

# Appendix

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*June 2021*

## Simulation of a HPP

Recall that for a HPP, the interarrival times between events,  $W$ , are exponentially distributed. In this simulation of a HPP, after initializing the initial time,  $t$ , and the time vector,  $t_{vector}$ , we generate exponential random variables and use them to index the interarrival times between events.

Figure 2 as shown previously is a realization of a HPP with rates that are roughly constant at  $\lambda = 10$ .

### Algorithm 1: Simulation of a HPP

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Input  $\lambda, t_{max}$

1. Initialize  $t, t_{vector}$
  2. **while** ( $t \leq t_{max}$ )
  3.   Generate  $u \sim U(0, 1)$
  4.   Set  $t = t + w$  where  $w = -\log(u)/\lambda \sim \exp(\lambda^* = \lambda)$
  5.   **if** ( $t \leq t_{max}$ )
  6.   | Add  $t_{vector} = c(t_{vector}, t)$
  7.   **else**
  8.   | **return**  $\{t_k\}_{k=0,1,\dots}$
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## Simulation of a Hawkes Process

In this simulation of a Hawkes process, we use the thinning algorithm (or acceptance-rejection method) to simulate a temporal Hawkes process since it is one of the most popular choices for simulating both temporal and spatio-temporal NPP (Pasupathy, 2010). Broadly put, the thinning algorithm involves randomly deleting points from a point pattern. The process requires first simulating a HPP, creating a  $\lambda(t)$  function and applying it to the HPP, and using  $\min(\lambda^*/\lambda, 1)$  as the accepting probability to randomly keep or ‘thin’ the points.

Figure 5 as shown previously is a realization of a Hawkes process with parameters such that  $\mu = 0.5, \alpha = 0.5$ , and  $\beta = 0.7$ .  $\mu$  sets the background rate.  $\alpha$  and  $\beta$  control the shape and decay rate of the the exponentially decaying triggering function function.

## Algorithm 2: Simulation of a Hawkes Process via Thinning Algorithm

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Input  $\mu, \alpha, \beta, \lambda, t_{max}$

1. Simulate a HPP using Algorithm 1
  2. Create a  $\lambda(t)$  function where the function  $= \mu + \sum_{i:T_i < t} \alpha e^{-\beta x}$
  3. Set  $\lambda^* =$  apply the  $\lambda(t)$  function to the HPP
  4. Generate  $u \sim U(0, 1)$
  5. **if** ( $u < \min(\frac{\lambda^*}{\lambda}, 1)$ ) where the accepting probability  $= \min(\lambda^*/\lambda, 1)$
  6. | Keep the points
  7. **else**
  8. | “Thin” or reject the points and **return**  $\{t_k\}_{k=0,1,\dots}$
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## Simulations of a HPP, NPP, Cox and Matern Cluster Process in 2D

All of the corresponding plots in 2D are created using the **spatstat** package of **R** (Baddeley & Turner, 2005).

### HPP

The **rpoispp** function can be used to generate a random point pattern as a realization of a HPP or NPP. **lambda** controls the rate (or intensity) of a HPP and **win** sets the window in which the simulated pattern is observed. In Figure 3, we set **lambda** = 100 and **win** = *square*(1).

### NPP

Similar to the above simulation, **lambda** can be set to control the intensity of a NPP. In the second figure of Figure 3, **lambda** =  $400 * x * y$ .

### Cox Process

Instead of setting **lambda** to be a deterministic function as in the NPP case, here we can set **lambda** to be a random function. In Figure 4, **lambda** is set to be  $= \text{rexp}(n = 1, \text{rate} = 1/100)$ .

### Matern Cluster Process

Simulations of Matern cluster process are generated using the **rMatClust** function. Specifically, the process involves generating homogeneous Poisson parents and each parent gives rise to Poisson number of offspring uniformly distributed in a disc of radius  $r$  centered around the parent. **kappa** controls the intensity of the cluster centers and allows us to specify the number of clusters. **r** specifies how far away cluster is from one another in radius, and **mu** gives the mean number of points per cluster. In the second figure of Figure 4,  $\text{kappa} = 20, r = 0.05$ , and  $\text{mu} = 5$ .