Analysis and Control of Epidemics on Time Dependent Adaptive Networks

Ira B. Schwartz

US Naval Research Laboratory

Code 6792

Washington, DC

Luis Mier-y-Teran

JHU Bloomberg School of Public Health and NRL

Washington,DC

Leah B. Shaw

College of William and Mary

Williamsburg, VA

Brandon S. Lindley

NRL/Wagner Associates

Hampton, VA

Research supported by the Office of Naval Research, Air Force Office of Scientific Research and National Institutes of Health

Deep Dive STEM Meeting, 2014

Modeling Ebola Data

Camacho, A., et al., Potential for large outbreaks of Ebola virus disease. Epidemics (2014), http://dx.doi.org/10.1016/j.epidem.2014.09.003

Table 1
Previously published estimates of basic reproduction number, R_0, for Ebola.

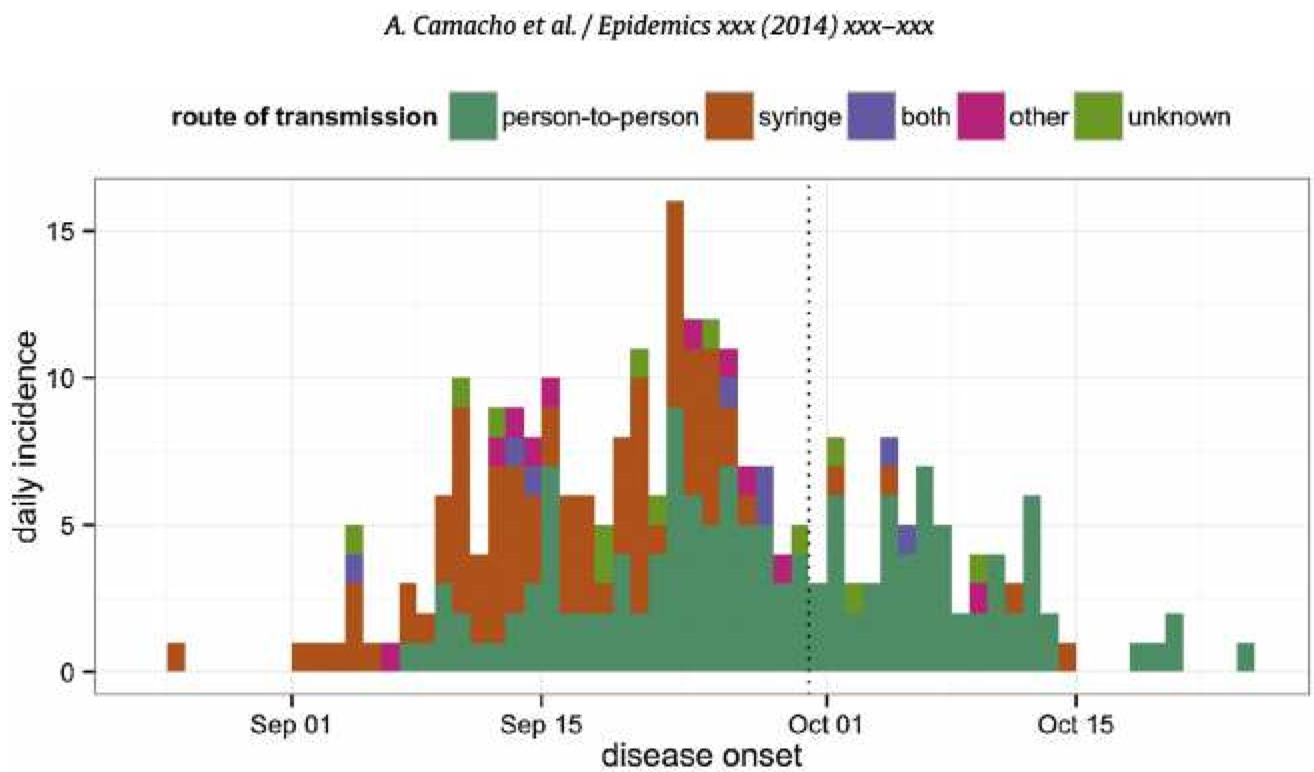
Location	Date	R_0	95% CI (if given)	Reference
DRC	1995	1.83		Chowell et al. (2004)
		3.65	3.05–4.33	Ferrari et al. (2005)
		2.7	1.9–2.8	Legrand et al. (2007)
		1.38		Lekone and Finkenstädt (2006)
		2.22	1.9–2.73	Ndanguza et al. (2013)
		1.93	1.74–2.78	White and Pagano (2008)
Uganda	2000/1	1.34		Chowell et al. (2004)
		1.79	1.52–2.30	Ferrari et al. (2005)
		2.7	2.5–4.1	Legrand et al. (2007)

Caveat: Hospital-based infection played a substantial role in parameter fitting

Not possible to identify route of transmission nor human behavior.

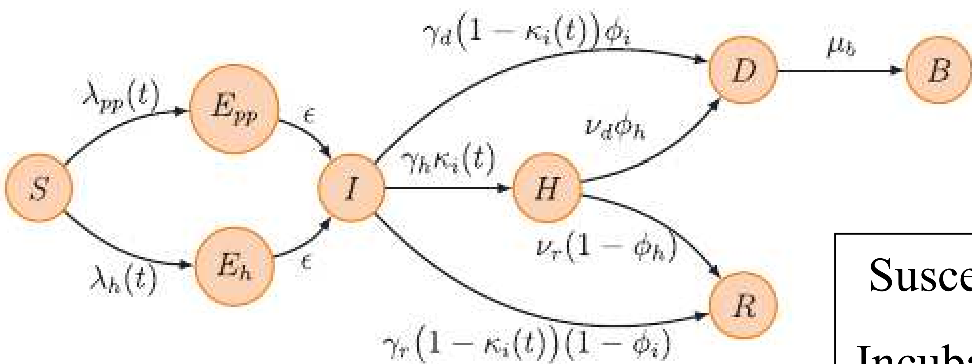
Revisited 1976 outbreak to reveal sources of transmission

