Emergence of voluntary vaccination behavior in a population of rational agents

CELEBRATING 50 years of CREATIVE SCIENCE 1962 – 2012

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in collaboration with

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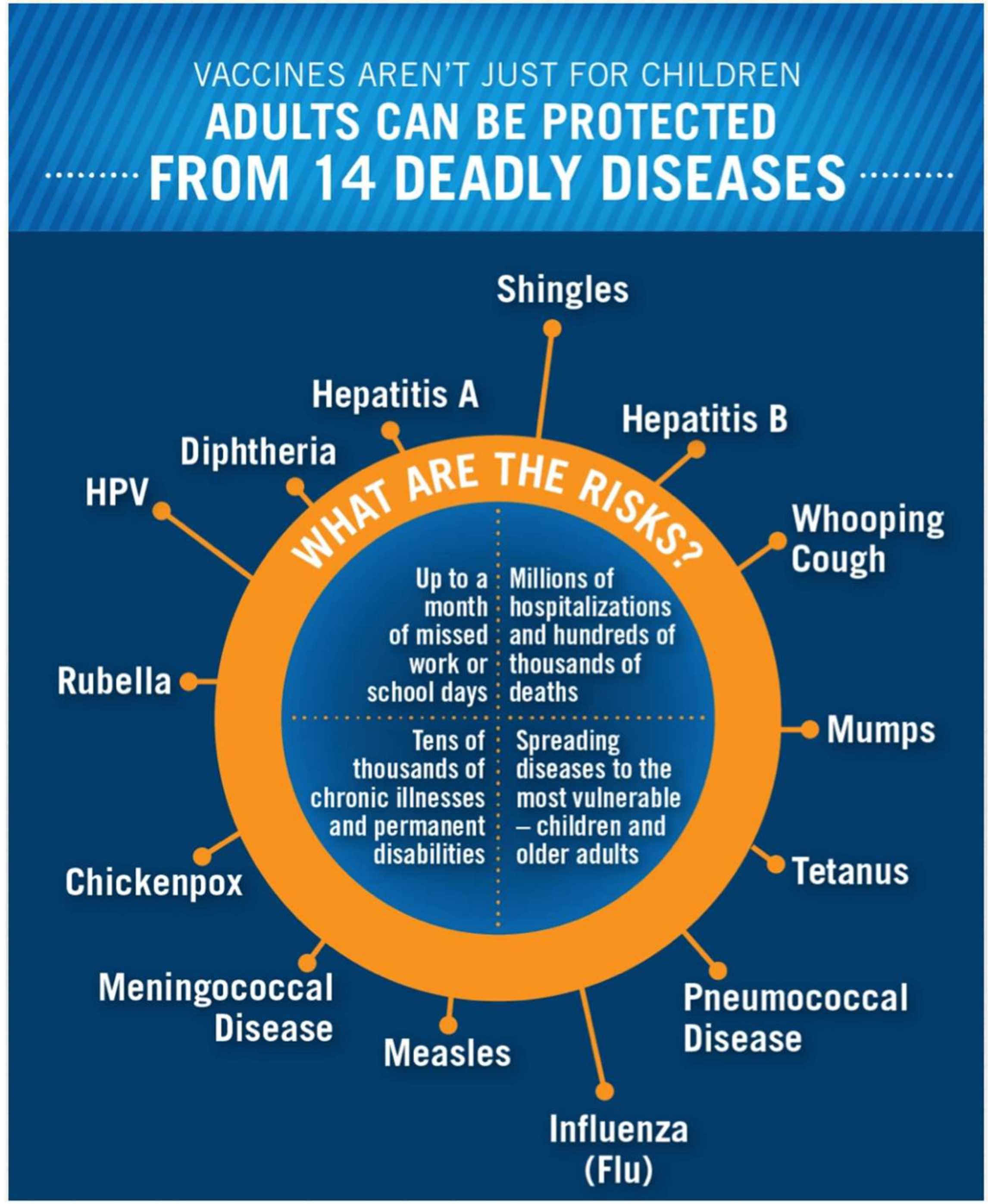
and V Sasidevan (IMSc)

Vaccination

Biggest contribution to public health of 20th century medicine



And yet….

Vaccine Preventable Disease Outbreaks

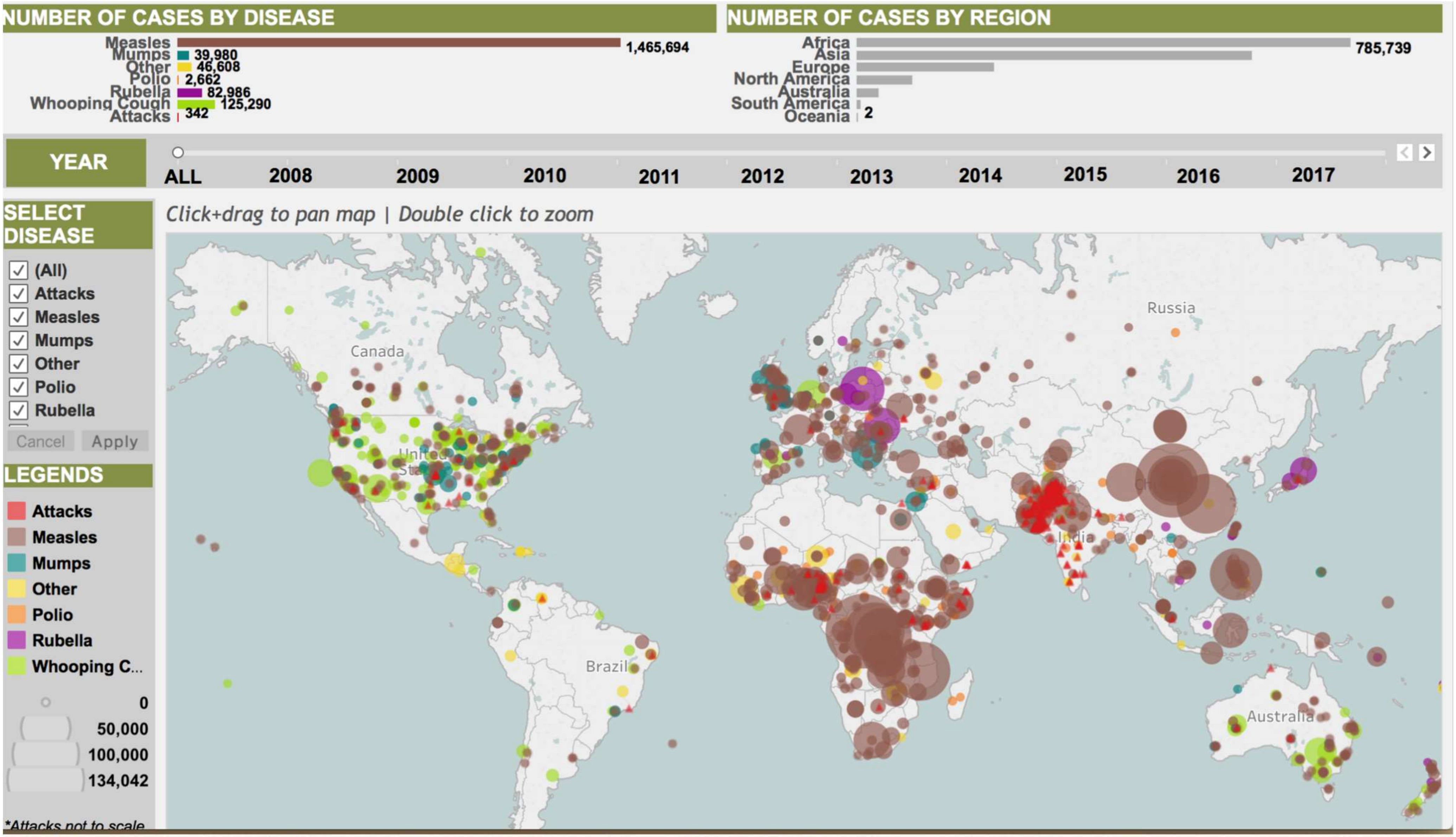


Image source: www.crf.org

Why ?

We need to consider

- ❑ How diseases spread through contact ?

  [Epidemiological model: SIR process on networks]

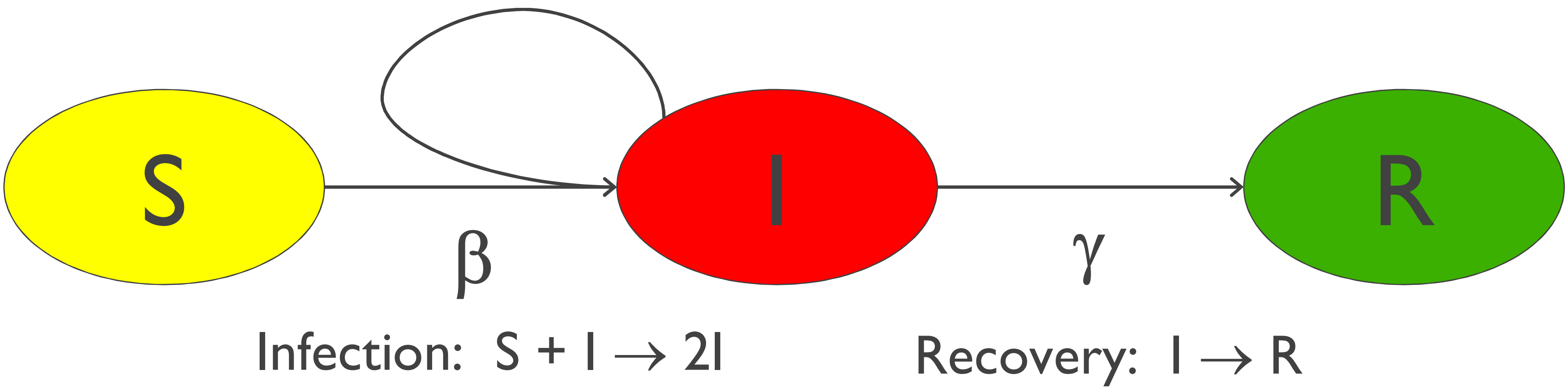
and

- ❑ How individuals voluntarily take decisions to get vaccinated (or vaccinate their children) ?

