Image: James Gillray (1802)

Individual vaccination decisions based on local information can lead to optimal public health outcomes

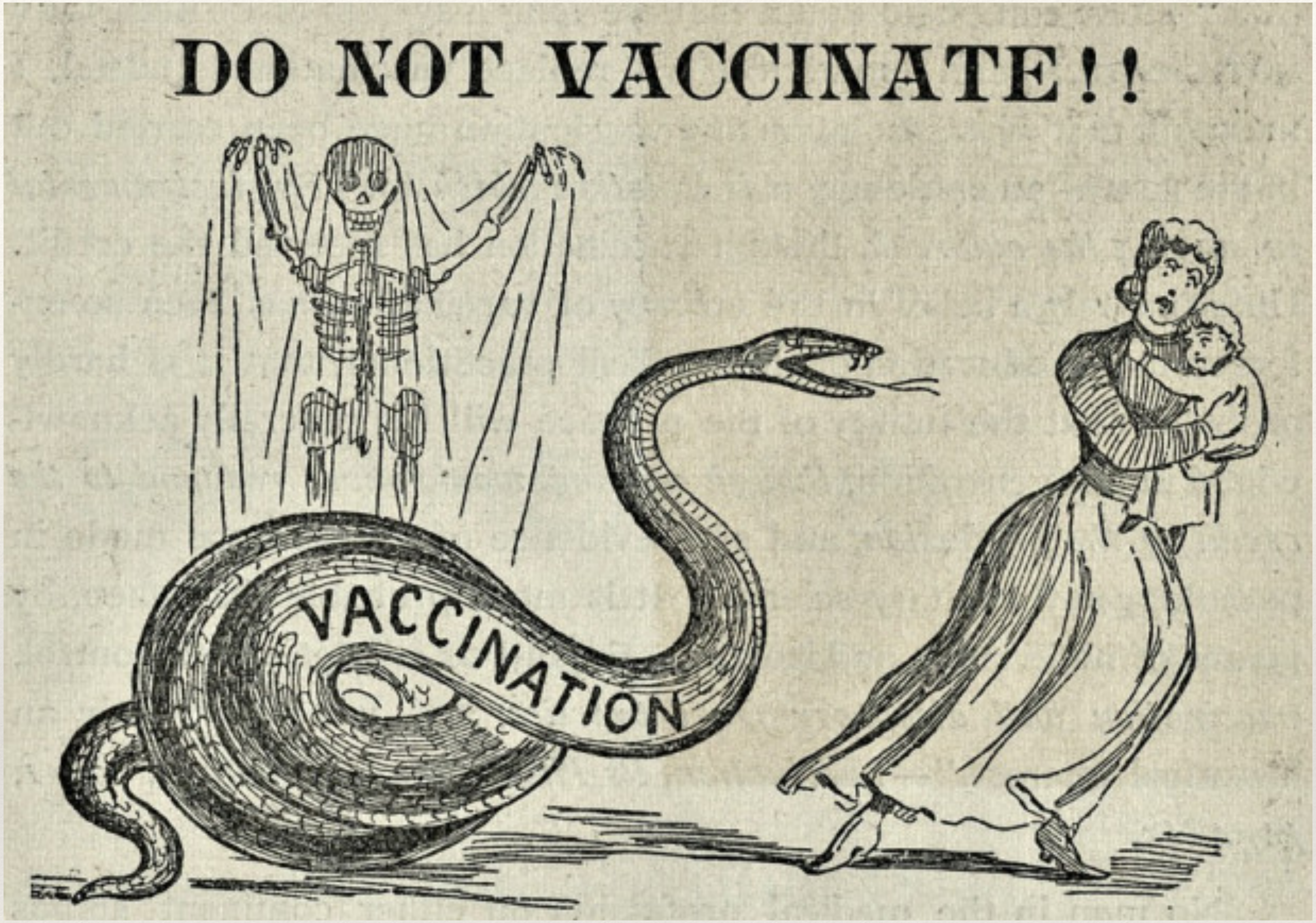
Shakti N. Menon

The Institute of Mathematical Sciences, Chennai, India

18th May 2019

Summer Research Program on Dynamics of Complex Systems (DCS2019)

Image: https://www.historyofvaccines.org



PART ONE

Vaccine Hesitancy

WHO: "Ten threats to global health in 2019"

Vaccine hesitancy

Vaccine hesitancy – the reluctance or refusal to vaccinate despite the availability of vaccines – threatens to reverse progress made in tackling vaccine-preventable diseases. Vaccination is one of the most cost-effective ways of avoiding disease – it currently prevents 2-3 million deaths a year, and a further 1.5 million could be avoided if global coverage of vaccinations improved.

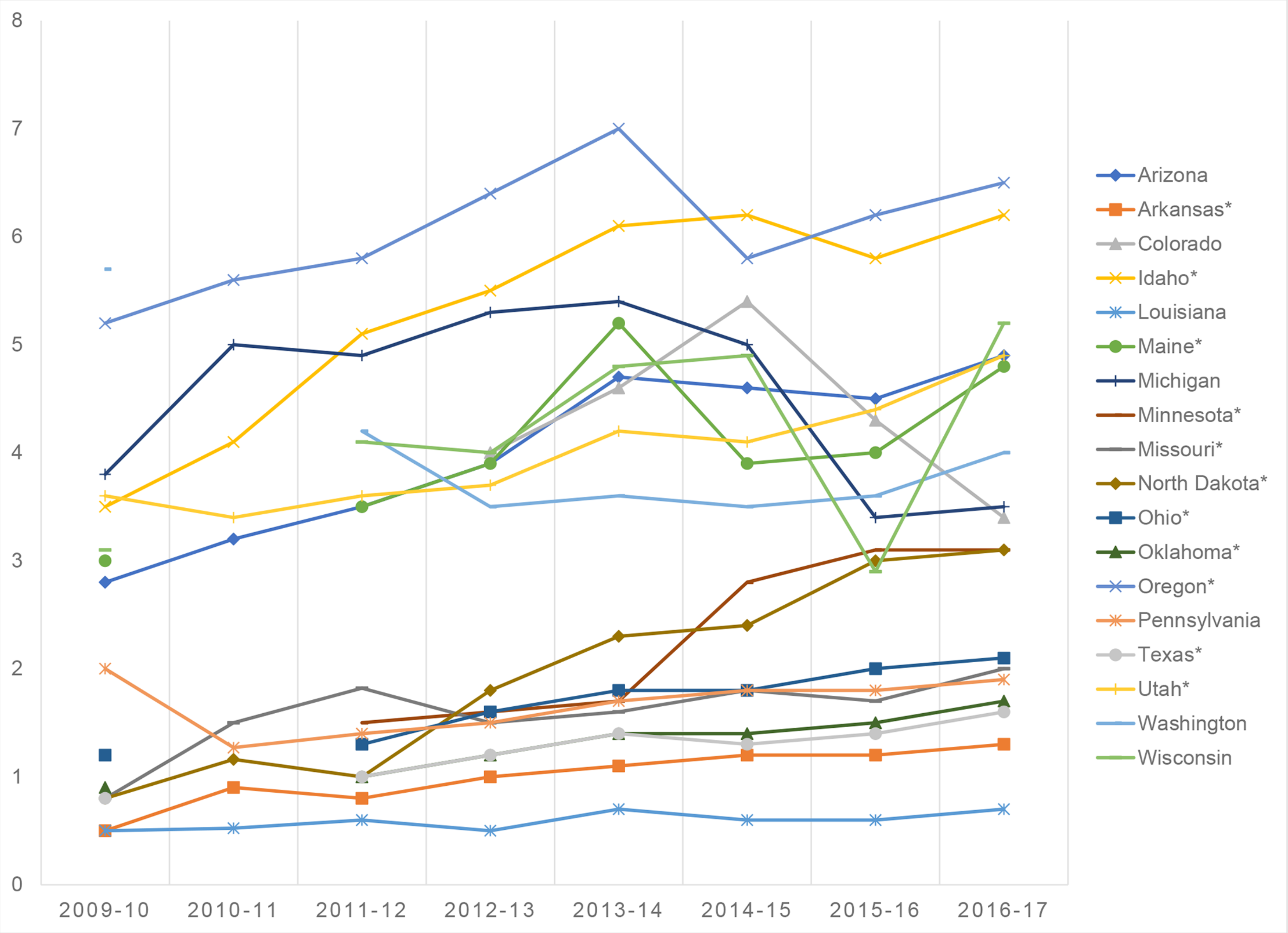
Measles, for example, has seen a 30% increase in cases globally. The reasons for this rise are complex, and not all of these cases are due to vaccine hesitancy. However, some countries that were close to eliminating the disease have seen a resurgence.

The reasons why people choose not to vaccinate are complex; a vaccines advisory group to WHO identified complacency, inconvenience in accessing vaccines, and lack of confidence are key reasons underlying hesitancy. Health workers, especially those in communities, remain the most trusted advisor and influencer of vaccination decisions, and they must be supported to provide trusted, credible information on vaccines.

In 2019, WHO will ramp up work to eliminate cervical cancer worldwide by increasing coverage of the HPV vaccine, among other interventions. 2019 may also be the year when transmission of wild poliovirus is stopped in Afghanistan and Pakistan. Last year, less than 30 cases were reported in both countries. WHO and partners are committed to supporting these countries to vaccinate every last child to eradicate this crippling disease for good.

https://www.who.int/emergencies/ten-threats-to-global-health-in-2019

Kindergarten vaccine nonmedical exemptions rates



J. K. Olive, P. J. Hotez, A. Damania & M. S. Nolan, PLoS Med ***15****(6): e1002578 (2018).*

Image: Mary Evans/Classicstock/Camerique

Vaccine Hesitancy (VH)

- VH is a nebulous concept, as its precise definition varies across studies.
- VH is defined as either a set of beliefs, attitudes or behaviours related to a reluctance to be vaccinated (or to vaccinate one's children).
- It is argued that VH is different from anti-vaccination (anti-vax) sentiments.
- VH is <u>not</u> dependent on socioeconomic status[1].
- In the most general sense, one can view VH as a decision-making process.

[1] *P. Peretti-Watel et al,* PLOS Currents Outbreaks, **7** *(2015).*

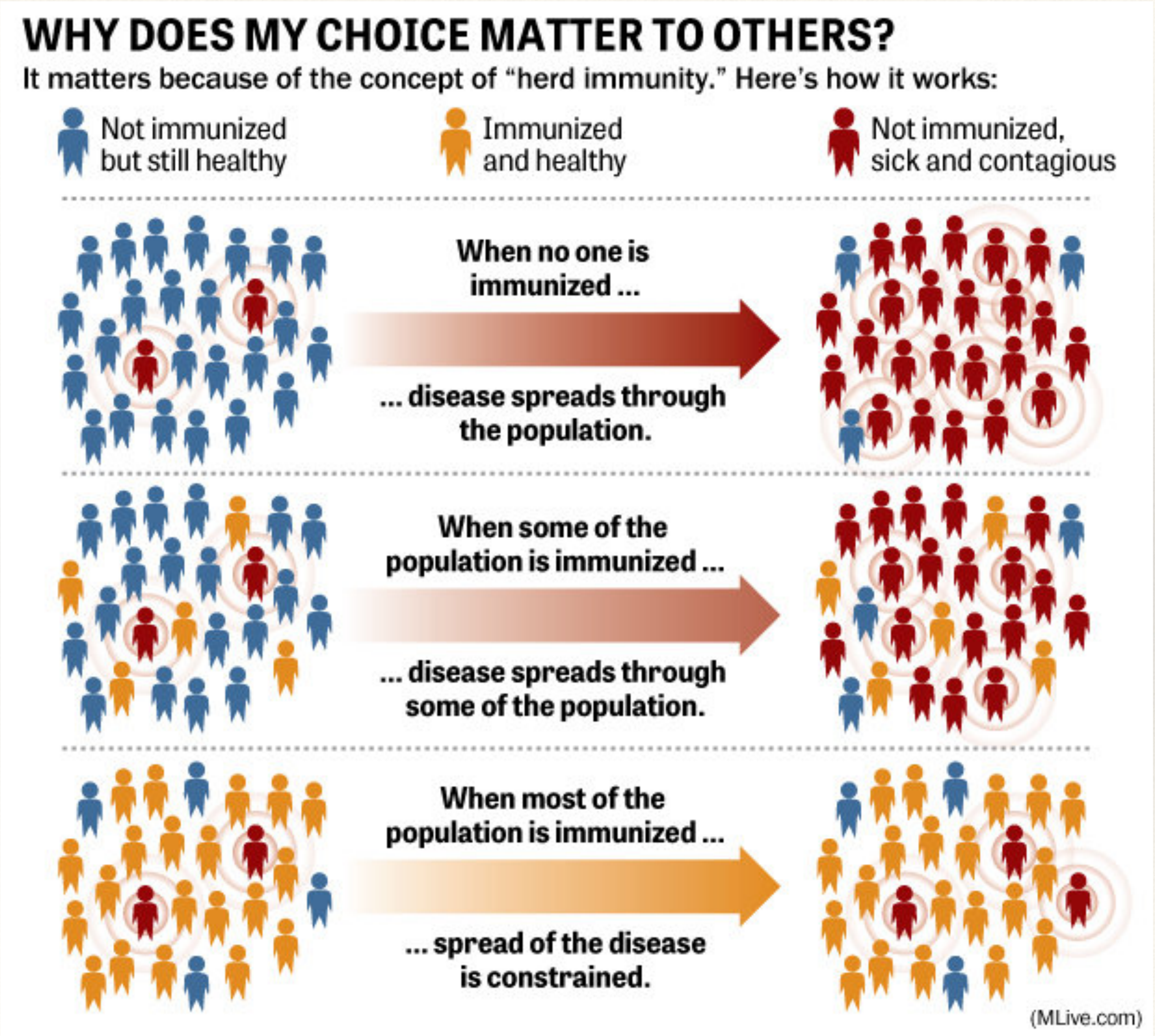
Image: https://www.saturdayeveningpost.com/2018/03/vintage-ads-polio-pertussis-plagues/

The societal benefits of vaccination

- From an epidemiological standpoint, vaccinated individuals are functionally similar to *quarantined* individuals in that other members of the population cannot catch a disease from members of either group.
- The obvious differences are that vaccinated individuals:
  - are highly unlikely to get infected.
  - are not "removed" from their social contact network.
- When a critical fraction of a community is vaccinated against an infectious disease, whole community is protected against it. This is called **herd immunity**.