Daily Incidence for Zaire 1976



Modeling Study of Ebola

A. Camacho et al. / Epic



$$
\begin{aligned}
\frac{dS}{dt} &= -(\beta_i(t)I + \boxed{\beta_h(t)H + \beta_d(t)D})\frac{S}{N} \\
\frac{dE_{pp}}{dt} &= (\beta_i(t)I + \beta_d(t)D)\frac{S}{N} - \epsilon E_{pp} \\
\frac{dE_h}{dt} &= \beta_h(t)H\frac{S}{N} - \epsilon E_h \\
\frac{dI}{dt} &= \epsilon(E_{pp} + E_h) - \Gamma_i(t)I \\
\frac{dH}{dt} &= \gamma_h\kappa_i(t)I - (\phi_h\nu_d + (1-\phi_h)\nu_r)H \\
\frac{dD}{dt} &= \gamma_d(1-\kappa_i(t))\phi_i I + \nu_d\phi_h H - \mu_b D \\
\frac{dR}{dt} &= \gamma_r(1-\kappa_i(t))(1-\phi_i)I + \nu_r(1-\phi_h)H \\
\frac{dB}{dt} &= \mu_b D
\end{aligned}
$$

Susceptible to infection (S).

Incubation exposed class (E),

Infectious (I).

Assumed latent and incubation periods are equivalent.

Recovered state (R);

Remain infectious and go into hospital (H);

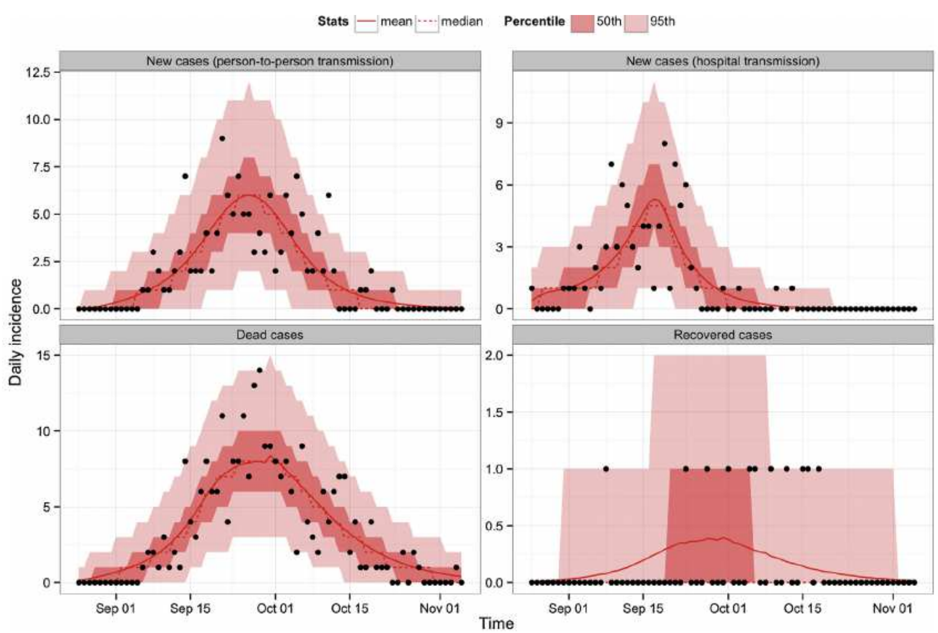
Or die and remain infectious (D) until buried (B).

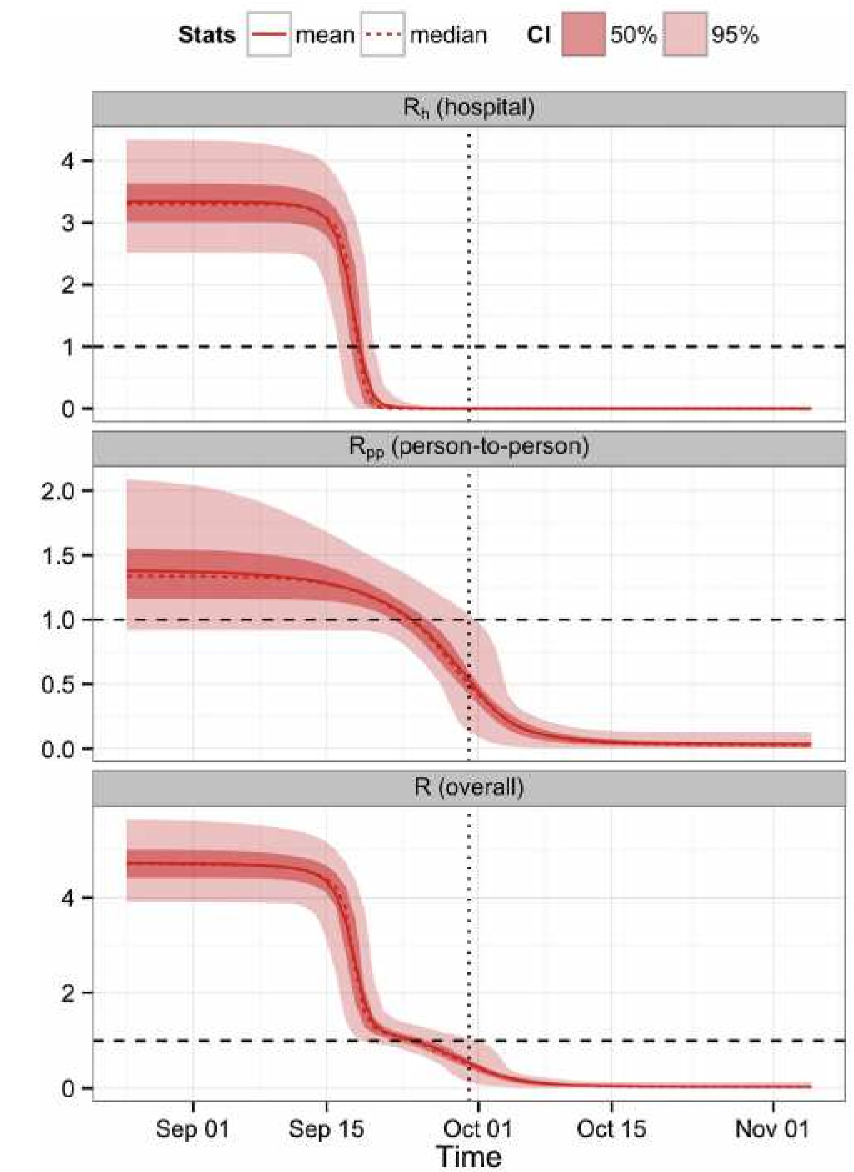
Following hospitalisation, infectious hosts also move either into the recovered or dead compartment.