  [Game-theoretic model of strategic choice made by rational agents based on information about outcomes]

Compartmental Model of Epidemic Dynamics

Under assumption of homogeneous mixing,
i.e., anyone is equally likely to infect anyone else:



β : rate of infection spreading

γ : recovery rate (= 1/average infectious period, τ_I)

SIR model (Kermack-McKendrick, 1927) [S+I+R = N constant]

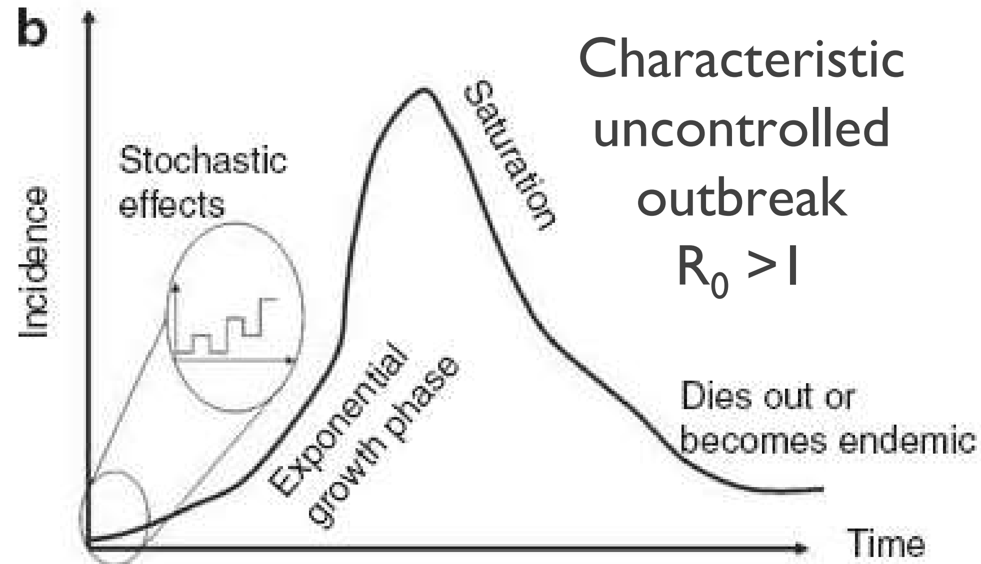
Susceptible population : $dS/dt = -\beta\ S\ I$

Infected population : $dI/dt = \beta\ SI - \gamma\ I$

Basic reproduction number R_0

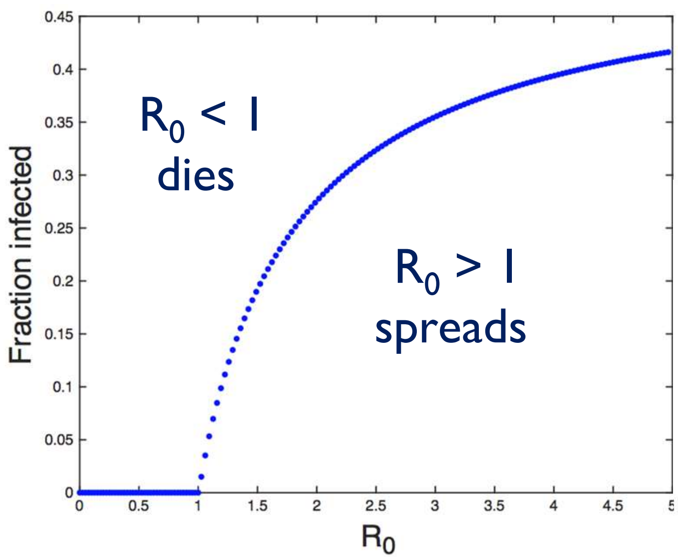
Initially contagion may die out due to stochastic fluctuations, but once established, can grow exponentially until pool of susceptible individuals is exhausted

R_0: Mean number of new infections caused by a single infectious individual in a wholly susceptible population (as in the beginning of an epidemic)

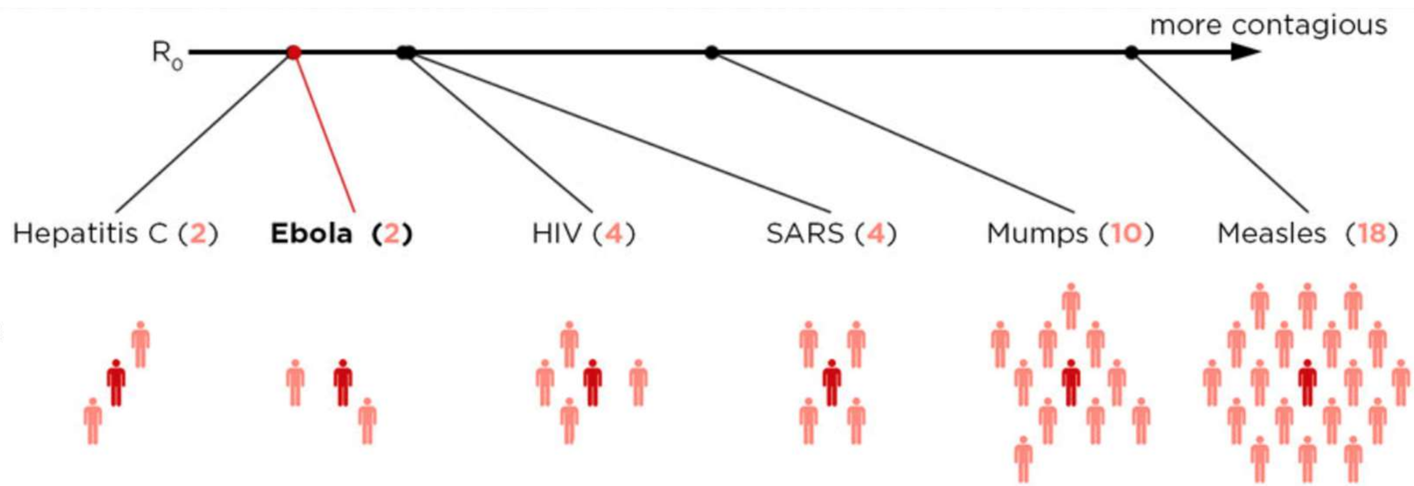


Hollingsworth, J Pub Health Policy, 2009

Characteristic uncontrolled outbreak $R_0 > 1$



If each infected person on average infects more than one other individual, $R_0 = N\,\beta\,\tau_I > 1 \Rightarrow$ Epidemic



Utility of R_0 : Minimum immunization coverage required

SIR model equation: $dI/dt = \beta SI - \gamma I$

$\Rightarrow$ To stop epidemic need to make $dI/dt < 0$, i.e., $S(t=0) < \gamma / \beta$

where

β : rate of infection spreading

γ: recovery rate (= [avg infectious period, $\tau]^{-1}$)

Let total population be N

Thus, proportion of the population that is susceptible, $s = S(t=0)/N$ needs to be made smaller than $1/(N\beta\tau_I) = 1/R_0$

$\Rightarrow$The fraction of population that needs to be immunized to stop the epidemic (assuming homogeneous mixing) is $p > 1 - (1/R_0)$

For Measles, $R_0 = 12 - 18 \Rightarrow p_c = 92 - 95$ %

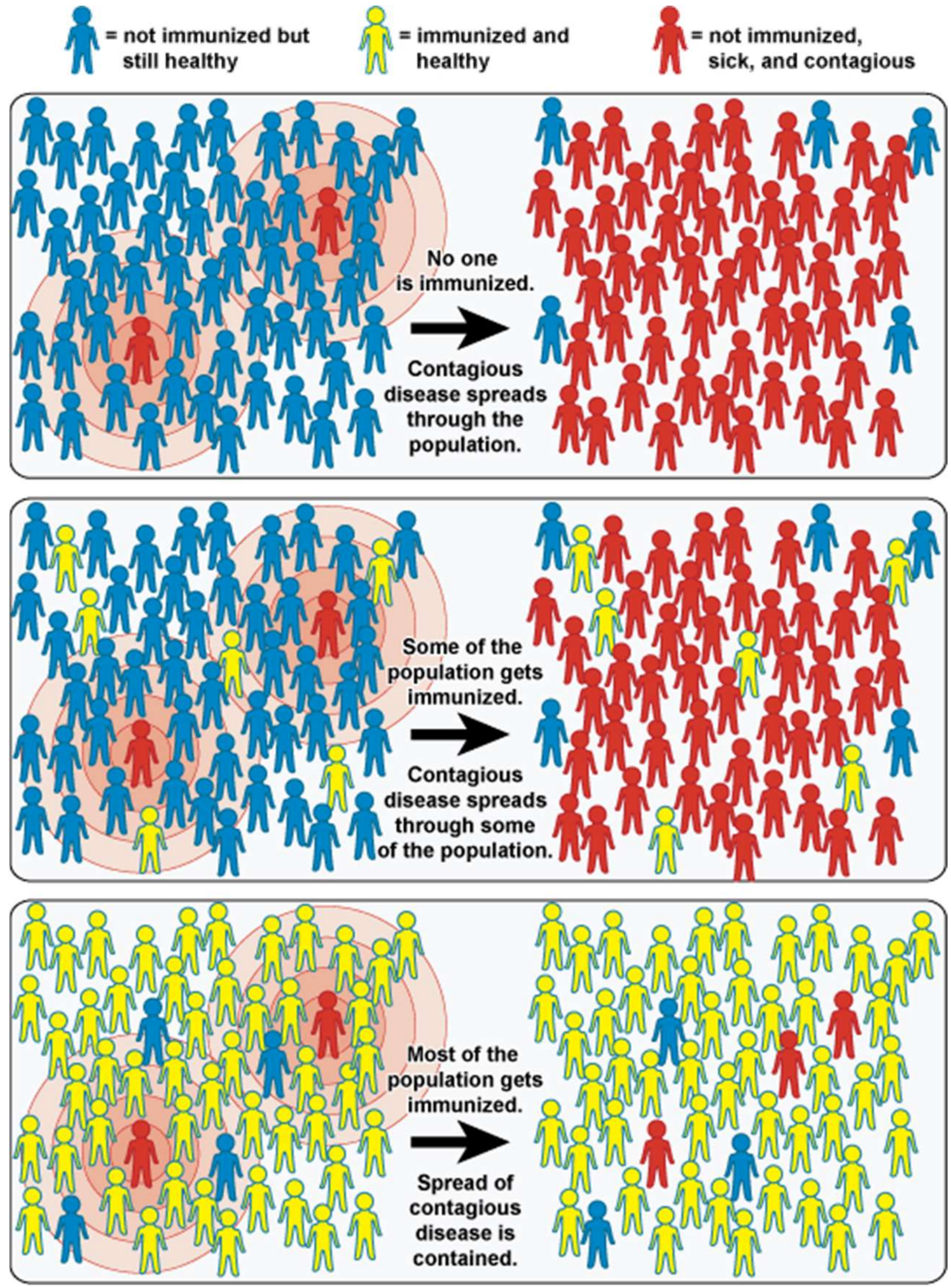
Smallpox, $R_0 = 5 - 7 \Rightarrow p_c = 80 - 86$ %

Influenza, $R_0 = 1.2 - 1.8 \Rightarrow p_c = 33 - 44$ %

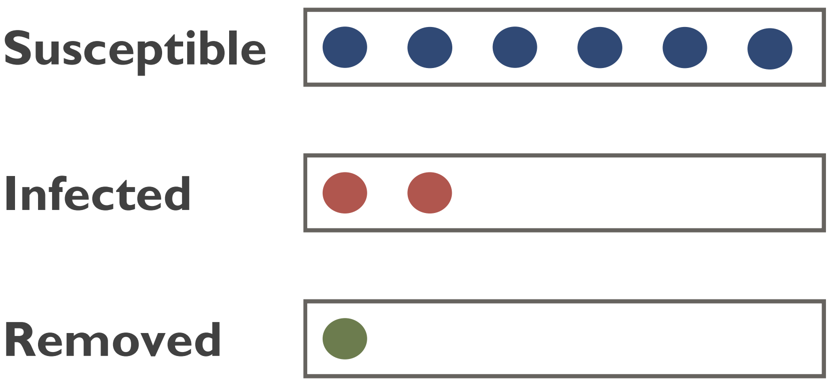
Immunization via vaccination not only benefits the individual receiving it but also benefits the community (a "public good") through

Herd Immunity

When a critical fraction of a community is immunized against an infectious disease (i.e., those individuals moved from S to R directly), even unvaccinated individuals are protected against it – eliminating the possibility of an epidemic



Modeling Epidemic Spreading among Individuals with Voluntary Vaccination



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

$$\begin{aligned} \beta &= \text{transmission probability,} \\ k_{inf} &= \text{no. of infected neighbour,} \\ \tau_i &= \text{average infectious period,} \\ \pi &= \text{vaccination probability.} \end{aligned}$$

