Extended SEIR Model for COVID-19

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Abstract

We propose an extension of the standard Susceptible Incubation Infection and Recovered (SEIR) model to capture the specifics of COVID-19 virus. In particular our model takes into account that (i) transmissions rates before and after lockdown interventions are different (ii) the majority of positive case are asymptomatic or goes unreported , and (iii) there is lag between the time an infected subject is tested and the day this is publicly reported. Besides a new model we use automatic differentiation to estimate the gradients (of the loss function) to learn the parameters of the model. While the trained model predicts and forecasts all the SEIR compartments, only the confirmed cases are required for fitting. To test our model we use data from China, Italy, France, Spain, Germany, New York (USA) and New South Wales (Australia). Our forecasts are updated everyday and available at `covid.qcri.org/seir`.

1 Introduction

As of the first week of April, the pandemic caused by COVID-19 has resulted in more than one million cases, fifty one thousand deaths and nearly three billion people living under government enforced lockdowns[1]. A key challenge in epidemiological research is to understand how the virus has spread and predict the impact of measures like social distancing and lockdowns.

2 Extension of SEIR Model

We propose E-SEIR, an extension of the classic SEIR model to capture the novel features of COVID19 the most distinctive being that many people who are infected remain asymptomatic or have mild symptoms [1]. In E-SEIR, each person is assigned to one of seven compartments (categories) and the the transition to move from one compartment to another is governed by a system of ordinary differential equations or discrete transition models. See Figure 1.

Here S, E, I and R are the standard compartments of SEIR model representing Susceptible (S), Exposed (E), Infected (I) and Removed (R). The new compartments we propose are Tested (T), UnTested (U) and Confirmed (C). These compartments enable us to capture unique features of the COVID-19 pandemic. For example a large percentage of those who are infected are likely to transition from the Infected (I) to the Untested (U) compartment, while an additional Confirmed compartment is need to account for the delay that exists from symptoms onset to when the case is officially reported to the public. Note that **only the Confirmed compartment is observed.**

[1] https://www.worldometers.info/coronavirus/

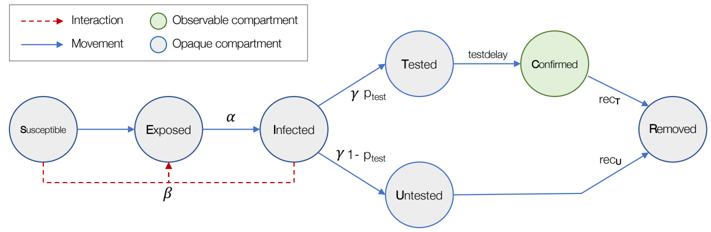

Figure 1: The proposed E-SEIR model. Only the confirmed compartment is observed.

The model has seven parameters. These are β_0 : transmission rate before intervention; β_t : transmission rate after intervention; α : incubation period; γ : infectious period; `testdelay:` period between ; p_{test} probability of infected to be tested; I_0 : number of infected subjects in the first timestep. The initial timestep t_0 is variable, given by $t_{obs} - (\alpha + \gamma + \texttt{testdelay})$, thus it depends on the current parameters values.

3 Parameter Inference

The complete state of the ODEs is x $= x_S, x_E, x_I, x_U, x_T, x_C$, x_N, x_R, while only x_N is observable. The objective function over all the states is $L(x_N, y) = \sum_t (x_N(t) - y_t)^2 + (\sum_t x_N(t) - \sum_t y_t)^2$ where y_t is the observed confirmed cases at discretized timestep t. We use a quasi-Newton method that approximates the Hessian using the Broyden–Fletcher–Goldfarb–Shanno algorithm (BFGS).

To estimate the parameters we use real time-series country and state data of COVID19 available from Johns Hopkins University [2]. For computing the gradient of the objective function with respect the model parameters we use the automatic differentiation python package `autograd`.

4 Experiments and Results

For each data set we infer the model parameters using data before and after the proposed social distancing and lockdown measures. At each time step we predict the cumulative error percentage of the next N days.

References

[1] Chaolong Wang, Li Liu, Xingjie Hao, Huan Guo, Qi Wang, Jiao Huang, Na He, Hongjie Yu, Xihong Lin, An Pan, et al. Evolving epidemiology and impact of non-pharmaceutical interventions on the outbreak of coronavirus disease 2019 in wuhan, china. *medRxiv*, 2020.

[2] https://github.com/CSSEGISandData/COVID-19