Temporal Reproductive rates

Table 3
Estimates of the basic reproduction number, R_0, split into different component transmission routes.

Parameter	Route of transmission	Estimates: median (95% CI)
R_{0h}	Hospital via syringe	3.32 (2.53–4.34)
R_{0pp}	Person-to-person (in community and during funeral)	1.34 (0.92–2.11)
R_0	Overall	4.71 (3.92–5.66)





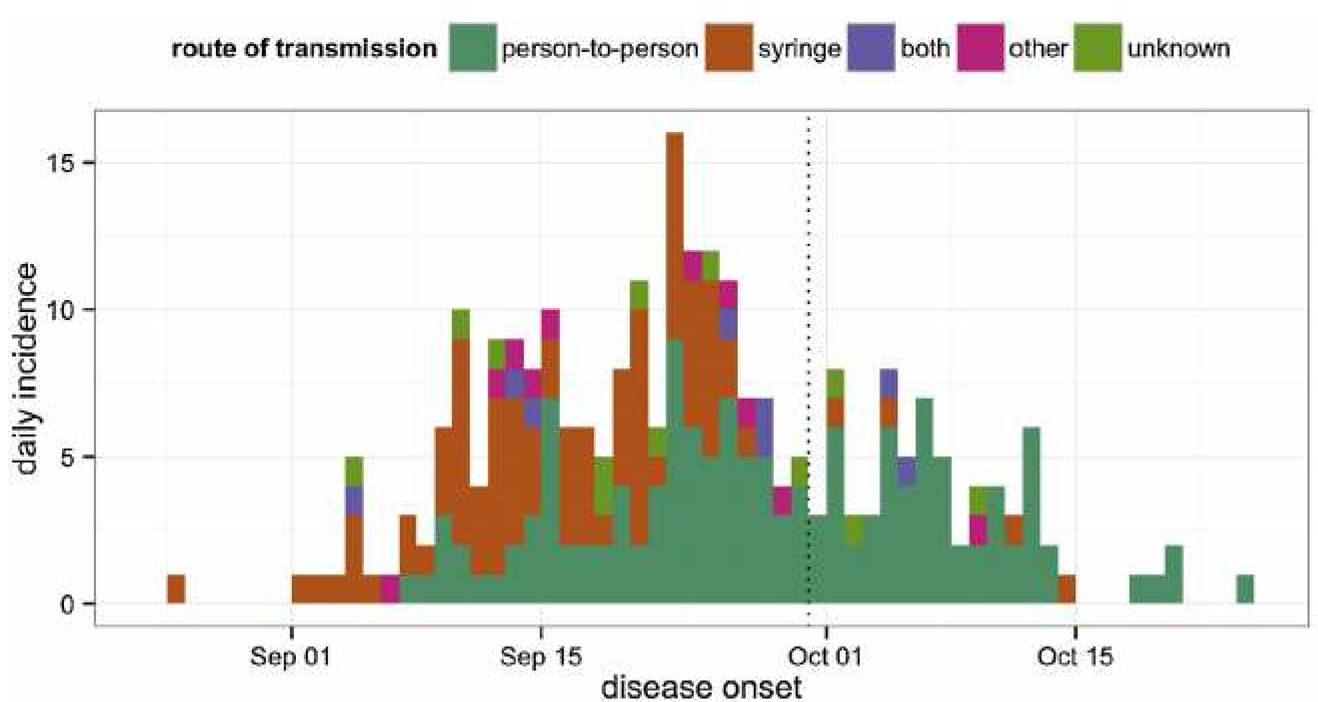
Conjectured Human Behavior

There was evidence that hospital and person-to-person transmission declined over the course of the 1976 outbreak.

Epidemiological reports the community stopped coming to the outpatient department as they associated the epidemic with the Yambuku Mission Hospital, which eventually was closed on 30th September.