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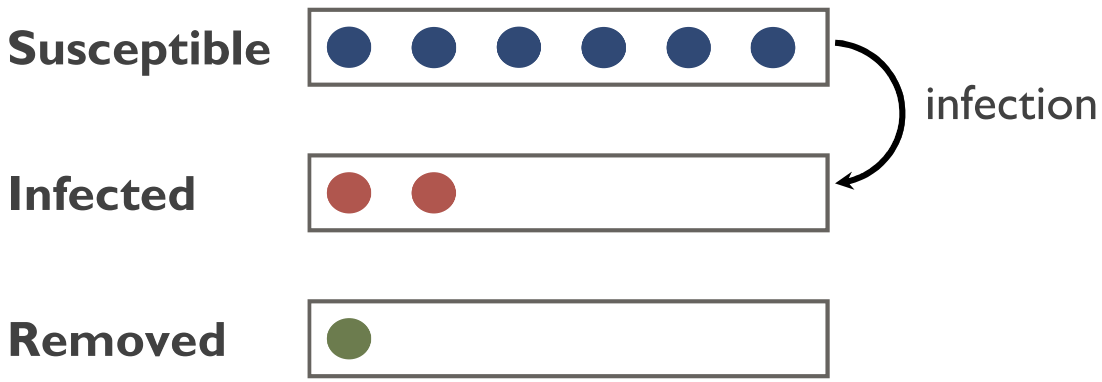

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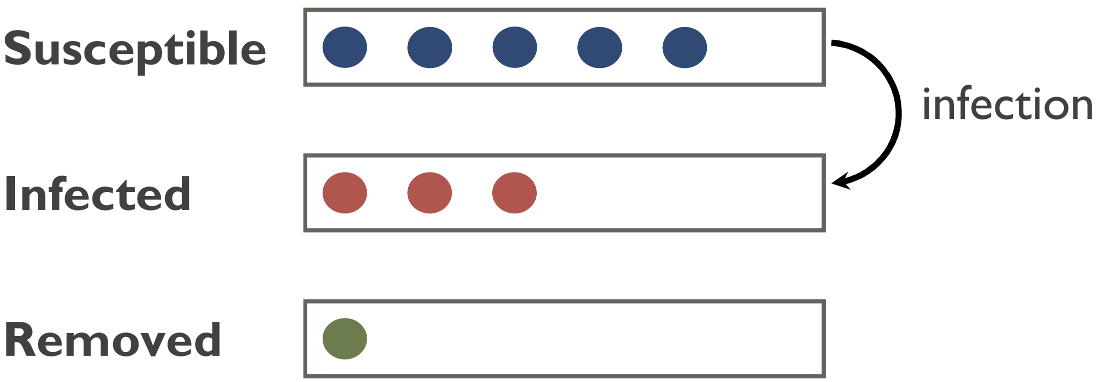

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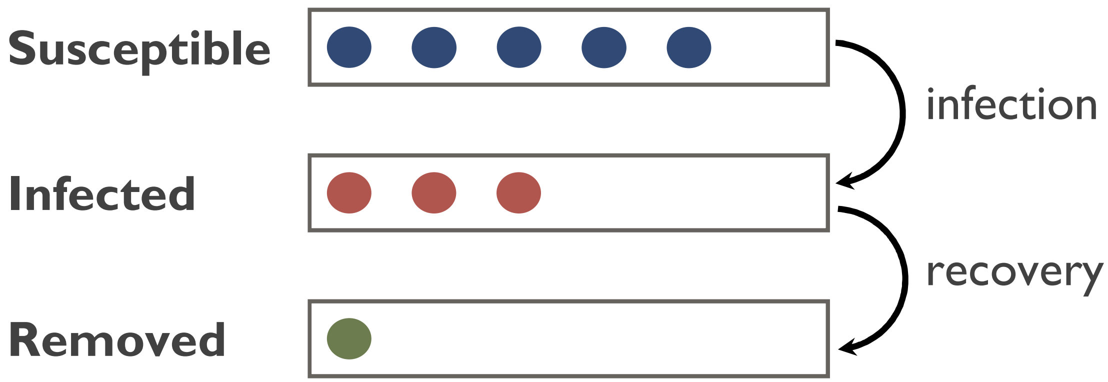

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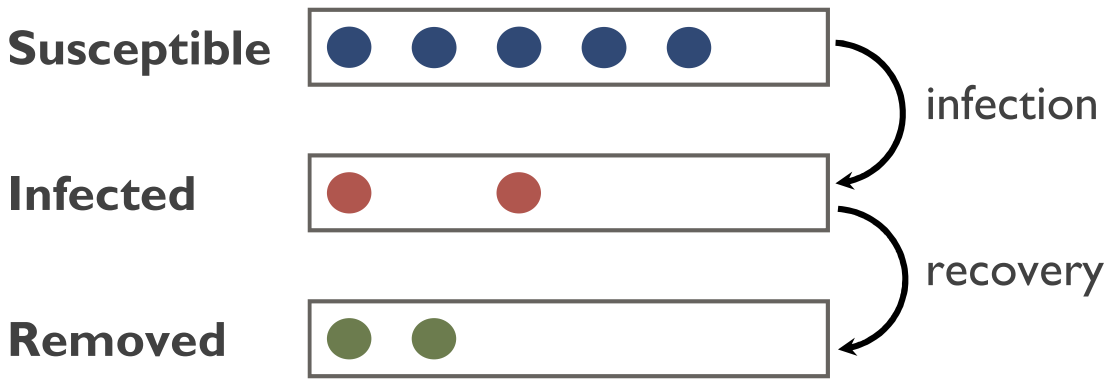

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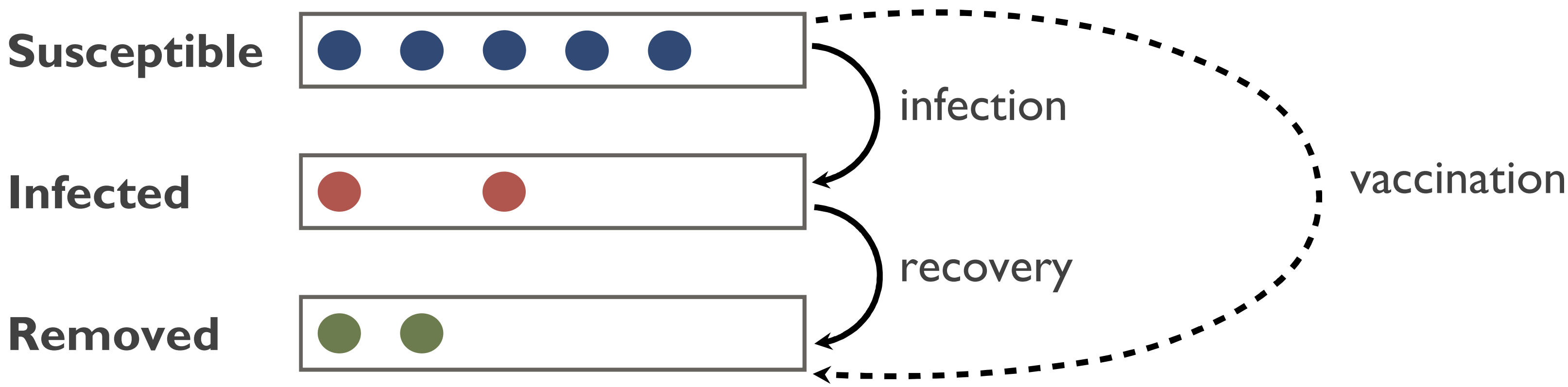

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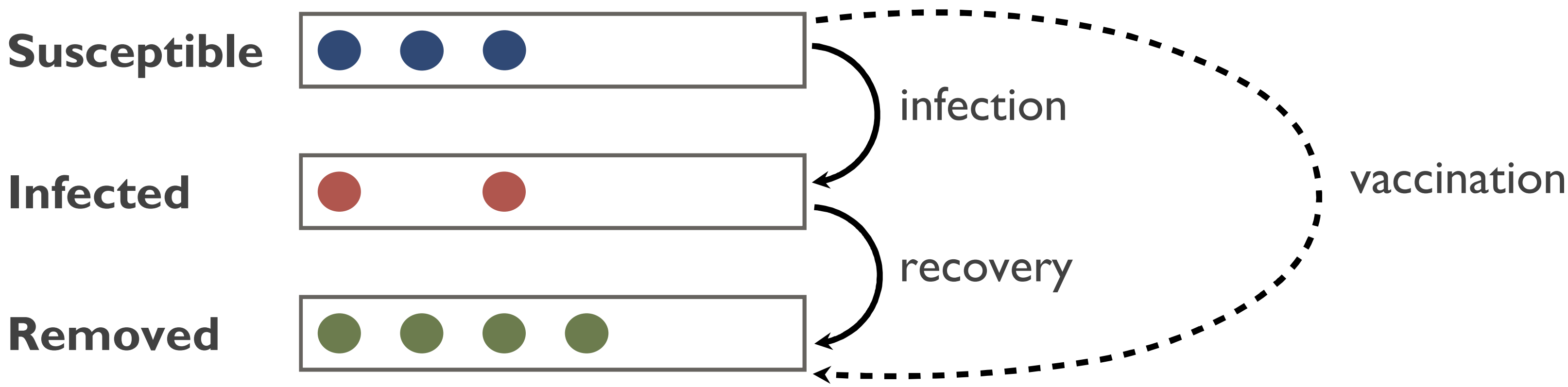

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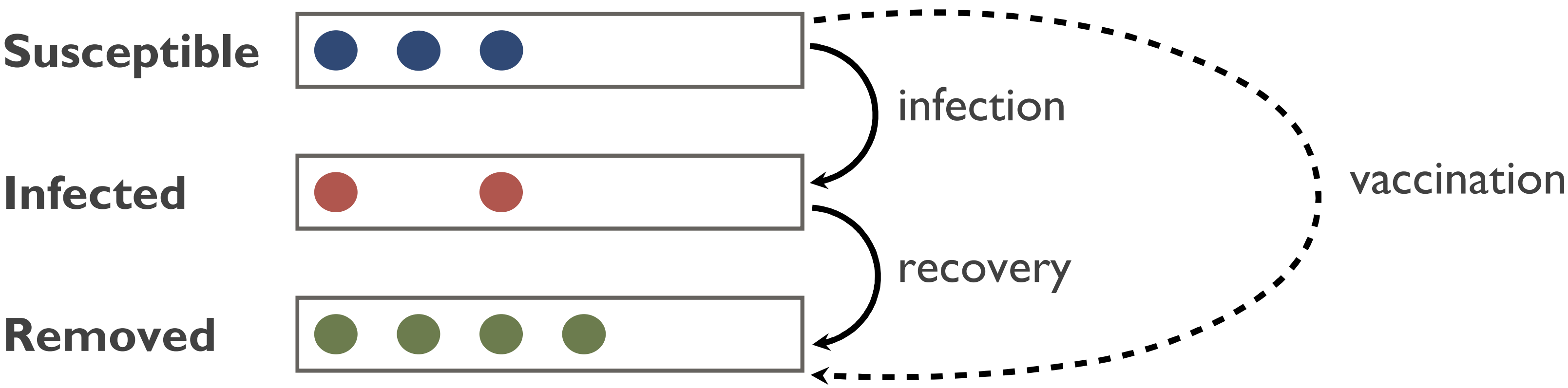