Image: https://www.mlive.com

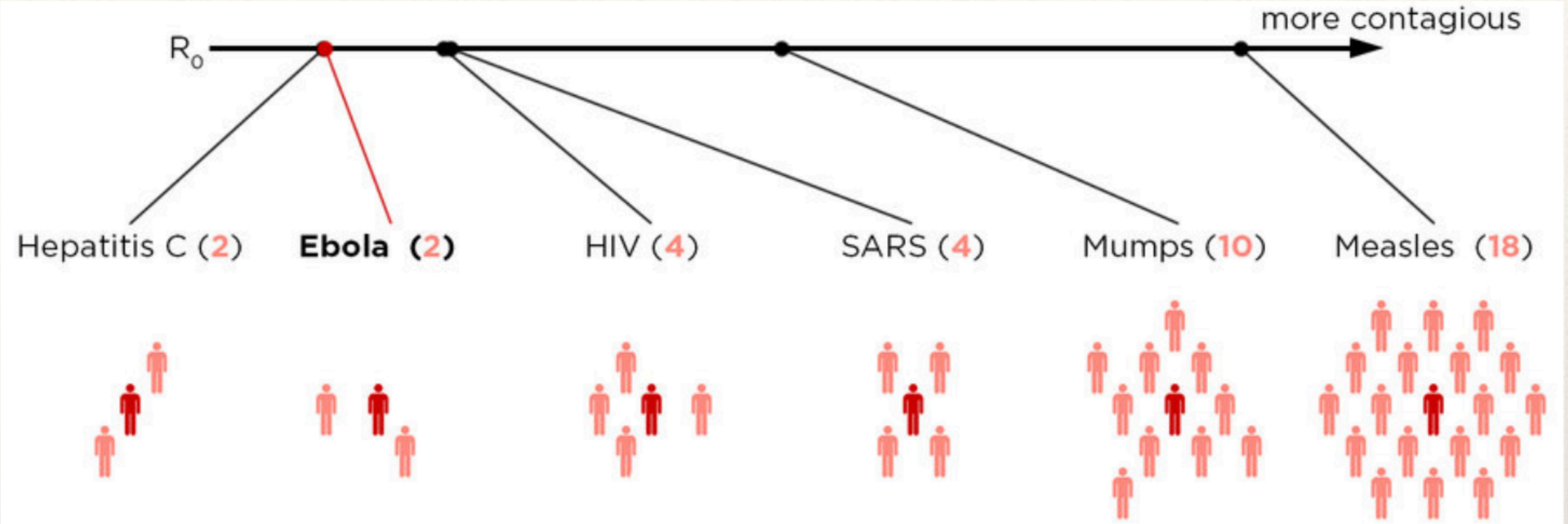
Vaccination and "herd immunity"



Infectious Disease Epidemiology

R_0

The basic reproduction number: the average number of secondary cases arising from a typical infected case in a population of <u>susceptible</u> individuals.



For an epidemic to occur in a population of healthy individuals, R_0 must be greater than one.

$R_0 > 1 \rightarrow$ epidemic takes off

$R_0 < 1 \rightarrow$ epidemic dies out

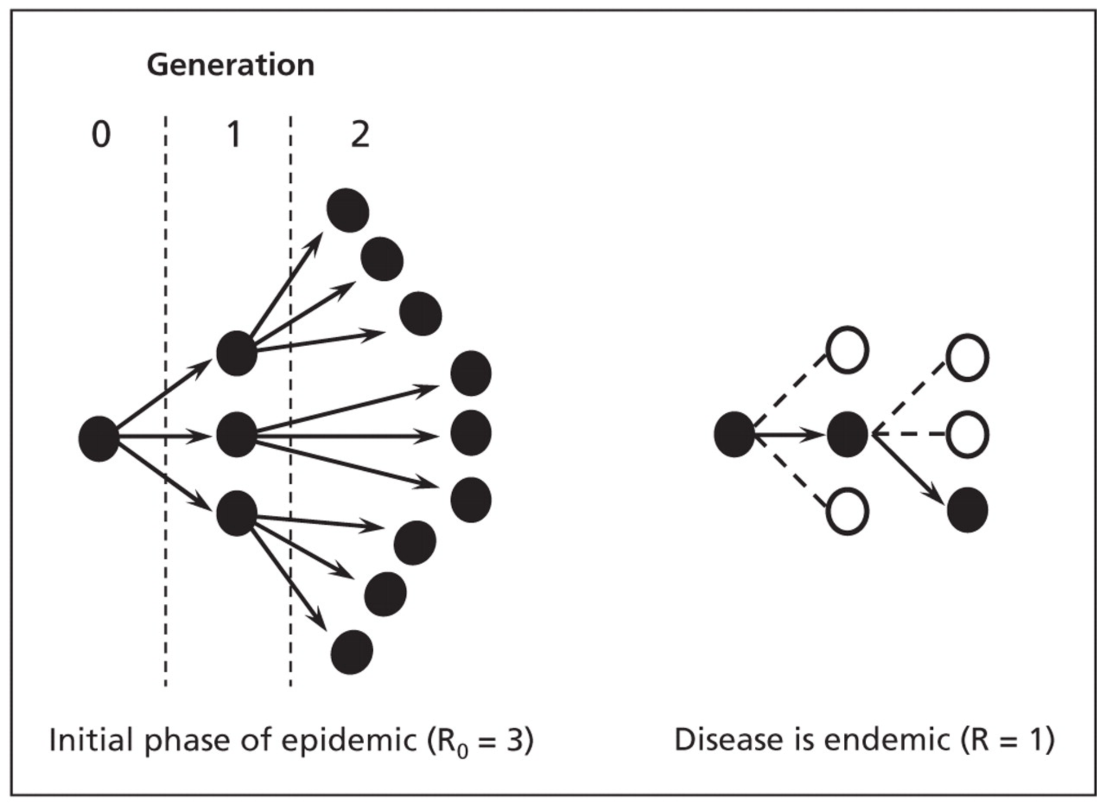


Image: CMAJ August 04, 2009 181 (3-4) 171-173

Infectious Disease Epidemiology

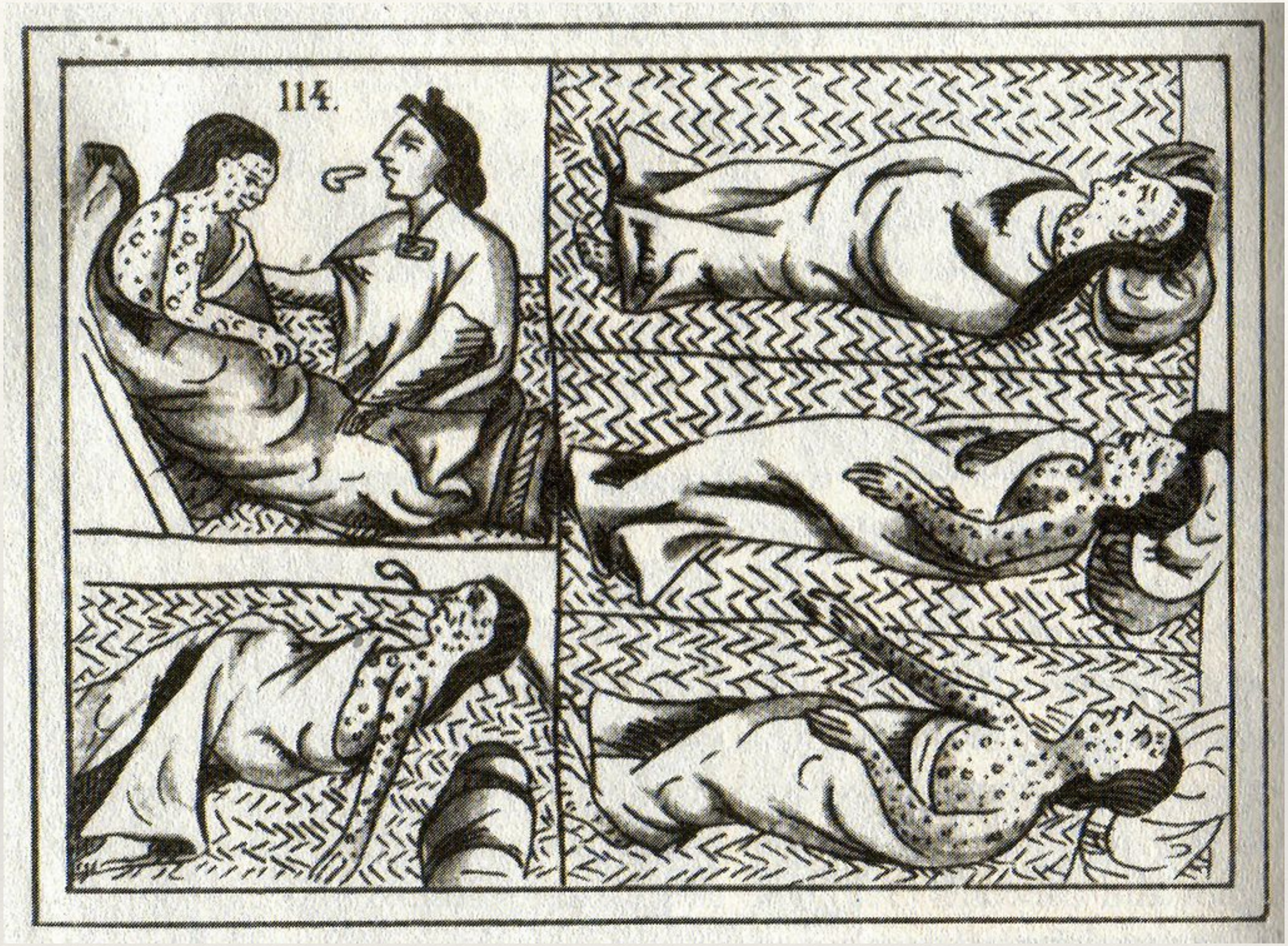
R_0 also provides information regarding *the critical fraction of the population that needs to be vaccinated to provide herd immunity.* For a homogeneous or well-mixed population, assuming p is the proportion of the population that is vaccinated, an epidemic will not arise if $R_v = R_0 (1 - p) < 1$.

Hence, the critical fraction of the population that need to be vaccinated is:

$$p_c = 1 - \frac{1}{R_0}$$

Disease	R0	Threshold (%)
Mumps	4-7	75–86
Polio	5-7	80–86
Smallpox	5-7	80–85
Diphtheria	6-7	85
Rubella	6-7	83–85
Pertussis	12-17	92–94
Measles	12-18	83–94

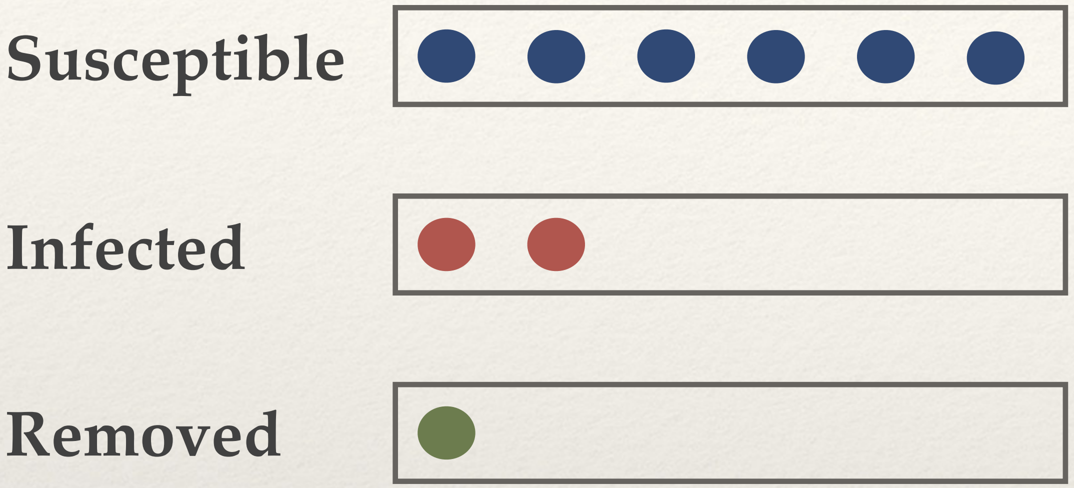
Image: Biblioteca Medicea Laurenziana, Florence



PART TWO

Disease spreading

Modelling the spread of a disease



Event	Transition	Probability
infection	$(s,i,r) \to (s-1,i+1,r)$	$1-(1-\beta)^{k_{inf}}$
recovery	$(s,i,r) \to (s,i-1,r+1)$	$1/\tau_i$
vaccination	$(s,i,r) \to (s-1,i,r+1)$	π

$$
\begin{aligned}
\beta &= \text{transmission probability,} \\
k_{inf} &= \text{no. of infected neighbour,} \\
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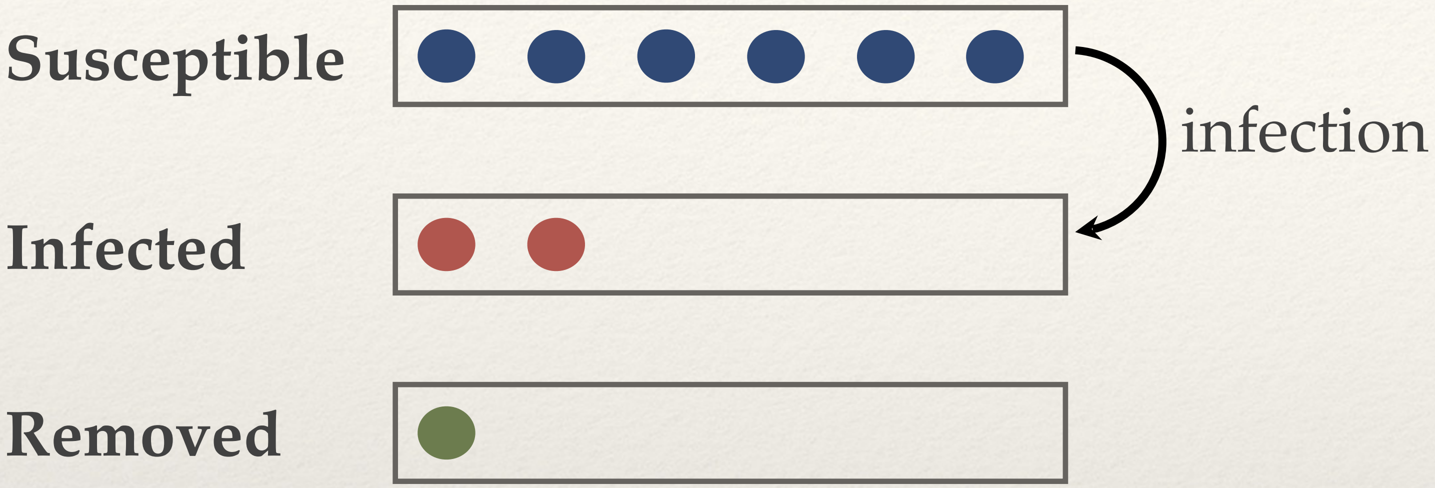
\end{aligned}
$$