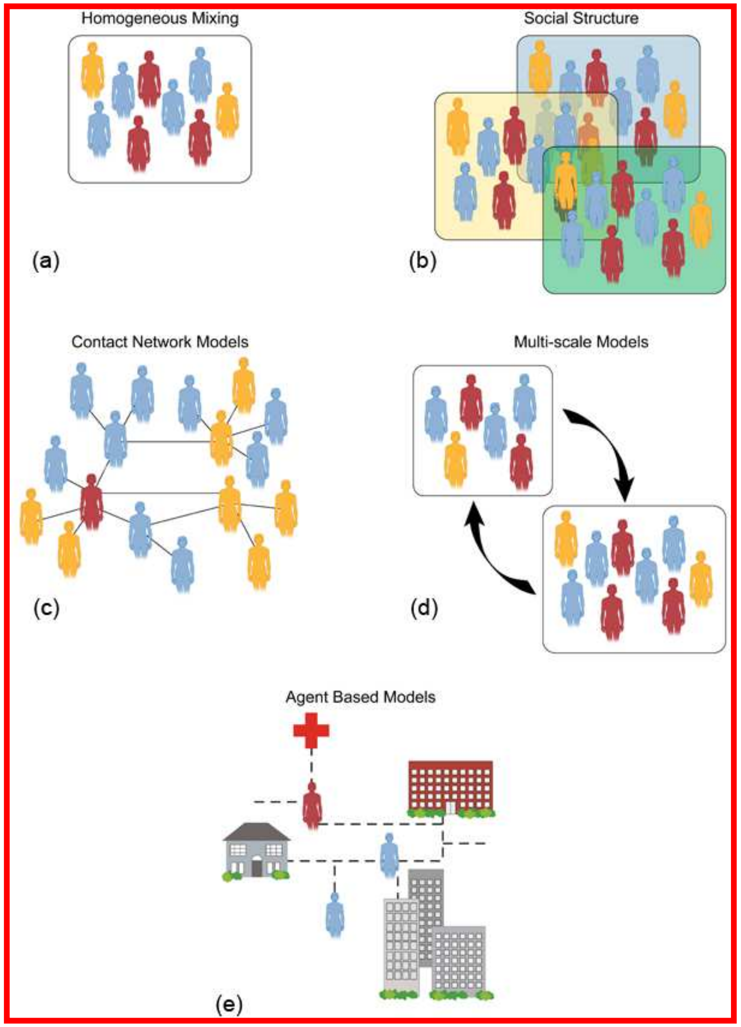
As time went on the population became very “suspicious” and did not touch the corpses anymore, not even to bury them.

A. Camacho et al. / Epidemics xxx (2014) xxx–xxx



Background: Networks

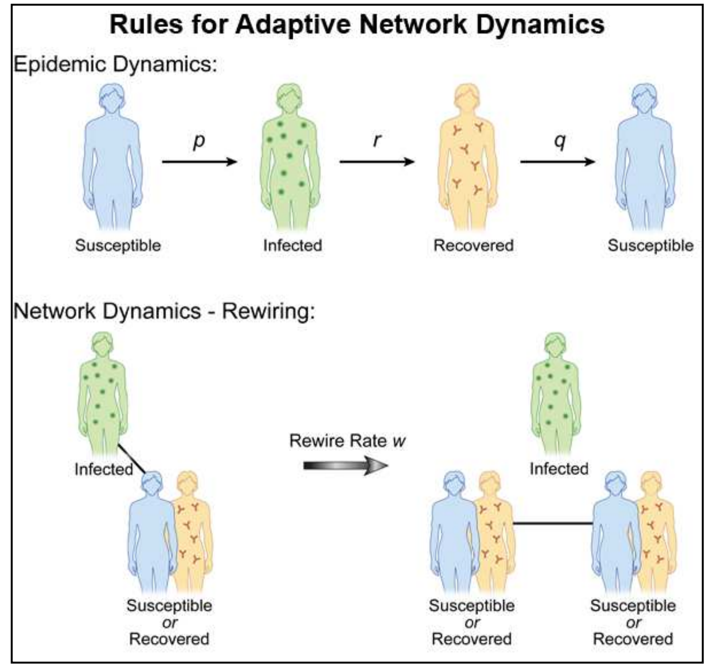
- Interconnected systems are often modeled as a network
- Structure of static networks has been well studied (Albert and Barabasi 2002, Newman 2003, plus gazillions of others)
- Some aspects of network dynamics have been studied (usually link dynamics **or** node dynamics)
  - Network growth-(Ben-Naim 2011)
  - Synchronization dynamics on nodes (Arenas et al. 2008)

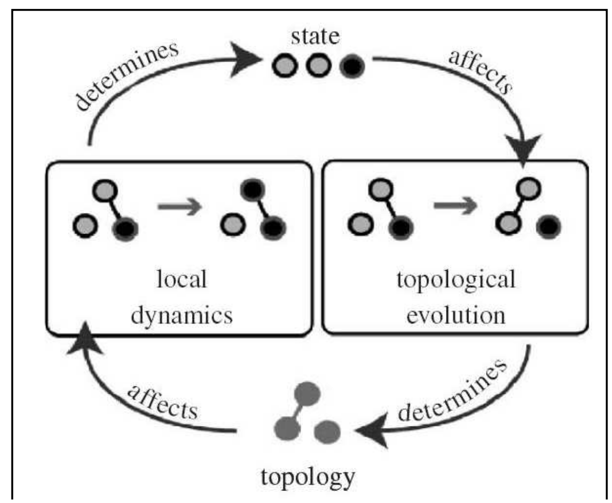


Rewiring for adaptation, IB Schwartz, LB Shaw, Physics 3 (17) (2010)

Adaptive Epidemic Networks

- In real networks, both the nodes and links change in time – Dynamic networks
- Node dynamics affects network geometry
  Network geometry affects node dynamics
  Adaptive networks
- Feedback loop interaction
- Many applications
  - Human social networks
  - Fads, terrorist cell networks
  - Self-healing communications networks
  - Swarming of autonomous agents
  - Immune system networks
    Dimension/connection changing
  - Biological networks (e.g., food webs)
    Lobsters (Behringer, Nature 2006)