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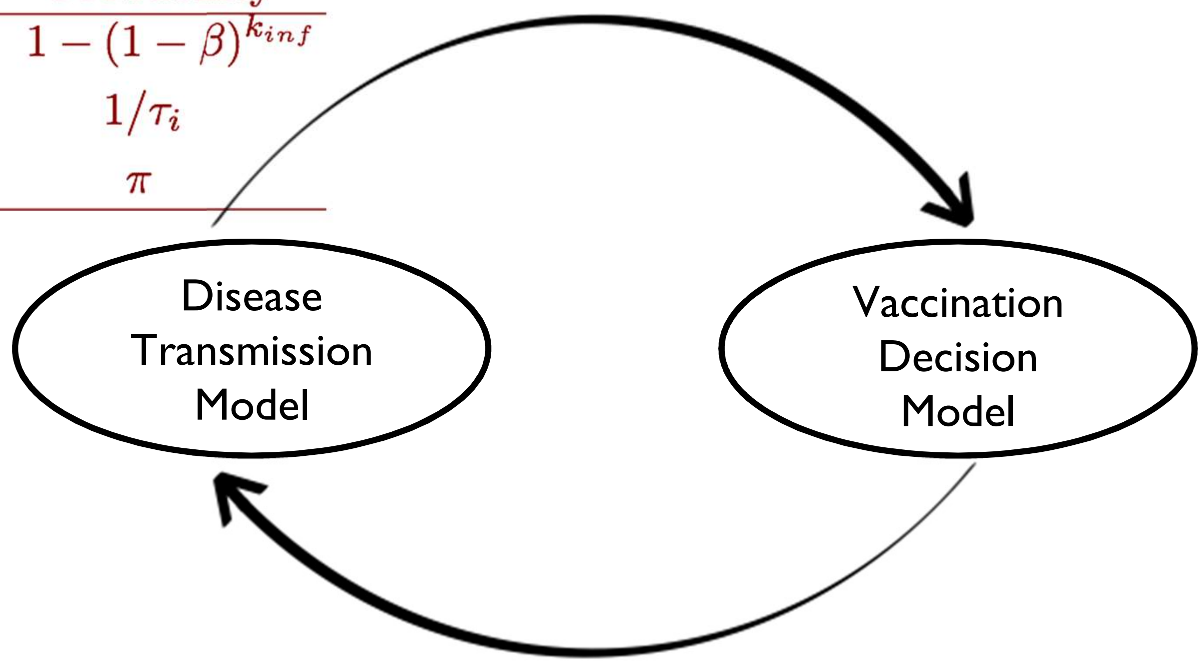


How to model the process by which agents take vaccination decision ?

Assuming agents are rational individuals trying to maximize their personal individual based upon information available to them…

… we can use the theory of games (strategic decision-making)

Why game theory ?

Players → **Actions** → **Payoffs**

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

Why game theory ?

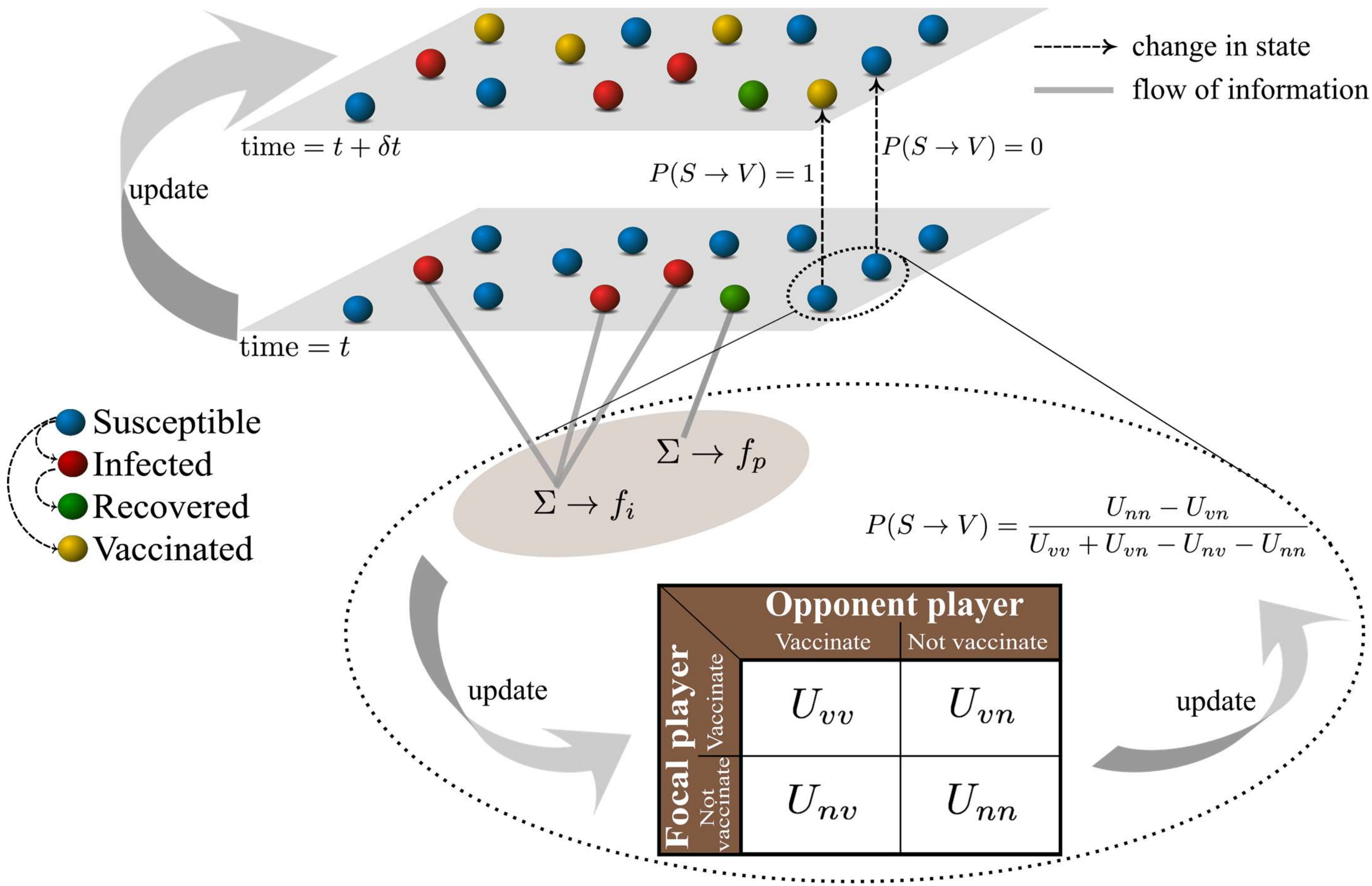
Players → **Actions** → **Payoffs**

Individuals → **Vaccinate or not** →
- ❑ **Risk of infection**
- ❑ **Cost of vaccination**

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

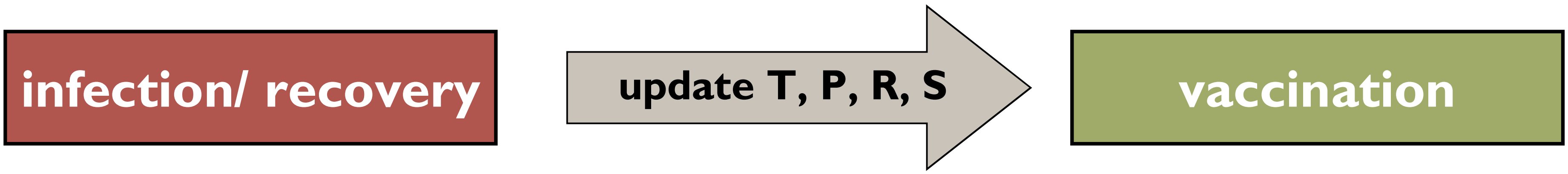
		Focal player	
		Vaccinate	Not vaccinate
Opponent	Vaccinate	Cost of vaccine and no risk of infection	No cost of vaccine and no risk of infection
	Not vaccinate	Cost of vaccine and high risk of infection	No cost of vaccine and high risk of infection

The model


change in state
flow of information
time = $t + \delta t$
update
$P(S \to V) = 1$
$P(S \to V) = 0$
time = t
Susceptible
Infected
Recovered
Vaccinated
$\Sigma \to f_p$
$\Sigma \to f_i$
$P(S \to V) = \frac{U_{nn} - U_{vn}}{U_{vv} + U_{vn} - U_{nv} - U_{nn}}$
Opponent player
Vaccinate
Not vaccinate
Focal player
Vaccinate
Not vaccinate
U_{vv}
U_{vn}
U_{nv}
U_{nn}
update
update

Coupling Epidemic Propagation & Vaccination

Two step process:



step 1 infection spreads (SIR model on contact network) resulting in change of prevalence

step 2 each agent *i* receives information about the state of its all neighbors, i.e. f_i and f_p, and calculate its T, P, R and S, which decides the nature of game.
Based on *Nash equilibrium* for that game, susceptible agent *i* chooses its action (V or NV).

For **Nash Equilibrium**, the probability of agent *i* getting vaccinated at time *t* is given by

$$\pi_i = \frac{P_i - S_i}{R_i + P_i - T_i - S_i}.$$

Step 1: Using prevalence information

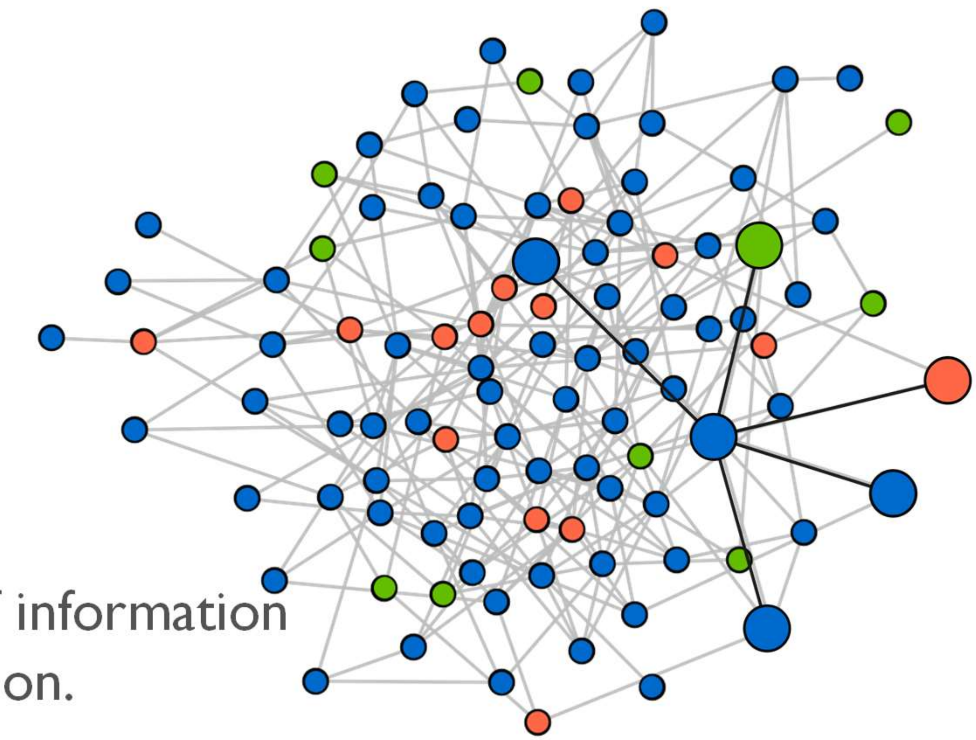
f_p is the fraction of neighbours that are protected against prevalent infection

f_i is the fraction of infected agents and is 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

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



By using parameter α, we tune the nature of information being used in making decision about vaccination.

