

# Illuminating the Hidden Elements and Future Evolution of Opioid Abuse Using Dynamic Modeling, Big Data and Particle Markov Chain Monte Carlo

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# Background

- ❑ Annual deaths resulting from **drug overdose** have increased continuously over the past 20 years in the United States.
- ❑ The history of opioid abuse indicates that previously instituted **public health strategies have proven inadequate** for preventing the current opioid epidemic.
- ❑ In recent years, **System Dynamic (SD) models** have become popular in addressing opioid abuse in public health domain
- ❑ Such models suffer from rapid obsolescence and marked data gaps
- ❑ **Machine learning algorithm** have made it easier to incorporate empirical data into dynamic models, helping the model to “learn” from incoming data

***The objective of this study is to provide a framework to inform policy discourse that addresses the key needs of opioid abuse.***

# Goals

- Marked data gaps (e.g., around illegal trade) ⇒ To
  - Apply a method that will allow for estimating poorly understood & measured areas of the system
  - Integrate a wide variety of empirical data
- Rapidly changing nature of opioid epidemic ⇒ To
  - Create dynamic model that “learns” from and adapts to incoming data & always stays current
  - Use high-velocity data sources where possible
- Need to anticipate coming trends ⇒ To use a dynamic model to project forward from the current state
- Need to evaluate policy scenarios ⇒ Utilize a dynamic model capable of running “what if” scenarios running forward

# Methods

The **PMCMC algorithm**- and specifically, the ***Marginal Metropolis Hastings (MMH)*** variant of that algorithm are employed here.

