Abstract

- Covid has affected XX people
- Forecasts useful for public health resource planning, intervention planning (vaccine trials), and disease burden
- Basic Mechanistic Models unable to capture complexities of real world disease epidemics due to
  - Complexities of interventions
  - Issues with testing and reporting
- We propose a novel forecasting algorithm to overcome
  - Under-reporting of cases
  - Time-varying interventions
- Bayesian end to end estimation using both cases and deaths in numpyro

MECHANISTIC BAYESIAN FORECASTS OF COVID19

GRAHAM GIBSON

1. Introduction

- Emergence and spread of covid
- Forecasts useful for public health
  - Resource allocation
  - Intervention Planning
  - Disease burden
- Cite Flu Forecasting
- Describe COVID-HUB
  - Number of participating teams as evidence of importance
  - Soliciting forecasts for incident and cumulative deaths
- Mechanistic models have been around since K&K
- Demonstrated success in modeling infectious disease
- Since they were developed around the last pandemic their usefulness as applied forecasting models has gone untested
- Extensions to basic model needed
  - Observations on cases and deaths
  - Time-varying detection probability for varied testing
  - Non-parametric model of interventions
  - Full Bayesian fitting due to unidentifiability of parameters given only a time series of cases and deaths.
- MechBayes outperforms in two settings
  - COVID-HUB relative to baseline model
  - Ablation test relative to basic SEIR model

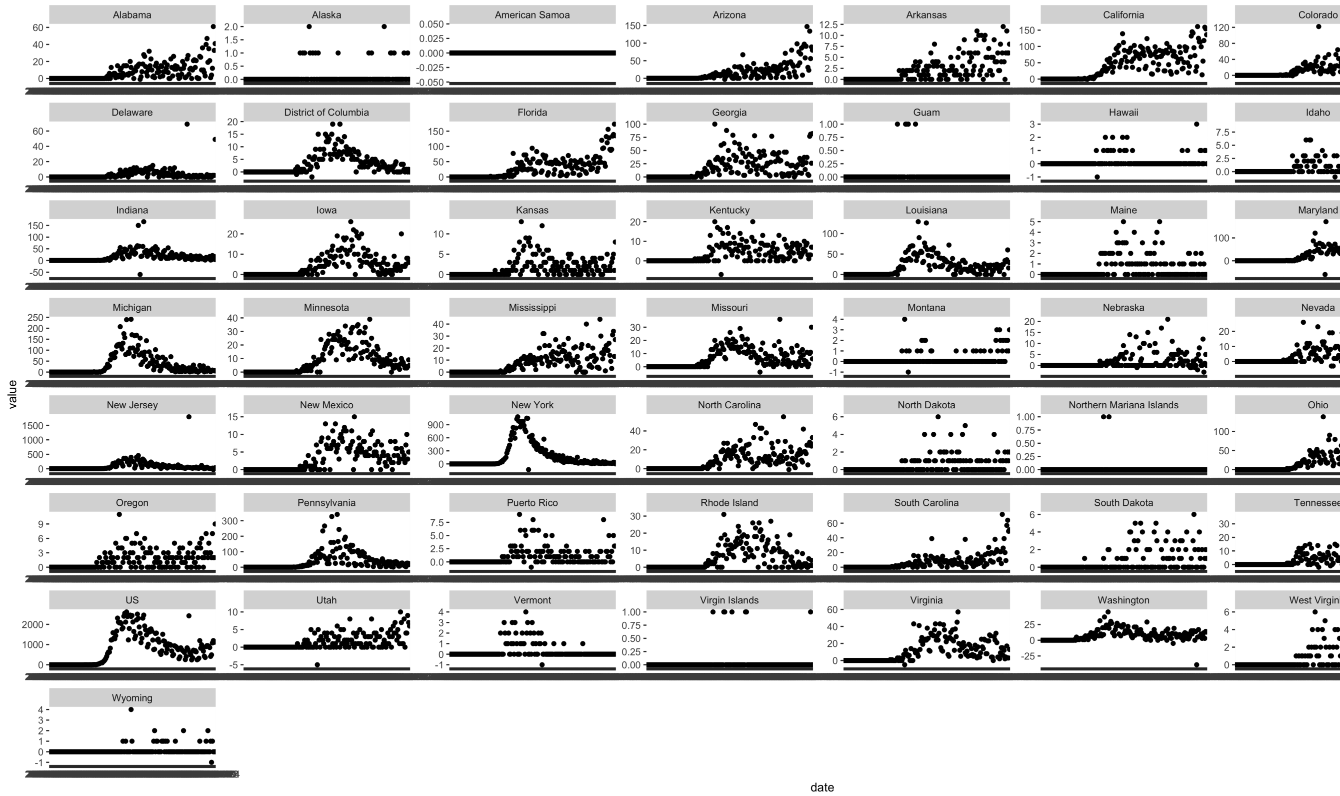

Figure 1. Deaths by state.