Epidemics on Adaptive Social Networks

Epidemic dynamics: Avoidance Behavior

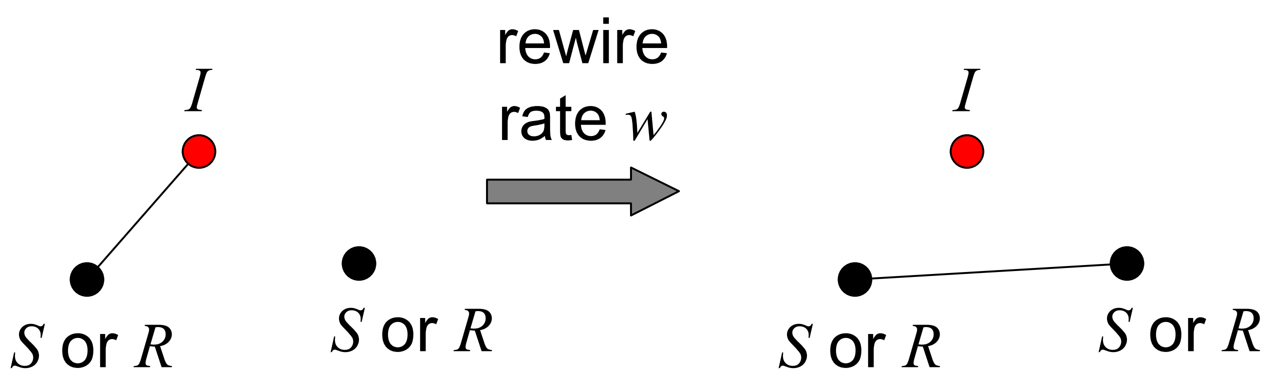
$$\boldsymbol{S} \xrightarrow{p} \boldsymbol{I} \xrightarrow{r} \boldsymbol{R} \xrightarrow{q} \boldsymbol{S}$$

$\boldsymbol{S}$: susceptible
$\boldsymbol{I}$: infected
$\boldsymbol{R}$: recovered

N_{AB}: AB links

$\boldsymbol{p}$: infection rate
$\boldsymbol{r}$: recovery rate
$\boldsymbol{q}$: resusceptibility rate
$\boldsymbol{w}$: rewiring rate

Network dynamics—rewiring:

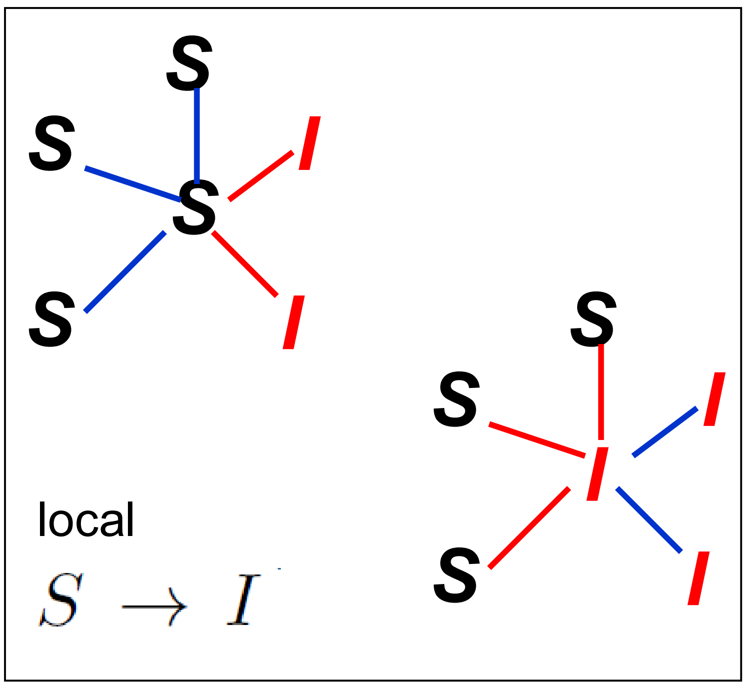


Run Monte Carlo simulation for $\boldsymbol{N}$=10^4 nodes, $\boldsymbol{K}$=10^5 links

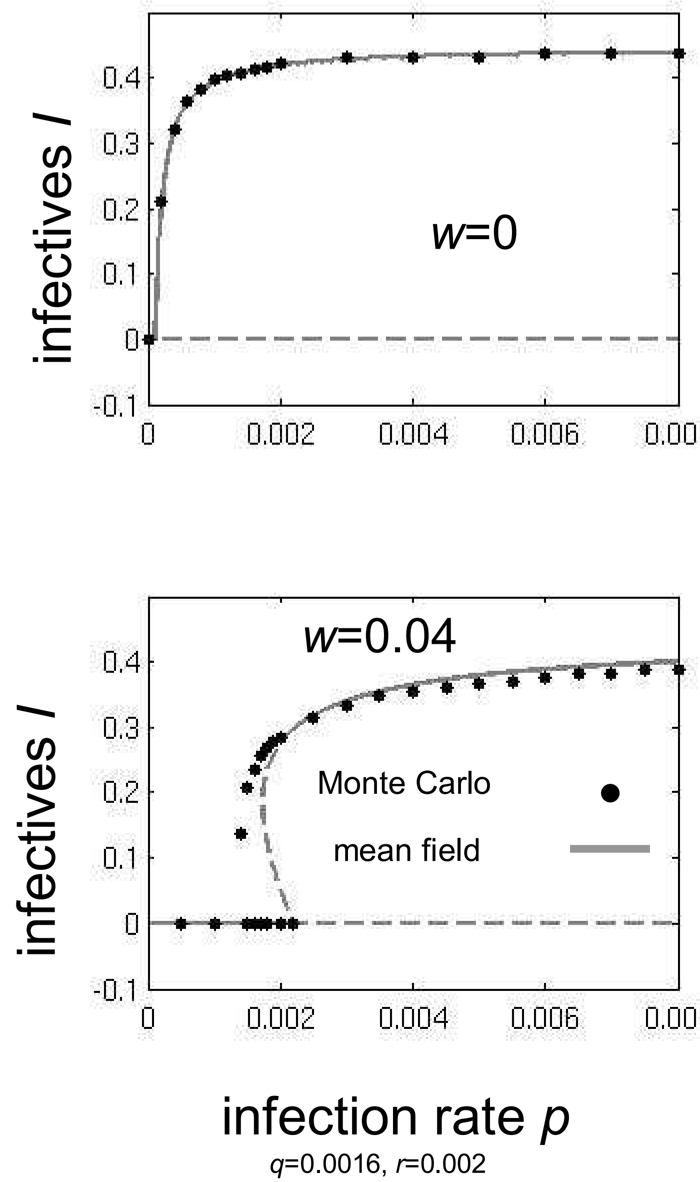
(Shaw and Schwartz PRE 77: 066101, 2008)

