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 [1].
- There have been more than ***350,000 opioid overdose*** deaths between 1999 and 2016 [1].
- 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.
- Researchers have suggested that ***additional data*** related to opioid abuse would ***enhance the validity of the dynamic models*** [2].
- Modern ***machine learning algorithm*** have made it easier to incorporate empirical data into dynamic models.

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

Data and Methods

- **SD modelling** is used to capture the dynamic behavior of complex opioid system.

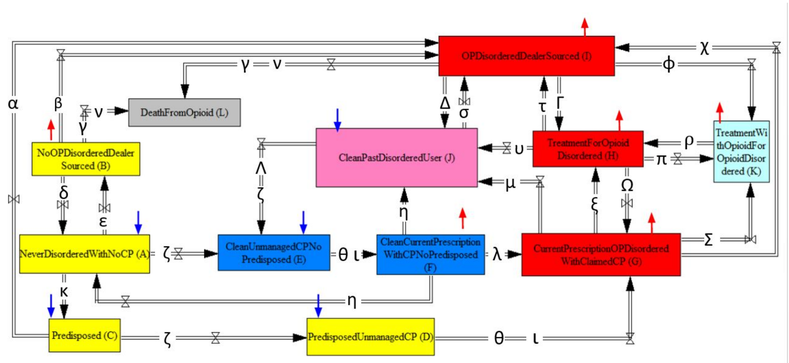
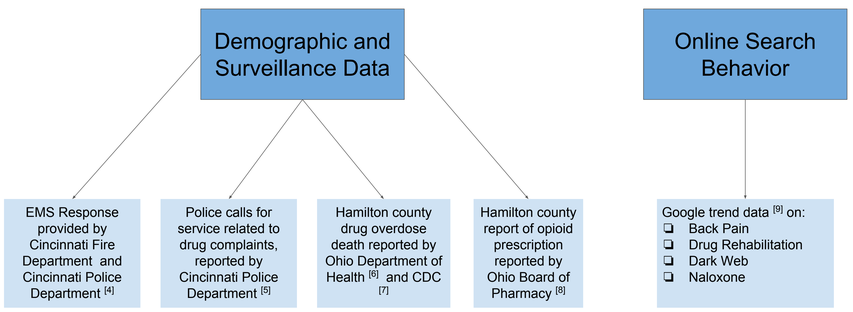
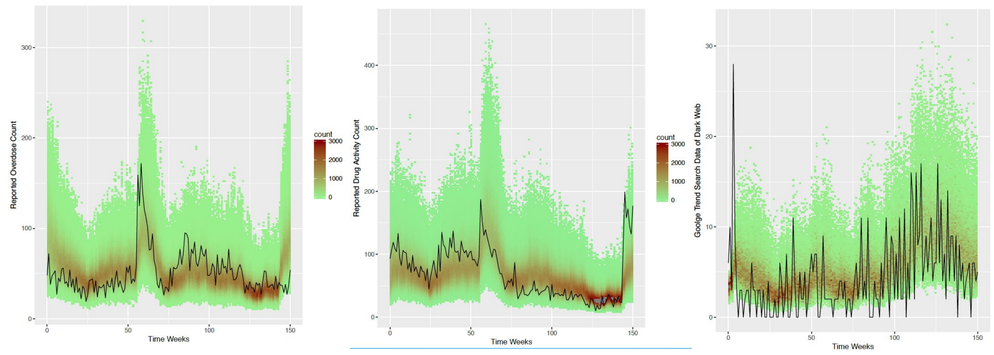


Figure 1: General structure of the opioid system dynamics model.

- The **PMCMC algorithm**- and specifically, the ***Marginal Metropolis Hastings (MMH)*** variant of that algorithm employed here [3].
- Large amount of empirical dataset related to Cincinnati was used.

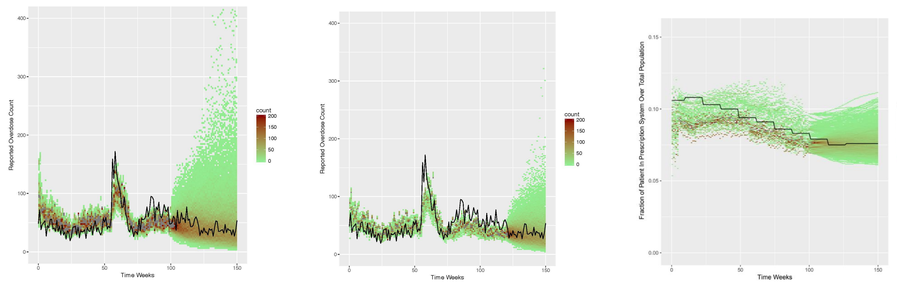


Results



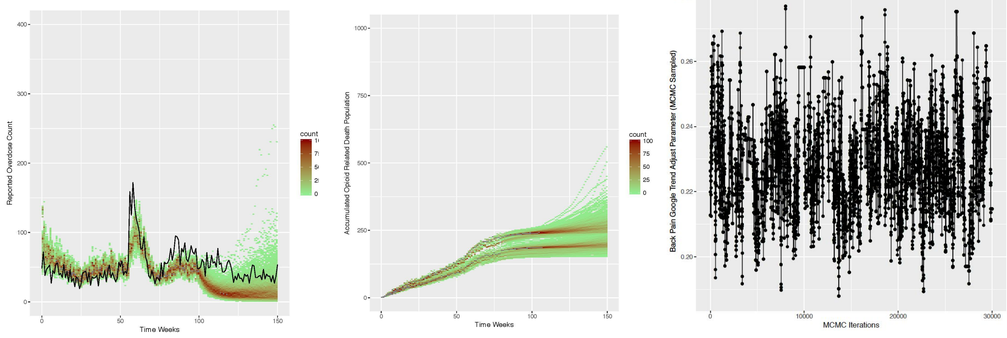
(a) Overdose count (b) Drug Activity Count (c) Google Trend (Dark Web)

Figure 2: Comparison of the model results and empirical datasets



(a) Overdose count (week 100) (b) Overdose count (week 120) (c) Patients under prescription system (week 100)

Figure 3: Predicted plots



(a) Overdose count (intervention at week 100) (b) Accumulated death population (intervention at week 80)

Figure 4: Intervention Plots

Figure 5: the trace plot of parameter sampled by MCMC algorithm

Major Findings

- This study may be the ***first contribution*** exploring leveraging the cutting-edge machine learning algorithm, PMCMC with dynamic modeling in the health or social domains.
- This research provides a good opportunity to explore the performance of the powerful, contemporary PMCMC model when combining a ***relatively large number of empirical datasets***, including social media.
- The model will further afford ***data-informed probabilistic projection*** of the evolution of the opioid epidemic.
- The model will support probabilistic projections of policy tradeoffs for the Cincinnati context, in a fashion that ***takes into account uncertainties*** regarding the latent state of the model.

Future Study

- The convergence of the PMCMC to the asymptotic distribution associated with the underlying MCMC needs to be assessed more rigorously.
- The model would benefit greatly from additional data sources in key areas, such as those related to prescription dynamics, from police intelligence related to the drug trade, and from drug rehabilitation service-seeking

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