## **BAYESIAN CHANGEPOINT DETECTION**

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- Introduction
- 2 Model Descriptions
- 3 Analysis and Results
- 4 Discussion



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## **MOTIVATING PROBLEM**



Given a sequential data

### We might interest in;

Changes in the streamed data

#### Assume:

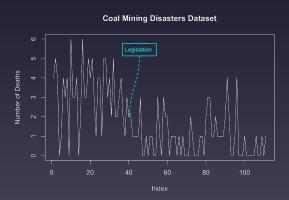
- Data is a result of such a generative process
- Generative process is changing in the changepoints

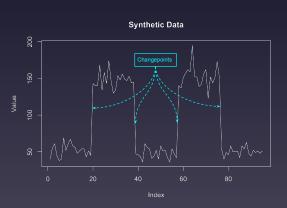
## Goal;

• Find the changes in the parameters of the generative process

## DATASET









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### **MODELS**



#### Comparable Implemented Models

- Poisson-Gamma Single Changepoint Model (SCM) [2, 3]
- Poisson-Gamma Double Changepoint Model (DCM) [2, 3]

## Other Implemented Model

Bayesian Online Changepoint Detection Algorithm (BOCM)[1]

## POISSON-GAMMA CHANGEPOINT DETECTION MODELS



## Single Changepoint Model

Means of the Intervals

$$e \sim Gamma\left(1,1\right)$$

$$l \sim Gamma(1,1)$$

Changepoint

$$s \sim Uniform(1,T)$$

$$X_t \sim Poisson(\lambda)$$
 
$$\lambda = \left\{ \begin{array}{ll} e & \text{if} \ t < s_1 \\ l & \text{if} \ s_1 <= t < s_2 \end{array} \right.$$

#### Double Changepoint Model

Means of the Intervals

$$e \sim Gamma(1,1)$$

$$l \sim Gamma(1,1)$$

$$m \sim Gamma(1,1)$$

Changepoints

$$s_1 \sim Uniform(1,T)$$

$$s_2 \sim Uniform(1,T)$$

$$\lambda = \begin{cases} e & \text{if } t < s_1 \\ l & \text{if } s_1 <= t < s_2 \\ m & \text{else} \end{cases}$$

## **BAYESIAN ONLINE CDM**



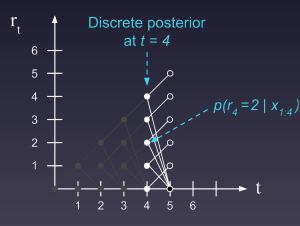


Figure 1: Run Length<sup>1</sup>[4]

#### Model

$$\alpha_{1:T} \sim Gamma(1, 1)$$
 $X_t \mid r_t \sim Poisson(\alpha_{t-r_t})$ 

## **Changepoint Prior**

$$P\left(r_{t}|r_{t-1}\right) = \begin{cases} H\left(r_{t-1}+1\right) & \text{if } r_{t}=0\\ 1-H\left(r_{t-1}+1\right) & \text{if } r_{t}=r_{t-1}+1\\ 0 & \text{otherwise} \end{cases}$$
 
$$H(\tau) = 0.01$$



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# **CONVERGENCE OF ALGORITHM**



## **Convergence Diagnostics**

- All  $\hat{R}$  values are 1.
- $n_{eff}/n_{transitions} > 0.001$  for all parameters.
- All of the
  - tree depth
  - E-BFMI
  - divergences

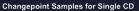
are looking good.

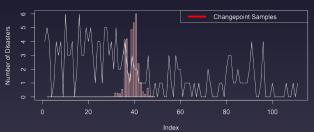
| loo comparison     | elpd diff | se diff |
|--------------------|-----------|---------|
| sigle model        | 0.0       | 0.0     |
| double model       | -3.2      | 5.7     |
| hierarchical model | -5.0      | 6.4     |

Table 1: Result of loo comparison

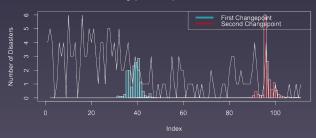
## POSTERIOR INFERENCE - CHANGEPOINT ESTIMATIONS







#### Changepoint Samples for Double CD



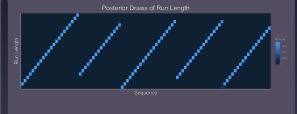
## Posterior Inference - Run Length Estimations







#### Synthetic Data - Analytical solution



#### Coal Mining Dataset - MCMC posterior samples



#### Synthetic Data - MCMC posterior samples





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#### **DISCUSSION**



#### Conclusion and Future Work

- The second changepoint is controversial
- Overall, Bayesian Online Changepoint Model is superior to other models.
- More generic versions of the MCMC solutions for Online Bayesian CD Model

#### More results at;

https://github.com/onurpoyraz/bcpm-stan/

## REFERENCES I



- R. P. Adams and D. J. MacKay. Bayesian online changepoint detection. arXiv preprint arXiv:0710.3742, 2007.
- C. Fonnesbeck, A. Patil, D. Huard, and J. Salvatier. Pymc user's guide.
- S. U. Guide.
  Change point models.
- G. Gundersen.Bayesian online changepoint model.

## **APPENDIX**



## Marginal Predictive Distribution

$$P\left(x_{t+1} \mid \boldsymbol{x}_{1:t}\right) = \sum_{\boldsymbol{x}} P\left(x_{t+1} \mid r_{t}, \boldsymbol{x}_{t}^{(r)}\right) P\left(r_{t} \mid \boldsymbol{x}_{1:t}\right)$$

### Recursive Run Length Estimation

$$P(r_{t}, \boldsymbol{x}_{1:t}) = \sum_{t=1}^{n} P(r_{t} \mid r_{t-1}) P(x_{t} \mid r_{t-1}, \boldsymbol{x}_{t}^{(r)}) P(r_{t-1}, \boldsymbol{x}_{1:t-1})$$