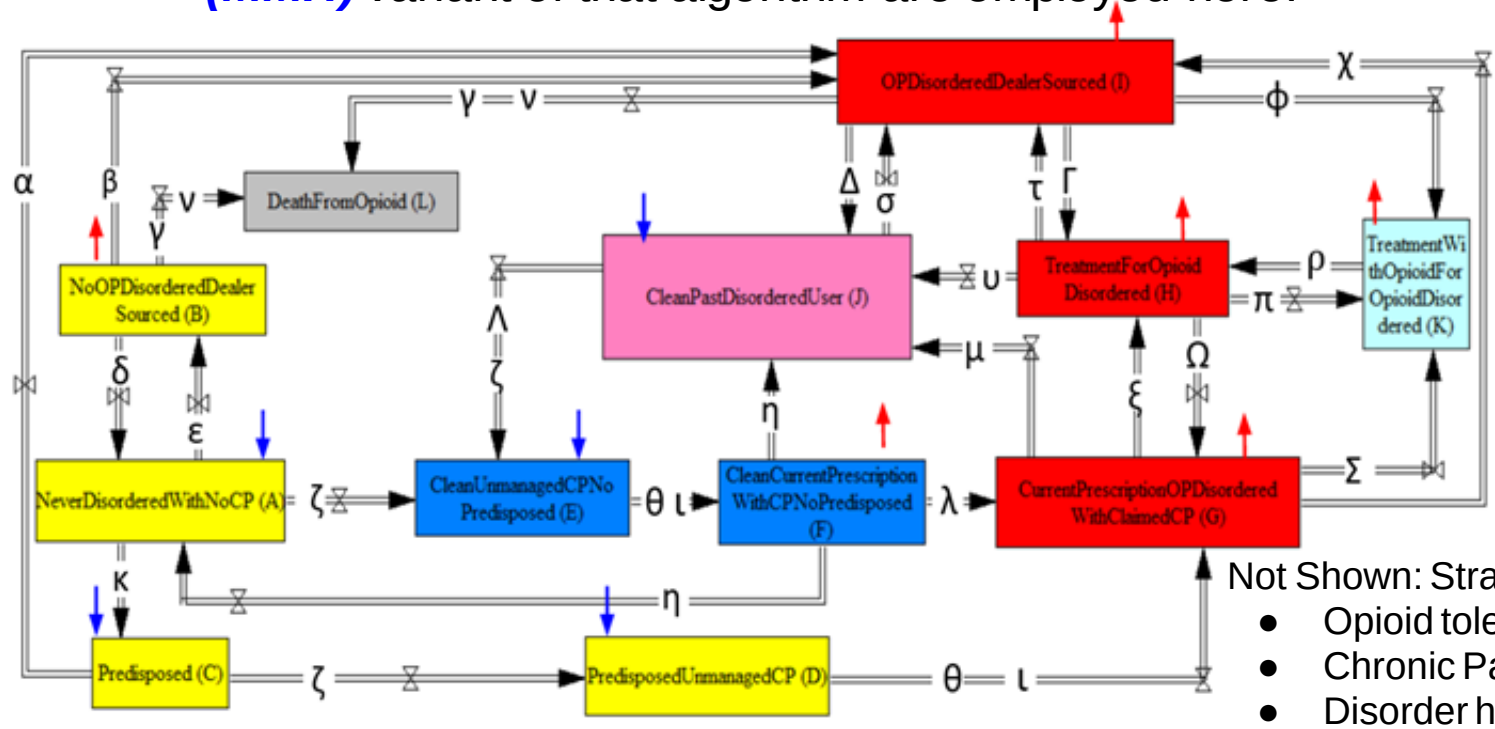


**Figure 1: General structure of the opioid system dynamics model.**

# Particles in Particle Filtering

- .Can be automatically run to incorporate new data
- Each “hypothesis” regarding state is represented by a “particle”
  - At any time, the particles represent a sampling from the state of that model at that time
  - We compute statistics on particles to approx. applying such statistics to the full distribution
  - There is typically a fixed number of particles retained through the simulation
- Each particle is associated with
  - Copy of model state
  - A normalized weight
- “Survival of the fittest”: Particles reproduce and survive or perish according to their quality of match to the empirical observations
  - **Learning**: Trajectories more consistent with the data survive

# Data

Large amount of empirical dataset related to Cincinnati was used.

Online Search Behavior

Google trend data :

- ☐ Back Pain
- ☐ Drug Rehabilitation
- ☐ Dark Web
- ☐ Naloxone

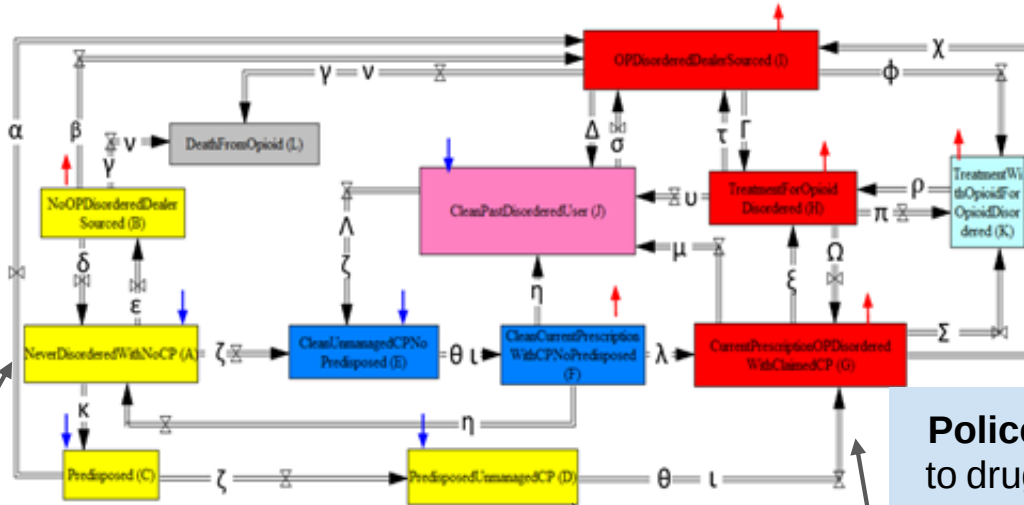
Demographic and Surveillance Data

**Police calls** for service related to drug complaints, reported by Cincinnati Police Department

**Hamilton county drug overdose death** reported by Ohio Department of Health and CDC

**Hamilton county report of opioid prescription** reported by Ohio Board of Pharmacy

**EMS Response** provided by Cincinnati Fire Department and Cincinnati Police Department



# Likelihood Functions

- Likelihood functions give the likelihood of the empirical datum, given the model state
- **Binomial**