- We show improvements in MAE and WIS relative to baseline model in both experimental setups

2. Data

- We use cases/deaths from JHU
- Under-reporting issues
- Batch reporting issues
- Revision Issues
- Weekly cycle issues
- High variability in incident data
- Ref Figure 1

3. Compartmental Model

- Basic SEIR model description
- Definition of compartmental model (description of diff eq as flow between compartments)

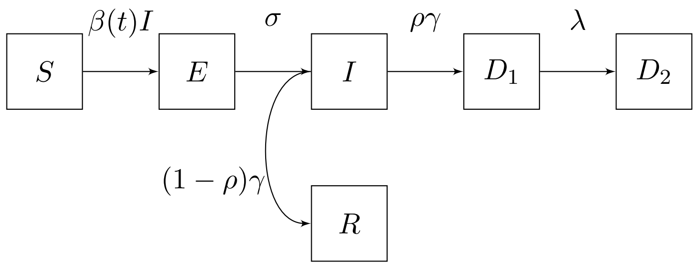

FIGURE 2. Comparmental model parameters

- Ref Figure 2
- Interpretation of parameters in basic SEIR model
  - Sigma
  - Gamma
  - beta

3.1. **Observations on cases and deaths.**

- Bayesian model has observations on both cases and deaths
- We can weight likelihood of one over the other
- Explain how cases inform deaths on average 10 days later

3.2. **Time-varying beta parameter.**

- Non-parametrically models time-varying transmissibility through a random walk
- Makes forecasts conditional on current level of interventions
- Requires no external intervention data to make forecasts
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3.3. **Time-varying detection probability.**

- Non-parametrically models time varying testing and overall detection of case issues
- Allows for "data dumps"
- Logistic random walk
- Fixed detection probability on deaths

3.4. **Seeding Epidemic.**

- Because of detection probability we cannot seed using initial reported data, since this is an underestimate
- Put priors on initial seed

3.5. **Priors.**

- We choose tight priors based on literature
- Fundamental unidentifiability due to renewal equation expression where $I(t)$ is a convolution between R_t and Seiral interval
- Cannot estimate both simultaneously

- Most flexibility comes in with beta and detection random walk
- Ideal for forecasting, maybe not for inference

3.6. **Fitting.**

- Fully Bayesian HMC on parameters
- Why we choose deterministic compartmental model with only uncertainty on parameters and observations
- Estimation in numpyro very fast

4. Experimental Setup

4.1. **COVID-HUB.**

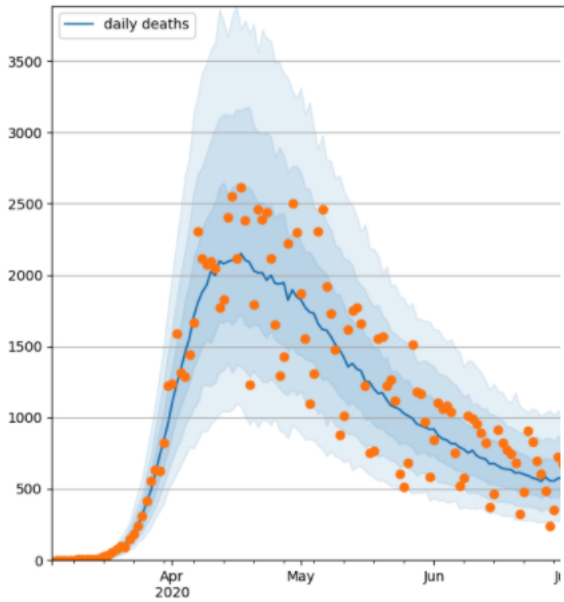
- Real-time forecasting evaluation for 14 weeks starting April 20th 2020.
- Forecasts submitted every Monday using incident data up until Sunday
- Cumulative forecasts generated by aggregation of incident forecasts
- 1-4 week ahead targets generated from 28 day ahead predictions

4.2. **Ablation Test.**

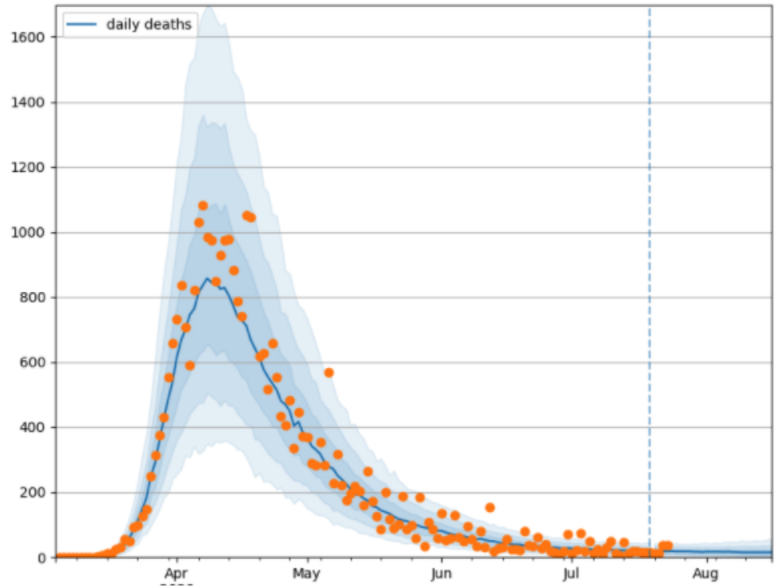
- Evaluate a set of nested models
  - Basic SEIR model with observations only on deaths
  - SEIR with joint observations
  - SEIR with joint observations and random walk detection probability
- We omit the test that involves no random walk on beta since a model must take into account interventions.

