X-SEAIPR - A compartmental model for studying Covid19 spread in India
Executive Summary

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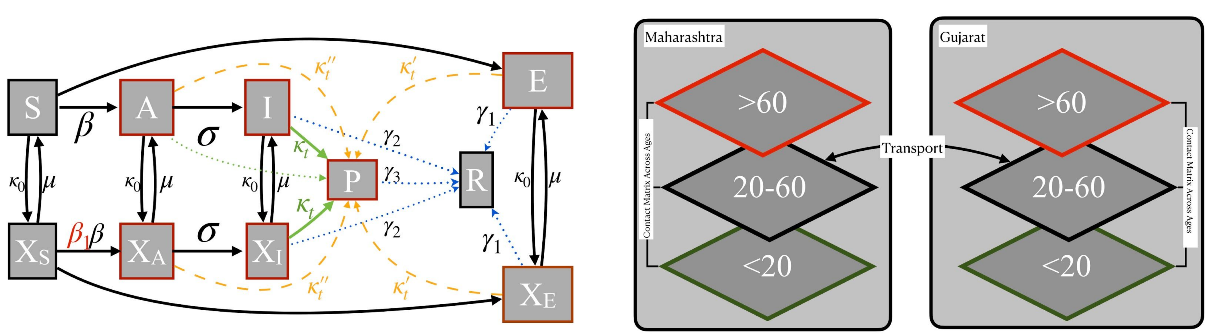
Basic Features of the Model

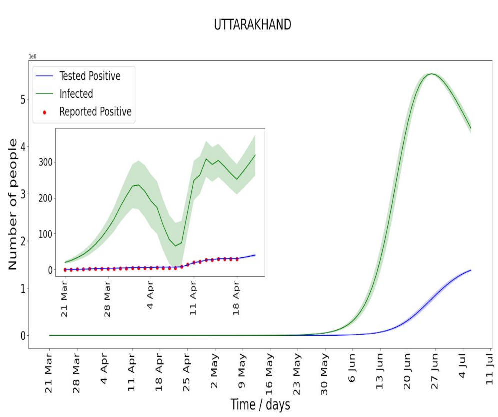
We construct a generalised SEIR model (X-SEAIPR, pronounced *"x-cipher"*) to incorporate the intrinsic characteristics of the disease alongside state level data available in India on transport and reported infections alongside implemented and proposed interventions. Our simulation is a compartmental model run at the state level (and also at the district level for Maharashtra) that includes compartments that model the susceptible (S), Asymptomatic (E, which we interpret as truly asymptomatic but mildly infectious), presymptomatic (A), symptomatic infected (I), removed (R) and a new compartment to incorporate those who have tested positive for COVID-19 (P). Furthermore, we include lockdown compartments that correspond to all but the P and R compartments to simulate the ongoing policy of the government till May 03, 2020. The basic structure of the model is shown in Fig. 1(a) below.

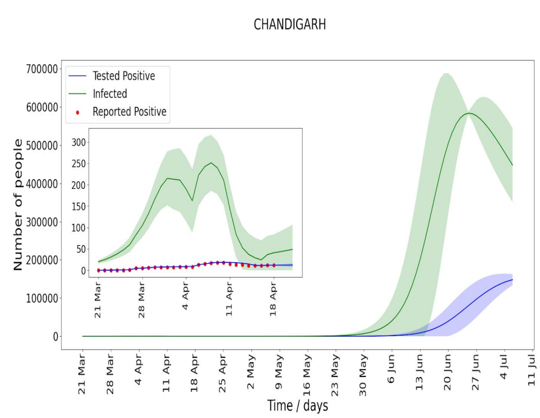


Since mortality is significantly different for different age groups, we also stratified the model for each state along age, namely people below 20, people between 20 and 60 years of age and people above 60. Each compartment can transfer its population to other compartments as shown in Figure 1(b) via a contact matrix [1]. In addition, intercompartmental transport happens via a transportation matrix incorporated as indicated in Figure 1(b). This transportation matrix is constructed using migration data at a district level for working age population in India [2]. Since the initial conditions for the model are not known very well, the probable trajectories and the corresponding uncertainties were extracted using well known Bayesian techniques. Preliminary results for state level model are presented in the next section.