$\alpha = 0$ → $\alpha = 1$

Entirely local information → ***Entirely global information***

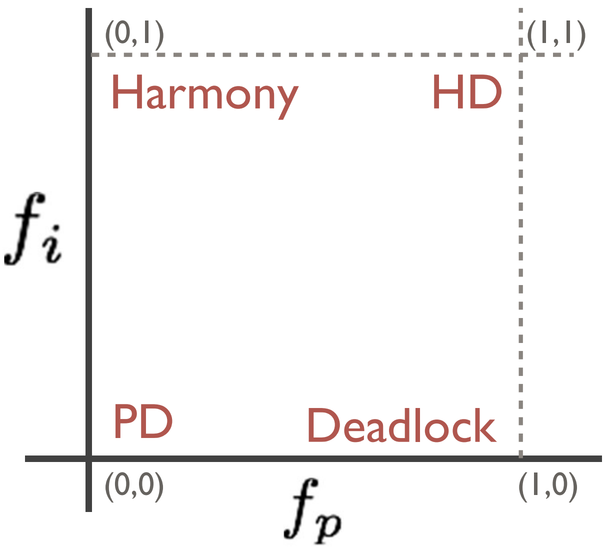
Step 2: Decisions by rational agents

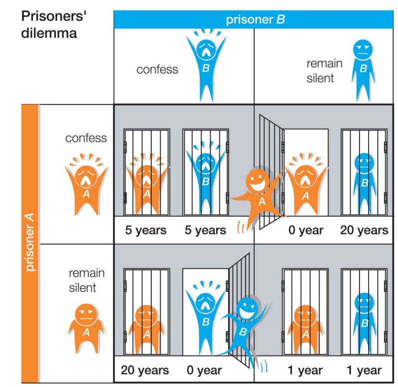
T $U_{nv} = af_p + b,$

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

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

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





PD: T > R > P > S

HD: T > R > S > P

PD: $U_{nv} > U_{vv} > U_{nn} > U_{vn}$ ⟶ b > h > d > f

Deadlock: $U_{nv} > U_{nn} > U_{vv} > U_{vn}$ ⟶ a+b > c+d > h > f

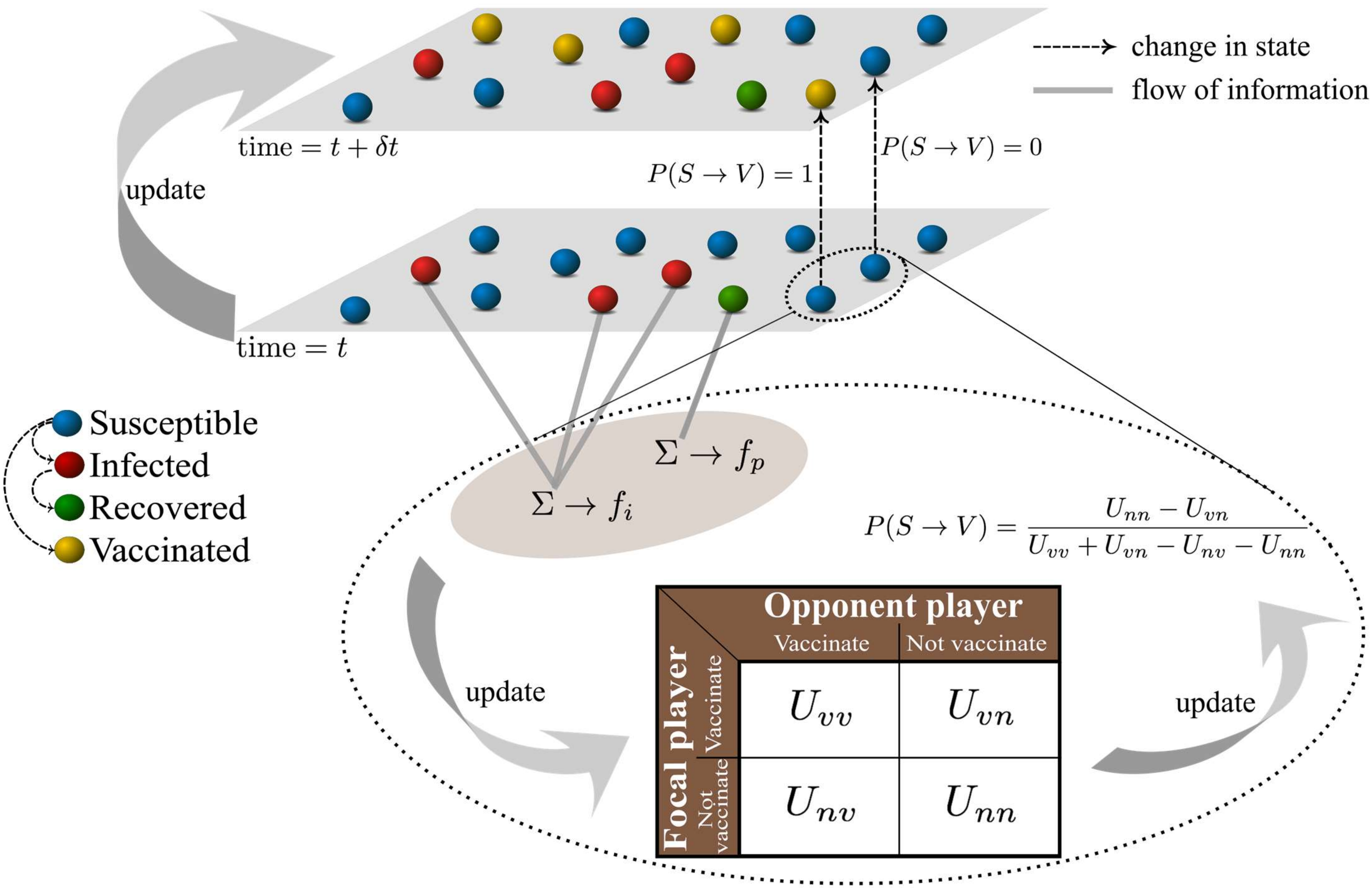
HD: $U_{nv} > U_{vv} > U_{vn} > U_{nn}$ ⟶ a+b > g+h > e+f > c+d

Harmony: $U_{vv} > U_{vn} > U_{nv} > U_{nn}$ ⟶ g+h > e+f > b > d

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

a+b > e+h > e+f > b, c+d > h > d > f

The model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update
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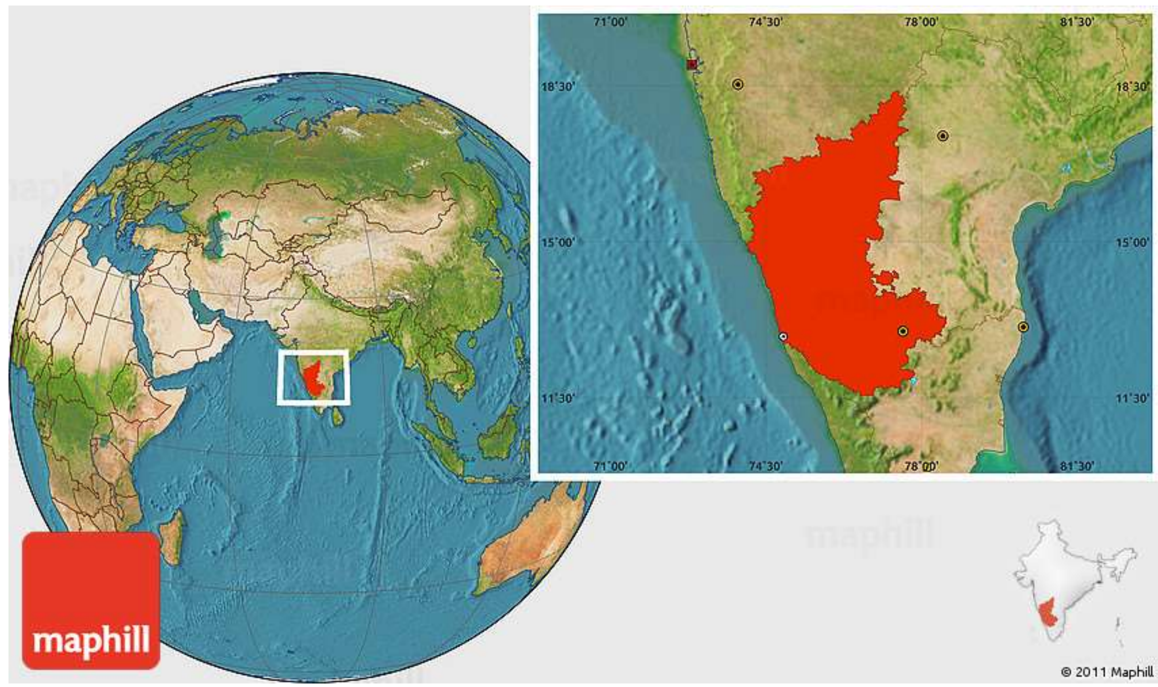
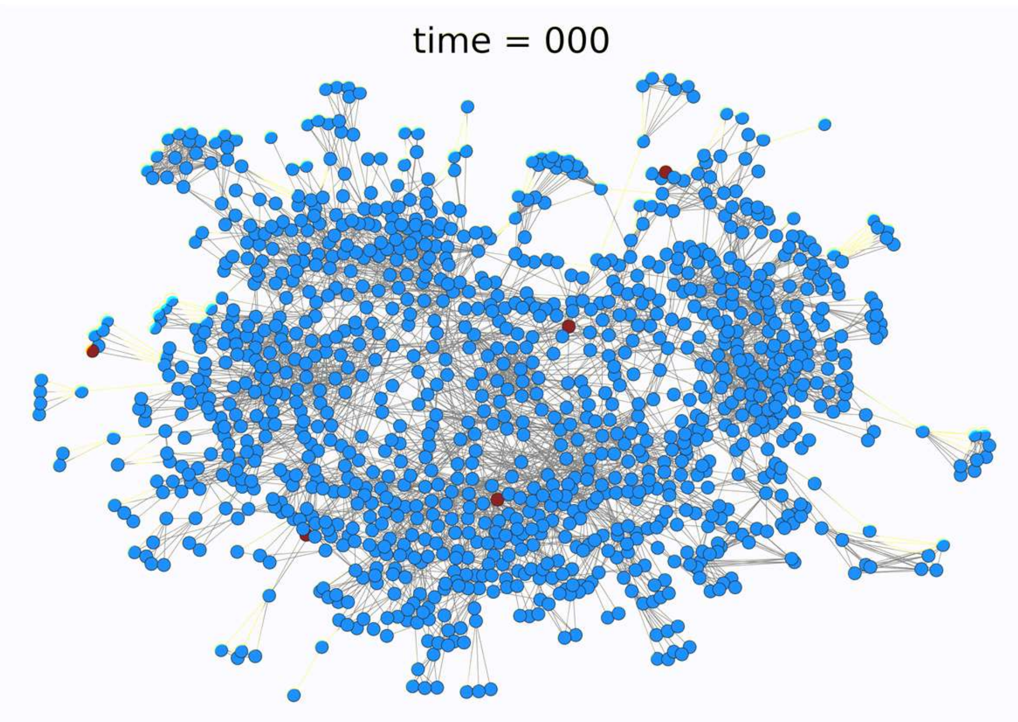
Empirical Social Network