BifurcationStructure- Creation of New States

- Rewiring leads to bistable behavior
  - Extinct and endemic states
- As rewiring rate w increases, larger infection rate p is needed for disease to persist



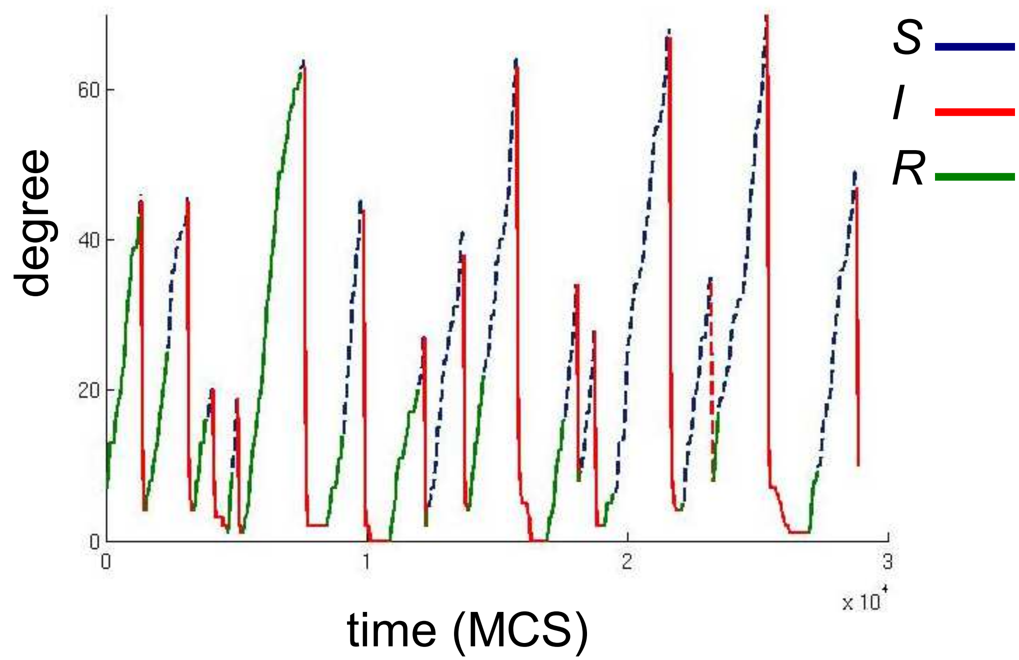
(Erdos-Renyi graph)

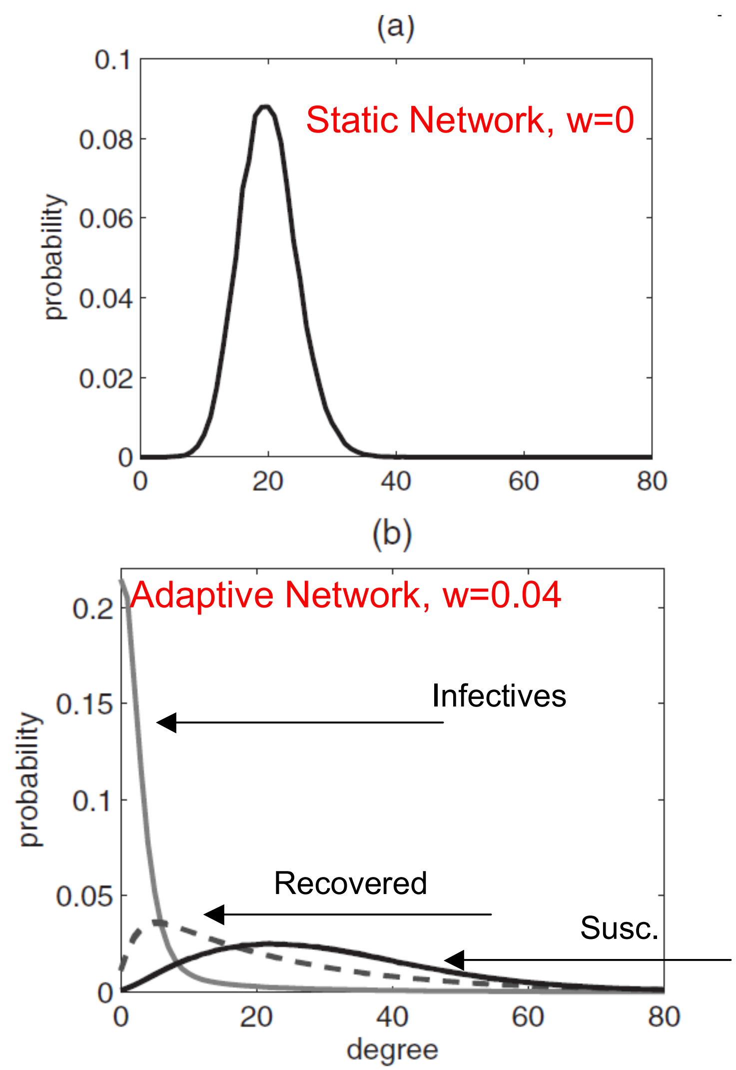


Network structure analysis-
Degree Distribution

q=0.0016, *r*=0.002

Time series for degree of a single node:





Node degree cycles in time

I loses links

R and S gain links

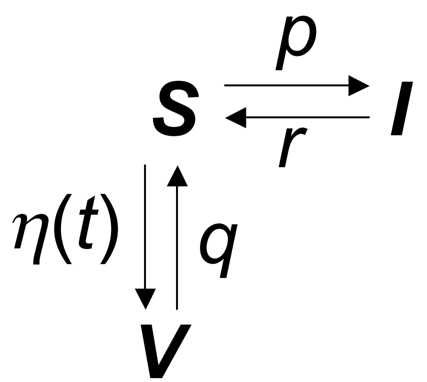
Extinction Processes

And

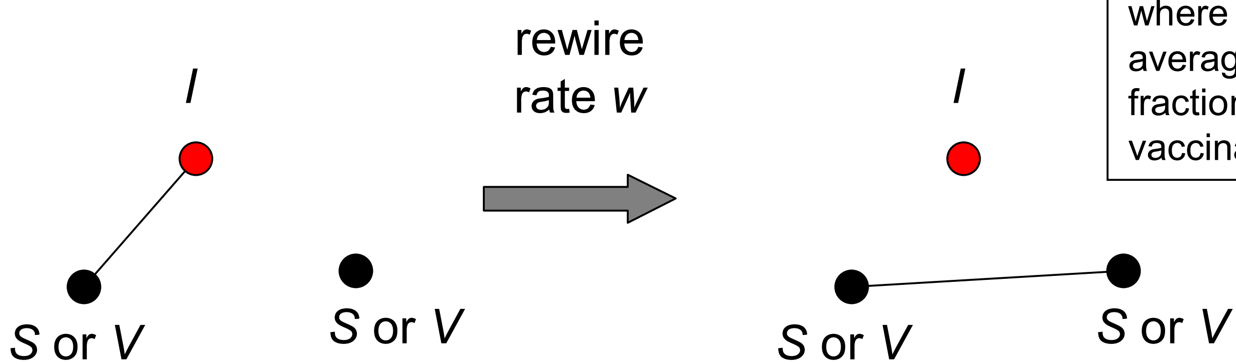
Vaccination Control

Rules for Network Dynamics with Vaccination

Epidemic dynamics:



Network dynamics—rewiring:



S: susceptible
I: infected
V: vaccinated

p: infection rate
r: recovery rate
η(***t***): vaccination rate
q: resusceptibility rate
w: rewiring rate

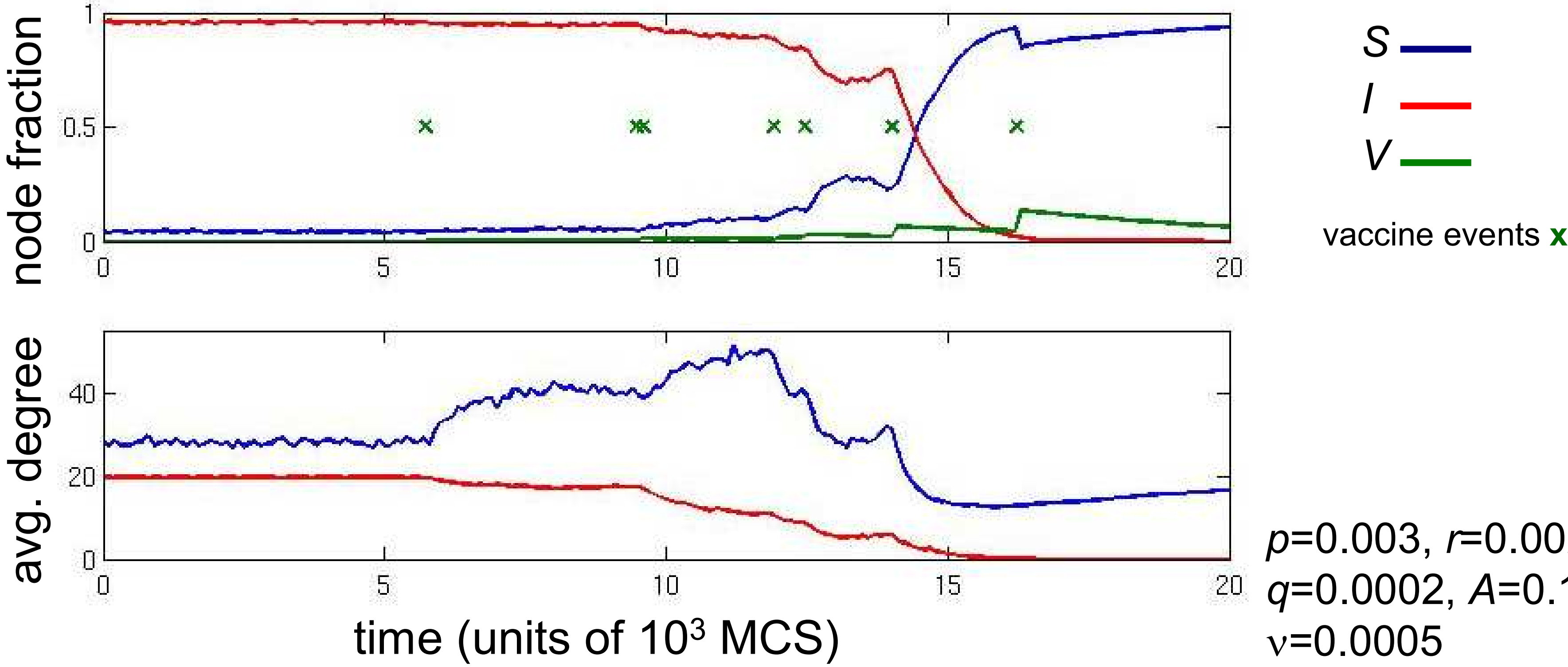
Vaccination rate is Poisson where events happen with average frequency ν and a fraction A of susceptibles are vaccinated in each event.