Modelling the spread of a disease



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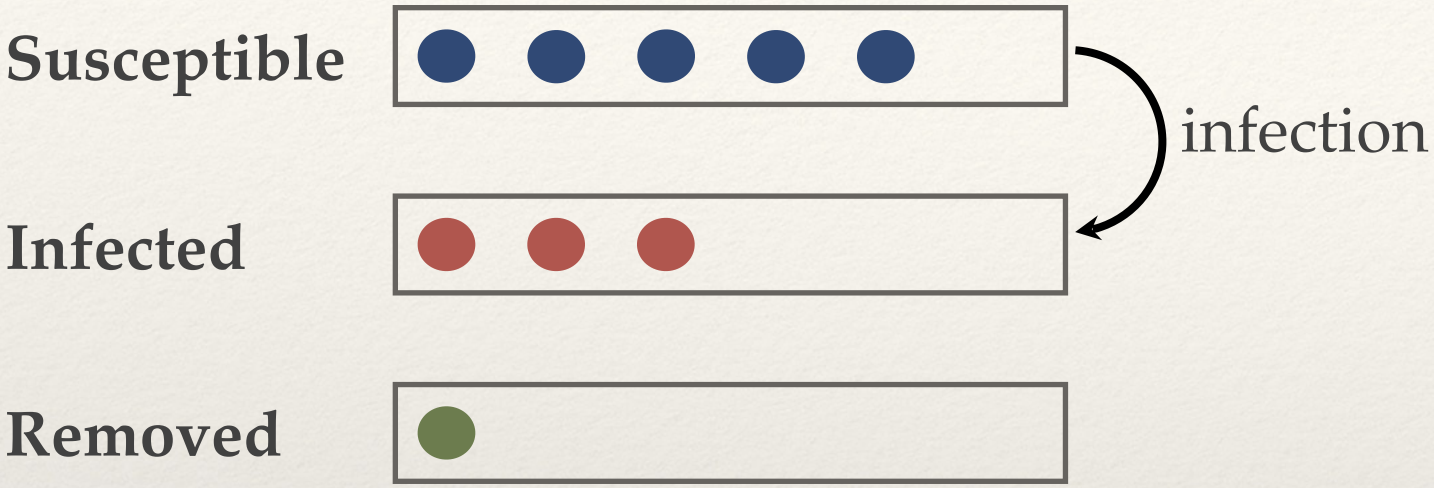

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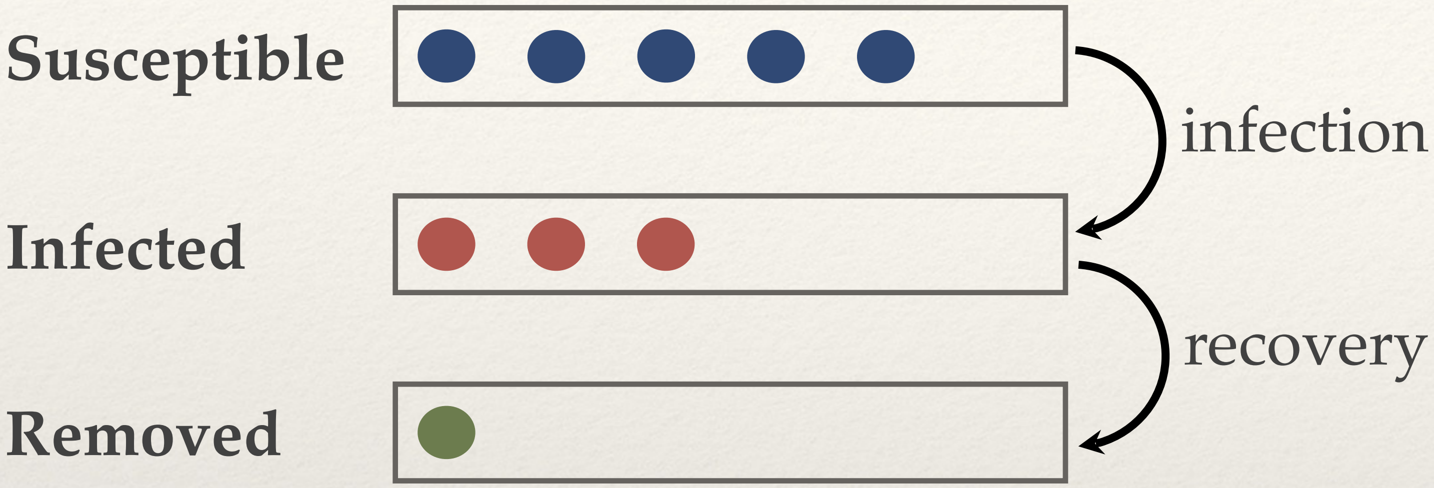

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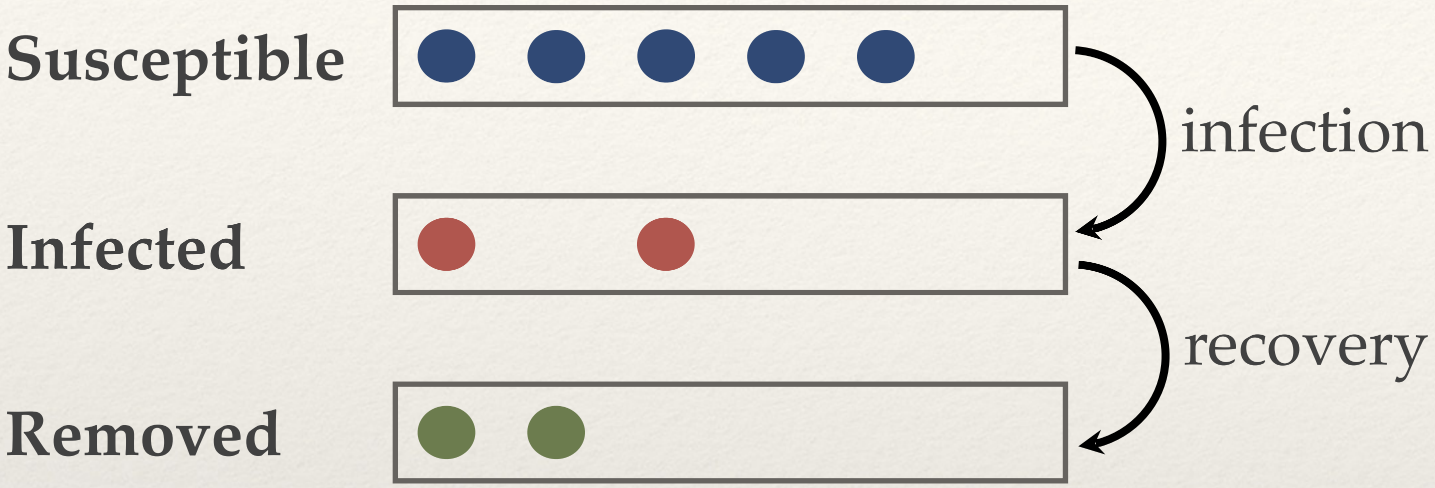

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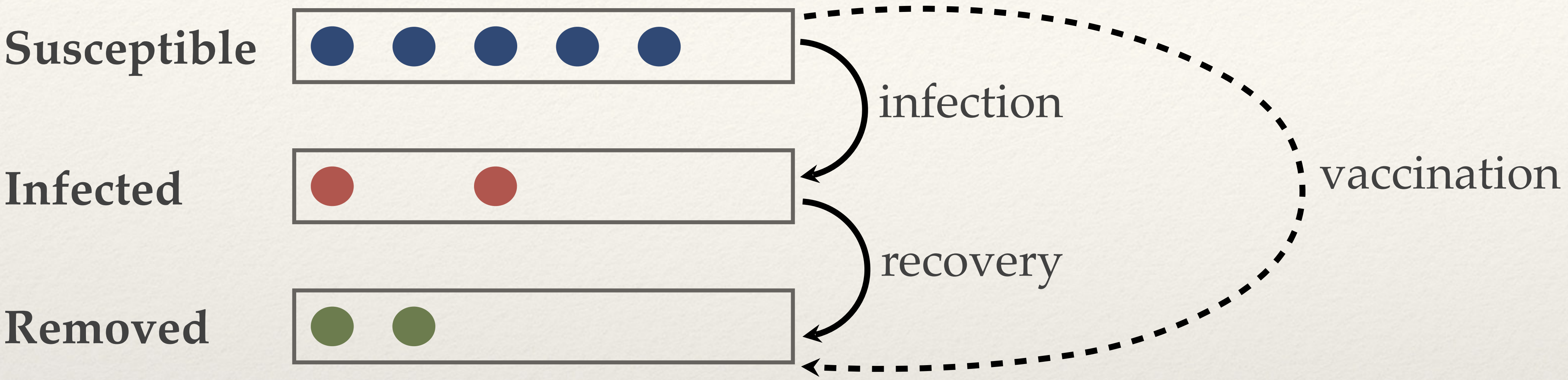

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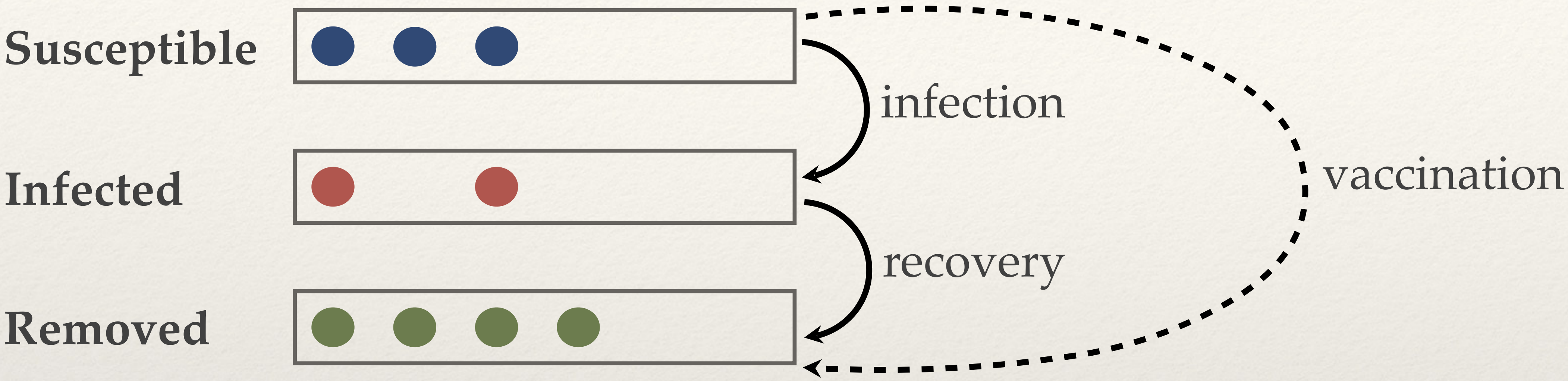
Modelling the spread of a disease



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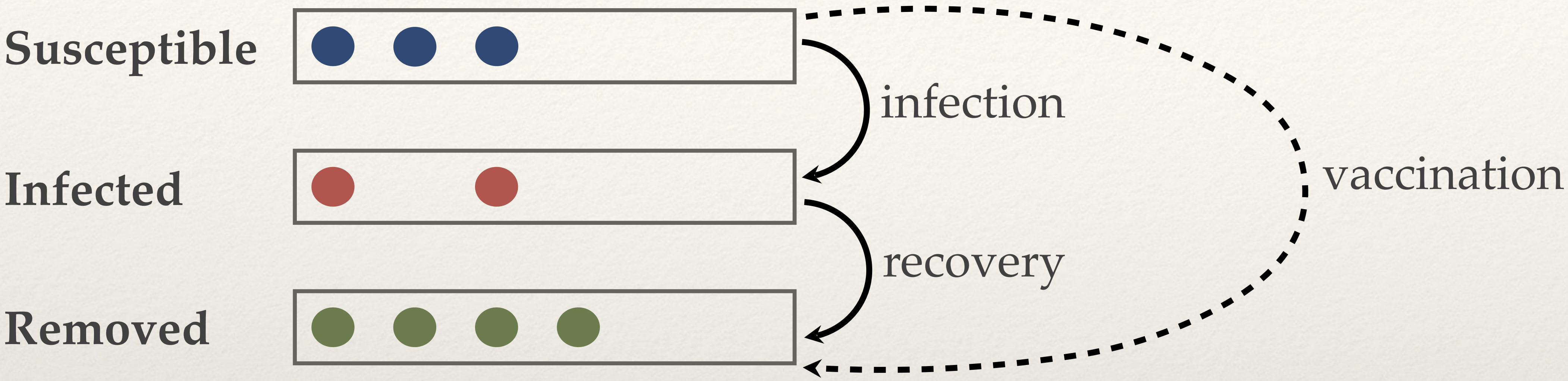

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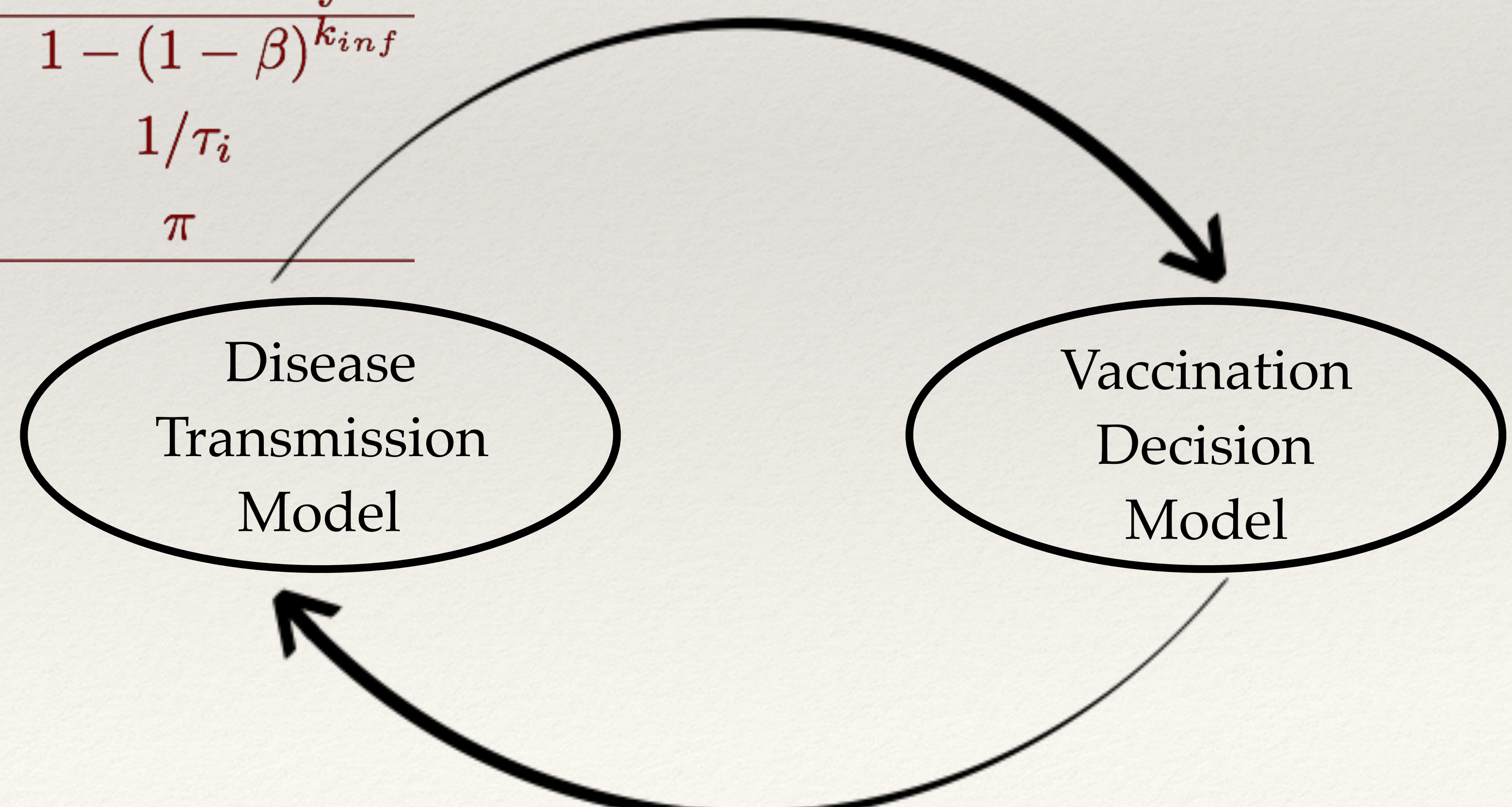