$$y_t | x_t^s \equiv y_t | i_t \sim \text{Binomial}(i_t, p)$$

Here, reports are some of i.i.d. Bernoulli draws, with reporting probability  $p$

Difficulty: Stiff upper bound of  $i_t$  in reported count ( $p(y_t | i_t) = 0$  for  $i_t < y_t$ ) can lead to singularities when all particles  $s$  have state  $i_t^s < y_t$

- **Negative Binomial**

This  $p(y_t | i_t)$  is non-zero for all  $i_t > 0$

$$y_t | x_t^s \equiv y_t | i_t \sim \text{NegativeBinomial}(i_t, r)$$

# Result: Population Tomography

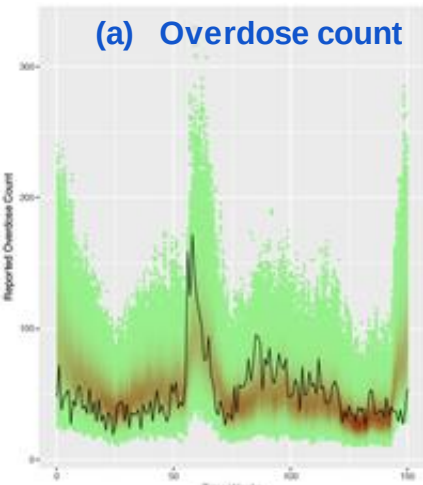


# Scenarios

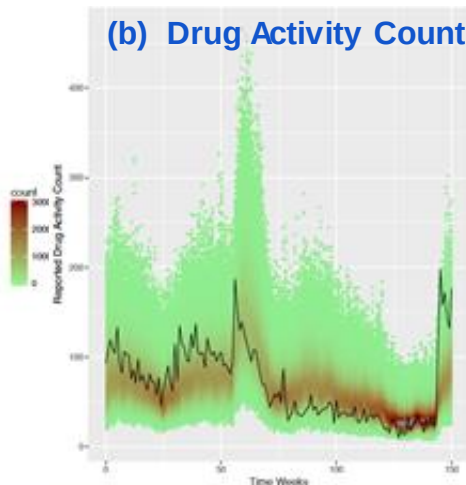
- Assessment/Calibration
- Projection (prediction)
- Proof-of-concept Policy investigation

