A Physics-Informed Neural Network approach for compartmental epidemiological models

Caterina Millevoi[1,*], Damiano Pasetto[2], Massimiliano Ferronato[1]

[1] Department of Civil, Environmental and Architectural Engineering, University of Padua, Italy

[2] Department of Environmental Sciences, Informatics and Statistics, Ca' Foscari University of Venice, Italy

Compartmental models provide simple and efficient tools to analyze the relevant transmission processes during an outbreak, produce forecasts under scenarios, and assess the impact of vaccination campaigns. However, many factors contribute to the rapid change of the transmission dynamics during an epidemic, for example changes in the individual awareness, the imposition of non-pharmacological interventions, and the emergence of new variants. As a consequence, model parameters such as the transmission rate, are doomed to change in time, making their assessment more challenging.

Here, we propose to use Physics-Informed Neural Networks (PINNs) [1] to track the temporal changes in the state variables and transmission rate of an epidemic based on the SIR model equation and infectious data. PINNs consider both the information from data (typically uncertain) and the governing equations of the system, and their ability to identify unknown model parameters makes them particularly interesting for the solution of ill-posed inverse problems.

We develop a reduced-split approach for the implementation of PINNs, which splits the training first on the epidemiological data and then on the residual of the system equations, and reduces the number of functions that are approximated, thus eliminating any redundant term in the loss function. Our results show that this implementation of PINNs outperforms the standard approach in terms of accuracy (up to one order of magnitude) and computational times (20% speed up), and the model can well retrieve the key changes in the transmissivity when there is a relatively high number of infected individuals [2]. When considering only data on the reported infections, the solutions present large fluctuations in periods of low transmission, that are partially reduced if adding less-biased data on the hospitalized individuals.

The proposed PINN-based approach is a robust and easy-to-implement tool to monitor the spreading of a disease when dealing with uncertain reported data. It provides estimates of the time-dependent model parameters and state variables, allowing for more accurate short-term forecasts. The split approach can be easily adapted to more complex compartmental models (which, for example, consider an exposed compartment, deaths, re-infections, and vaccinations). Moreover, transfer learning, i.e. storing knowledge by training a neural network on a problem and then applying it to a similar one, can yield cheap and fast generalizations of the model to different epidemics.

[1] Raissi, M., Perdikaris, P., Karniadakis, G.E. *Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations.* Journal of Computational Physics 378, 686–707, 2019.

[2] Millevoi, M., Pasetto, D., Ferronato, M., *A Physics-Informed Neural Network approach for compartmental epidemiological models.* Submitted.