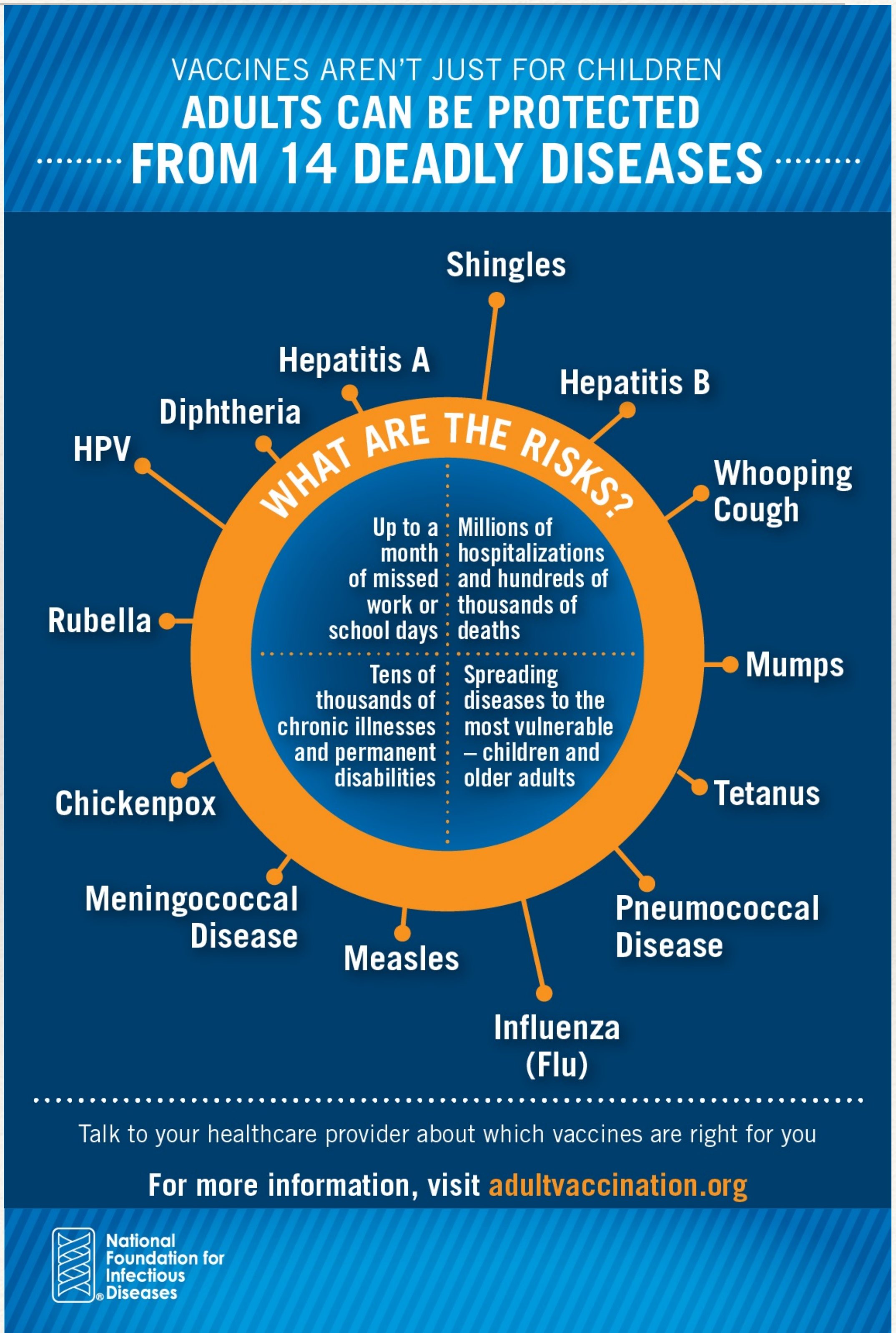
PART THREE

Deciding to be vaccinated

Image: http://www.adultvaccination.org/

What is the "rational" decision?

- In reality, an individual's decision-making process involves a myriad of complex factors.
- We consider a scenario with a **minimal** number of extra assumptions on an individual's behaviour, namely one where they simply try to maximize potential "payoffs".
- When presented with a binary decision (viz. to vaccinate or not?) each individual weighs the costs and benefits associated with being vaccinated.
- In the framework of *game theory*, such individuals are referred to as <u>rational</u>.



Canonical payoff matrix for a two-player cooperative game

	Defect	Cooperate
Defect	P, P	T, S
Cooperate	S, T	R, R

T: **Temptation** (to defect while the other cooperates)

R: **Reward** (for mutual cooperation)

P: **Punishment** (for mutual defection)

S: **Sucker's payoff** (for cooperating while the other defects)

The above matrix can, for example, describe a "Prisoner's Dilemma" game if:

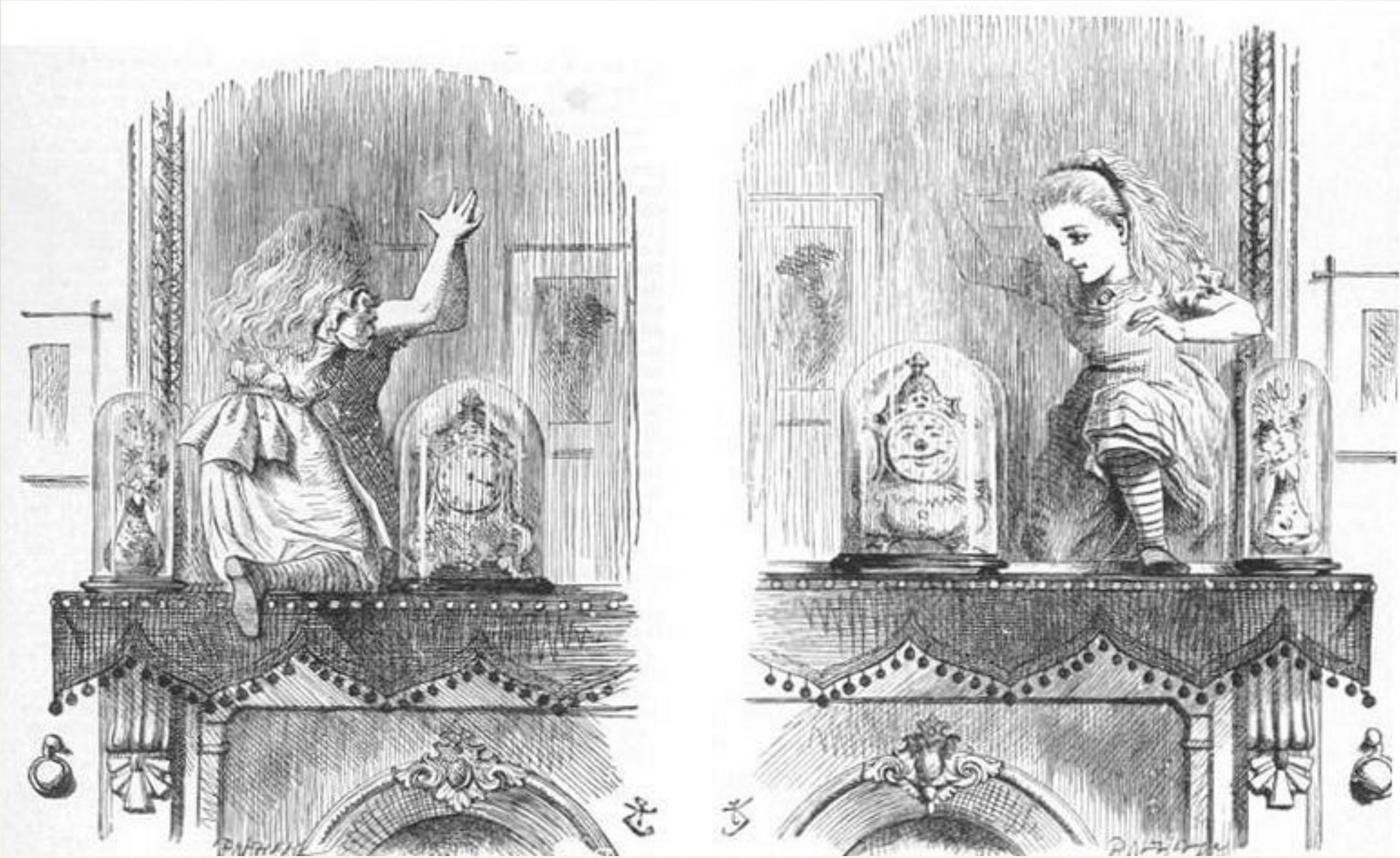
$$T > R > P > S$$

In this case, defection is the *dominant strategy* for both players, and hence the Nash equilibrium* is **mutual defection.**

** Unilateral deviation from this situation will not benefit either player*

Who is the "opponent"?

- In a real-world scenario, individuals typically do not compete when making decisions to get vaccinated: they simply choose whether it is the best option for themselves.
- However, the decision-making process *itself* can be viewed as a competition between two distinct choices.
- We may hence consider the following framework to describe the decision-making process of individuals: they effectively play a game with a **virtual opponent** that posses identical information, and which has the same set of choices before it.



Applying game theory to vaccination

Players → **Actions** → **Payoffs**

Individuals → Vaccinate or not →
- Risk of infection
- "Cost" of vaccination

		Opponent	
		Cooperate	Defect
Focal player	Cooperate	Reward	Sucker's payoff
	Defect	Temptation	Penalty

		Opponent	
		Vaccinate	Not vaccinate
Focal player	Vaccinate	Cost of vaccine and no risk of infection	Cost of vaccine and high risk of infection
	Not vaccinate	No cost of vaccine and no risk of infection	No cost of vaccine and high risk of infection

PART FOUR

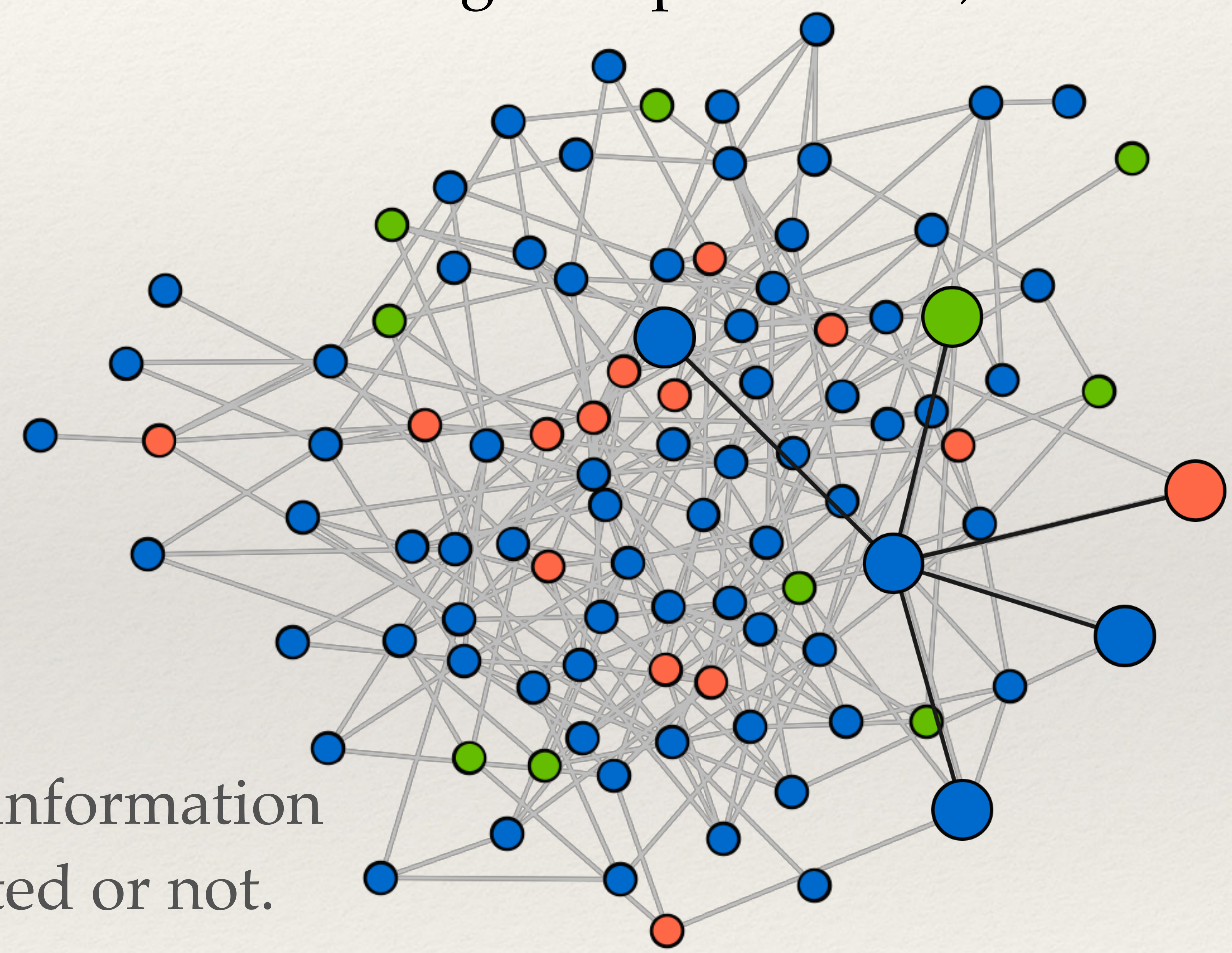
The model

Image source: Wikimedia Commons

Step 1:

f_p is the fraction of neighbours that are protected against the disease (either vaccinated or recovered)

f_i is the fraction of infected agents (a combination of local and global prevalence)



Local prevalence: fraction of infected agents in the neighbourhood, k_{inf}/k

Global prevalence: fraction of infected agents in the whole network, I/N

$$f_i = \alpha(I/N) + (1-\alpha)(k_{inf}/k).$$

Using the parameter α we tune the nature of information that agents use to decide whether to get vaccinated or not.

