Physics-Informed Neural Networks for Informed Vaccine Distribution in Heterogeneously Mixed Populations

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Accurate numerical and physical models play an important role in modeling the spread of infectious disease as well as informing policy decisions. Vaccination programs rely on the estimation of disease parameters from limited, error-prone reported data. Using physics-informed neural networks (PINNs) as universal function approximators of the SIR compartmentalized differential equation model, we create a data-driven framework that uses reported data to estimate disease spread and approximate corresponding disease parameters. We apply this to data from a London boarding school, demonstrating the framework's ability to produce accurate disease and parameter estimations despite noisy data. However, real-world populations contain sub-populations, each exhibiting different levels of risk and activity. Thus, we expand our framework to model meta-populations of preferentially-mixed subgroups with various contact rates. Optimal parameters are estimated through PINNS which are then used in a negative gradient approach to calculate an optimal vaccine distribution plan for informed policy decisions. Together, our work creates a data-driven tool for future infectious disease vaccination efforts in heterogeneously mixed populations.