



Introduction

The majority of **network-based** epidemiological models rely on the paradigm of **static networks**. They neglect **mutual interactions** that may exist between the **states of the nodes** and the underlying **network topology**.

Adaptive networks are a new class of networks in which there exists a **feedback loop** between the dynamics **on** the network and the dynamics **of** the network.

*Why adaptive networks in epidemiology?
Healthy individuals may avoid contacts with those who are infectious to reduce their chances of catching the disease.*

Existing analytic approaches: based on mean-field formalisms derived from low-order moment closure approximations.

Advantages

- Low complexity.
- Sufficient to highlight novel dynamical features.

Main drawback

- Unable to reproduce the time evolution of disease and topology from various initial configurations.

Our goal is to develop an **integrated analytic approach** able to describe with accuracy the **time evolution** of both dynamical elements of adaptive networks, **process** and **structure**.

Model

Network model. A population of N individuals is represented by a **contact network** of N nodes and M links.

SIS dynamics. At a given time t , each individual is in a specific **state**:

- **Susceptible** individuals do not have the disease but can get infected by their infectious neighbors.
- **Infectious** individuals have the disease and can transmit it to their susceptible neighbors. They recover and become susceptible again after a given infectious period.

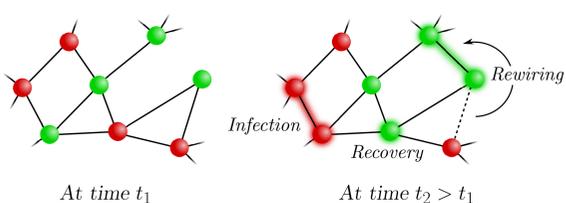
Adaptive rewiring. For every link between a susceptible (S) and an infectious (I) individual (SI link), the S individual can decide to **break** the connection and **reconnect** it with another randomly chosen S individual in the network.

[Gross et al., 2006]

Important parameters:

- α : rate at which I individuals recover.
- β : rate at which I individuals infect their S neighbors.
- γ : rate at which links are rewired.
- $\langle k \rangle$: average degree of the network ($\langle k \rangle = 2M/N$).

Illustration:



Formalism

Improved compartmental formalism in which nodes are categorized according to **their state** but also according to **the state of their neighbors**.

[Noël et al., 2009, Marceau et al.]

- $S_{kl}(t)$: fraction of nodes that are susceptible and have k neighbors of which l are infectious at time t .
- $I_{kl}(t)$: fraction of nodes that are infectious and have k neighbors of which l are infectious at time t .
- $p_k(t)$: fraction of nodes that have k neighbors at time t .

Zeroth order moments:

$$S \equiv \sum_{kl} S_{kl}, \quad I \equiv \sum_{kl} I_{kl}$$

First order moments:

$$S_S \equiv \sum_{kl} (k-l)S_{kl}, \quad S_I \equiv \sum_{kl} lS_{kl}, \quad I_S \equiv \sum_{kl} (k-l)I_{kl}, \quad I_I \equiv \sum_{kl} lI_{kl}$$

Second order moments:

$$S_{SI} \equiv \sum_{kl} (k-l)lS_{kl}, \quad S_{II} \equiv \sum_{kl} l^2 S_{kl}, \quad \text{etc.}$$

Dynamical equations

$$\begin{aligned} \frac{dS_{kl}}{dt} &= \alpha I_{kl} - \beta l S_{kl} + \alpha \left[(l+1)S_{k(l+1)} - lS_{kl} \right] \\ &\quad + \beta \frac{S_{SI}}{S_S} \left[(k-l+1)S_{k(l-1)} - (k-l)S_{kl} \right] \\ &\quad + \gamma \left[(l+1)S_{k(l+1)} - lS_{kl} \right] + \gamma \frac{S_I}{S} \left[S_{(k-1)l} - S_{kl} \right] \\ \frac{dI_{kl}}{dt} &= -\alpha I_{kl} + \beta l S_{kl} + \alpha \left[(l+1)I_{k(l+1)} - lI_{kl} \right] \\ &\quad + \beta \frac{S_{II}}{S_I} \left[(k-l+1)I_{k(l-1)} - (k-l)I_{kl} \right] \\ &\quad + \gamma \left[(k-l+1)I_{(k+1)l} - (k-l)I_{kl} \right] \end{aligned}$$

Initial conditions. The dynamics is initialized by infecting at random a fraction ϵ of the individuals in the population:

$$\begin{aligned} S_{kl}(0) &= (1-\epsilon)p_k(0) \binom{k}{l} \epsilon^l (1-\epsilon)^{k-l} \\ I_{kl}(0) &= \epsilon p_k(0) \binom{k}{l} \epsilon^l (1-\epsilon)^{k-l} \end{aligned}$$

Conservation of nodes: $S + I = 1$

Conservation of links: $S_S + S_I + I_S + I_I = \langle k \rangle$

Undirected nature of links: $S_I = I_S$

Observables

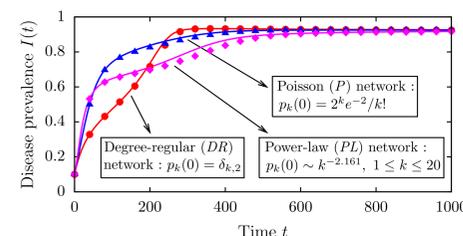
Several **relevant observables** can be readily computed from this formalism. They can help us to understand the interplay between disease and topology in the system.