$\alpha = 0$ → $\alpha = 1$

Entirely local information

Entirely global information

Step 2:

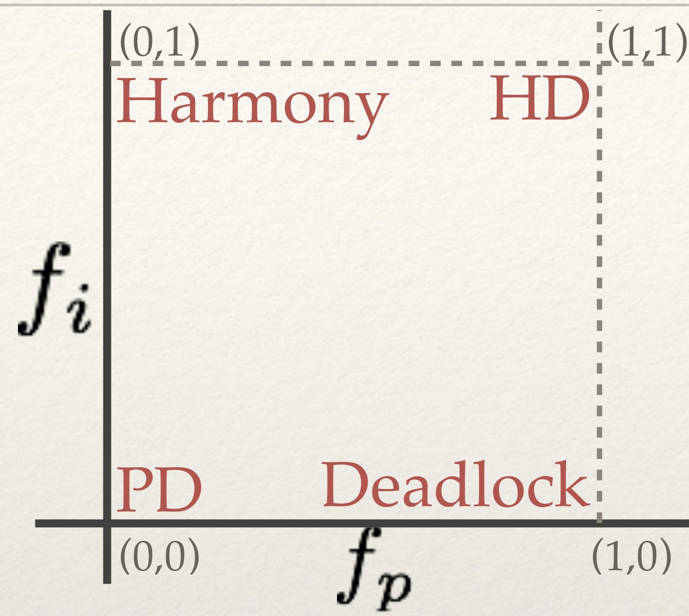
We assume that:

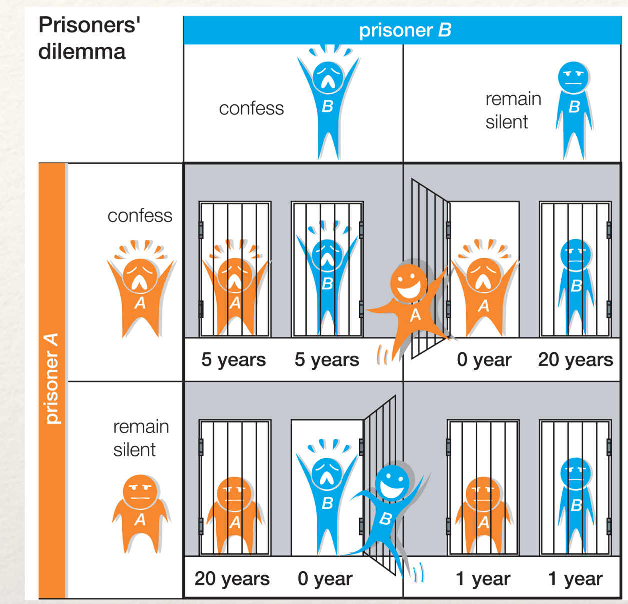
T $U_{nv} = af_p + b,$

P $U_{nn} = cf_p + d,$

S $U_{vn} = ef_i + f,$

R $U_{vv} = gf_i + h.$



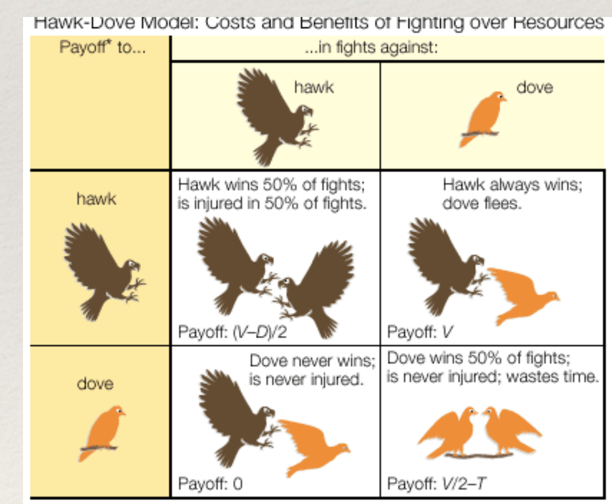


PD: T > R > P > S

We have $U_{nv}>U_{nn}$ and $U_{vv}>U_{vn}$,

so we can take a=c, e=g

Prisoners' Dilemma:	$U_{nv} > U_{vv} > U_{nn} > U_{vn}$
Deadlock:	$U_{nv} > U_{nn} > U_{vv} > U_{vn}$
Hawk Dove:	$U_{nv} > U_{vv} > U_{vn} > U_{nn}$
Harmony:	$U_{vv} > U_{vn} > U_{nv} > U_{nn}$



HD: T > R > S > P

We choose the coefficients in the functional forms of T, P, R and S such that the following inequalities hold:

$$a+b > e+h > e+f > b, \quad a+d > h > d > f$$

The expected payoff

		Player 2	
		Defect	Cooperate
Player 1	Defect	P, P	T, S
	Cooperate	S, T	R, R

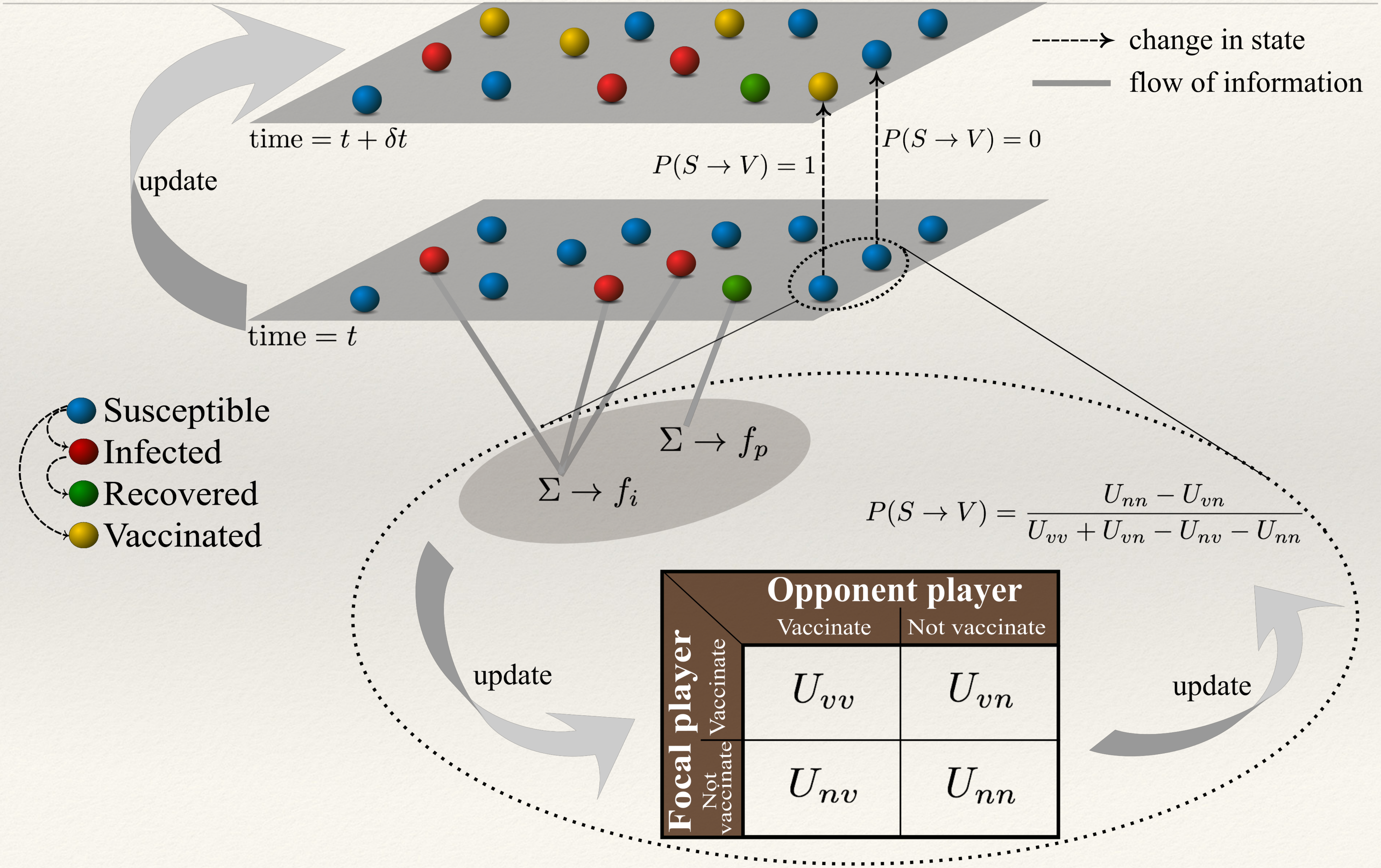
- In a two-player game, agents may use "mixed strategies", where actions are selected with a certain probability.
- Assuming players 1 and 2 decide to cooperate with probabilities p_1 and p_2, respectively, the payoff received by player 1:

$$p_1(p_2(R+P-T-S)+S-P)+p_2(T-P)+P$$

- As the game is symmetric, we can see that if a mixed strategy Nash equilibrium exists, it is the same for both players. Hence:

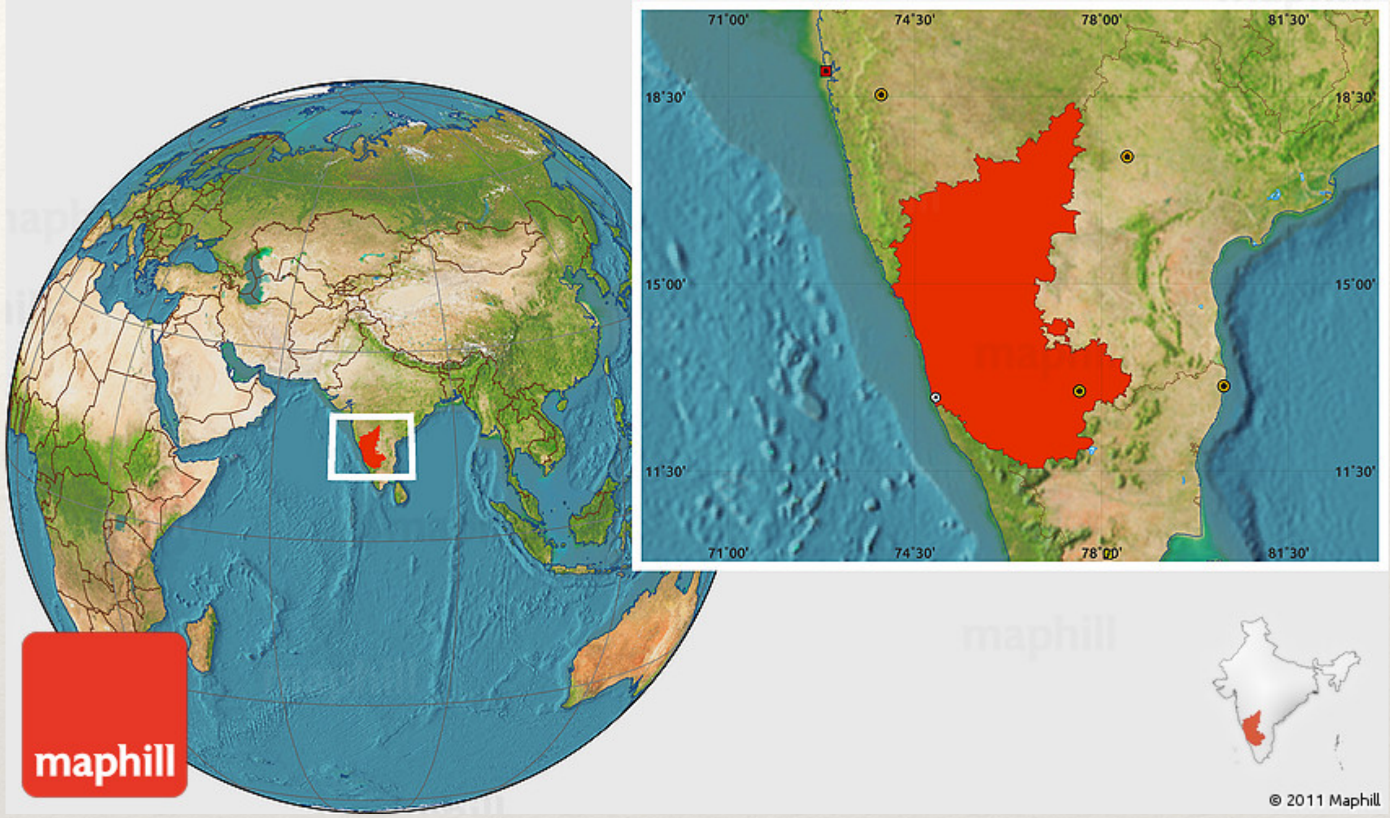
$$p_1^* = p_2^* = \frac{P-S}{R+P-T-S}$$

Overview of the model



Empirical Social Networks

- We consider empirical social contact networks that were constructed [by Banerjee et al (2013)] from detailed network data. This data was originally collected by surveying households of 75 villages in **Karnataka**, a state in southern India.



- A wide range of interactions such as *kinship, social engagement, visiting homes, borrowing and lending money or essential items*, etc., were recorded for surveyed individuals.

- For our study, we consider (undirected) networks obtained from the union of all interactions between individuals in a village as a representation of the social contact network over which a disease can spread.

Data source: A. Banerjee, A. G. Chandrasekhar, E. Duflo & M. O. Jackson, *Science* **341**, 1236498 (2013).

