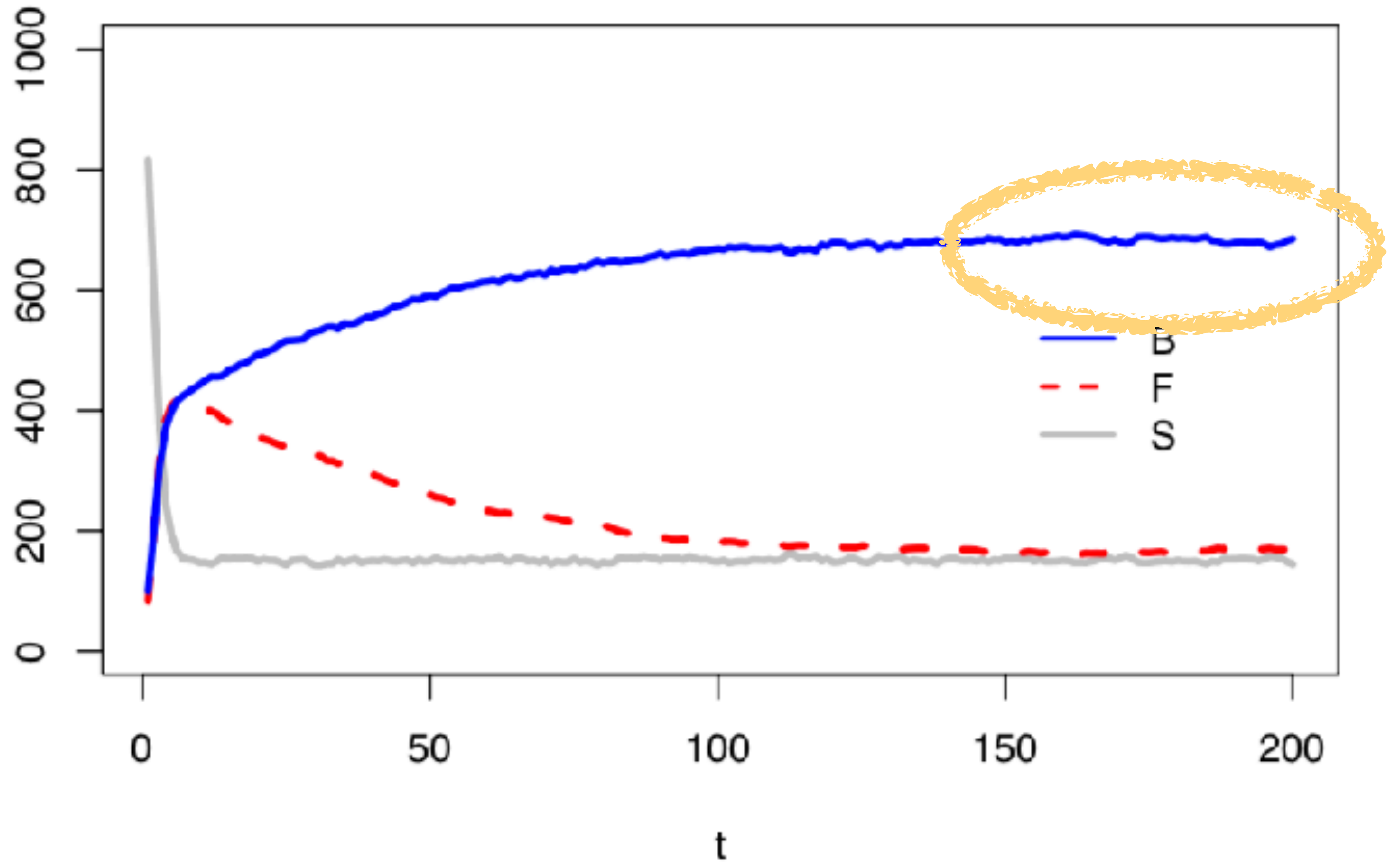
skeptical group:

- α: 0.3
- ~~seeders FC: 10%~~
- **seeders are eFC**

Simulation start



Simulation results



better, but still…

Hubs as eternal fact-checkers

Setting

segregation: 0.92 (high)

forgetting: 0.1 (low)

