Modeling conditional waiting times: a new approach to human mobility

Joan T. Matamalas[1], Manlio de Domenico[1] and Alex Arenas[1]

[1]Departament d'Enginyeria Informàtica i Matemàtiques,
Universitat Rovira i Virgili, 43007, Tarragona, Spain

Understanding how people move within a geographic area [1], e.g. a city, a country or the whole world, is fundamental in several applications, from predicting the spatio-temporal evolution of an epidemics [2, 3] to inferring migration patterns [4]. The possibility to gather information about the population through mobile phone data recorded by mobile carriers triggered a wide variety of studies showing, for instance, that mobile phones heterogeneously penetrated both rural and urban communities, regardless of richness, age or gender, providing evidences that mobile technologies can be used to build realistic demographics and socio-economics maps of low-income countries, and also provide an excellent proxy of human mobility, showing for instance, that movements exhibit a high level of memory, i.e. the movements of the individuals are conditioned by their previous visited locations [5].

However, the precise role of memory in widely adopted proxies of mobility, as mobile phone records, is unknown. We have used 560 millions of call detail records from Senegal [6] to show that standard Markovian approaches, including higher-order ones, fail in capturing real mobility patterns and introduce spurious movements never observed in reality. We introduce an adaptive memory-driven approach to overcome such issues. At variance with Markovian models, it is able to realistically model conditional waiting times, i.e. the probability to stay in a specific area depending on individual's historical movements.

Our results demonstrate that in standard mobility models the individuals tend to diffuse faster than what observed in reality, whereas the predictions of the adaptive memory approach significantly agree with observations. We show that, as a consequence, the incidence and the geographic spread of a disease could be inadequately estimated when standard approaches are used, with crucial implications on resources deployment and policy making during an epidemic outbreak.

The differences between the diffusion of the infective process using each mobility model are quite visible in Fig. 1. The spreading is faster for Markovian models, with some arrondissement populated by more infected individuals than adaptive memory. The incidence, i.e. the fraction of infected individuals in an arrondissement, follows different spatial patterns in the three models (Fig. 1 a – c), with a higher incidence observed in the origin of the infection that decreases as we move far from there. This effect is significantly stronger using adaptive memory because it tends to concentrate more infectious individuals close to the origin (Fig. 1d).

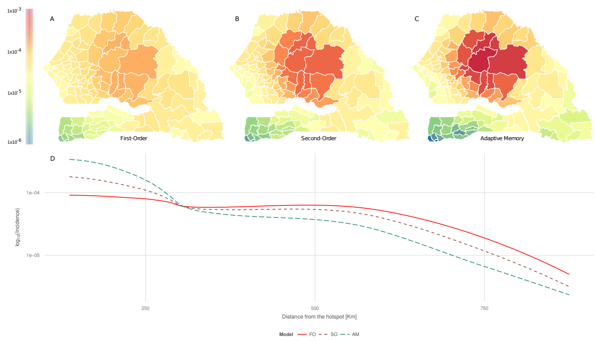

Figure 1: We show the incidence of an influenza-like virus over Senegal arrondissements a week after the infection onset, using first-order (A), second-order (B) and adaptive 2-memory (C) mobility models. The infection started in Barkedji (center of Senegal), where three individuals are initially infected. A SEIR compartmental dynamics with parameters $\beta = 0.05$, $\epsilon = 0.2$, $\gamma = 0.5$ is used to simulate the spreading of the disease within each arrondissement. We found that the number of arrondissements with infected individuals is higher using Markovian dynamics. Conversely, the adaptive memory favors a higher concentration of infected individuals in the arrondissements around the initial location of the infection. In fact, the location of the onset of the epidemic can be better identified using adaptive memory rather than Markovian models.(D) Relation between the incidence in a region and the distance from the hotspot of the infection using the three models. Adaptive memory models spread the incidence on regions closer to the hotspot and this effect is even more evident when higher memory is used.

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