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

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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

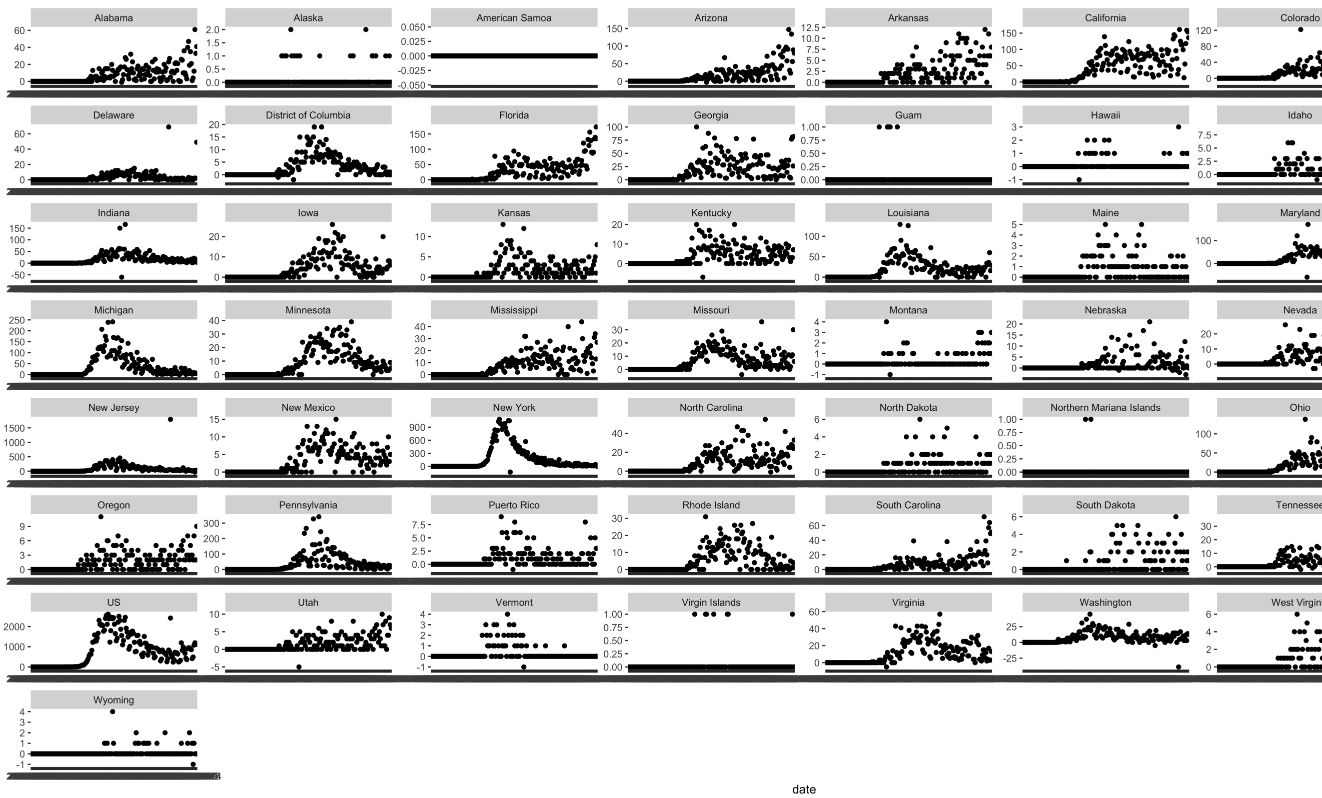

Figure 1. Deaths by state.

- 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)