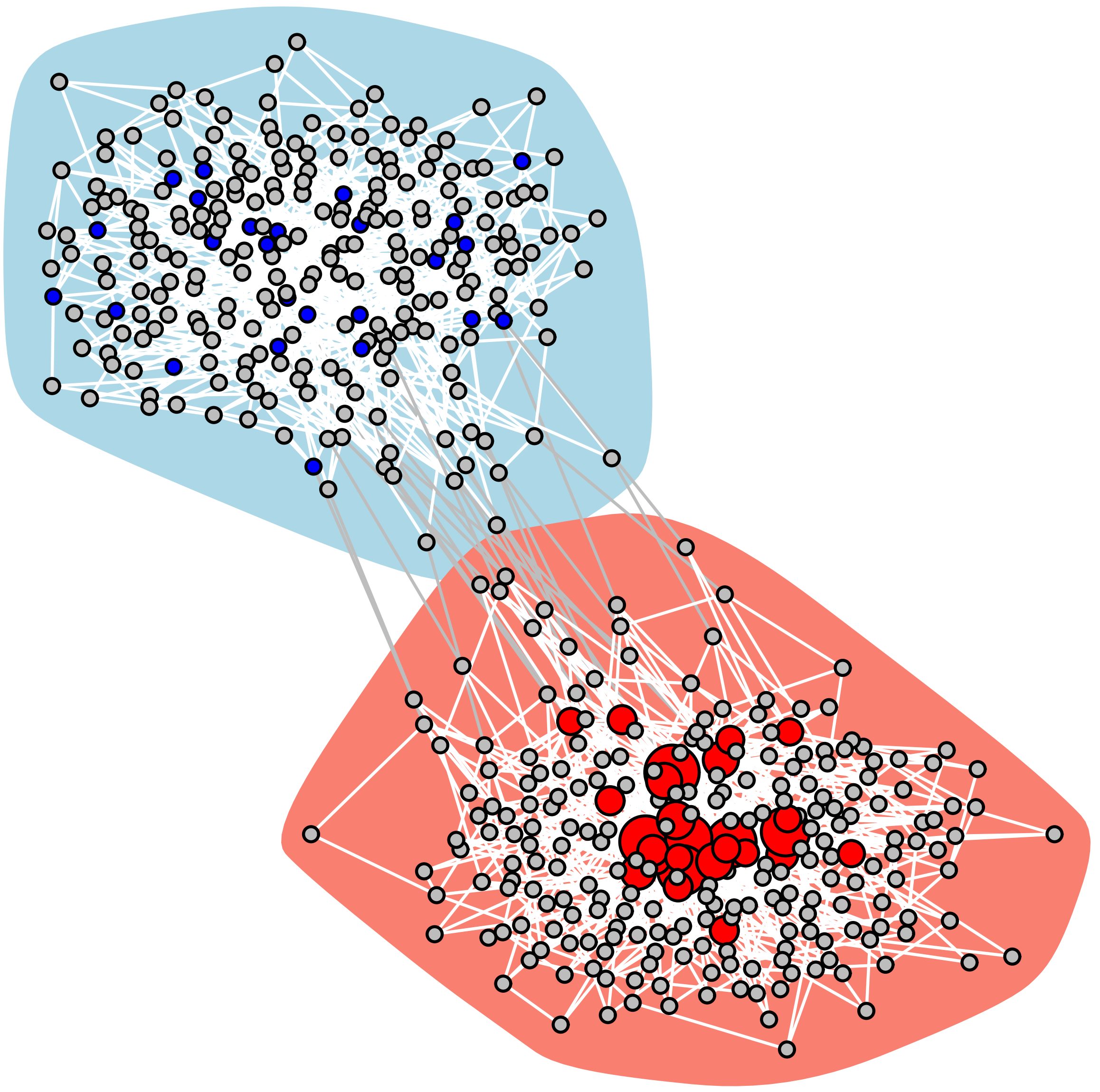
gullible group:

- α: 0.8
- seeders B: 10%

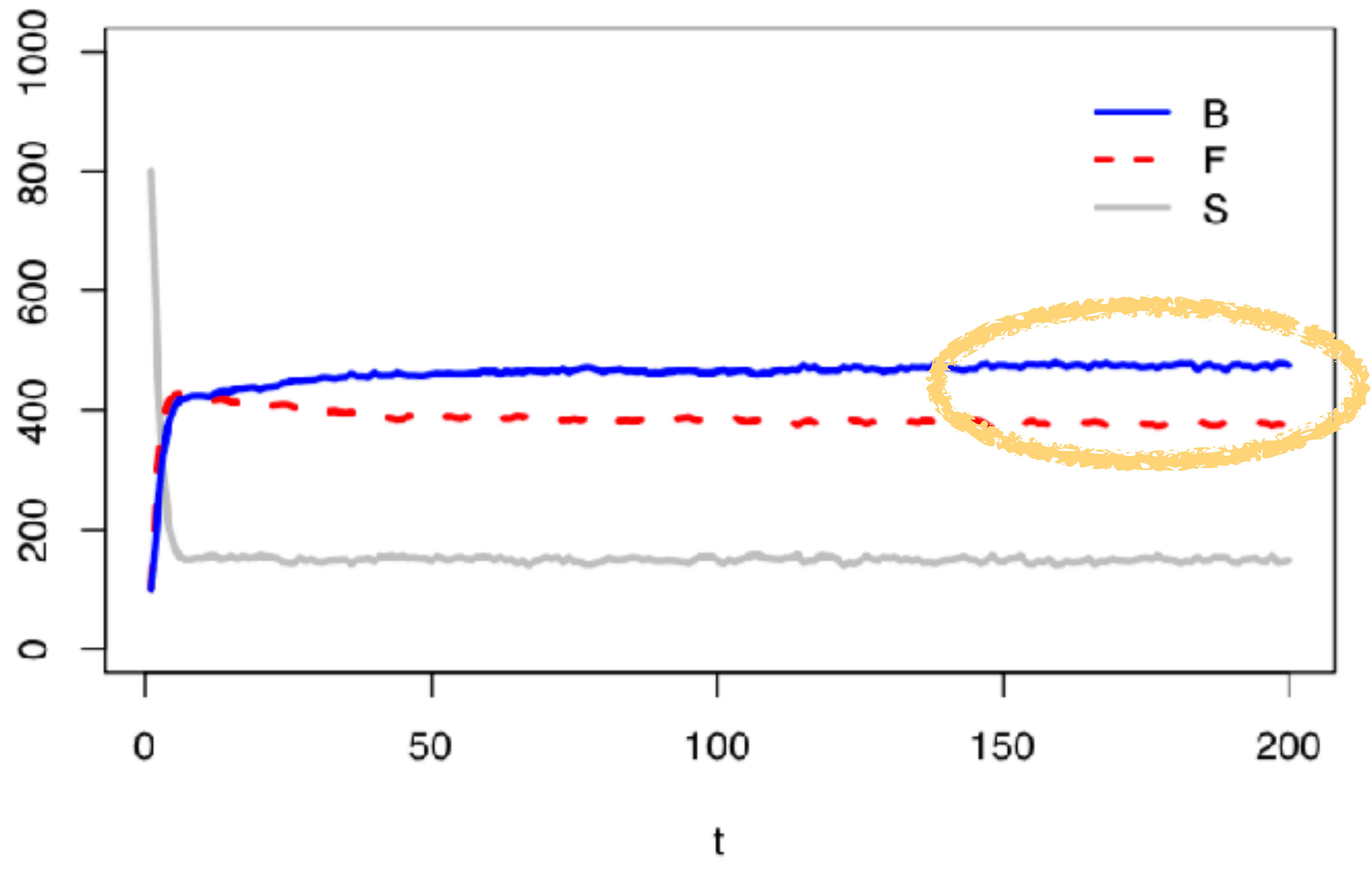
skeptical group:

- α: 0.3
- seeders FC: 10%
- **HUBS are eFC!**

Simulation start



Simulation results



better

Bridges as eternal fact-checker

Setting

segregation: 0.92 (high)

forgetting: 0.1 (low)

