

# Spatial point processes: introduction

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1. Introduction
2. Repetitions, inhomogeneity, anisotropy, 2D→3D
3. Example 1: Analysis and modeling of epidermal nerve fiber patterns  
Repetitions and non-spatial covariates
4. Example 2: Air pore structure in polar ice  
Anisotropy (3D) and missing information

Illian *et al.* (2008)

R library spatstat used (Baddeley and Turner, 2005).

# Definition

A point process  $N$  is a stochastic mechanism or rule to produce point patterns or realisations according to the distribution of the process.

A marked point process is a point process where each point  $x_i$  of the process is assigned a quantity  $m(x_i)$ , called a mark. Often, marks are integers or real numbers but more general marks can also be considered.

## Two interpretations

- ▶  $N$  is a counting measure. For a subset  $B$  of  $\mathbb{R}^d$ ,  $N(B)$  is the random number of points in  $B$ . It is assumed that  $N(B) < \infty$  for all bounded sets  $B$ , i.e. that  $N$  is locally finite.
- ▶  $N$  is a random set, i.e. the set of all points  $x_1, x_2, \dots$  in the process. In other words

$$N = \{x_i\} \text{ or } N = \{x_1, x_2, \dots\}$$

Therefore,  $x \in N$  means that the point  $x$  is in the set  $N$ . The set  $N$  can be finite or infinite. If it is finite the total number of points can be deterministic or random.

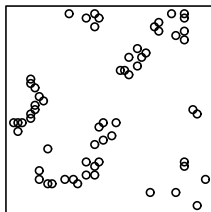
**Remark 1:** We assume that all point processes are simple, i.e. that there are no multiple points ( $x_i \neq x_j$  if  $i \neq j$ ).

**Remark 2:** There is a large literature on processes  $\{Z(t) : t \in T\}$ , where  $T$  is a point process in time. There is an overlap of methods for point processes in space and in time but the temporal case is **not** only a special case of the spatial process with  $d = 1$ . Time is 1-directional.

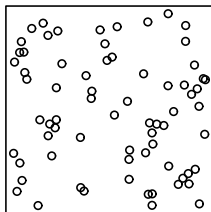
**Remark 3:** To avoid confusion between points of the process and point of  $\mathbb{R}^d$ , the points of the process or point pattern (realization) are called events (or trees or cells).

# Spatial point patterns

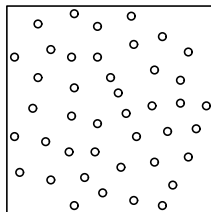
**clustered**



**completely random**



**regular**

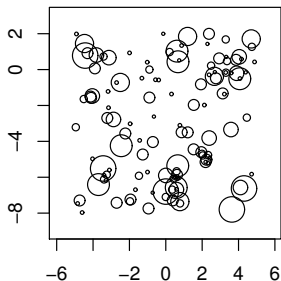


- ▶ Locations of betacells within a rectangular region in a cat's eye (regular)
- ▶ Locations of Finnish pine saplings (clustered)
- ▶ Locations of Spanish towns (regular)
- ▶ Locations of galaxies (clustered)

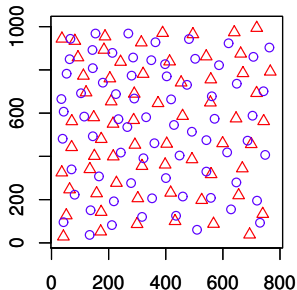
**Remark:** Very different scales, from microscopic to cosmic

# Marked point patterns

**Finish pines**



**Betacells**



Finnish pine saplings: locations and diameters

Beta-type retina cells in the retina of a cat: locations and type (red triangles "on", blue circles "off")



# First-order properties (without marks)

The mean number of points of  $N$  in  $B$  is  $\mathbb{E}(N(B))$  (depends on the set  $B$ ). We use the notation

$$\Lambda(B) = \mathbb{E}(N(B))$$

and call  $\Lambda$  the intensity measure.

Under some continuity conditions, a density function  $\lambda$ , called the intensity function, exists, and

$$\Lambda(B) = \int_B \lambda(x) dx.$$

# Some properties of point processes: stationarity and isotropy

A point process  $N$  is stationary (translation invariant) if  $N$  and the translated point process  $N_x$  have the same distribution for all translations  $x$ , i.e.

$$N = \{x_1, x_2, \dots\} \text{ and } N_x = \{x_1 + x, x_2 + x, \dots\}$$

have the same distribution for all  $x \in \mathbb{R}^d$ .

A point process is isotropic (rotation invariant) if its characteristics are invariant under rotations, i.e.

$$N = \{x_1, x_2, \dots\} \text{ and } rN_x = \{rx_1, rx_2, \dots\}$$

have the same distribution for any rotation  $r$  around the origin. If a point process is both stationary and isotropic, it is called motion-invariant.