# Results

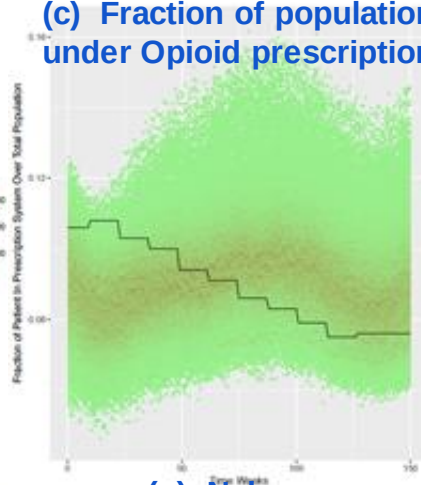
(a) Overdose count



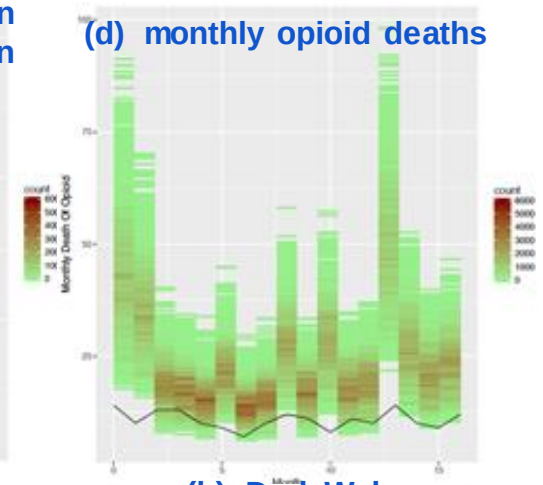
(b) Drug Activity Count



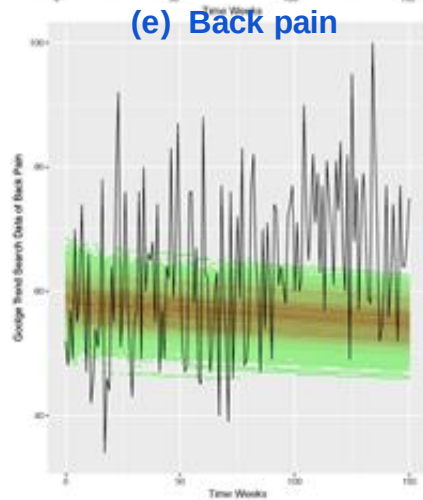
(c) Fraction of population under Opioid prescription



