Data-driven deep learning algorithm for Asymptomatic COVID-19 model with time-varying transmission rate.

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Abstract

The fight against COVID-19 has been largely successful due to the adoption of several pharmaceutical and non-pharmaceutical mitigation measures, these measures directly impact the transmission of COVID-19. As a result, in this study, we develop an asymptomatic mathematical model, and an Epidemiology Informed Neural Network algorithm is introduced to learn the nonlinear time-varying transmission rate from data. The accuracy of the algorithm developed for the model is demonstrated using error metrics in a data-driven simulation of COVID-19.

Introduction

Time-varying transmission rates have been suggested to efficiently model the spread of COVID-19. In [1], a first-principle machine learning approach was presented to predict time-dependent parameters, but these parameters require good initial guesses. In March and April 2020, many countries instituted widespread lockdown. A model-fitting approach for lockdown and lockdown relaxation is presented in [4], which requires good estimation of the model parameters as well as quantification of the impact of relaxation. In order to overcome the limitations of statistical approaches, we present an Epidemiology Informed Neural Network (EINN) inspired by the Physics Informed Neural Network (PINN) [3] for epidemiology models. Given that it may not be possible to know the most accurate form of a time-varying transmission rate, EINN algorithms is a viable option to learn time-varying infection rate and to detect the impact of mitigation measures from data.

EINN for an Asymptomatic-SIR model

Consider the interaction between the compartments shown below [2]

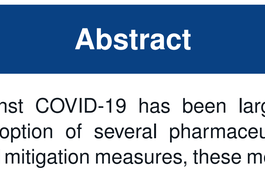

Figure 1: Compartments in Asymptomatic-SIR model with vaccination

EINN is a form of Feedforward Neural Network that includes the known epidemiology dynamics in its loss function.

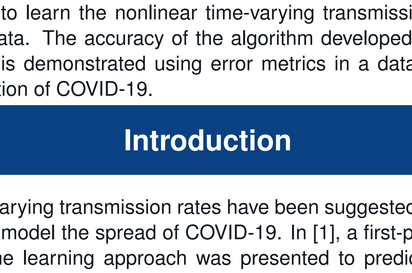

Figure 2: Schematic diagram of the Epidemiology Informed Neural Network with nonlinear time-varying infection rate

Data-driven simulation results for time-varying infection rate

$$\beta(t) = \begin{cases} \beta_0, & 0 \le t \le K, \\ \beta_0 \exp\left(-\eta(t-K)\right), & K < t \end{cases}$$

where K signifies the onset of government intervention including isolation, quarantine and lock-down. η is the rate at which human contact decreases.

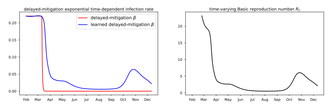

Figure 3: Using COVID-19 data from Italy, where we set $K = 40$ and and $\xi = 0.37$. We obtained $\beta_0 = 0.22$, using early data and nonlinear regression. EINN learns $\eta = 0.87$, the rate at which human contact decreases.

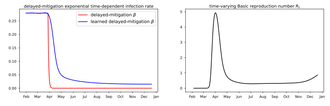

Figure 4: Using COVID-19 data from USA, where we set $K = 40$ and and $\xi = 0.46$. We obtained $\beta_0 = 0.279$, using early data and nonlinear regression. EINN learns $\eta = 0.60$, the rate at which human contact decreases.

Data-driven simulation results for Vaccination efficacy

Vaccination effectiveness for USA and United Kingdom. The red curve represent no vaccination, here $\kappa = 0$. The blue curve, is based on a projection of 1000000 daily vaccination in the USA. The magenta curve, we learned κ using the daily vaccination data.