# First-order properties

If  $N$  is stationary, then

$$\Lambda(B) = \lambda|B|,$$

where  $0 < \lambda < \infty$  is called the intensity of  $N$  and  $|B|$  is the volume of  $B$ .

$\lambda$  is the mean number of points of  $N$  per unit area, i.e.

$$\lambda = \frac{\Lambda(B)}{|B|} = \frac{\mathbb{E}(N(B))}{|B|}.$$

## Two distribution functions

1. Let  $D_1$  denote the distance from an arbitrary event to the nearest other event. Then, the nearest neighbour distance function is

$$G(r) = P(D_1 \leq r)$$

If the pattern is completely spatially random (CSR),  
 $G(r) = 1 - \exp(-\lambda\pi r^2)$ . For regular patterns  $G(r)$  tends to lie below and for clustered patterns above the CSR curve.

2. Let  $D_2$  denote the distance from an arbitrary point to the nearest event. Then,

$$F(r) = P(D_2 \leq r)$$

If the pattern is completely spatially random,  
 $F(r) = 1 - \exp(-\lambda\pi r^2)$ . For regular patterns  $F(r)$  tends to lie above and for clustered patterns below the CSR curve.

## Combination of the two

Using  $G$  and  $F$  we can define the so-called  $J$  function as

$$J(r) = \frac{1 - G(r)}{1 - F(r)}$$

(whenever  $F(r) > 0$ )

If the pattern is completely spatially random,  $J(r) \equiv 1$ . For regular patterns  $J(r) > 1$  and for clustered patterns  $J(r) < 1$ .

## Second-order properties

The 2nd order properties of a stationary and isotropic point process can be characterized by Ripley's  $K$  function (Ripley, 1977)

$$K(r) = \lambda^{-1} \mathbb{E}[\# \text{ further events within distance } r \text{ of a typical event}].$$

Often, (in 2D) a variance stabilizing and centered version of the  $K$  function (Besag, 1977) is used, namely

$$L(r) - r = \sqrt{K(r)/\pi} - r,$$

which equals 0 under CSR. Values less than zero indicate regularity and values larger than zero clustering.

## Note on estimation of $G$ , $F$ , $J$ and $K$

- ▶ Typically, a point pattern is observed in a (bounded) observation window and points outside the window are not observed.
- ▶ Estimators (except for  $J(r)$ ) need to be edge-corrected
- ▶ Edge correction methods include plus sampling, minus sampling, Ripley's isotropic correction and translation (stationary) correction

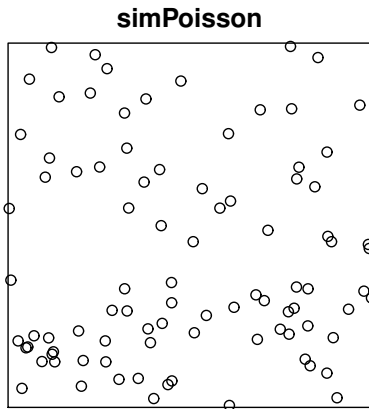
A point process is a homogeneous Poisson process (CSR) if

- (P1) for some  $\lambda > 0$  and any finite region  $B$ ,  $N(B)$  has a Poisson distribution with mean  $\lambda|B|$
- (P2) given  $N(B) = n$ , the events in  $B$  form an independent random sample from the uniform distribution on  $B$

Inhomogeneous Poisson process: intensity  $\lambda$  (in homogeneous Poisson process) replaced by an intensity function  $\lambda(x)$

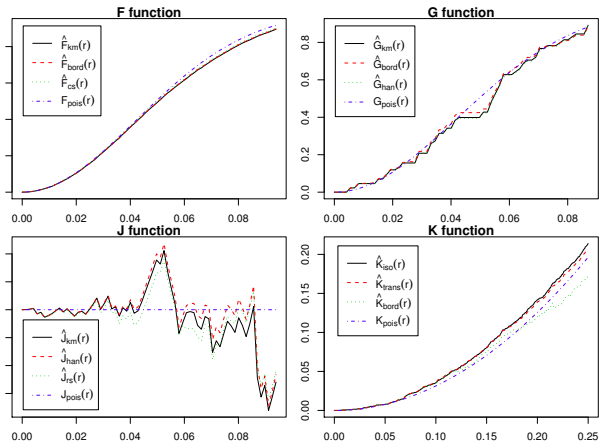


# Realization of a homogeneous Poisson process



Poisson process with intensity 100

allstats(simPoisson)



# Matérn cluster process

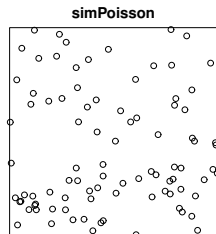
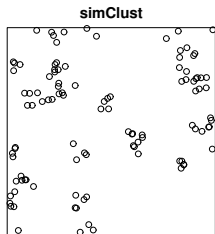
Cluster processes are models for aggregated spatial point patterns

For Matérn cluster process

- (MC1) parent events form a Poisson process with intensity  $\lambda$
- (MC2) each parent produces a random number  $S$  of daughters (offsprings), realized independently and identically for each parent according to some probability distribution
- (MC3) the locations of the daughters in a cluster are independently and uniformly scattered in the disc of radius  $R$  centered at the parent point.