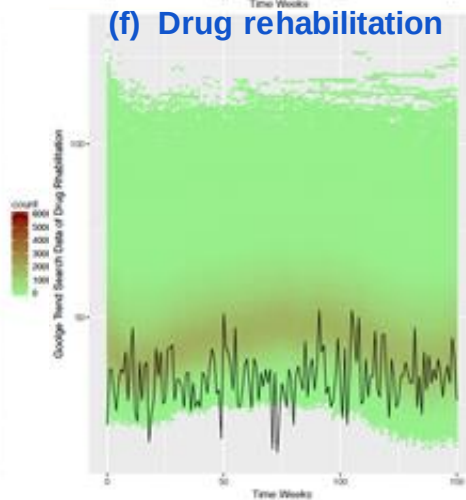
(d) monthly opioid deaths



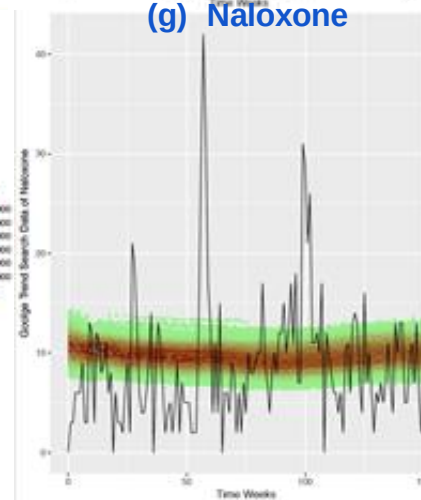
(e) Back pain



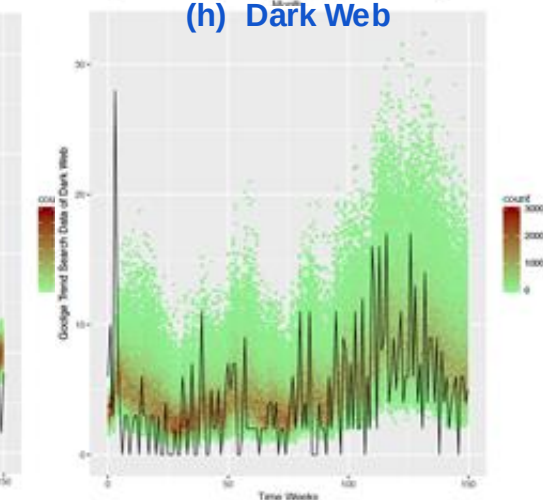
(f) Drug rehabilitation



(g) Naloxone

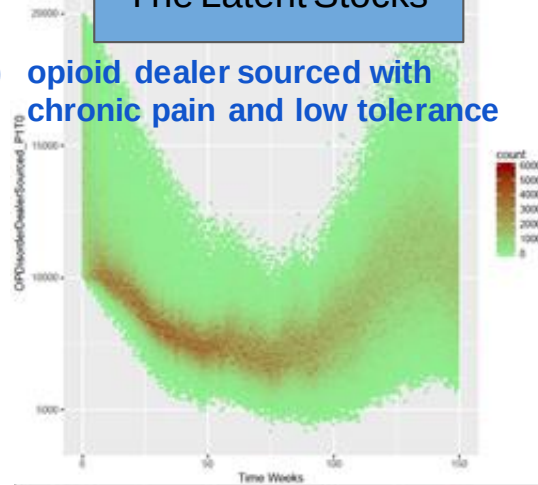


(h) Dark Web

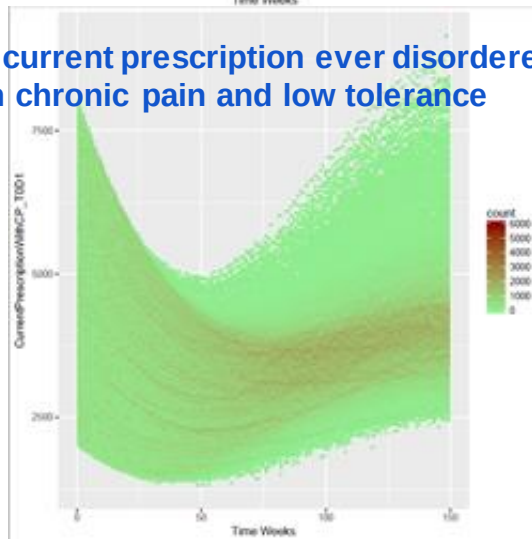


## The Latent Stocks

(a) opioid dealer sourced with chronic pain and low tolerance

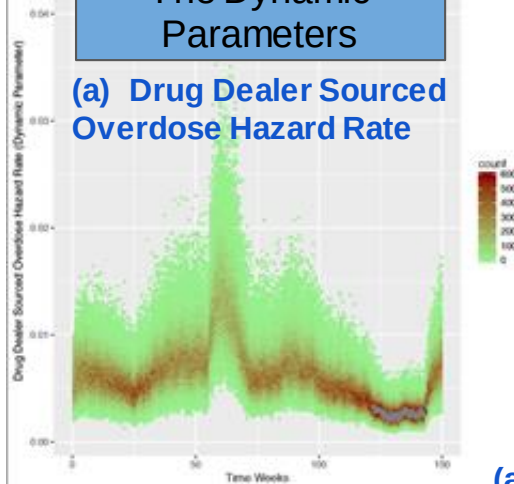