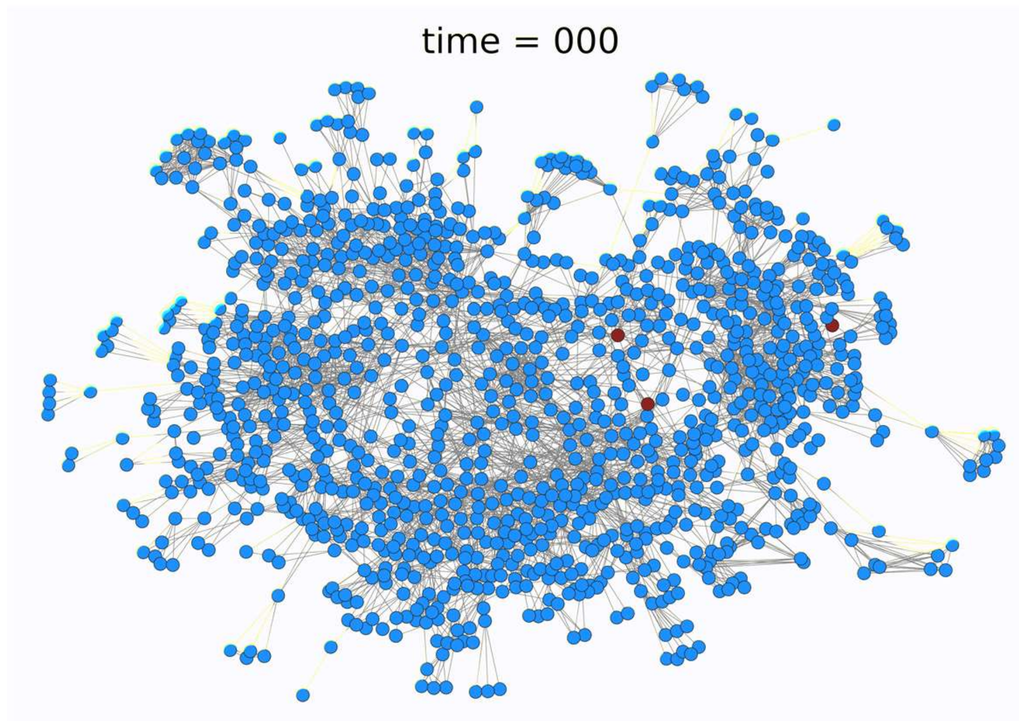
Detailed information about social contact networks between individuals from 75 villages in Karnataka



For Karnataka village social network

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





$\alpha = 0$ $\alpha = 1$

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

Susceptible Infected+Recovered Vaccinated

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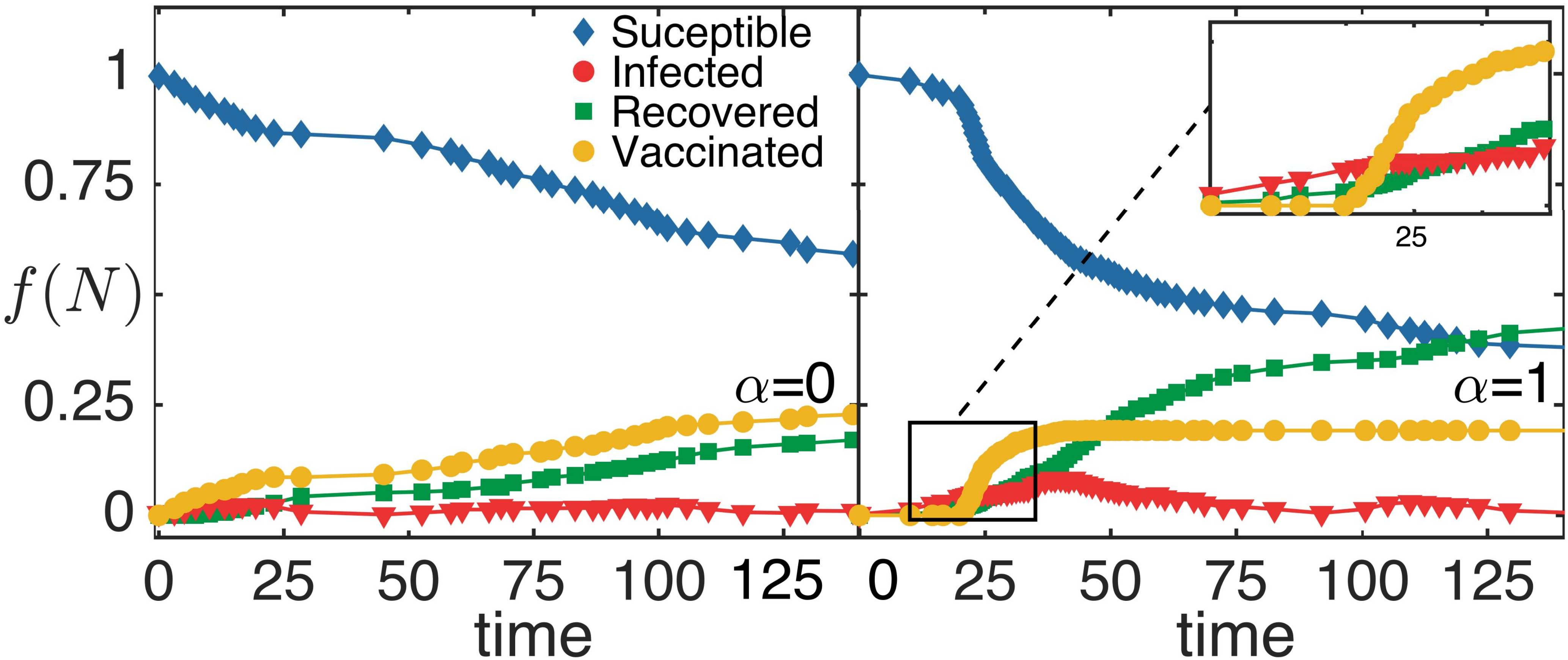

$f(N)$ is the fraction of agents at any time *t*.

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

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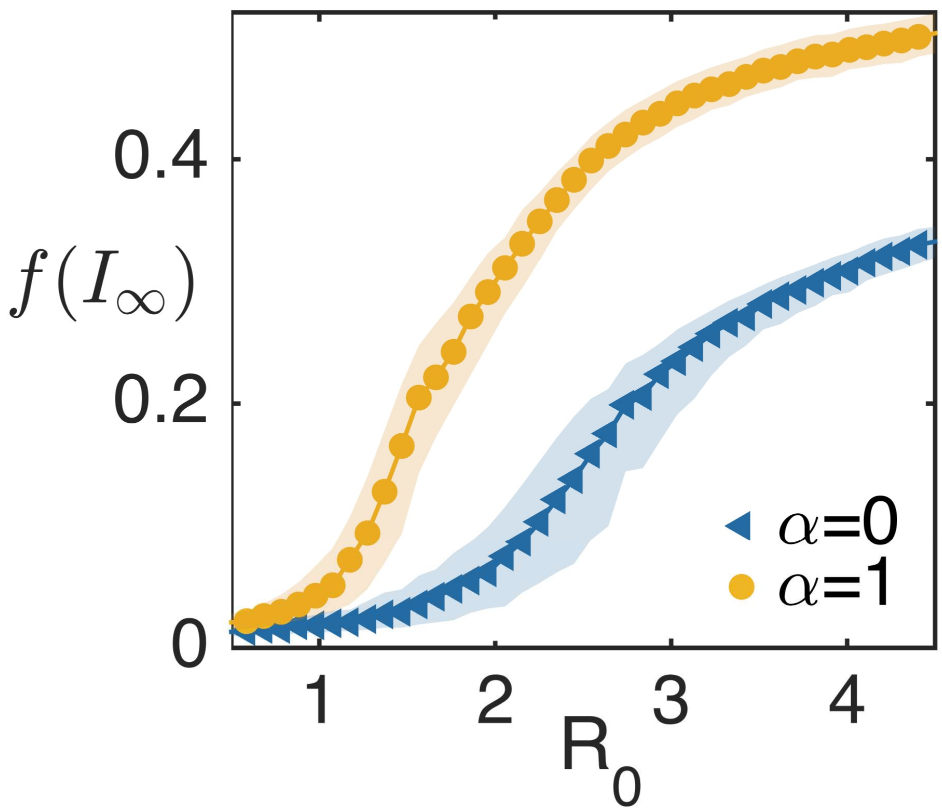
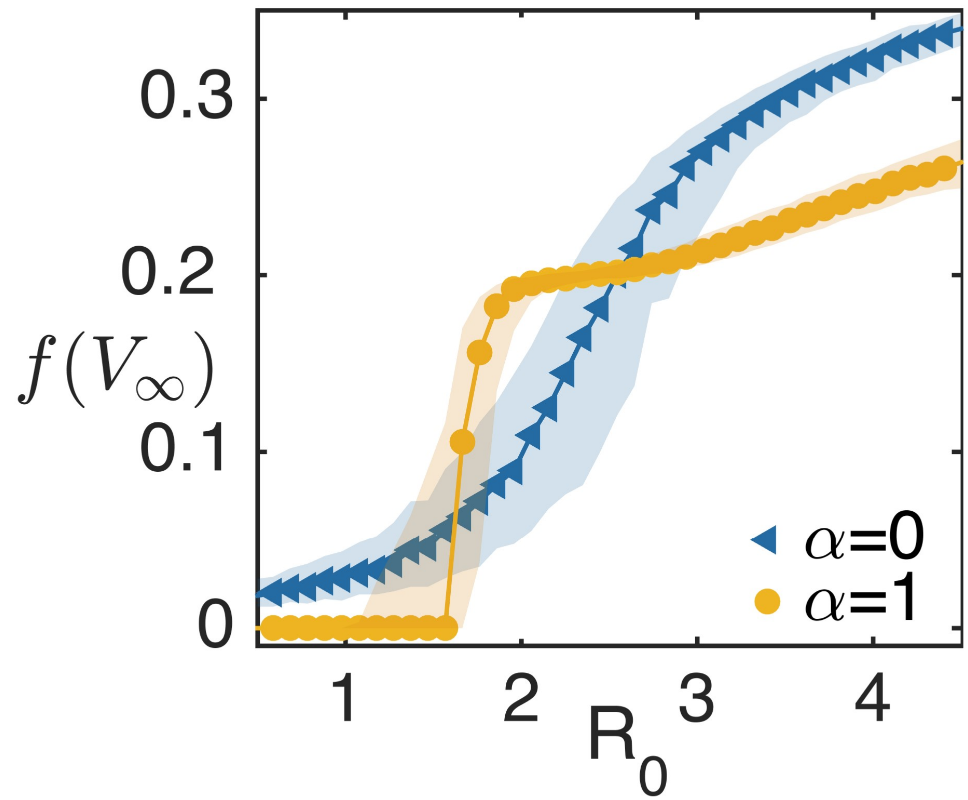




$f(I_\infty)$is the fraction of nodes that get infected over the whole course of simulated epidemic.