The cluster process consists only of the daughter points.

# Realization of a Matérn cluster process

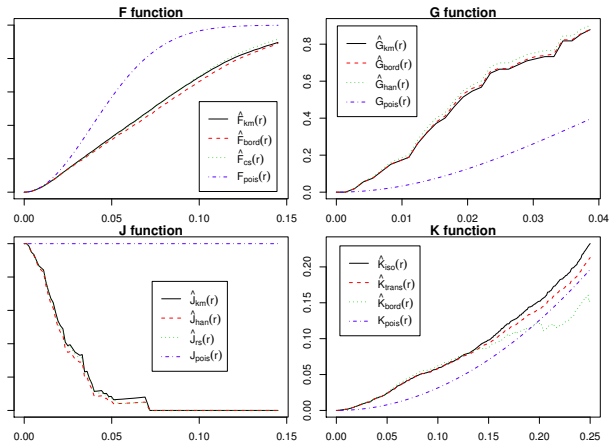


**Left:** Parent point intensity 20, cluster radius 0.05, average number of daughter points per cluster 5

**Right:** Poisson process with intensity 100

# Summary statistics

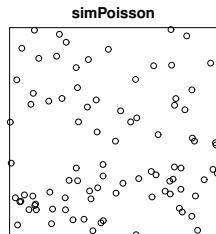
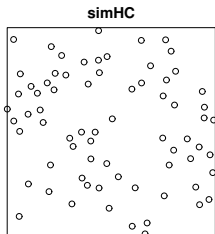
allstats(simClust)



# Matérn I hard-core process

- ▶ Hard-core processes are models for regular spatial point patterns
- ▶ There is a minimum allowed distance, called hard-core distance, between any two points
- ▶ Matérn I hard-core process: A Poisson process with intensity  $\lambda$  is thinned by delating all pairs of points that are at distance less than the hard-core radius apart.

# Realization of a Matérn I hard-core process

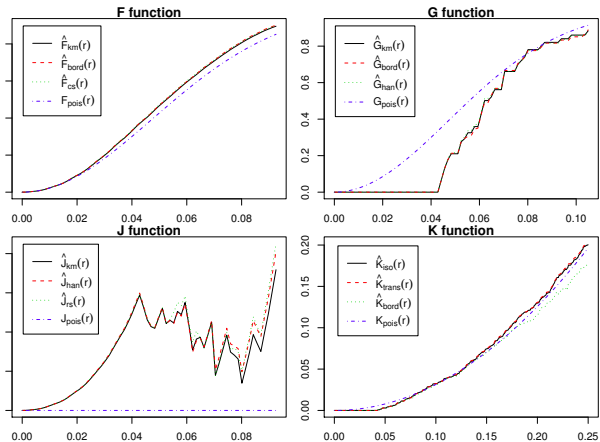


**Left:** Hard-core process with the initial Poisson intensity 300, hard-core radius 0.04

**Right:** Poisson process with intensity 100

# Summary statistics

allstats(simHC)





# Pairwise interaction processes

- ▶ Pairwise interaction processes are a subclass of Markov point processes which are models for point patterns with interaction between the events
- ▶ There is interaction between the events if they are "neighbours", e.g. if they are close enough to each other
- ▶ Models for inhibition/regularity

# Pairwise interaction processes: Strauss process

- ▶ Two points are neighbours if they are closer than distance  $R$  apart
- ▶ The density function (with respect to a Poisson process with intensity 1) is

$$f(x) = \alpha \beta^{n(x)} \gamma^{s(x)}, \quad \beta > 0, \quad \gamma \geq 0,$$

where

- ▶  $\beta > 0$  is the effect of a single event (connected to the intensity of the process)
- ▶  $0 < \gamma \leq 1$  is an interaction parameter
- ▶  $n(x)$  is the number of points in the configuration
- ▶  $s(x)$  is the number of  $R$  close pairs in the configuration, where  $R > 0$  is an interaction radius (range of interaction)
- ▶  $\alpha$  is a normalizing constant

- ▶ Baddeley, A., Turner, R. Spatstat: an R package for analyzing spatial point patterns. *J. Stat. Softw.* 12 (2005) 1-42.
- ▶ Besag, J.E., 1977. Comment on “Modelling spatial patterns” by B. D. Ripley. *Journal of the Royal Statistical Society B* (Methodological) 39 (1977) 193-195.
- ▶ Illian, J., Penttinen, A., Stoyan, H., Stoyan, D. *Statistical Analysis and Modelling of Spatial Point Patterns*. Chichester: Wiley (2008).
- ▶ Ripley, B.D. Modelling spatial patterns. *Journal of the Royal Statistical Society B* 39 (1977) 172-212.