(b) current prescription ever disordered with chronic pain and low tolerance

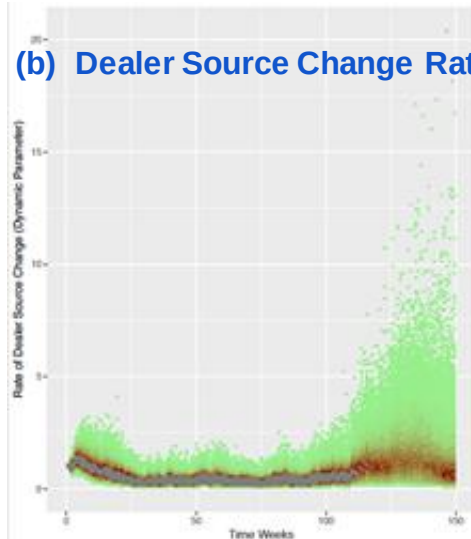


## The Dynamic Parameters

(a) Drug Dealer Sourced Overdose Hazard Rate

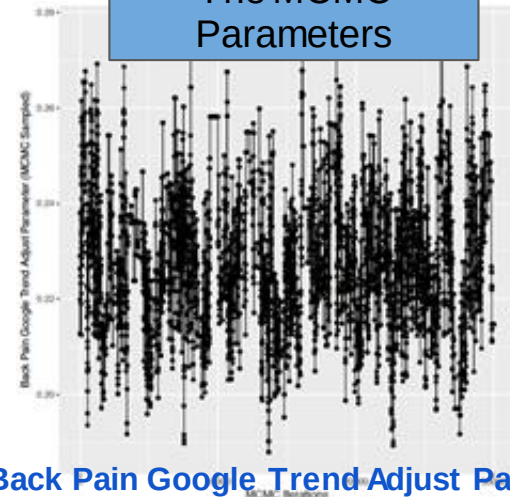


(b) Dealer Source Change Rate

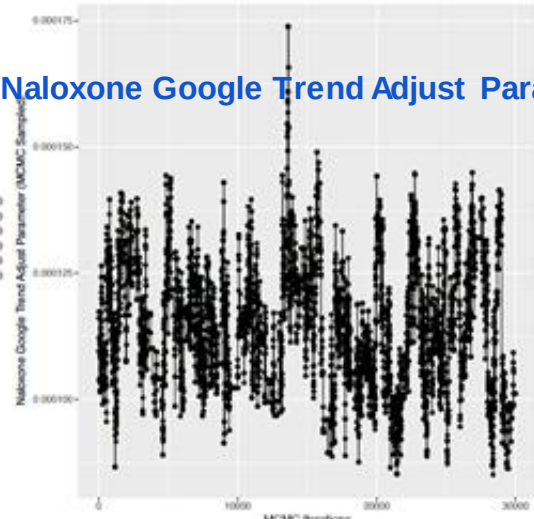


## The MCMC Parameters

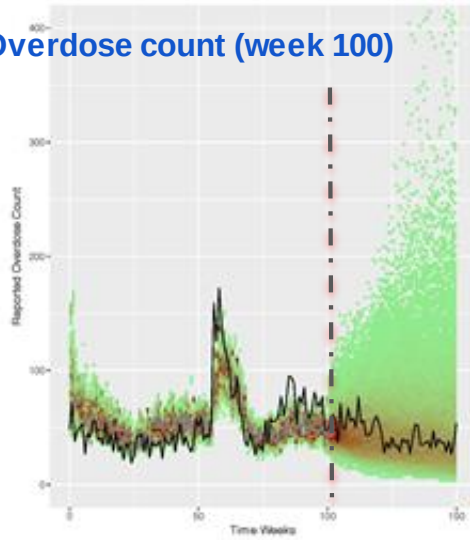
(a) Back Pain Google Trend Adjust Parameter



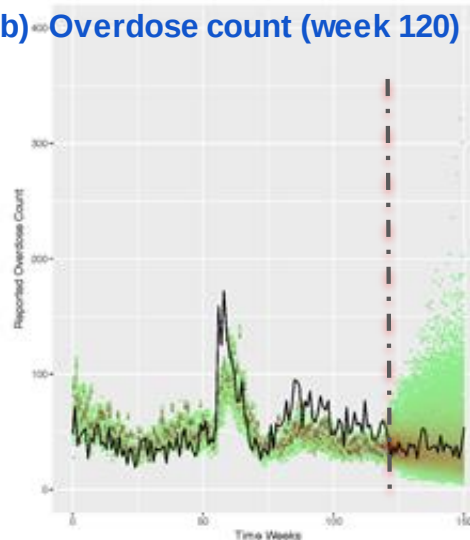
(b) Naloxone Google Trend Adjust Parameter



