

SIRNET: Understanding Social Distancing Measures with Hybrid Neural Network Model for COVID-19 Infectious Spread

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Abstract

The SARS-CoV-2 infectious outbreak has rapidly spread across the globe and precipitated varying policies to effectuate physical distancing to ameliorate its impact. In this study, we propose a new hybrid machine learning model, SIRNET, for forecasting the spread of the COVID-19 pandemic that couples with the epidemiological models. We use categorized spatiotemporally explicit cellphone mobility data as surrogate markers for physical distancing, along with population-weighted density and other local data points.

We demonstrate at varying geographical granularity that the spectrum of physical distancing options currently being discussed among policy leaders have epidemiologically significant differences in consequences, ranging from viral extinction to near-complete population prevalence. The current mobility inflection points vary across geographical regions. Experimental results from SIRNET establish preliminary bounds on such localized mobility that asymptotically induce containment. The model can support in studying non-pharmacological interventions and approaches that minimize societal collateral damage and control mechanisms for an extended period of time.

1 Introduction

Machine learning techniques have offered solutions to many modeling problems, assuming there is abundant data to train a system [Obermeyer and Emanuel, 2016]. With the rapid impact of COVID-19, several research groups have begun exploring statistical and mathematical models to study the spread of the disease. One of the early studies of COVID-19 using AI [Bogoch *et al.*, 2020] identified the global spread of the disease through commercial airlines. Numerous approaches to forecasting and predicting the spread of COVID-19 have since been explored. These include mathematical forecasting models [Petrooulos and Makridakis, 2020; Ribeiro *et al.*, 2020], fitting parameters to epidemic models [Roda *et al.*, 2020], and machine learning models [Wang *et al.*, 2020]. In response to efforts for controlling the spread of

COVID-19 across the globe, many research groups have begun a more relevant problem is including the effects of non-pharmaceutical intervention as a factor in forecasting models [Brauner *et al.*, 2020], whether it is epidemic models [Dehning *et al.*, 2020; Lorch *et al.*, 2020], or machine learning [Yang *et al.*, 2020; Tomar and Gupta, 2020]. There are several inefficiencies with the current data available for COVID-19 research, such as limited testing capabilities and high variability within the testing rate (e.g., 22.08/1,000 in Italy, 11.16/1,000 in the US, to 0.27/1,000 in India [Hasell *et al.*, 2020; Ryan-Mosley, 2020]), inconsistencies in reporting (under-reporting), and publicly available data on infection rates currently are unreliable. Particularly lacking is an understanding of the underlying factors which impact the spread, accuracy and availability of reported cases on a small scale, and quantifiable metrics for how social distancing and quarantine efforts impact the spread. To overcome these challenges in providing forecasting models of the spread of COVID-19, we combine compartmentalized models with a data-driven machine learning approach. In doing so, we address a potential pitfall of machine learning (ensuring compliance with the laws of epidemic dynamics) and a limitation of epidemiological models (enabling the creation of complex mappings from available data sources to critical modeling parameters).

2 Methodology

Here, we formalize the general form of this problem. We then propose a hybrid neural-compartmental model to perform forecasting given historical case and mobility data.

2.1 Problem Statement

We are given a set of time series that temporally enumerates active, recovered, and fatal cases of COVID-19. The data exhibits varying levels of geographical granularity, i.e., grouping by country, region, sub-region, etc., and irregular onset of the first case. Each sequence $\mathbf{Y} \in \mathbb{R}^{T \times 2}$ comprises T timesteps, which varies between samples, each with the count of active cases and recovered cases. Provided this data, we desire to learn a model that is able to forecast future values of \mathbf{Y} . To aid in improving the fit, additional factors should be considered that may impact the infection, recovery, or mortality rates pertaining to the disease. We refer to these additional attributes as features which can be either

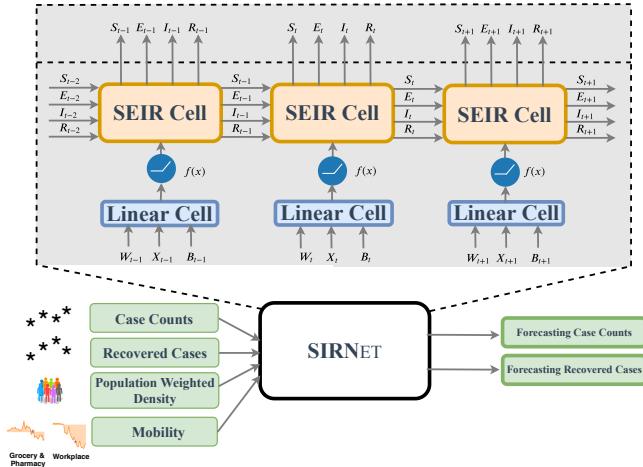


Figure 1: High level visualization of the SIRNET architecture.