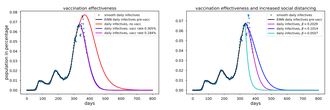

Figure 5: USA vaccination

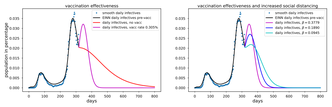

Figure 6: UK vaccination

Error metrics for data-driven simulation

Data split	R_2 score	MSE	MAE	Max Error
Random Split	9.9994×10^{-1}	3.9365×10^{-4}	1.2440×10^{-2}	6.6720×10^{-2}
Shuffle split	9.2104×10^{-1}	4.4006×10^{-1}	4.9789×10^{-1}	1.3683×10^{0}

Table 1: Using random and shuffle splits for Italy COVID-19 infected cases (I) data, where 40% of the dataset is used for testing.

Error metrics for data-driven simulation

The figures below represent MSE at different Epochs, different number of hidden layers and different number of neurons per layer. The learning rate of 0.001 is used.

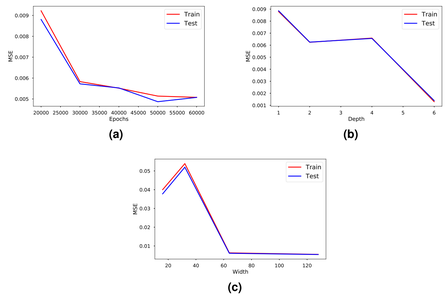

Fig. 7: Error metrics

EINN for a Multi-variant Asymptomatic-SEIJR model

Many mutating variants of the COVID-19 virus have been reported in recent months. In the fight against COVID-19, it has become imperative to study the transmission of various variants in the presence of pharmaceutical and non-pharmaceutical mitigation measures.

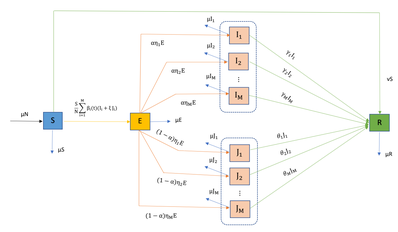

Figure 8: Transfer diagram between the compartments

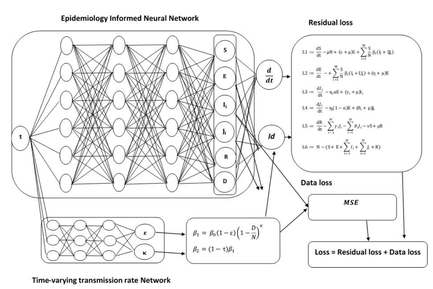

Figure 9: Schematic diagram of the Epidemiology Informed Neural Network with nonlinear time-varying infection rate for COVID-19 variants.

Data-driven simulation of COVID-19 variants

Here, the time-varying transmission rate of the variants are given by;

$$\beta_1(t) = \beta_0\Big(1-\epsilon(t)\Big)\Big(1-\frac{D(t)}{N}\Big)^{\kappa(t)}$$

for the original variant, and

$$\beta_i(t) = (1+\tau_i)\beta_1(t) \;\; i \ge 2$$

for the ith mutating variants. In Tennessee (a), Alabama (b), and Missouri (c), we have assumed only one dominant mutating variant, and obtained $1+\tau$ to be 2.0001502, 2.0000263, and 2.0000281 respectively.

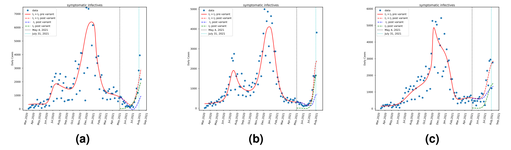

Fig. 10: COVID-19 variants

Conclusion

In this work, we presented a data-driven deep learning framework for learning time-varying transmission rates for an epidemiological model. These nonlinear time-dependent transmission rates are able to capture the impact of pharmaceutical and non-pharmaceutical mitigation measures.

Acknowledgements

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References

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[2] K.D. Olumoyin, A.Q.M. Khaliq, and K.M. Furati. “Data-driven deep learning algorithm for Asymptomatic COVID-19 model with varying mitigation measures and transmission rate”. In: *Epidemiologia* (Under review).

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