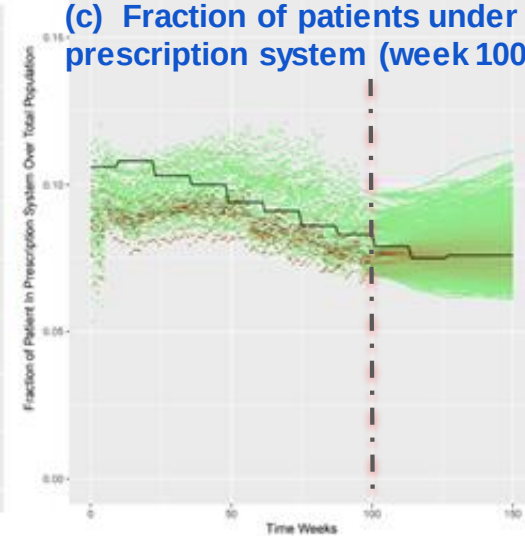
(a) Overdose count (week 100)



(b) Overdose count (week 120)

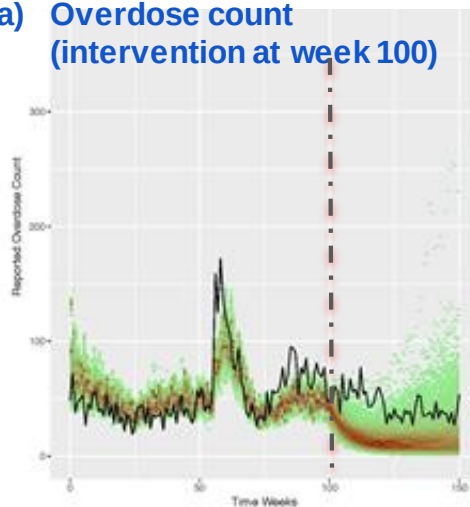


(c) Fraction of patients under prescription system (week 100)

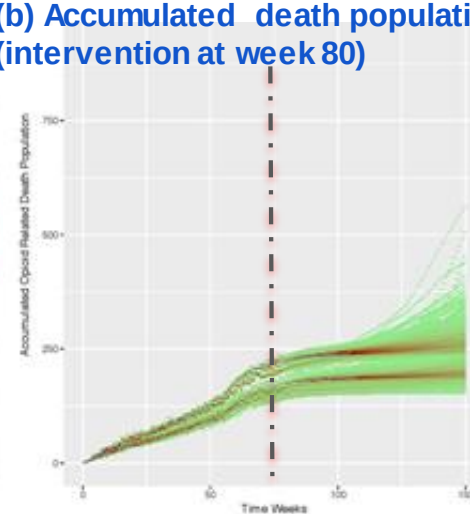


Prediction  
results

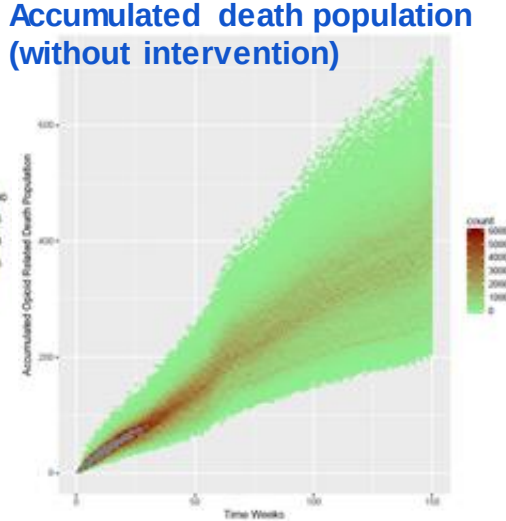
(a) Overdose count  
(intervention at week 100)



(b) Accumulated death population  
(intervention at week 80)



Accumulated death population  
(without intervention)



Intervention  
results

# Findings

- PMCMC offers a promising means for creating self-learning models kept perpetually current via leveraging diverse incoming lines of data
- Combining machine learning, high temporal-density data, dynamic modeling can allow for effective estimation of latent and observed system state
- PMCMC based models can allow for projection forward based on understanding of latent state
- PMCMC methods allow for assessing tradeoffs between interventions
- Much additional technical investigation & parallelization is required to fully exploit the potential of these methods