Stochastic SIR-based Examination of the Policy Effects on the COVID-19 Spread

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Summary

- Since the global outbreak of the novel COVID-19, many research groups have studied the epidemiology of the virus for short-term forecasts and to formulate the effective disease containment and mitigation strategies. The major challenge lies in the proper assessment of epidemiological parameters over time and of how they are modulated by the effect of any publicly announced interventions.
- Here we attempt to examine and quantify the effects of various (legal) policies/orders in place to mandate social distancing and to flatten the curve in each of the U.S. states. Through Bayesian inference on the stochastic SIR models of the virus spread, the effectiveness of each policy on reducing the magnitude of the growth rate of new infections is investigated statistically.
- This will inform the public and policymakers, and help them understand the most effective actions to fight against the current and future pandemics. It will aid the policy-makers to respond more rapidly (select, tighten, and/or loosen appropriate measures) to stop/mitigate the pandemic early on.

List of Policies/Interventions Considered

- state of emergency declared
- stay at home/shelter
- closed K-12 schools, day cares
- closed businesses, restaurants, movie theaters, gyms
- mandated face mask in public spaces
- religious gatherings exempt w/o social distance mandate
- banned visitors to nursing homes
- stopped personal visitation in state prisons
- stopped initiation/enforcement of evictions
- waived waiting period for unemployment insurance
- ordered freezing utility shutoffs
- SNAP waiver
- allowed/expanded Medicaid coverage incl. telehealth
- suspended elective medical procedures
- reopened ACA enrollment

SIR Model

- Susceptible-Infected-Recovered (SIR)
  - well-established *compartmental* model for disease dynamics
  - based on ordinary differential equations (ODE)

$$\frac{d}{dt}S(t) = -\lambda(t)S(t)\frac{I(t)}{N}$$
$$\frac{d}{dt}I(t) = \lambda(t)S(t)\frac{I(t)}{N} - \mu I(t)$$
$$\frac{d}{dt}R(t) = \mu I(t)$$

* stationary recovery rate μ

* additive spreading rate $\lambda(t)$

$$\lambda(t) = \lambda_0 + \sum_{i=1}^{m} \lambda_i \cdot J(t_i^{beg} \leq t \leq t_i^{end})$$

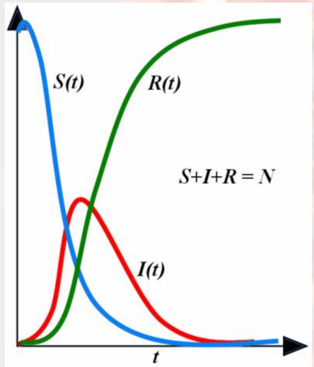
where λ_i = intervention-specific spreading rate in the time range $[t^{beg}, t^{end}]$

* static population size N

- other variations available (*e.g.*, inclusion of the incubation period, re-infection, etc.)

Bayesian Inference

- incorporate the *prior* knowledge
- approximate the posterior distribution via ***MCMC sampling***
  - Markov chains initialized through automatic differentiation variational inference (ADVI)
  - 1000 *burn-in* (tuning) for each chain to sample from an equilibrium distribution
  - 4000 steps for each chain to approximate the posterior (ergodicity), and convergence checked



- estimate parameters *evolving* over time
- enable short-term forecast w/ uncertainty quantification (UQ)

Figure 1. Graphical illustration of the temporal evolution of the SIR model

Observations

- different states do ***not*** exhibit the same effects of reducing the spread rate $\lambda(t)$ by each intervention/policy; *divergent* in quite a few cases.
  - more covariates needed to understand the reasons
- inference and forecasts got complicated by the delay of 2 to 4 weeks since the onset of each intervention.
  - created major uncertainties to deal with
- *lifting* certain policies should be implemented more carefully.

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