Spreading processes in intermittent networks

Juliane T. de Moraes and Silvio C. Ferreira
Universidade Federal de Viçosa, Brazil

Keywords: Networks, Spreading phenomena, Epidemics, Renewal processes.

Many efforts have been devoted to understand spreading phenomena [1]. The importance of developing methods and models in epidemics becomes more evident with the SARS-CoV-2 pandemic. These models can improve health strategies and help the forecast of new outbreaks. In addition, studies of dissemination processes can also be applied to social dynamics [2].

Spreading processes are commonly related to social interactions and can be investigated considering complex networks [3, 4] as underlying substrates for dissemination, in which nodes represents the agents and links the interactions between them. An approach can be derived by picturing the following situation - considering a period of time, one individual has a given number of acquaintances. However, the contacts are intermittent. Therefore, we investigate spreading processes on intermittent networks, in which nodes (or links) become active or inactive across the time. In Fig. 1, an illustration of the intermittent dynamics is shown for nodes and links.

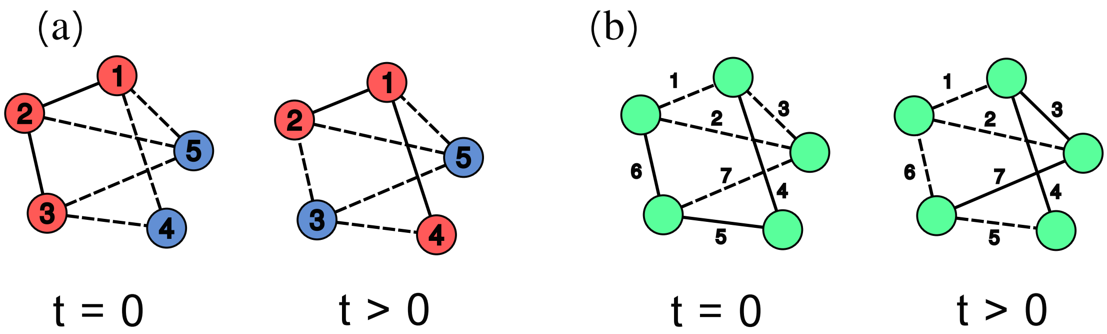

Figure 1: Illustration of the intermittency applied to static networks in different times. (a) Node intermittency, where nodes in red are active and in blue are inactive. (b) Link intermittency, in which links can be active (solid line) or inactive (dashed line).

In our simulations we start building a network structure for an initial condition in which some nodes (or links) are active and the remaining are inactive. The states of each node alternate between active and inactive following independent random processes with inter event times obeying a given probability distribution. If this distribution is exponential, these events are Poisson processes [4]. However, in a more general case, the inter-event time distribution can be chosen, characterizing a general renewal process. For our analysis, we used two classes of inter-event time distributions: exponential $\psi(\tau) \sim e^{-\alpha\tau}$ and power law $\psi(\tau) \sim \tau^{-\nu}$.

We used the uncorrelated configuration model to generate underlying power law degree distributed networks without degree correlations [5]. We observe that the network remains uncorrelated over time. This can be understood by the fact that the intermittency maintains the number of active nodes (or links) approximately constant depending on the activity and inactivity probability distributions. This behavior occurs for the two types of inter-event time distributions investigated.

In the SIS model an individual (or node) can be Susceptible and become Infected upon contact with another infected node with a given infection rate λ. Also, it can heal and return to the Susceptible state at other given rate [6]. This model, although quite simple, is known to undergo a phase transition between an inactive and an endemic (active) regime as the infection rate λ is varied. A method to estimate the critical value of λ is the susceptibility χ, which presents a peak near the epidemic threshold λ_c [7]. In Fig. 3, the susceptibility as a function of infection rate for a static network is compared with the ones obtained with intermittency. As expected, the node intermittency shows a stronger effect, increasing the epidemic threshold, since the contacts are more limited than in the link intermittency. Our forthcoming analysis includes to increase the size and time of simulation and to apply the intermittency for other network substrates. Also, we intend to study the phase transitions and scaling properties of these networks.

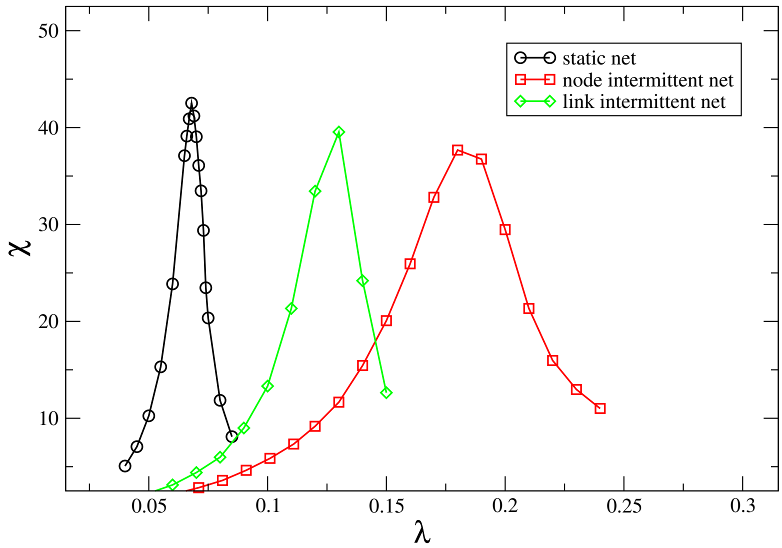

Figure 2: Susceptibility as a function of infection rate for power law degree distributed networks with exponent $\gamma = 2.75$ and size $N = 10^4$. Black symbols are related to the static network, without intermittency. Green and red symbols refer, respectively, to link and node intermittency for the underlying network using a exponential inter-event time distribution with parameter $\alpha = 0.5$

Financial support: CAPES, CNPq, FAPEMIG and INCTSC .

References

[1] M. J. Keeling and P. Rohani, *Modeling Infectious Diseases in humans and animals.* Princeton University Press, 2008.

[2] W. Cota, S. C. Ferreira, R. Pastor-Satorras, and M. Starnini, "Quantifying echo chamber effects in information spreading over political communication networks," *EPJ Data Science*, vol. 8, no. 1, 2019.

[3] A.-L. Barabási, *Network science.* Cambridge University Press, 2016.

[4] N. Masuda and R. Lambiotte, *A guide to temporal networks.* No. vol. 4 in Series on complexity science, New Jersey: World Scientific, 2016.

[5] M. Catanzaro, M. Boguñá, and R. Pastor-Satorras, "Generation of uncorrelated random scale-free networks," *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, vol. 71, no. 2, pp. 1–4, 2005.

[6] W. Cota, A. S. Mata, and S. C. Ferreira, "Robustness and fragility of the susceptible-infected-susceptible epidemic models on complex networks," *Physical Review E*, vol. 98, no. 1, pp. 1–12, 2018.

[7] S. C. Ferreira, C. Castellano, and R. Pastor-Satorras, "Epidemic thresholds of the susceptible-infected-susceptible model on networks: A comparison of numerical and theoretical results," *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, vol. 86, no. 4, pp. 1–8, 2012.