5. Results

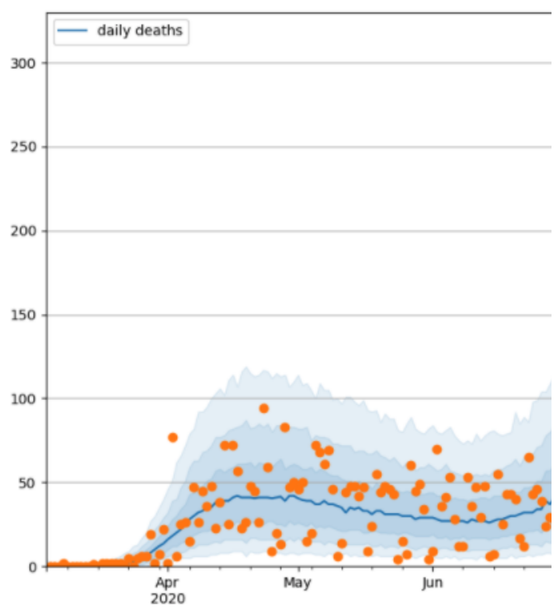
- MechBayes is uniformly better than baseline model



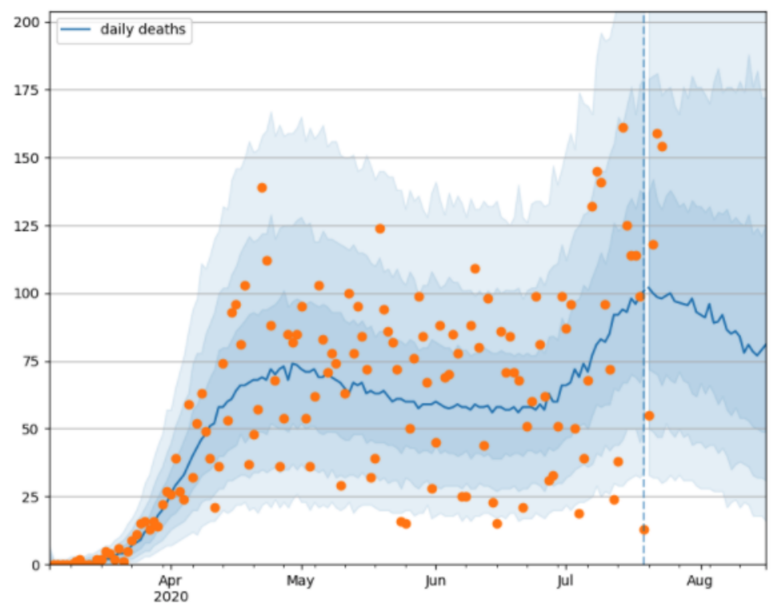
(A) Connecticut



(B) New York



(C) Georgia



(D) South Carolina

Figure 3. Example case counts over time along with dates of intervention for 4 randomly sampled states. Data for all states is included in the appendix

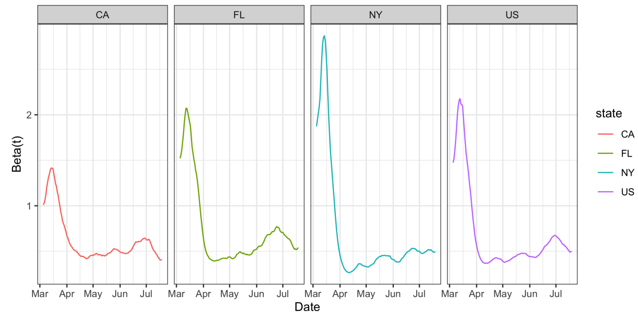


FIGURE 4. Deaths by state.

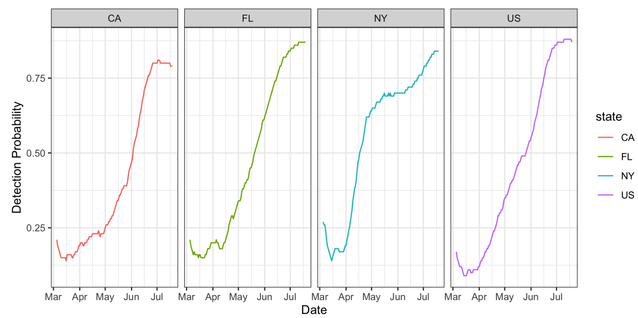


FIGURE 5. Deaths by state.