Run Monte Carlo simulation for ***N***=10^4 nodes, ***K***=10^5 links

L. B. Shaw and I. B. Schwartz, Phys. Rev. E (2010).

<u>Effect of vaccination and rewiring on degree</u>

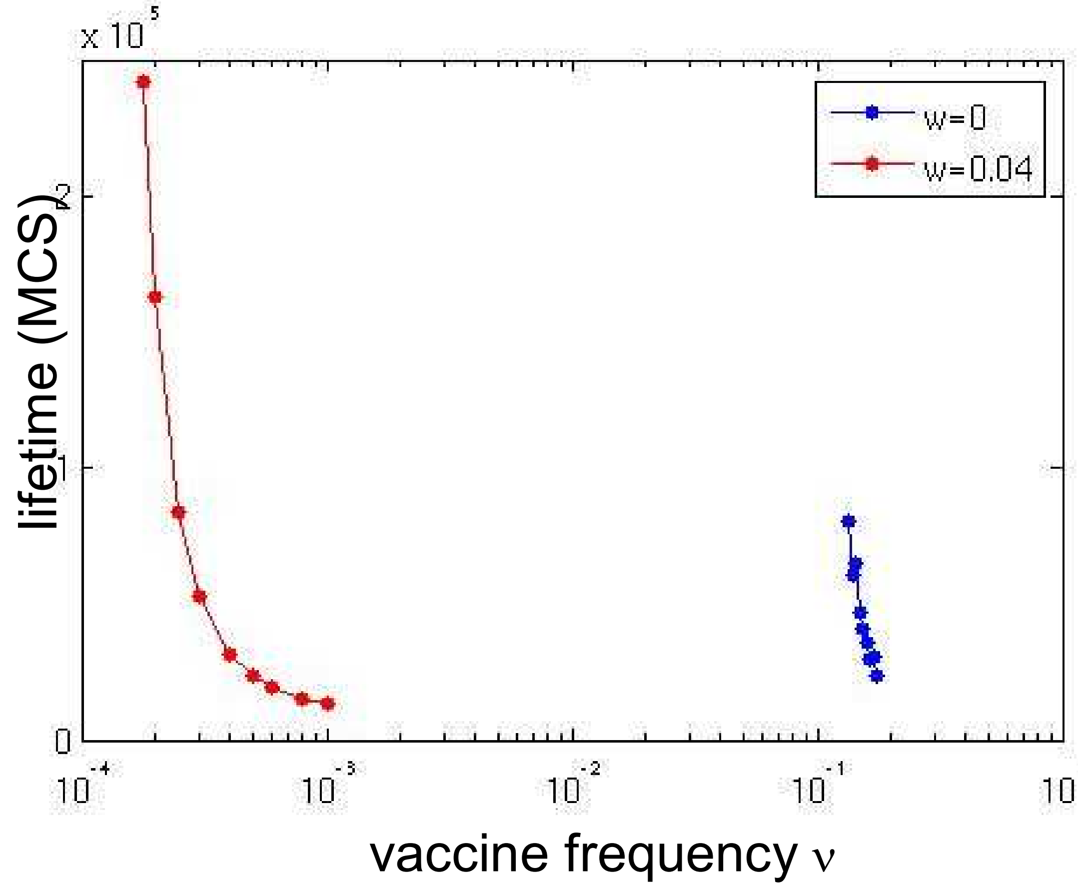
- Vaccination occurs on susceptible nodes
- In the adaptive network, susceptible nodes have higher degree due to rewiring
- Vaccination of high degree nodes provides better protection (e.g., Pastor-Satorras and Vespignani PRE 65: 036104, 2002)
- In the static network, high degree nodes tend to be infected and are not vaccinated



p=0.003, r=0.002, q=0.0002, A=0.1, ν=0.0005

Controlling Adaptive Networks: Lifetime of Endemic State

- Poisson-distributed pulse vaccine control
- Compute lifetime of the infected state
- Average over 100 runs
- Rewiring in combination with vaccination significantly shortens the disease lifetime



p=0.003, r=0.002, q=0.0002, A=0.1

Summary

- Developed a model for epidemics with adaptation to account for social interactions
- Developed and analyzed a corresponding mean field model, which captures many aspects of the full adaptive network system
- We identified regimes of onset thresholds, new state creation as functions of rewiring rates (adaptivity)-Possible oscillations

.

List of Publications

- Fluctuating epidemics on adaptive networks, LB Shaw, IB Schwartz, Physical Review E 77 (6), 066101 (2008)
- Noise induced dynamics in adaptive networks with applications to epidemiology, L. B. Shaw and I. B. Schwartz, in Adaptive Networks, Understanding Complex Systems, eds. T. Gross and H. Sayama, pp. 209-227 (2009).
- Enhanced vaccine control of epidemics in adaptive networks, L. B. Shaw and I. B. Schwartz, Phys. Rev. E 81: 046120 (2010).
- Rewiring for adaptation, I. B. Schwartz and L. B. Shaw, Physics 3: 17 (2010).
- Maximal sensitive dependence and the optimal path to epidemic extinction, E. Forgoston, S. Bianco, L. B. Shaw, and I. B. Schwartz, Bull. Math. Biol. 73: 495-514 (2011).
- Converging towards the optimal path to extinction, I. B. Schwartz, E. Forgoston, S. Bianco, and L. B. Shaw, J. Roy. Soc. Interface doi: 10.1098/rsif.2011.0159 (2011)
- Recruitment dynamics in adaptive social networks, MS Shkarayev, IB Schwartz, LB Shaw, J. Phys. A: Mathematical and Theoretical 46 (24), 245003 (2013)
- An iterative action minimizing method for computing optimal paths in stochastic dynamical systems, BS Lindley, IB Schwartz, Physica D: Nonlinear Phenomena 255, 22-30 (2013)