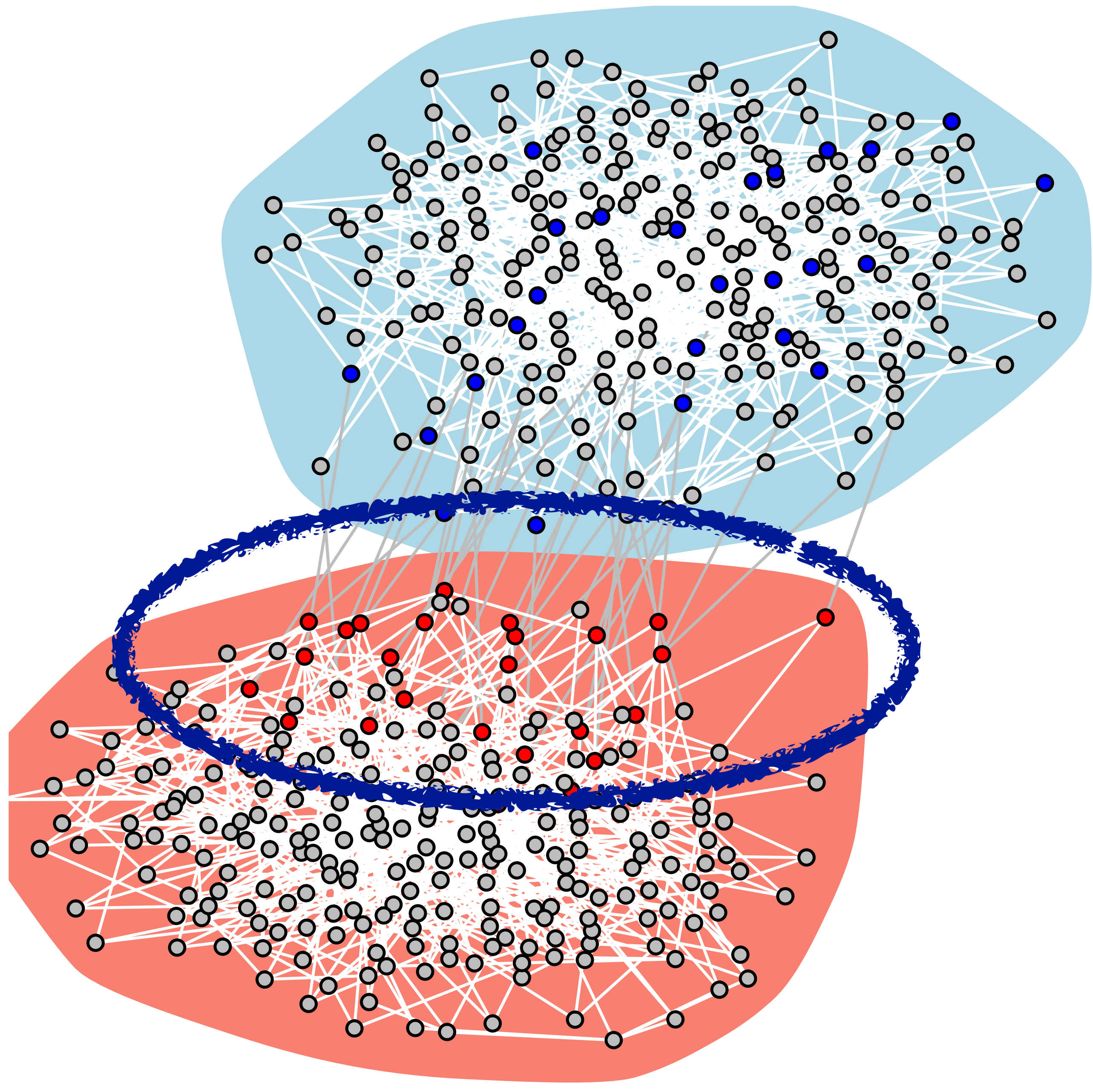
gullible group:

- α: 0.8
- seeders B: 10%

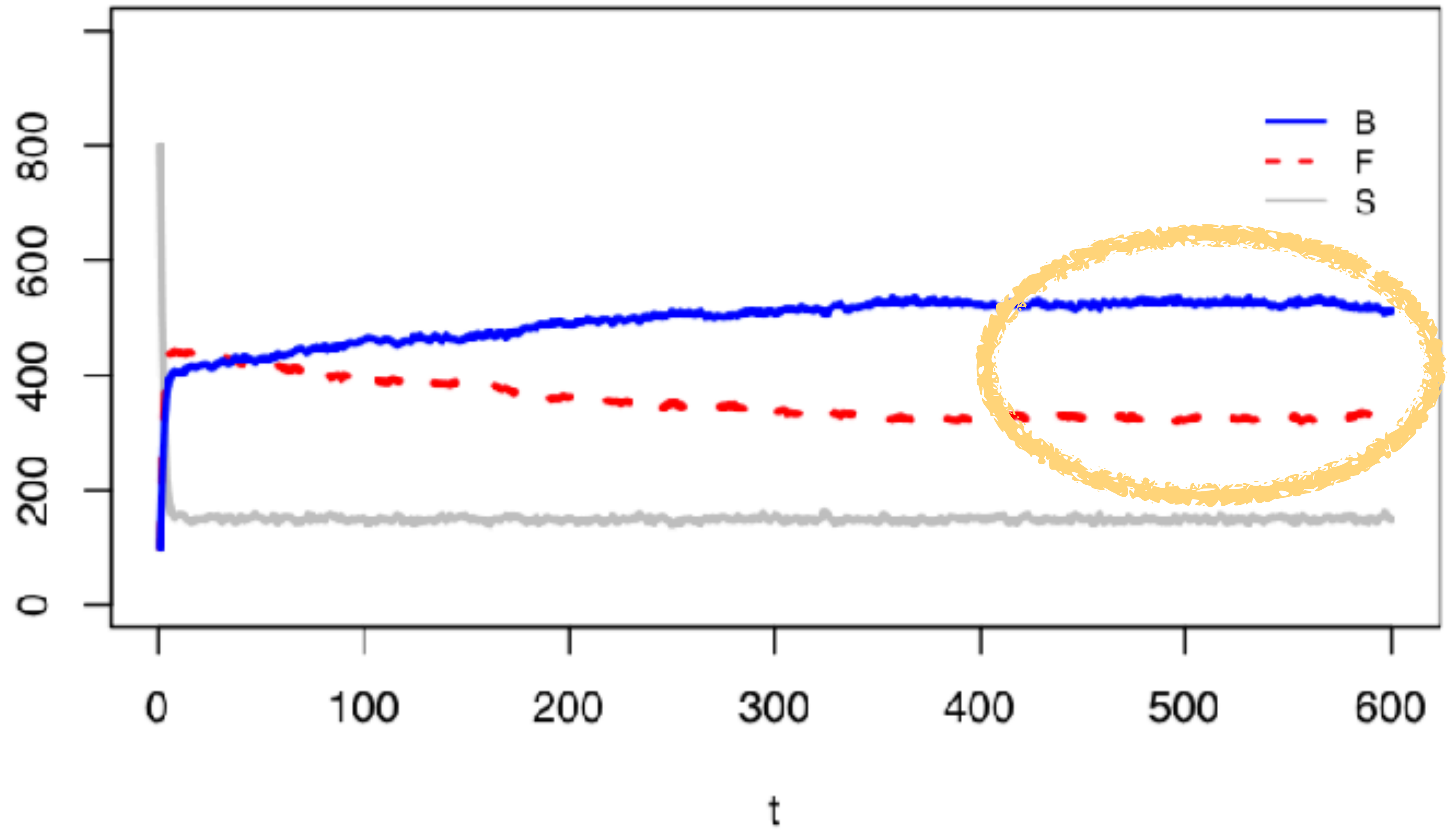
skeptical group:

- α: 0.3
- ~~seeders FC: 10%~~
- **BRIDGES are eFC!**

Simulation start



Simulation results



comparable, more realistic

Lessons learned and observations

- **Debunking activism** is often considered useless or **counterproductive**
- However, a world without fact-checking is harmless against fake-news circulation: **skeptics exposed to misinformation** will turn into **believers** because of **social influence**
- **Skeptics with links to gullible subjects** should be the first to be exposed to the fact-checking: misinformation will survive in the network, but their communities can be 'protected' by such **gatekeepers**
- Note: no socio-psychological assumption so far. Real world is much more complicated

M Tambuscio, G. Ruffo, Fact-checking strategies to limit urban legends spreading in a segregated society, in Applied Network Science 4, 116 (2019), Springer, https://appliednetsci.springeropen.com/articles/10.1007/s41109-019-0233-1

protect the vulnerable, encourage skepticism

Who is the gatekeeper?

Finland is reported as winning the war against fake news in the classrooms: **education** first

Teachers and the education system have a great **responsibility**

CNN

SPECIAL REPORT

Finland is winning the war on fake news. What it's learned may be crucial to Western democracy

By Eliza Mackintosh, CNN
Video by Edward Kiernan, CNN

Helsinki, Finland (CNN) – On a recent afternoon in Helsinki, a group of students gathered to hear a lecture on a subject that is far from a staple in most community college curriculums.

Standing in front of the classroom at Espoo Adult Education Centre, Jussi Toivanen worked his way through his PowerPoint presentation. A slide titled "Have you been hit by the Russian troll army?" included a checklist of methods used to deceive readers on social media: image and video manipulations, half-truths, intimidation and false profiles.