

# Edge Corrections for Spatial Point Processes

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**Review:**  $N_B$ ,  $B \subseteq \mathbb{R}^p$  denotes a stationary point process with intensity  $\lambda$ . Thus,

$$E[N_B] = \lambda \nu_p(B),$$

where  $\nu_p(B)$  is the  $p$ -dimensional volume of  $B$ . Some quantities of interest are

$$p(t) = P[N_{B(x,t)} > 0],$$

$$G(t) = P[N_{B(x,t)} > 1 | x \in \mathcal{N}],$$

and

$$K(t) = \frac{1}{\lambda} E[N_{B(x,t)} - 1 | x \in \mathcal{N}],$$

where

$$\mathcal{N} = \{x \in \mathbb{R}^p : N_{\{x\}} > 0\},$$

$$B(x, t) = \{y \in \mathbb{R}^p : d(x, y) \leq t\},$$

and  $d(x, y)$  is the Euclidean distance from  $x$  to  $y$ .

**Example:** For a Poisson process,  $N_B$  has a Poisson distribution for every  $B$ , and  $N_{B_1}, \dots, N_{B_m}$  are independent when  $B_1, \dots, B_m$  are mutually exclusive.

For a Poisson process in  $\mathbb{R}^2$ ,

$$p(t) = 1 - e^{-\lambda \pi t^2},$$

$$G(t) = p(t),$$

$$K(t) = \pi t^2.$$

**Data:** Suppose that the process is observed throughout a region  $E \subseteq \mathbb{R}^p$ .

**Estimating  $K$ .** Let

$$\tilde{K}_0(t) = \frac{1}{\lambda n} \sum_{x \in \mathcal{N} \cap E} \#\{y \in \mathcal{N} : 0 < d(x, y) \leq t\},$$

where

$$n = N_E,$$

and

$$\hat{K}_0(t) = \frac{1}{\lambda n} \sum_{x \in \mathcal{N} \cap E} \#\{y \in \mathcal{N} \cap E : 0 < d(x, y) \leq t\}.$$

Then (Ripley says)

$$E[\tilde{K}_0(t)] = K(t),$$

$$\hat{K}_0(t) \leq \tilde{K}_0(t),$$

and, therefore,

$$E[\hat{K}_0(t)] \leq E[\tilde{K}_0(t)].$$

That is,  $\hat{K}_0$  has a negative bias.

**Fact:** For a Poisson process: Given  $N_E = n$ , the  $n$  points are independently and uniformly distributed over  $E$ .

**The Magnitude of the Bias:** For a Poisson Process. Observe that for  $n \geq 2$ ,

$$\frac{\lambda \hat{K}_0(t)}{n-1} = \frac{\#\{(x, y) : x, y \in \mathcal{N} \cap E, 0 < d(x, y) \leq t\}}{n(n-1)}.$$

So, for  $n \geq 2$ ,

$$E\left[\frac{\lambda \hat{K}_0(t)}{n-1} \mid n\right] = P[d(X, Y) \leq t] = F(t), \text{ say,}$$

where

$$X, Y \sim^{ind} \text{Uniform}(E).$$

$F(t)$  can be computed for some shapes and approximated more generally.

**Example.** If  $E$  is a rectangle in  $\mathbb{R}^2$ , then

$$F(t) = \frac{\pi t^2}{a} - \frac{2ut^3}{3a^2} + \frac{t^4}{2a^2},$$

where

$$a = \text{area},$$

$$u = \text{perimeter},$$

provided that  $t$  does not exceed the length of the shorter sides.

**Approximation:** Based on this and other examples, Ripley suggests the approximation

$$F(t) \approx \frac{\pi t^2}{a} - \frac{2ut^3}{3a^2}$$

for small  $t$  for convex  $E$ .

**Back to  $\hat{K}_0$ .** Writing

$$\hat{K}_0(t) = \frac{n-1}{\lambda} \times \frac{\lambda \hat{K}_0(t)}{n-1}$$

leads to

$$\begin{aligned} E[\hat{K}_0(t)] &= E\left\{\frac{n-1}{\lambda} E\left[\frac{\lambda \hat{K}_0(t)}{n-1} \mid n\right]\right\} \\ &= E\left[\frac{n-1}{\lambda} F(t)\right] \\ &= \frac{\lambda a - 1}{\lambda} F(t); \end{aligned}$$

or

$$E[\hat{K}_0(t)] \approx \frac{\lambda a - 1}{\lambda} \left[ \frac{\pi t^2}{a} - \frac{2ut^3}{3a^2} \right].$$

There are two sources of bias here

$$\frac{\lambda a - 1}{\lambda} < a$$

and

$$a \left[ \frac{\pi t^2}{a} - \frac{2ut^3}{3a^2} \right] < \pi t^2 = K(t).$$

The second is typically the more serious, at least if  $a\lambda = E(n)$  is large.

