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## **Perfect Simulation of Matérn Type III Repulsive Point Processes** <sup>1</sup>Department of Mathematics, <sup>2</sup>Department of Statistical Science, Duke University, Durham, NC, USA

**Overview** 



Spatial data are often more dispersed than would be expected if the points were independently placed. Such data can be modeled with *repulsive point* processes, where the points appear as if they are repelling one another. Various models have been created to deal with this phenomenon. Matérn created three algorithms that generate repulsive processes.

Here, Matérn Type III processes are used to approximate the likelihood and posterior values for data. Perfect simulation methods are used to draw auxilliary variables for each spatial point that are part of the type III process.



Leads to a density g(x) with respect to a unit rate Poisson point process.

 $A_{\theta}(x, t) = \lambda \cdot \text{volume of shadow in spacetime}$ 

 $g_{\lambda,R}(x) \propto \int_{t \in [0,1]^n} \exp(A_{\theta}(x,t)) dt$ 

Goal: use g(x) to infer  $\lambda$  and R.

#### Metropolis-Hastings chain

With density, can formally write MH chain.

Calculating  $A_{a}(x,t)$  difficult (even in 2D).

Use thinned Poisson point process to avoid computing MH ratio.

Choose a point v

Propose new time stamp for v

If increase shadow, accept

Else draw Pois. proc. in change in shadow if no points, accept

#### **Bounding chains**

Standard problem with Markov chains difficult to analyze mixing time.

Perfect simulation methods draw from stationary distribution without need to know mixing time.

Bounding chains + coupling from the past (CFTP) gives method for converting MH chain into perfect simulation algorithm.

### **Product Estimator**

Disadvantage: slow

Advantage: immune to multimodal dist's Take sequence of parameters:

 $0 < \lambda_1 < \cdots < \lambda_k$ 

Estimate ratios in sequence:

 $\frac{g_{\lambda_{1,R}}}{g_{\lambda_{2,R}}} \frac{g_{\lambda_{2,R}}}{g_{\lambda_{k,R}}} = g_{\lambda_{k,R}}$  $g_{0,R} g_{\lambda_1 R} g_{\lambda_{k-1},R}$ 



•Huber (2004) Perfect sampling using bounding chains. Ann. of Applied Prob., 14(2):734-753

## **Results for data set of 40 town locations in Spain** Algorithm running time seems to scale linearly in $\lambda$ :



At each step in the M-H chain, a Poisson point process with intensity  $\lambda$  over the region close to a random point is generated in order to determine whether the proposed time stamp is accepted or rejected. Therefore each step takes time linear in  $\lambda$  as well. Combining, the total time to generate a set of time stamps will be quadratic in  $\lambda$ .

In contrast, the basic acceptance/rejection method for drawing perfect samples requires time exponential in  $\lambda$ .

Posterior of  $\lambda$  and R (Uses flat priors; note maximum over *i*,*j* of dist(x,x) is approx 0.10289)

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