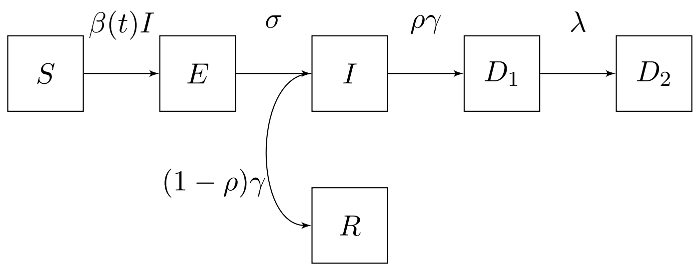

Figure 2. Comparmental model parameters

- 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.**

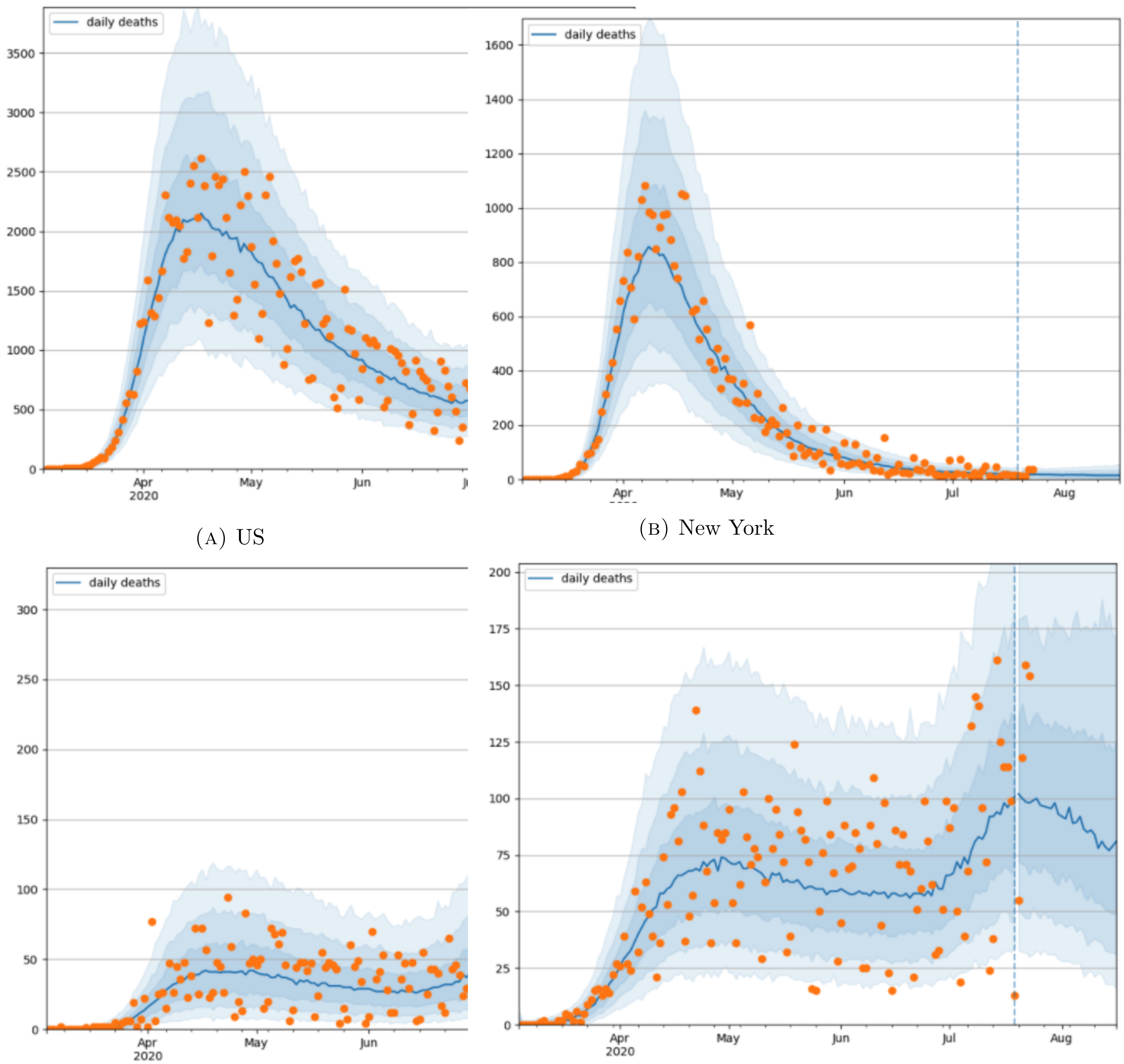
- Evaluate a set of nested models
  - Basic SEIR model with observations only on deaths
  - SEIR with joint observations
  - SEIR with joint observations and random walk detection probability
- We omit the test that involves no random walk on beta since a model must take into account interventions.

5. COVID-Hub Results

- MechBayes is almost always better than baseline model when broken down by region, target, and timezero after June 1st 2020.
- MechBayes has improved over time.
  - First two submissions did not have detection probability random walk
  - Observations were Normally distributed on cumulative deaths
  - Switched to current model
- Naive baseline is hard to beat
- MechBayes is biased high. This comes from uncertainty in the random walk leading to potentially huge growth rates.

6. Ablation Results

- Model ranking is as follows
  - MechBayes
  - MechBayes-Case Observations
  - MechBayes - no detection random walk
- This ordering is inu



(A) US (B) New York

(C) Florida (D) California

FIGURE 3. Example fit and forecast for four states.

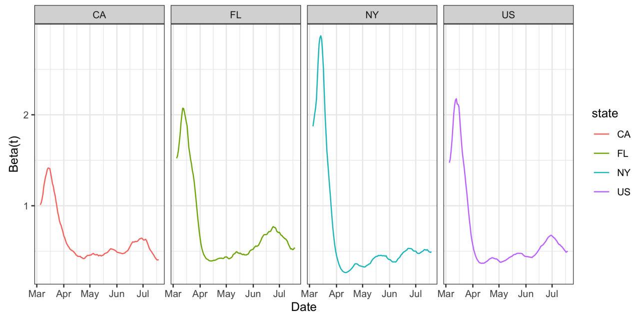


FIGURE 4. Deaths by state.