PART FIVE

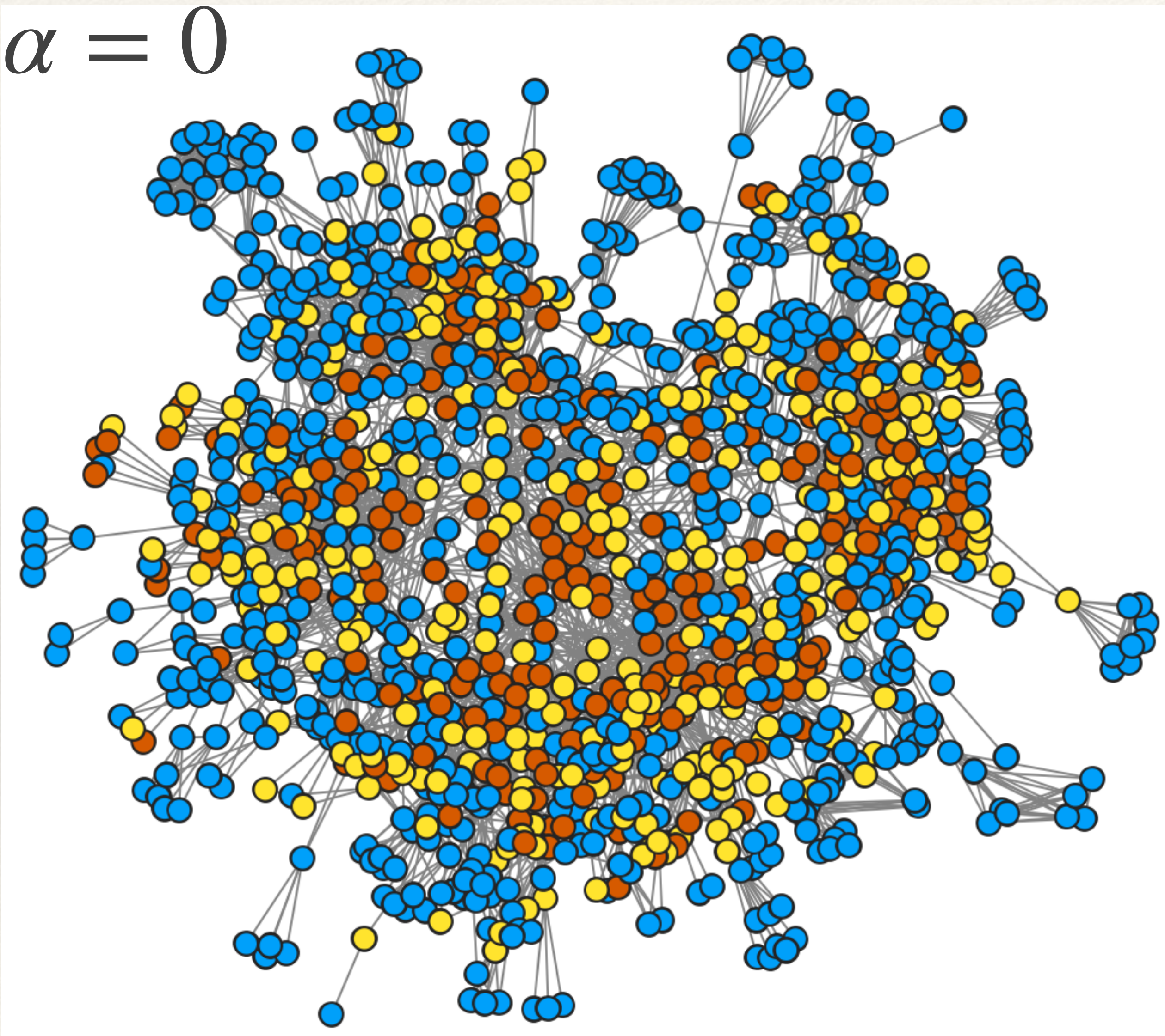
Results

Image source: Fox Photos / Getty Images

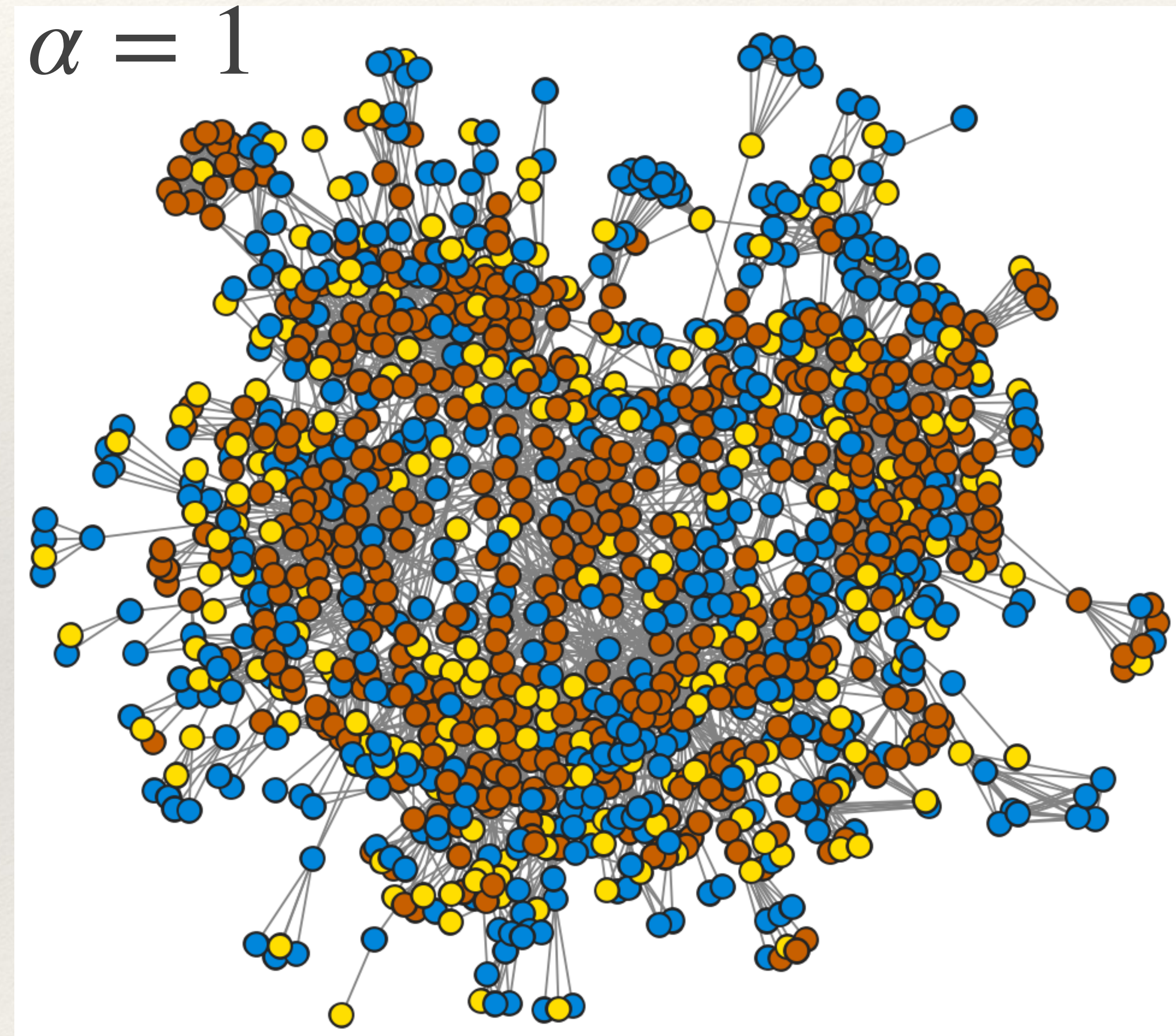
For Karnataka village social network

Village no. 55: N = 1180, Lcc = 1151, $\langle k \rangle = 7.964$, $\langle k_{eff} \rangle = 9.7888$

(Entirely local information)



(Entirely global information)

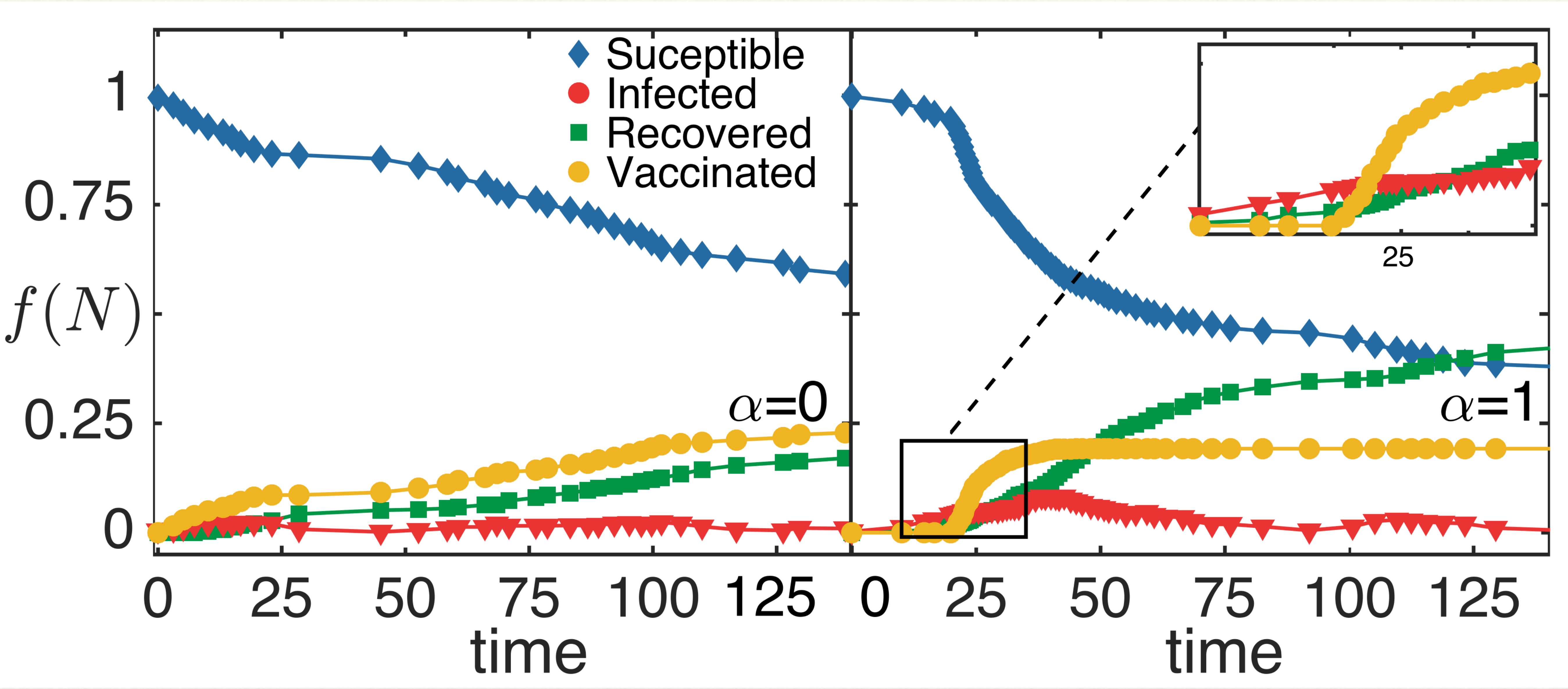


Simulated epidemic with $\beta = 0.25$ and $\tau_I = 10$

Susceptible Infected+Recovered Vaccinated

For Empirical Social Networks

Village no. 55: N = 1180, Lcc = 1151, <k> = 7.964, <k_{eff}> = 9.7888



$f(N)$ is the fraction of agents at any time *t*.