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

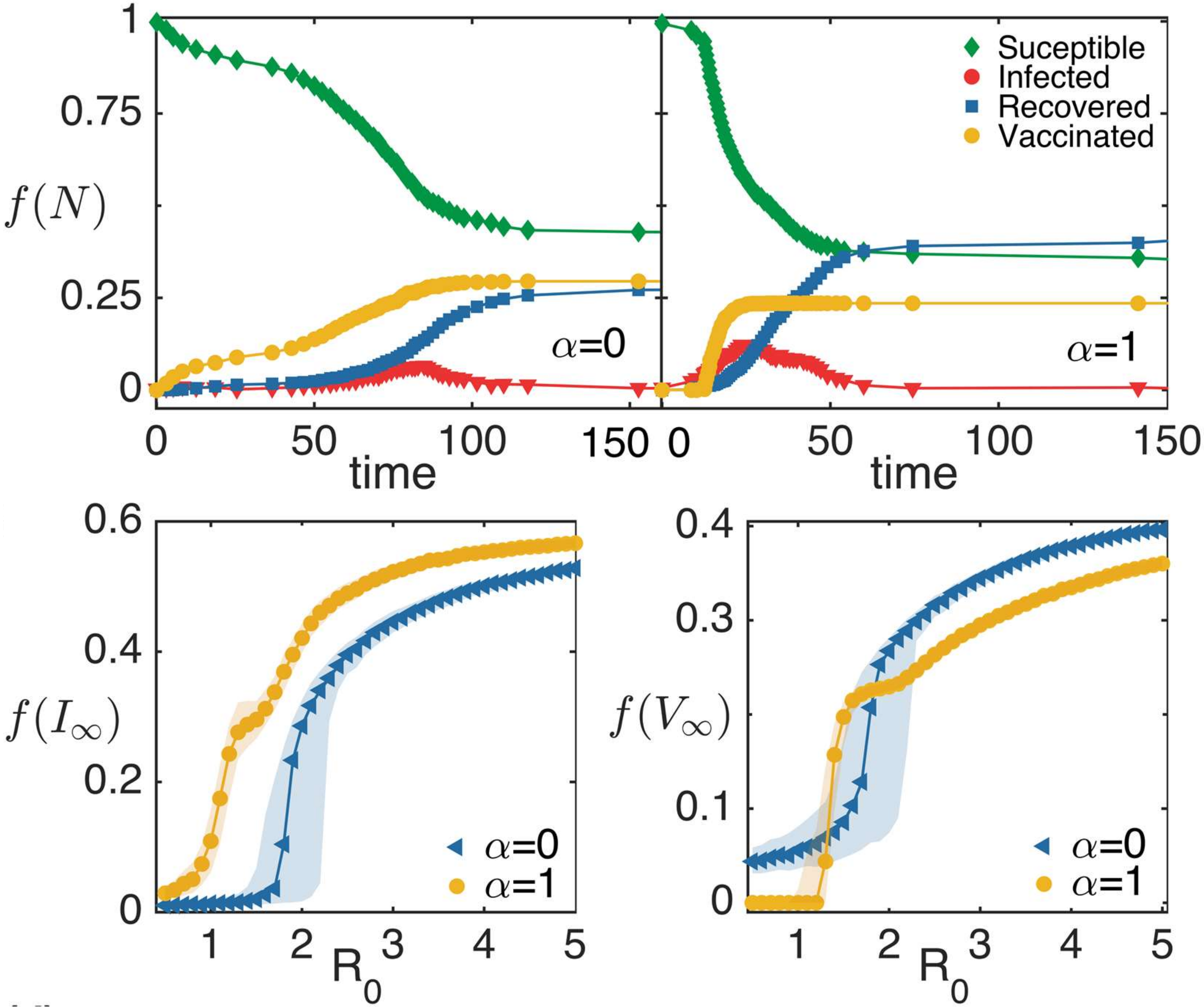
The importance of the information source

- Higher vaccine coverage is observed for the case when individuals assess their risk of catching infection based on the prevalence in the local social network neighborhood ($\alpha = 0$) as opposed to that in the whole population ($\alpha = 1$)
- The magnitude of global prevalence (expressed as the fraction of the entire population size) is low in the initial phase of the epidemic, and hence does not appear to pose a severe threat.
- The perception of risk in contracting the disease takes some time to become significant enough to incite vaccine uptake among individuals ($\alpha = 1$).
- By the time global prevalence becomes high enough so that the perceived risk of infection outweighs the cost of vaccination, the epidemic will have already affected a large fraction of the population.
- This delay in the emergence of vaccination behavior can sometimes manifest as a large final size of the epidemic despite high vaccine coverage.
- On the other hand, the presence of disease in an agent's neighborhood increases the risk of infection even at the early stage of an epidemic ($\alpha = 0$)
- Leads to an immediate increase in vaccine uptake and consequently reduces the final size of the epidemic

Vaccination acceptance depends on R_0 and nature of information

For ER random network

N = 1024, <k> = 10



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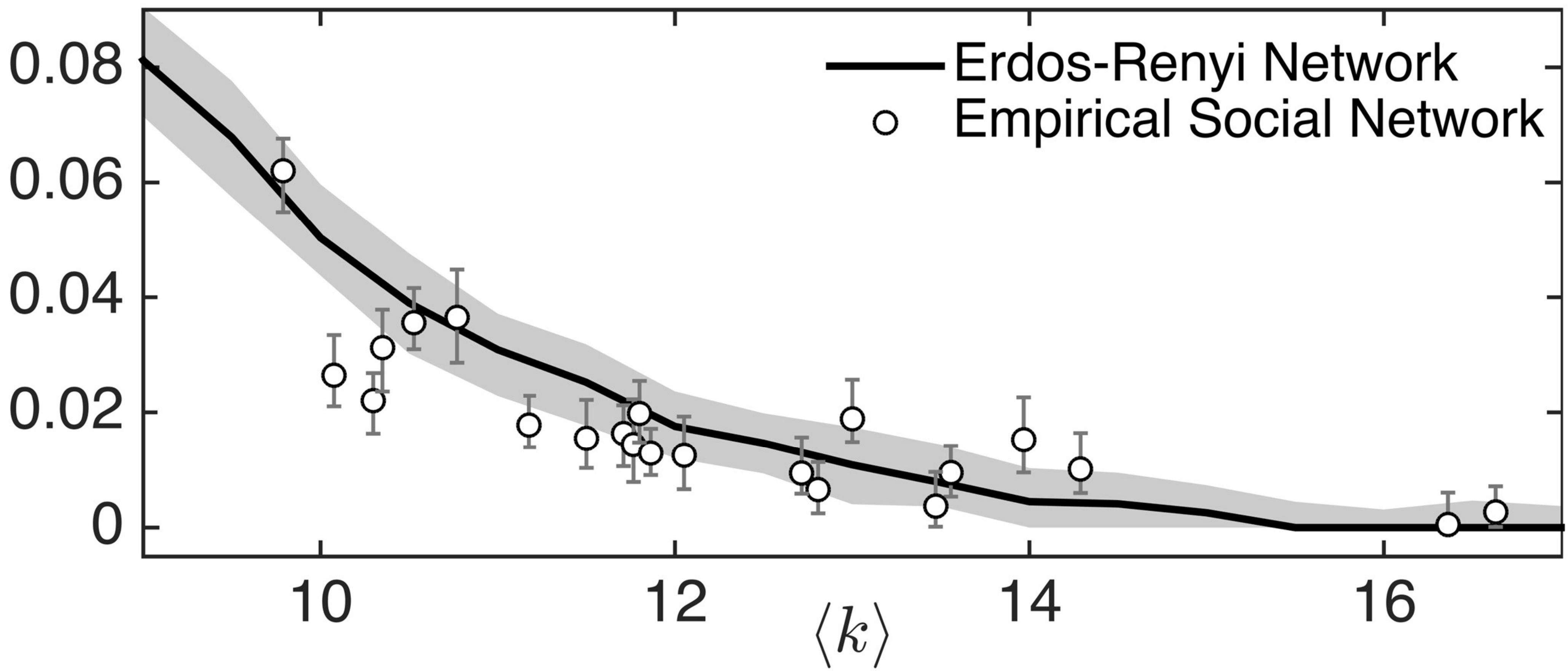
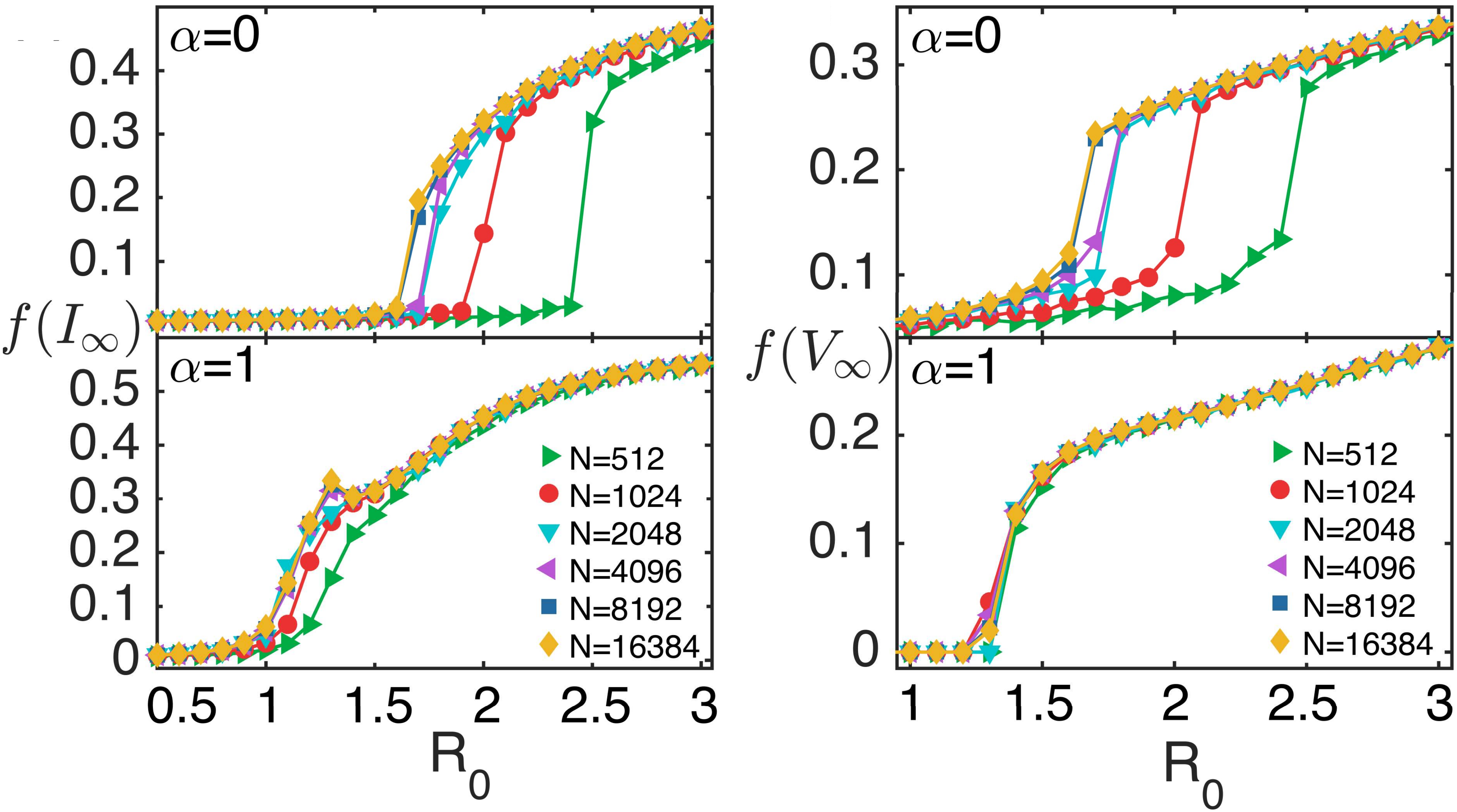
Empirical vs Model Networks