scalar $\mathbf{x} \in \mathbb{R}^F$, spatial $\mathcal{X} \in \mathbb{R}^{F_1 \times F_2 \times \dots \times F_n}$, and/or temporal $\mathbf{X} \in \mathbb{R}^{T \times F}$ ($\mathcal{X} \in \mathbb{R}^{T \times F_1 \times \dots \times F_n}$ if spatiotemporal)¹. With these definitions, the learning problem can be posed as follows (also see (1)). Given historical case data \mathbf{Y} and relevant attributes \mathcal{X} for an area or multiple areas, can we model (\mathcal{M}) the latent trends of this data to forecast future cases of COVID-19?

$$\text{minimize } \text{cost}(Y_{t+k}, \mathcal{M}(\mathcal{X}_t, Y_t; \theta_0, \theta_1, \dots)) \quad (1)$$

2.2 Proposed Hybrid Model: SIRNET

In this research, we focus on learning and forecasting the trends in time series via a hybrid model of neural networks and epidemiological models. The forecasting network, referred to as SIRNET (named after the foundational epidemiological model), learns from i) a sequence of prior trends that carry long-term contextual information (global time-series); ii) more recent data inputs that are raw (local time-series) and can inform the forecasting of any abrupt changes; and iii) compose differential equations as a neural network. One of the first papers on solving differential equations using neural networks was proposed by [Dissanayake and Phan-Thien, 1994], followed by several groups recently [Han *et al.*, 2018; Berg and Nyström, 2018; Sirignano and Spiliopoulos, 2018].

2.3 SEIR Cell

One standard approach to epidemic modeling is compartmentalized models such as SEIR - with Susceptible S , Exposed E (latent infected, but not yet infectious), Infected I , and Recovered R (no longer infectious, also referred to as removed) states. The rate of change in these parameters is represented by the ordinary differential equations (2)-(5) and parameterized by β (effective contact rate/infectious rate learned from mobility data), σ (the incubation rate), and γ (recovery rate).

$$\frac{dS}{dt} = -\beta SI \quad (2)$$

¹A tensor \mathcal{T} is a multilinear data structure and is denoted by bold uppercase calligraphic font.

$$\frac{dE}{dt} = \beta SI - \sigma E \quad (3)$$

$$\frac{dI}{dt} = \sigma E - \gamma I \quad (4)$$

$$\frac{dR}{dt} = \gamma I \quad (5)$$

The basic reproduction number representing the number of secondary infections from a primary individual in a completely susceptible population can be computed by,

$$R_0 = \frac{\beta}{\gamma} \quad (6)$$

In the proposed SIRNET model, we explore variations of machine learning to learn β based on latent information of the contact rate. In particular, the model attempts to learn $\beta(t)$ by mapping $\beta(x^t(t), x^s)$, where x^t represents relevant temporal data (we consider only time steps of one day) and x^s represents relevant spatial data.

While our approach can be extended to many types of data, our work here is focused on one type in particular: mobility data. Contact rate is a key parameter of the model and its modification through quarantine measures is an effective way to control the spread of the virus. Contact rate is a function of population density as well as how people move and interact with each other. Traditional modeling can retrospectively estimate the change in contact rate brought about by policy changes (step-function changes), in our approach we build upon this technique to allow the integration of richer, daily information based on the actual activities of a population. To this end, we begin with cell-phone based mobility information.

The mobility input vector, x , consists of mobility ratios (current mobility divided by nominal mobility) in 6 categories provided through [Google Mobility Reports, 2020]. SIRNET's task is to use this feature vector to learn the resulting contact rate as a function of population mobility. Through the use of the SEIR cell, we can map the output to case counts

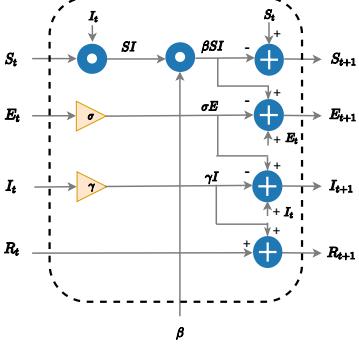


Figure 2: We frame the SEIR modeling as a recurrent neural network (RNN) architecture, introducing the SEIR-cell which encodes susceptible, exposed, infected, and recovered proportions in its hidden states. Code is open-sourced on *Github*.

and learn the underlying mobility to contact rate function in an end-to-end fashion. The SEIR cell’s hidden states consist of the four compartmental groups normalized by population.