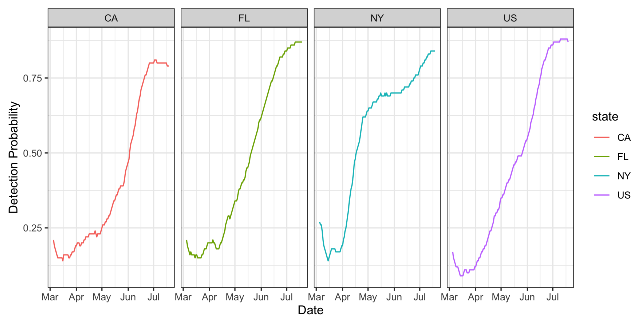


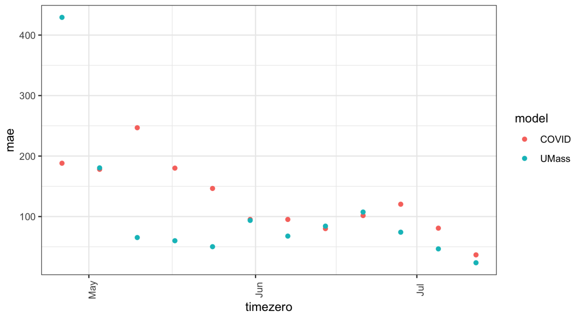
FIGURE 5. Deaths by state.

7. Discussion

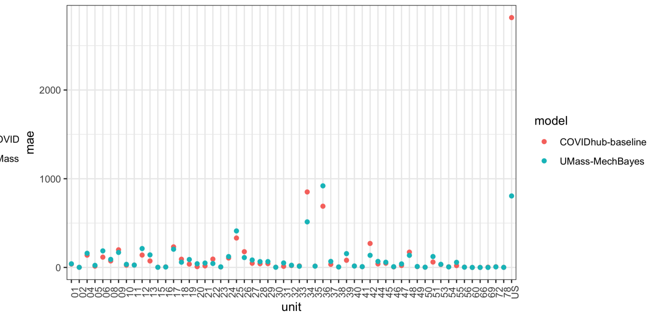
- Mech Bayes is a fast fully bayesian compartmental model capable of accounting for real-world modeling challenges during a pandemic.
- Demonstrated success across regions, targets, and timezeros
- Real-time model results show the practice of modeling during an epidemic. Results are improving.
- Ablation studies show the results are grounded in real model improvements using historical validation.
- Talk about how overall MAE obscures the huge geographic variability.

8. Conclusion

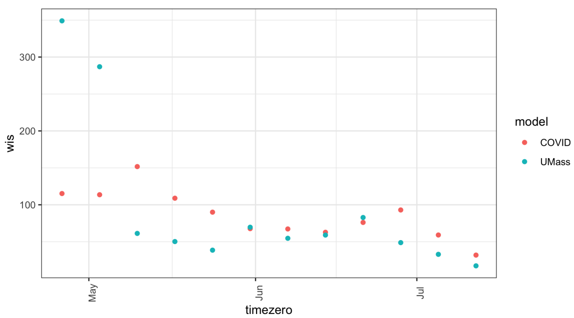
- Summarize mech bayes as bayesian compartmental model
- Further work: most of the model is about $\beta(t)$. Better methods for modeling it? Spline Etc.



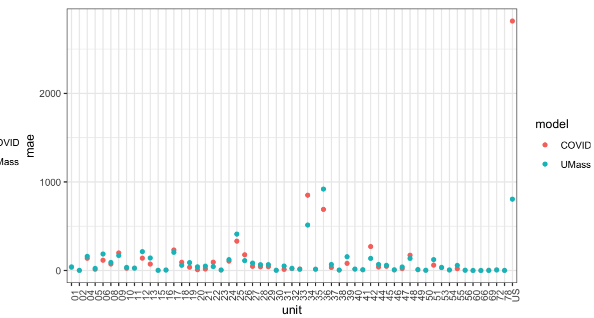
(A) MAE by timezero



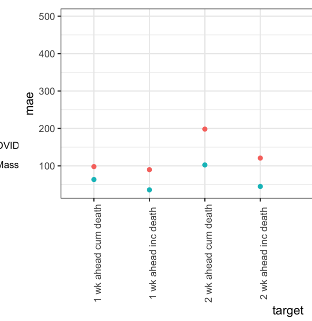
(B) MAE by region



(C) WIS by timezero



(D) WIS by region



(E) WIS by

Figure 6. Scores from covid-hub.