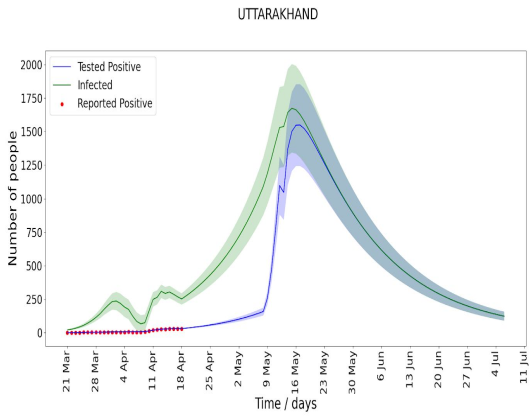
Preliminary Results of the Model

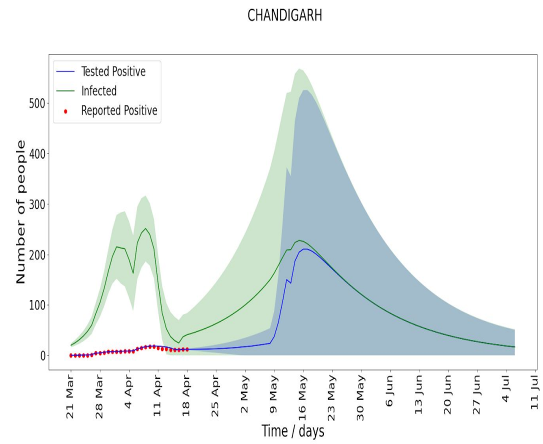
We show the results of the model below for two sample states,Uttarakhand and Chandigarh, upto a period of 11th July. The inset shows the fits of the reported number of positive Covid19 cases in that particular state (red circles) and the population in the P compartment (who have tested positive), until 16th April. The green curve shows the true number of infected people, as estimated from a Bayesian technique.





Similar projections can be obtained for all different states, and within a single state, at a district level as well. The shaded region around each curve measures the uncertainty of the projected estimates. Different intervention strategies can be tested within the model. As an example, we show below the effect of increased testing for these same two states.





As is apparent from the figures, an increased testing rate can serve to drastically reduce infected numbers. This relied on the strategy that effective quarantine of identified individuals can help limit the spread of the epidemic effectively.

Discussion

The model presented in this work has several main strengths that are important for an India-wide analysis of the current situation-

- For a population in lockdown, transmission happens at a rate which is lower than the bare transmission rate by a factor $\boldsymbol{\beta}_1$, where $\beta_1 = 0$ indicates a perfect lockdown, whereas $\beta_1 = 1$ indicates a completely leaky lockdown. This quantitative measure of lockdown effectiveness can then be used a input to policy decisions.
- By incorporating a compartment for people who have tested positive (P), and estimating the ratio of reported cases to true infected numbers via Bayesian techniques [3], we can match reported data directly to the P compartment and hence generate truer estimates of the time evolution of the epidemic.
- The model also allows for testing rates to be incorporated differentially, which means that the different states which are testing at different rates can be incorporated into our model easily. Hence heterogeneous interventions, whether at a state or a district level can be tested out within the model.

- By employing a robust Bayesian method we can incorporate the inherent uncertainty in the initial conditions. We plan to extend this to include uncertainty in the parameters as well. Hence we can estimate in a robust fashion with appropriate uncertainty windows predictions for various compartments stratified by age and state/district.

Simulations for national level results incorporating a country-wide transportation network are currently underway. Full results for different proposed interventions will be made available shortly.

References:

1. Projecting social contact matrices in 152 countries using contact surveys and demographic data, Prem et. al. PLoS Comp Bio (2017)
2. Avijit Maji and Udit Bhatia, unpublished (this report)
3. Inferring the number of COVID-19 cases from recently reported deaths, Jombart et. al. medRxiv preprint doi: https://doi.org/10.1101/2020.03.10.20033761 (2020)