

# Prelim topic: Likelihood-free MCMC

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# Paper

Darren Wilkinson's "Parameter inference for stochastic kinetic models of bacterial gene regulation," a book chapter in [1].

# Likelihood Free MCMC

## Cast of Characters

- $r_j$  is a menu item in a restaurant.
- $x_t$  is the amount of money in the cash register  $t$ .
- $\mathcal{D}_t$  incomplete observation of  $x_t$  with error.
- $c$  is the popularity of menu items.
- $\tau$  governs measurement error.
- $\theta$  is  $\tau$  and  $c$  together.

*what is the statistical problem?*

*why is it important?*

*why is it hard?*

*what attempts were made to solve it in previous work?*

*introduce a running example*

# Likelihood Free MCMC

To produce a chain of samples from  $P(\theta|D)$ , using a proposal  $q(\theta^*|\theta)$ , accept with probability  $p_{rej}(\theta^*|\theta) \equiv \min\{1, A\}$  if

$$A = \frac{q(\theta, x|\theta^*, x^*)}{q(\theta^*, x^*|\theta, x)} \times \frac{P(\theta^*, x^*|\mathcal{D})}{P(\theta, x|\mathcal{D})}$$

- *the method*
- *the theory behind it*

# Likelihood Free MCMC

Cast of Characters (things DW can't evaluate are in red)

- $P(\theta)$
- $P(x|\theta)$
- $P(\mathcal{D}|x, \theta)$
- $P(x, \theta|\mathcal{D})$

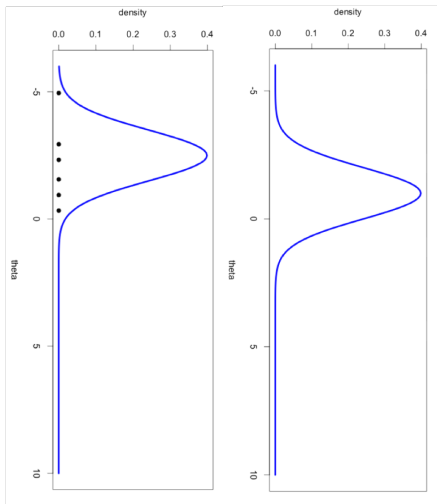
$$A = \frac{q(\theta, x|\theta^*, x^*)}{q(\theta^*, x^*|\theta, x)} \times \frac{P(\theta^*, x^*|\mathcal{D})}{P(\theta, x|\mathcal{D})}.$$

Quote: “Conditional on discrete-time observations, the Markov process breaks up into a collection of independent bridge processes that appear not to be analytically tractable.”

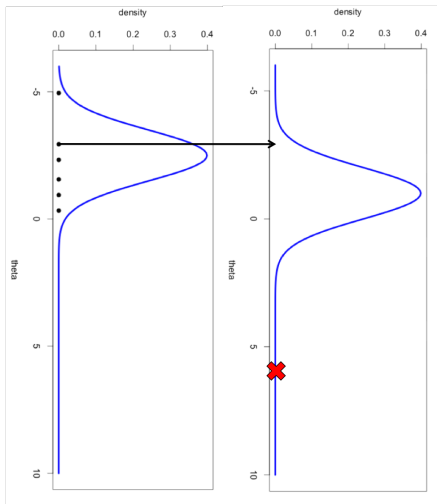
# Likelihood Free MCMC

$$\begin{aligned} & \frac{q(\theta^*, x^* | \theta, x)}{q(\theta, x | \theta^*, x^*)} \times \frac{P(x|\theta)}{P(x^*|\theta^*)} \times \frac{P(\theta)}{P(\theta^*)} \times \frac{P(\mathcal{D}|x, \theta)}{P(\mathcal{D}|x^*, \theta^*)} \\ &= \frac{f(\theta^*|\theta)}{f(\theta|\theta^*)} \times \frac{P(x^*|\theta^*)}{P(x|\theta)} \times \frac{P(x|\theta)}{P(x^*|\theta^*)} \times \frac{P(\theta)}{P(\theta^*)} \times \frac{P(\mathcal{D}|x, \theta)}{P(\mathcal{D}|x^*, \theta^*)} \\ &= \frac{f(\theta^*|\theta)}{f(\theta|\theta^*)} \times \frac{P(\theta)}{P(\theta^*)} \times \frac{P(\mathcal{D}|x, \theta)}{P(\mathcal{D}|x^*, \theta^*)}. \end{aligned}$$