Simulated epidemic with $\beta = 0.25$ and $\tau_I = 10$

For Empirical Social Networks

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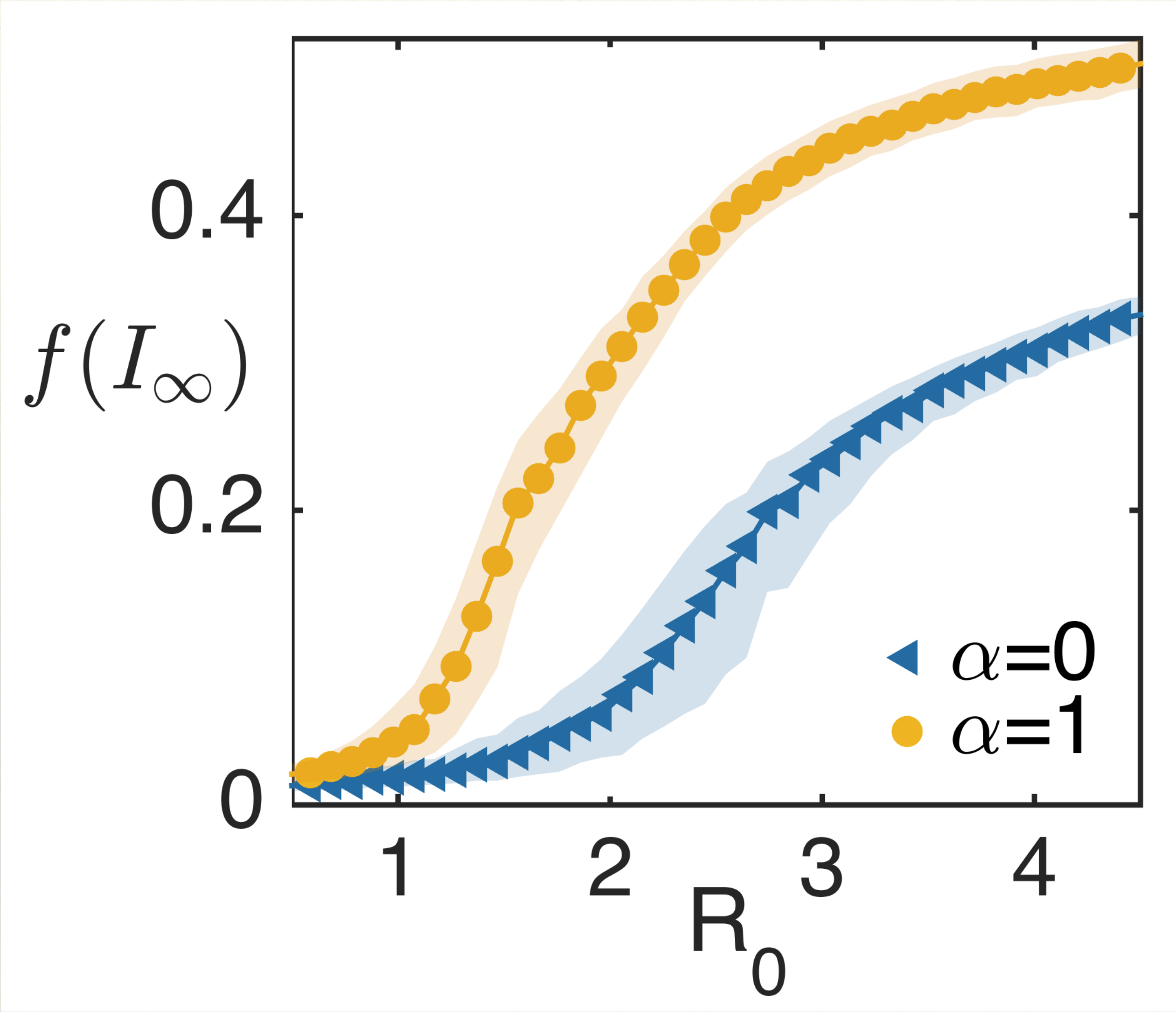
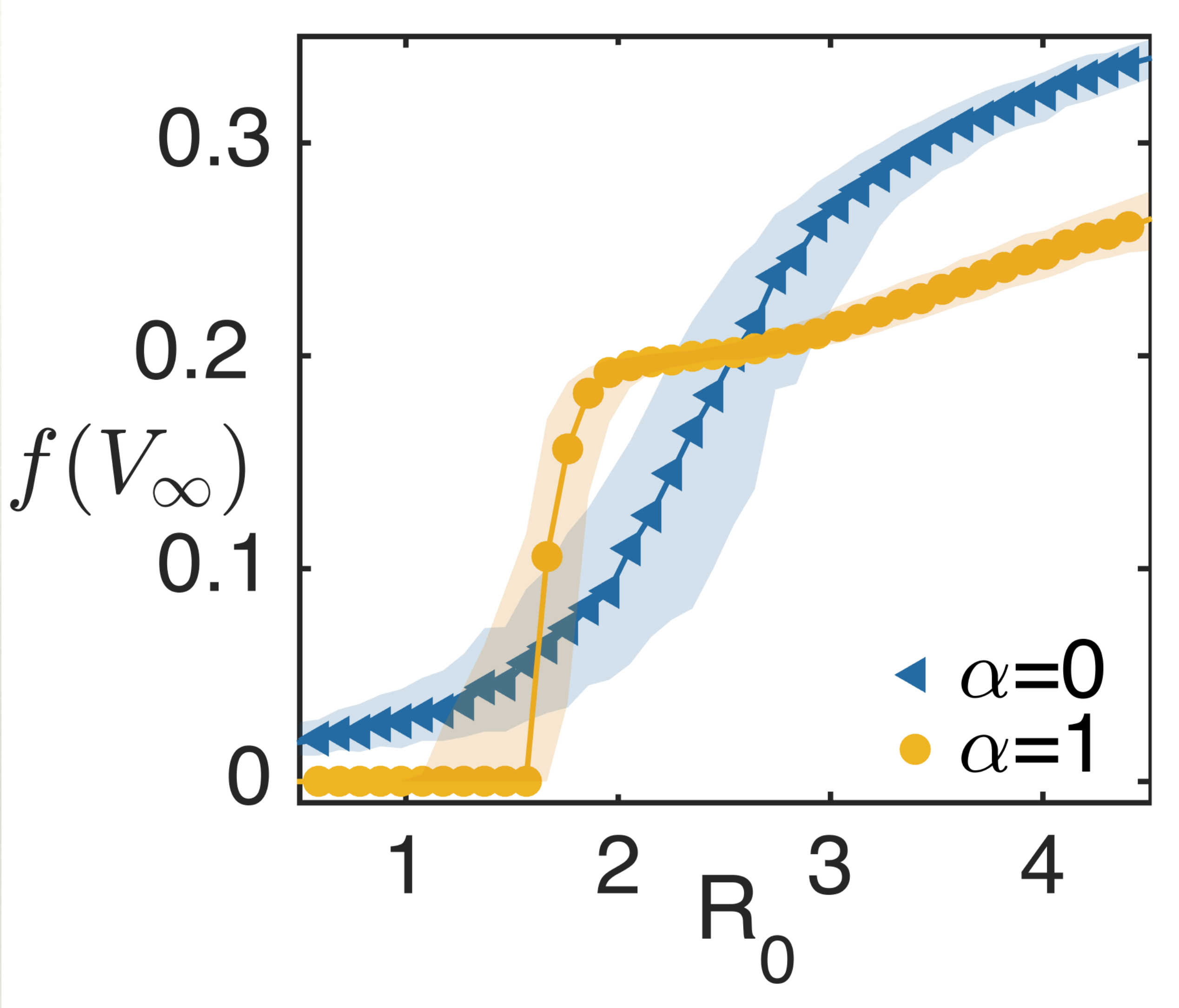




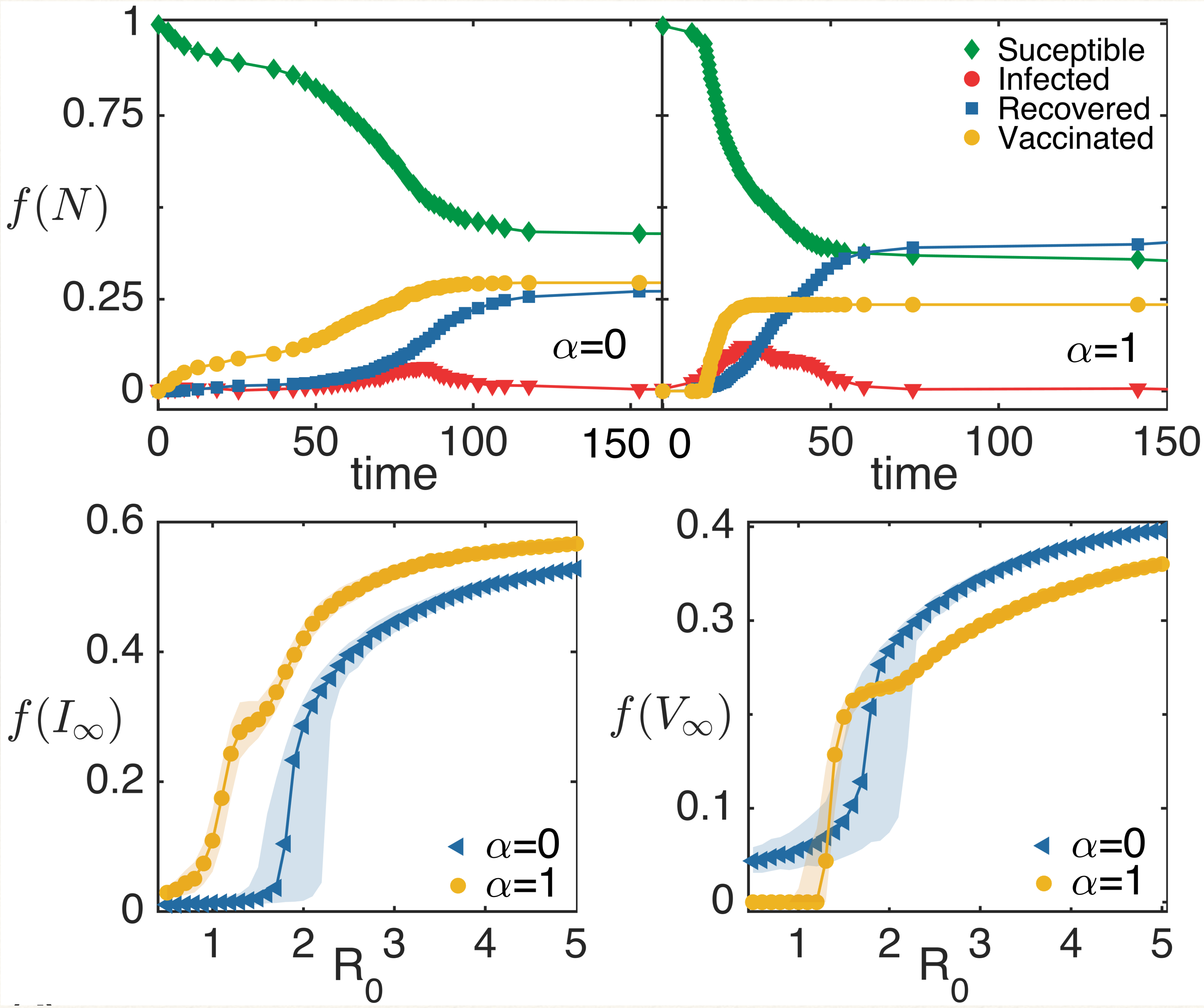
$f(I_\infty)$ is the fraction of nodes that get infected over the whole course of a simulated epidemic.

$f(V_\infty)$ is the fraction of nodes that get vaccinated over the whole course of a simulated epidemic.

Each point represents the median of 1000 simulations and the patches represent the interquartile range

For Erdos-Renyi (ER) random networks

N = 1024, <k> = 10

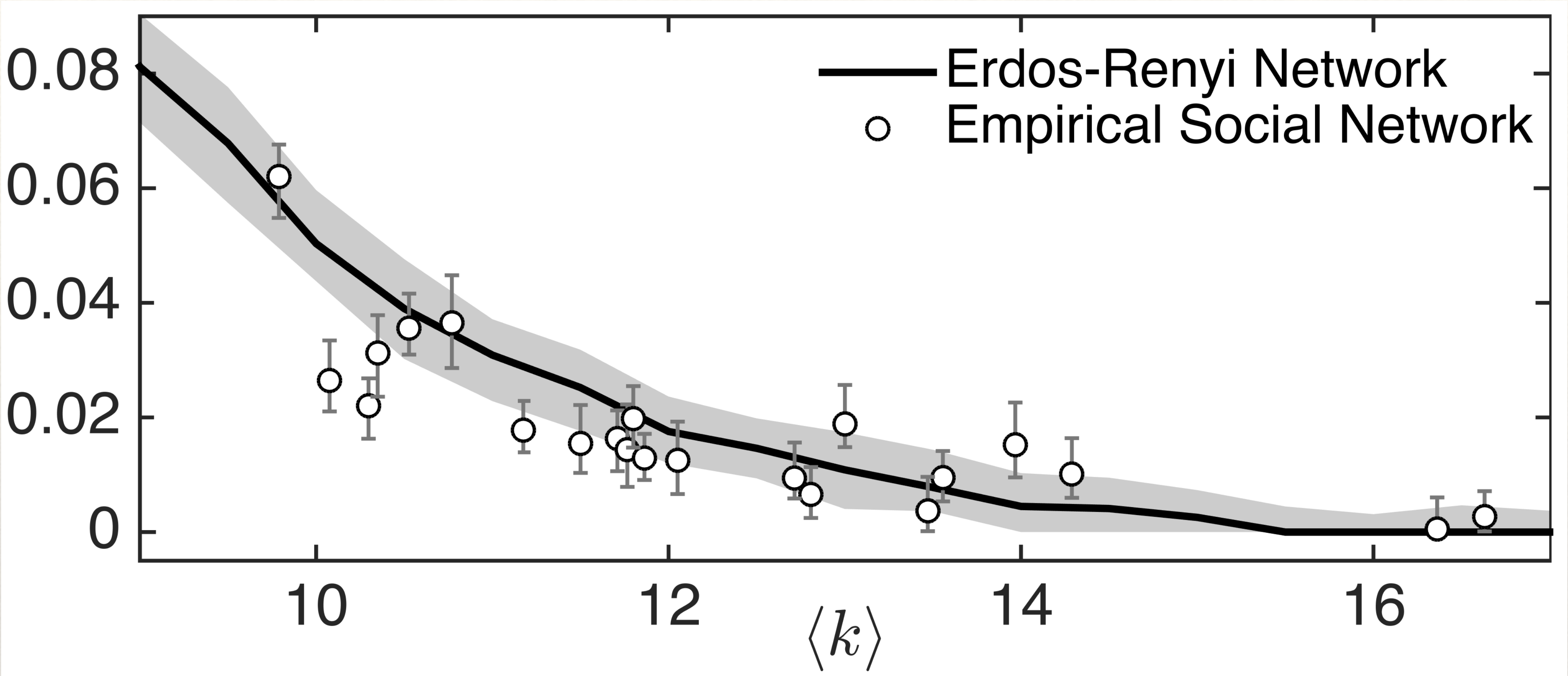


$f(N)$ is the fraction of agents at any time *t*.

$f(I_\infty)$ is the fraction of agents in the network that become infected over the course of a simulated epidemic.

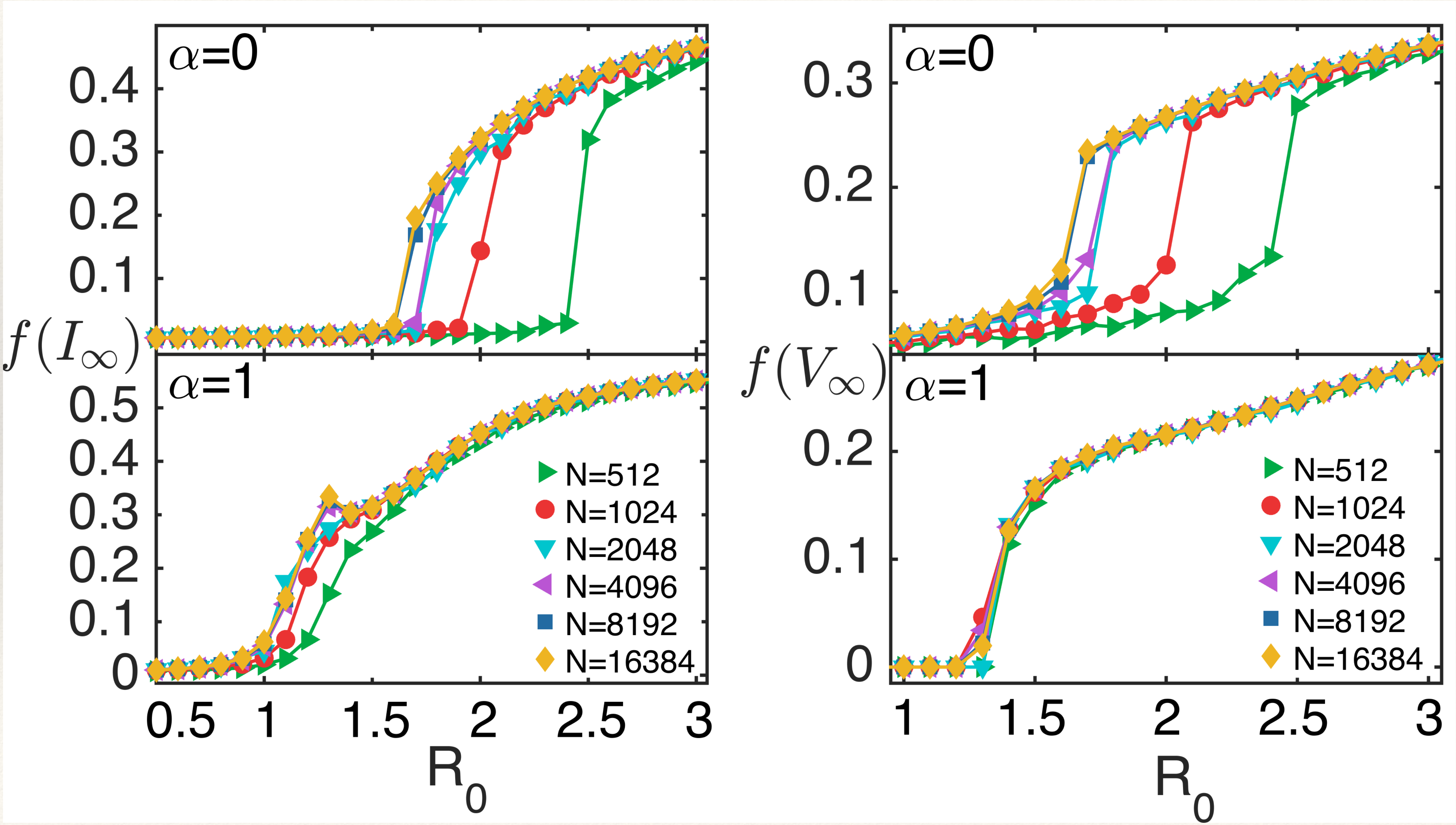
$f(V_\infty)$ is the fraction of agents in the network that get vaccinated over the course of a simulated epidemic.