For the mobility model, the general form for how the SEIR cell predicts contact rate is

$$\beta(t) = q \cdot f(x(t))^p \quad (7)$$

where $f(\cdot)$ can either be a non-linear activation function applied to a weighted linear summation of all mobility data, or a weighted norm of the mobility data. The power scaling is an optional learnable parameter which removes the need to justify a linear or quadratic relationship.

One of the primary challenges in modeling is that the underlying state is difficult to estimate. The only data that is reliably available is the total case count, and the case count only represents a fraction of actual cases (with an estimated 70%–95% being under-reported). It also lags the true state of the system by several days. Mobility data will drive exposure, exposure will drive the amount of the infectious, and the infections will in turn drive the number of cases. To account for all of these factors, we use the 5-day incubation period [Lauer *et al.*, 2020; Li *et al.*, 2020; Guan *et al.*, 2020] and add an additional 5 days to account for the delay between becoming infectious and receiving a positive test confirmation. This delay in testing is not constant across time, nor is it consistent from location to location, but the measurable impacts of mobility on contact rate are most apparent when delay is taken into account.

We initialize the hidden state with the number of active and recovered cases at the onset of the epidemic and available mobility data, I_0 such that $S = P - (I_0 + E_0 + R)$, $E = \frac{2.2}{5} * I_0$, $I = I_0$, and $R = R_0$.

3 Results and Analysis

Model analysis for different geographical regions: SIR-NET was evaluated on different geographical regions. Figure 3 shows the fit, total predicted cases, and forecast of the number of active cases at the country, state, and county levels. We show extended forecasts of total cases and fits for several other countries in Figure 4, states in the US in Figure 5, and

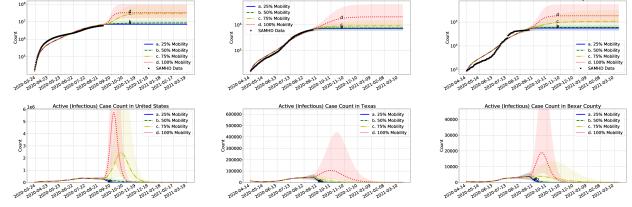


Figure 3: SIRNET predictions on previous and current CDC reported case data for the United States, Texas, and Bexar County showing how the model performs at decreasing levels of geographic granularity.

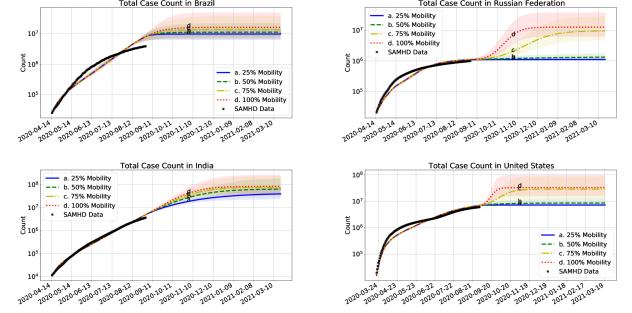


Figure 4: SIRNET predictions at the country level on previous and current CDC reported case data for Brazil, Russia, India, and the US.

counties in Texas in Figure 6. In order to forecast different mobility scenarios, we first train the model to learn the relation between mobility data and COVID-19 case data. We then fix the mobility data for all future days at different values to simulate 25% nominal mobility (75% reduction), 50% nominal mobility, 75% nominal mobility, and nominal mobility (all restrictions removed). To quantify the quality of the fit, we perform cross validation by holding out the final 25% of case data from the training data as a validation set. The trained model forecasts over the validation data, assuming a mobility rate over the period. As the case data scales with the population, numbers produced by a metric such as mean-squared-error are difficult to interpret. We thus use mean-absolute-percent error (MAPE) (8) to assess the quality of a fit.

$$MAPE = \frac{1}{N} \sum_t^N \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100\% \quad (8)$$

MAPE gives the average percent deviation from the target value Y_t that the predicted value \hat{Y}_t is. At the country level, the average MAPE of SIRNET fits is 10.2%.

In general, our results suggest a continuation of quarantine level mobility or at least below 50% nominal mobility in most regions, with some at least below 75% nominal mobility for the immediate future. Figure 7 highlights a sample of the mobility trends used in all our simulations. *It is important to note that this data reflects a sample space of mobility for the region and might be missing information on key populations that do not use specific types of devices. Adding finer granular information and data from multiple data providers can*

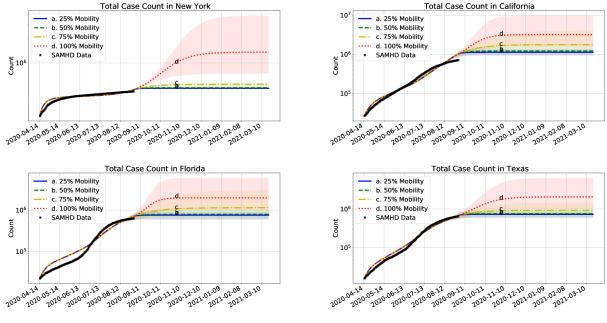


Figure 5: SIRNET predictions at the state level on previous and current CDC reported case data for New York, California, Florida, and Texas.