# Likelihood Free Particle MCMC

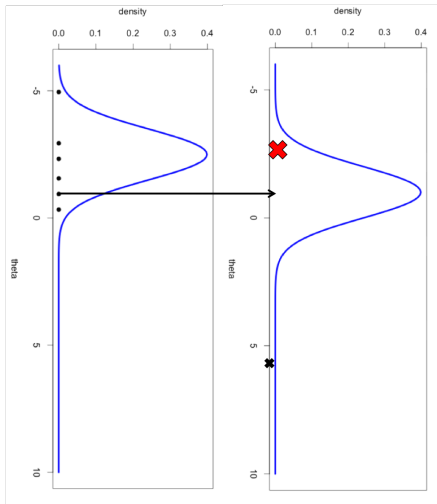


# Likelihood Free Particle MCMC

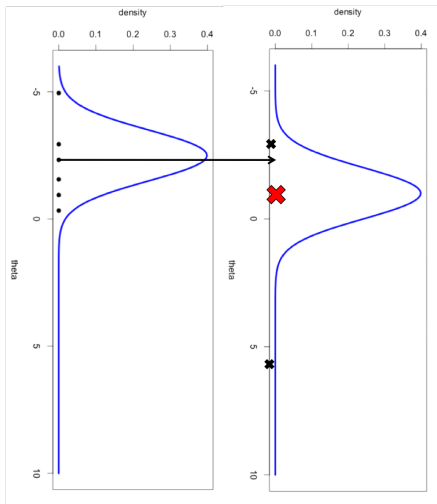




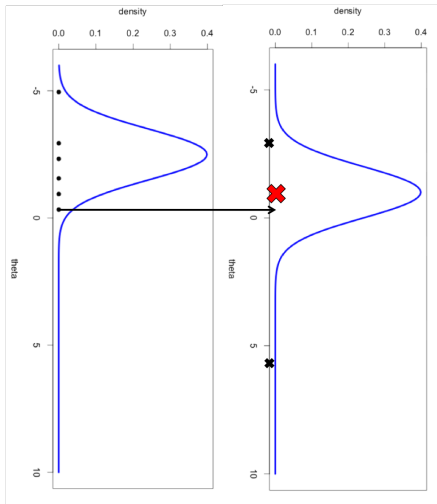
# Likelihood Free Particle MCMC



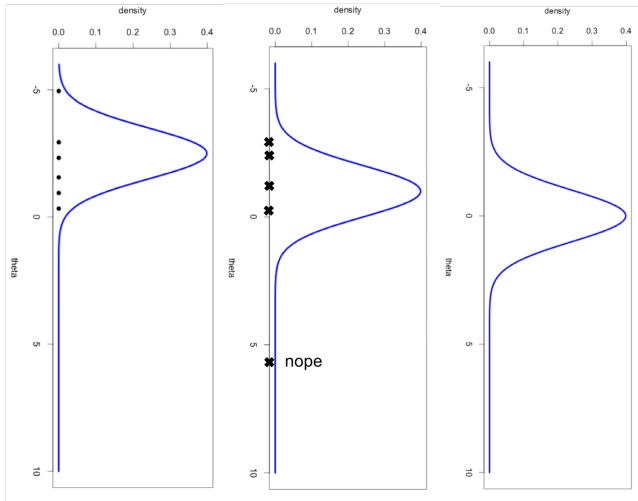
# Likelihood Free Particle MCMC



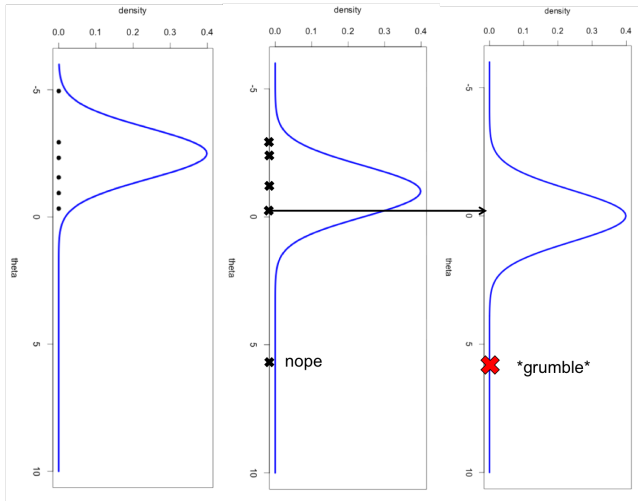
# Likelihood Free Particle MCMC



# Likelihood Free Particle MCMC



# Likelihood Free Particle MCMC



# Likelihood Free Particle MCMC

Given a hidden continuous-time Markov process  $\{x_t\}_{t=0}^T$  with:

- Unknown parameters  $\theta$  and known initial state  $x_0$

- Data points  $\mathcal{D}_{t_i}$  at times  $t_i$ ,  $i \in \{1, \dots, I\}$

- A simple, tractable error model  $P(\mathcal{D}_{t_i} | x_{t_i}, \theta)$

- A simulator for paths of  $x$  given  $\theta$

- An array  $B_0$  of 1,000,000 samples from a prior on  $\theta, x_0$

- Empty arrays  $B_i$  of the same length

For each time point (for  $i \in \{1, \dots, I\}$ ):

- Until  $B_i$  is full:

  - Draw  $(\theta^*, x_{t_{i-1}}^*)$  from  $B_{i-1}$  or a KDE of its contents

  - Using  $(\theta^*, x_{t_{i-1}}^*)$ , simulate up to  $x_{t_i}^*$ , the state at time  $t_i$