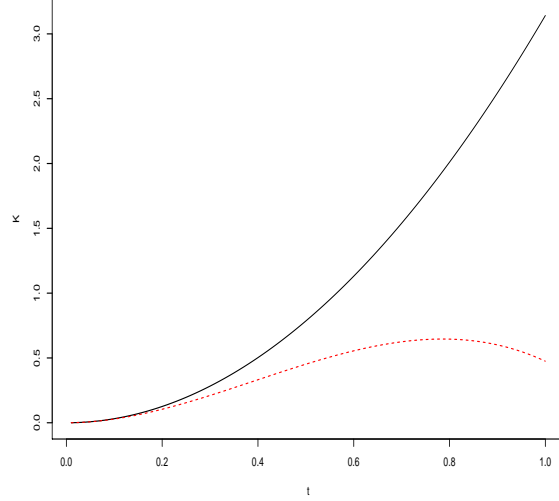


Figure 1: Approximate bias for a square and large  $\lambda$

**Some Corrected Estimators. Border Corrections.** Find sets  $E_t \subseteq E$  for which  $E_t + B(0, t) \subseteq E$ . Then let

$$\hat{K}_1(t) = \frac{1}{\lambda N_{E_t}} \#\{(x, y) : x \in E_t, y \in E, y \neq x, \& d(x, y) \leq t\}.$$

Here

$$E[\lambda N_{E_t}] = \lambda^2 \nu_p(E_t)$$

$$\begin{aligned} E[\#\{(x, y) : x \in E_t, y \in E, 0 < d(x, y) \leq t\}] \\ &= E\left\{ \sum_{x \in E_t} E[\#\{(x, y) : x \in E_t, y \in E, 0 < d(x, y) \leq t\} | x] \right\} \\ &= E[N_{E_t} \lambda K(t)] \\ &= \lambda^2 \nu_p(E_t) K(t), \end{aligned}$$

and  $K(t)$  is the ratio of the expectations.

$K_1(t)$  need not be a monotone function, however.

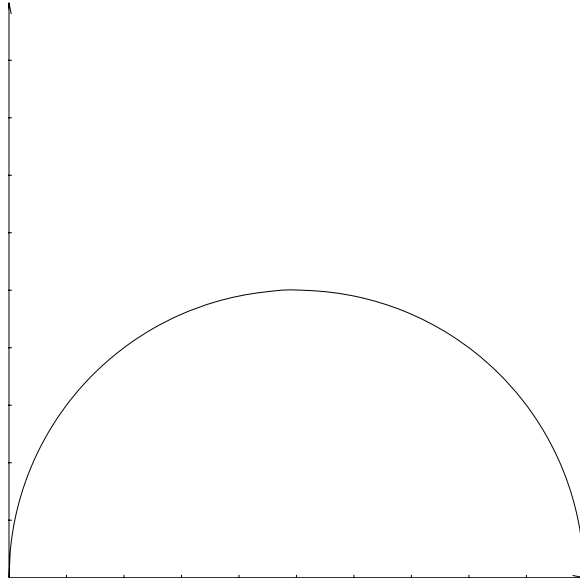


Figure 2: Boundary Length

*Reweighting.* Define  $k$  by

$$\frac{1}{k(x, y)} = \frac{|\partial B[x, d(x, y)] \cap E|}{|\partial B[x, d(x, y)]|},$$

where  $\partial B$  denotes the boundary of  $B$  and  $|\partial B|$  denotes its length, and

$$\hat{K}_2(t) = \frac{1}{\lambda a^2} \sum_{x, y \in \mathcal{N} \cap E} k(x, y) \mathbf{1}_{\{0 < d(x, y) \leq t\}}.$$

Then

$$E[\hat{K}_2(t)] = \dots = K(t),$$

under some general symmetry assumptions. For example, if  $E$  is the unit square and  $x = (.5, 0)$  and  $y = (0, 0)$ , then

$$\begin{aligned} |\partial B[x, d(x, y)] \cap E| &= \frac{1}{2}\pi + 1, \\ |\partial B[x, d(x, y)]| &= \pi, \end{aligned}$$

and

$$k(x, y) = \frac{2\pi}{\pi + 2}.$$

*More On Reweighting.* There are more elaborate versions of  $\hat{K}_2$ .