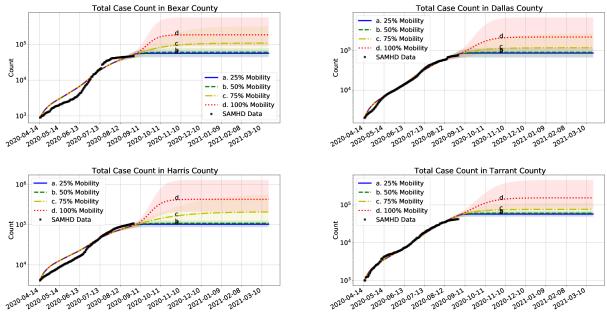


Figure 6: SIRNET predictions at the county level on previous and current CDC reported case data for Bexar County, Dallas County, Harris County, and Tarrant County.

alleviate this concern.

Error Tolerance: When using any ML or statistical model, to forecast trends, it is important to consider the confidence interval or margin of error for the predictions. SIRNET is currently trained on the specific region it is forecasting, with region-specific assumptions about under-reporting, start date for forecasting, delay in reporting, the recovery rate, and the transition rate from exposed to infected. In future work, it will be necessary to account for the error range for each of these variables based on globally reported data, and use this to predict the potential fluctuation in forecast scenarios. Another important extension to SIRNET is to extend learning to multiple regions, providing a more generalized forecast that can capture distinctions between different regions.

Dashboard: To provide a much broader analysis, we deployed the SIRNET model in a live interactive dashboard. The dashboard currently provides the model’s predictions for different counties of Texas and shows the trend in mobility in counties over time.

Conclusions and Discussion

Our work adopts a multidisciplinary approach in modeling the spread of COVID-19. SIRNET is a hybrid between epidemic modeling, physical science, and machine learning. The benefit of epidemic modeling is in constraining our network to produce meaningful variables from a physical standpoint;

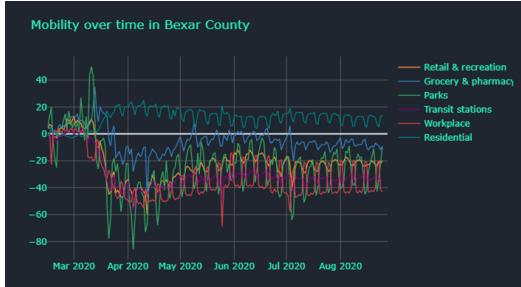


Figure 7: The dashboard view of the change in mobility over time with respect to the baseline mobility observed in the first week of January, 2020 in Bexar County, Texas. The mobility remained relatively high throughout the period thus leading to a spike in the cases. The dashboard can be accessed [here](#).

this adds an intuitive understanding of how the model is forecasting, and provides an approach for overcoming limited or missing real-world data samples. On the other hand, machine learning provides a tool for translating variables, such as mobility, non-pharmaceutical intervention, and population demographics, into variables that impact an epidemic model. It also allows us to discover relationships between real-world trends and the impact on the spread of COVID-19, as well as model scenarios, such as relaxing social distancing policies. We believe both components are necessary to develop an insightful model to aid in understanding the impact of non-pharmaceutical interventions on the spread of COVID-19.

Similar to other approaches, we base our study on several biologically observed data and real-world datasets. We demonstrate how new tools can be created to better exploit available quantitative measures in the fight against COVID-19. By integrating reliable metrics and well-studied infection dynamics, we create an approach that is deeply data-driven and epidemiologically grounded. Our studies confirm the effectiveness of reduced mobility for limiting the reach of the pandemic, and our models provide a means of forecasting the effects of different mobility scenarios.

Results shown only focus on translating mobility to contact rate of COVID-19. Exhaustive mobility data combined with non-pharmacological intervention datasets can improve the network predictions, incorporating factors such as mask policies. Since several datasets are proprietary and limited by data user agreements, it will be important to establish good data collection and standardization practices to address catastrophic events.

Given the substantial risk of reintroduction of the SARS-CoV-2, it is critical to reinforce balanced social distancing measures in the coming months to reduce the impact on the healthcare system, general public, and economic prosperity. Resource limitations in a rapidly growing pandemic demand compelling resource utilization choices. Of importance is to note that the data-driven AI models provide a window into understanding the potential impact and should be treated as a qualitative guidance due to the rapid changes and variability associated with the data collection, testing strategies, reporting, and the virus transmission.

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