  - Set  $A = \min(1, \frac{P(\mathcal{D}_{t_i} | x_{t_i}^*, \theta^*)}{P(\mathcal{D}_{t_i} | x_{t_i}, \theta)})$

  - With probability  $A$ , overwrite  $(\theta, x_{t_i})$  with  $(\theta^*, x_{t_i}^*)$

  - After burn-in and thinning, add  $(\theta, x_{t_i})$  to  $B_i$

# Likelihood Free Particle MCMC



# Likelihood Free Particle MCMC

$$\frac{P(x_{t_i}^* | x_{t_{i-1}}^*, \theta^*, \mathcal{D}_{t_{i-1}})}{P(x_{t_i} | x_{t_{i-1}}, \theta, \mathcal{D}_{t_{i-1}})} \frac{P(x_{t_{i-1}}^*, \theta^* | \mathcal{D}_{t_{i-1}})}{P(x_{t_{i-1}}, \theta | \mathcal{D}_{t_{i-1}})} \times$$
$$\frac{P(x_{t_i}^* | x_{t_{i-1}}^*, \theta^*, \mathcal{D}_{t_{i-1}})}{P(x_{t_i} | x_{t_{i-1}}, \theta, \mathcal{D}_{t_{i-1}})} \frac{P(x_{t_{i-1}}, \theta | \mathcal{D}_{t_{i-1}})}{P(x_{t_{i-1}}^*, \theta^* | \mathcal{D}_{t_{i-1}})} \frac{P(\mathcal{D}_{t_i} | x_{t_i}, \theta)}{P(\mathcal{D}_{t_i} | x_{t_i}^*, \theta^*)}$$

- *plan for experiments*

*(this part will be replaced later;*

*if you are Eric or Alec this part is optional)*



# Questions?

Wilkinson's paper is a chapter from this book:



Bernardo, J.M., Bayarri, M.J., Berger, J.O., Dawid, A.P., Heckerman, D., Smith, A.F.M., West, M.:

Ninth Valencia international meeting on Bayesian statistics, Benidorm, Spain, 03-08.06.2010.

Oxford U.P., Oxford (2012)