- $I(t)$: Total disease prevalence.
- $s_k(t) \equiv \sum_l S_{kl}/S$: Susceptible degree distribution.
- $i_k(t) \equiv \sum_l I_{kl}/I$: Infectious degree distribution.
- $S_I(t)$: Density of SI links.
- $\kappa_{IS}^S(t) \equiv S_{SI}/S_I$: Effective branching factor.
- $C_{SS}(t) \equiv \frac{S_S}{S_S + S_I}$: Susceptible aggregation coefficient.

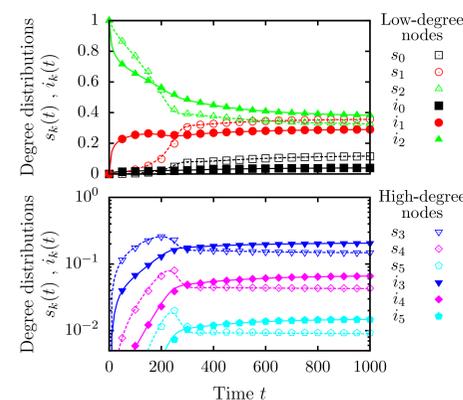
Time evolution

To attest the validity of our approach, we compared **analytic predictions (lines)** with results obtained from **Monte-Carlo simulations (symbols)** of the dynamics on networks of size $N = 25000$ with $\langle k \rangle = 2$. Parameters used are $\alpha = 0.005$, $\beta = 0.06$, $\gamma = 0.02$ and $\epsilon = 0.1$.

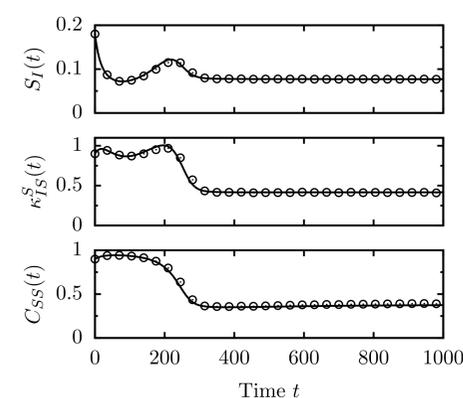
Evolution of the **disease prevalence** $I(t)$ on networks with different initial degree distributions:



Evolution of the **susceptible and infectious degree distributions** $s_k(t)$ and $i_k(t)$ on a DR initial network:



Evolution of the **topological observables** $S_I(t)$, $\kappa_{IS}^S(t)$ and $C_{SS}(t)$ on a DR initial network:

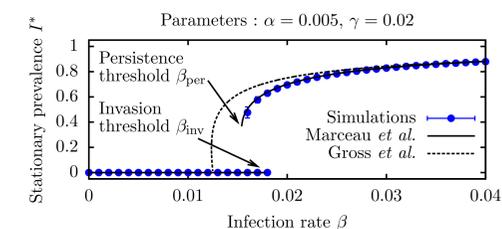


By analyzing the time evolution of disease and topology, we can bring new insights about their **interplay**. For example, in a DR initial network, the dynamics is characterized by two distinct phases:

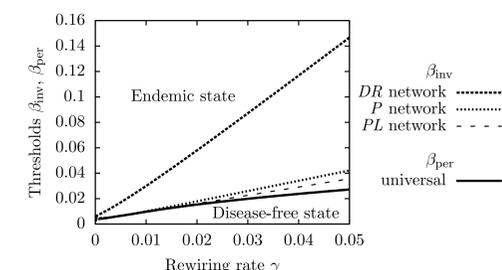
1. A **separation phase**, from $t = 0$ to $t \approx 200$, characterized by a segregation of the network in tightly connected susceptible and infectious communities.
2. An **invasion phase**, from $t \approx 200$, characterized by the invasion of the susceptible community.

Stationary states

Our formalism compares favorably with previous approaches about the **bifurcation structure** of systems with initial Poisson networks:



Location of the **persistence and invasion thresholds** for different initial networks (computed from our formalism):



Our results suggest two important conclusions:

- Link rewiring as a control strategy is **more efficient** on **homogeneous networks**.
- There exists a **universal endemic state**, which depends only on the density parameter $\langle k \rangle$ and interaction parameters α , β , and γ of the system. **Initial conditions** determine if this state can be reached.

Conclusion

We have introduced an **improved compartmental approach** able to reproduce with accuracy the **complete time evolution of disease and topology** on adaptive networks with various initial configurations.

Future directions

- **Analytical solution** for the endemic state.
- Inclusion of **more realistic features** in the model, e.g. community structure, preferential rewiring.
- Simultaneous evolution of the **disease** and the **population awareness**.



Gross et al., "Epidemic dynamics on an adaptive network," Phys. Rev. Lett. **96** 208701, 2006.

Noël et al., "Time evolution of epidemic disease on finite and infinite networks," Phys. Rev. E **79** 026101, 2009.

Marceau et al., "Adaptive networks: Coevolution of disease and topology," To be published.