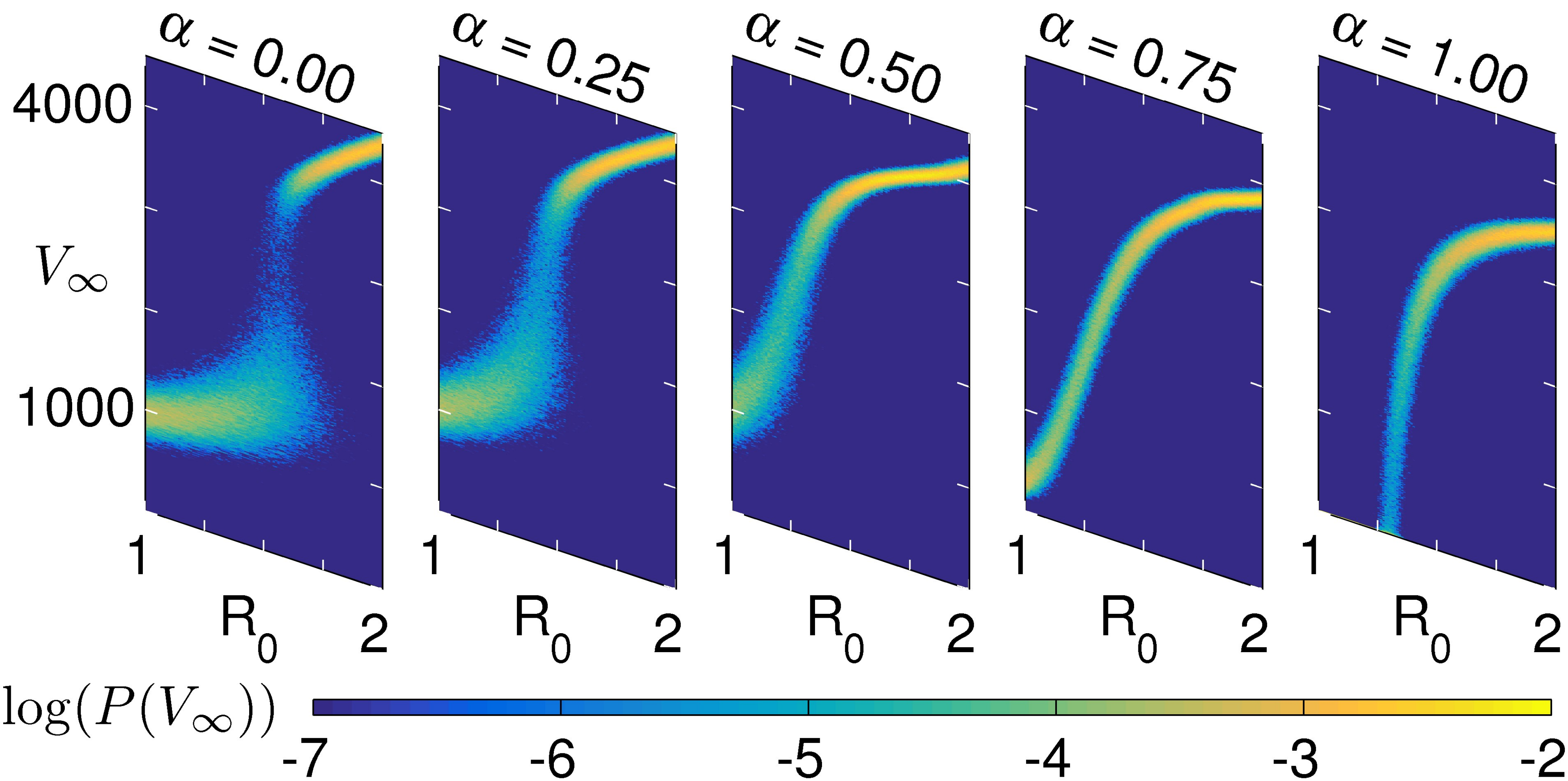
We selected the villages with Lcc >1000 to compare the results of simulated epidemic on empirical social network and ER random network. Results on empirical network follows a trend very similar to the results found for ER random network.

System size dependence



Phase transition

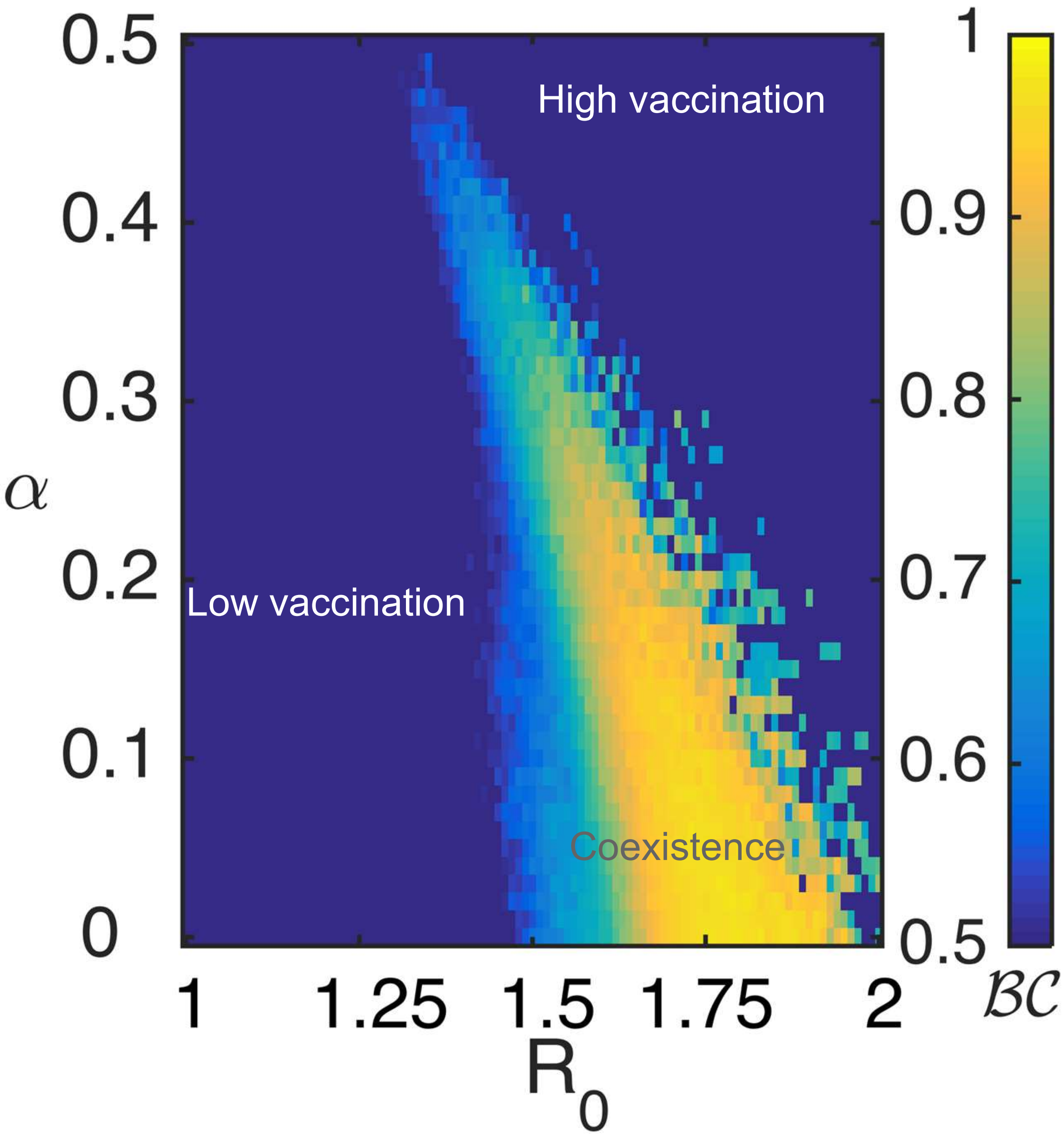
from low vaccination coverage to high coverage as R_0 is increased



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

Phase transitions

Discontinuous transition for low α, Continuous transition for high α



Bimodality coefficient* for P (V_∞)

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

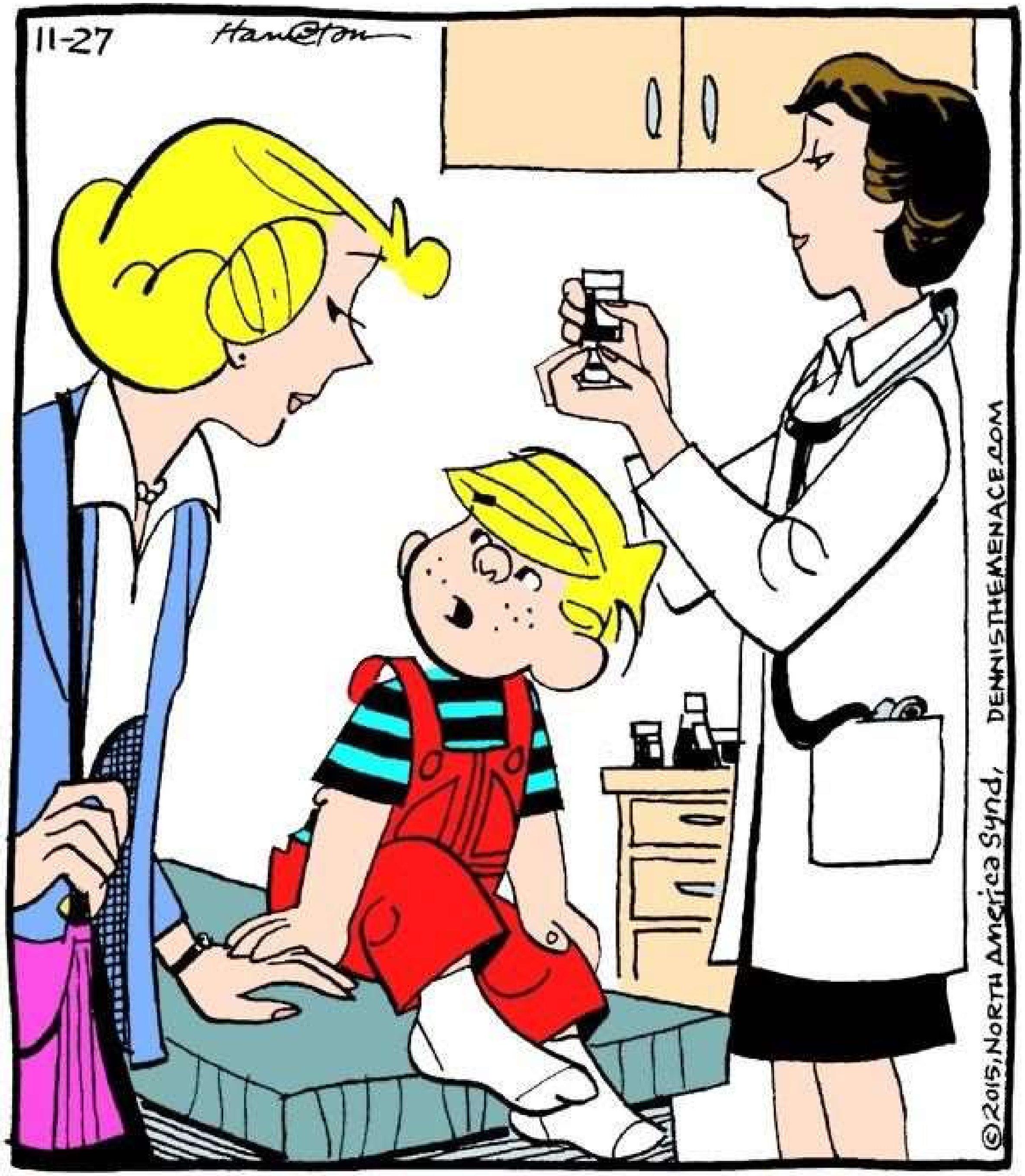
where, m_3 is the skewness of the distribution and m_4 is the kurtosis.

The benchmark value of BC_{crit} is 5/9, which suggests that the distribution is uniform. The values higher that 5/9 suggest the possibility of *biomodality* and lower values indicates *unmodality*.

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

Conclusions

- Vaccine hesitancy typically rises with decreasing disease incidence
- Consequence of reduced risk perception among individuals of contracting the disease.
- Understanding the mechanisms driving such behavior is important as it can reverse the success of any immunization program close to achieving the eradication of a disease.
- Simulate the spread of an infectious disease on a social network, where each agent can, at every time step, decide whether to get vaccinated.
- Decision-process of each agent is modelled by a game, payoff matrix for each agent varies over time as the epidemic progress and the immunization status of neighbors change.
- We show that a defining factor for efficient disease control through voluntary vaccination is the source of information (local or global).
- Higher vaccine coverage is observed for the case when individuals assess their risk based on the prevalence in the local social network neighborhood, as opposed to the global prevalence in the population.
- Results don't depend on population size & meso-level structural details, e.g., modularity, but depend strongly on the degree



"BUT IF EVERYBODY ELSE GETS A FLU SHOT, I WON'T NEED ONE, 'CAUSE THERE WON'T BE ANYBODY TO CATCH IT FROM."

arxiv:1709.07674

Thanks