Comparison



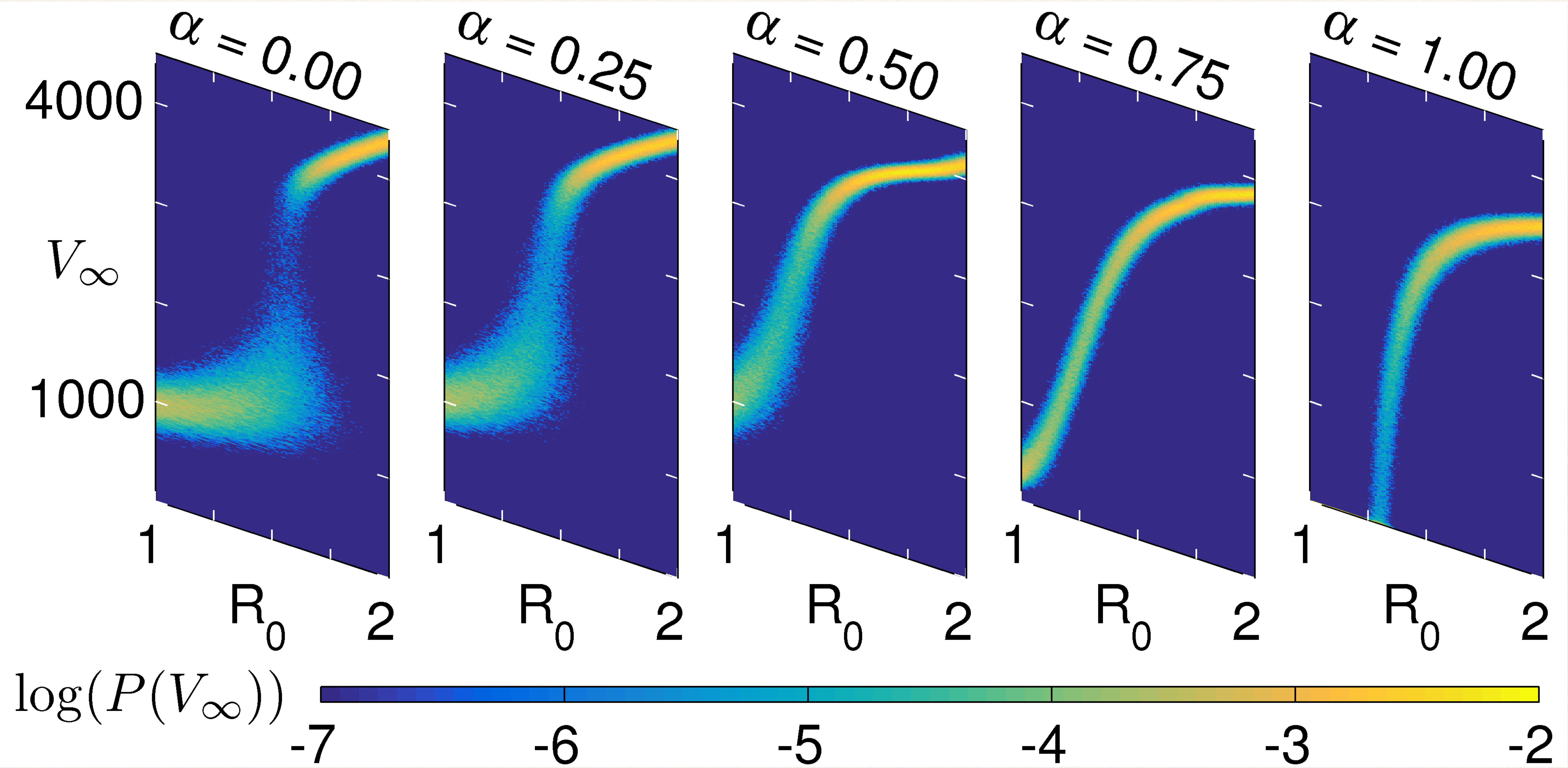
- We selected the villages with a largest connected component >1000 to compare the results of simulated epidemics on empirical social networks and ER random networks.
- We calculated the "crossover area": the area enclosed between the $f(V_\infty)$ vs R_0 curves for the two extreme values of α.
- We found that the results on empirical networks follows a very similar trend to those obtained with ER random networks.

System size dependence



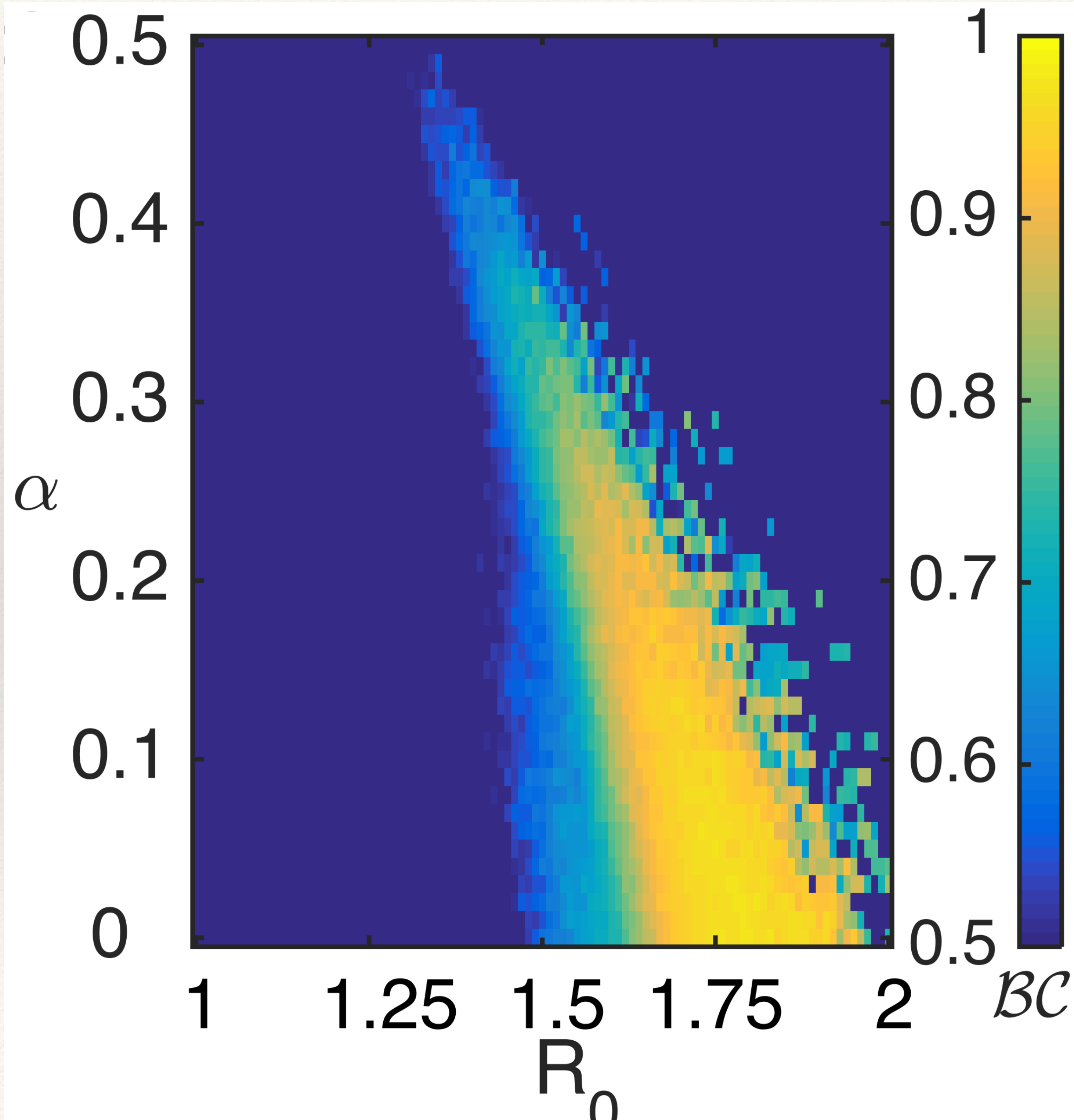
Bimodal behaviour

N=16384, <k>=10, 2000 trials



Probability distribution of V_∞ as a function of R_0 for different values of α.

Bimodal behaviour



Bimodality coefficient*:

$$\mathcal{BC} = \frac{m_3^2 + 1}{m_4 + 3\frac{(n-1)^2}{(n-2)(n-3)}}$$

where, m_3 is the skewness of the distribution, m_4 is the kurtosis and n is the no. of observations.

The benchmark value of BC_{crit} is 5/9. For values below this, the distribution is uniform. Values higher than 5/9 suggest the possibility of *bimodality* and lower values indicates *unimodality*.

*Roland Pfister et al., Front Psychol. 2013; 4: 700.

Conclusions

- Our approach presents a conceptual framework for characterising the circumstances under which voluntary vaccination emerges in a social network, when faced with the possibility of an epidemic outbreak.
- The **nature of information** (*local or global*) involved in the decision-making process of individuals is found to have a significant effect on the final vaccine coverage.
- The results are qualitatively very similar for both empirical and ER networks, and only appear to depend significantly on one aspect of network structure, namely its *average degree*.
- When agents decide to get vaccinated based on the information about the local prevalence of disease, the model exhibits **two different fates**, *near the epidemic threshold*, for same value of R_0.
- From the perspective of public health planning, the study suggests that the **availability of accurate and localized information** of disease outbreak is crucial for changing individuals' risk perception, and thereby their attitude towards vaccination, especially during the *initial phase of an epidemic*.

Reference

A. Sharma, S. N. Menon, V. Sasidevan & S. Sinha, *Epidemic prevalence information on social networks can mediate emergent collective outcomes in voluntary vaccine schemes*, PLoS Computational Biology (accepted)

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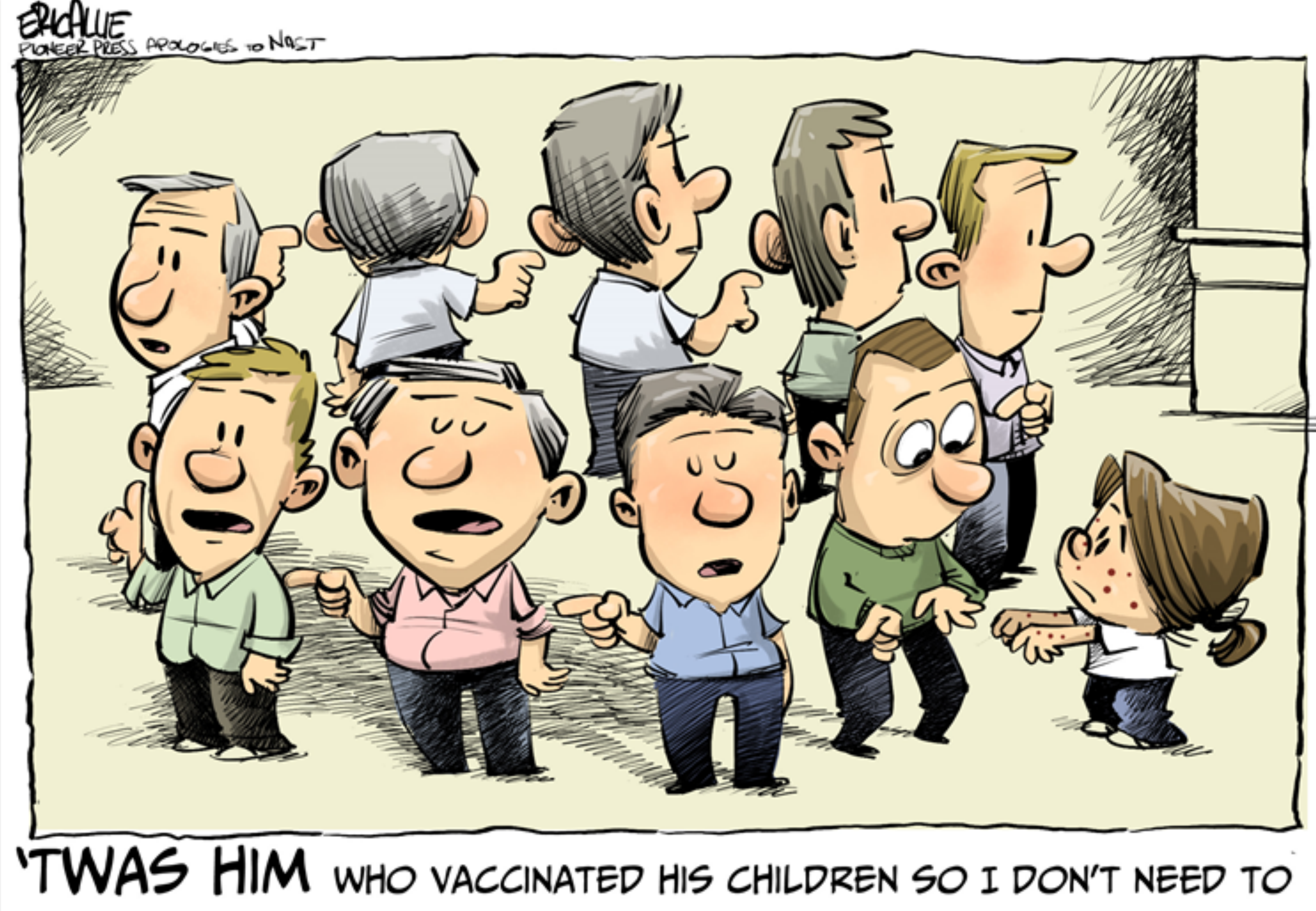

Thank you!

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