

# Quantifying repulsiveness of determinantal point processes

Christophe A. N. BISCIO, Frédéric LAVANCIER

August 26, 2015



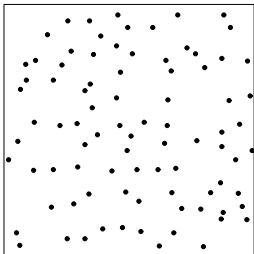
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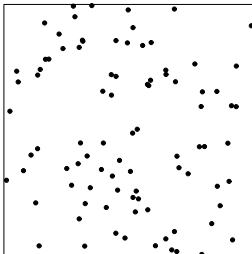
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- 5 Conclusion

# Different situations

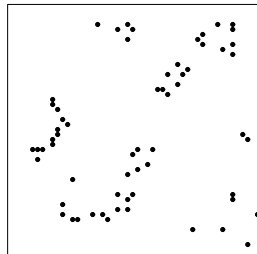
Inhibitive  
(Norwegian spruce trees)



No interaction  
(Poisson)

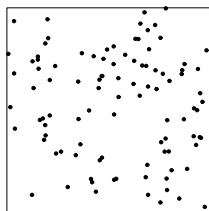


Clustering  
(California redwood tree)

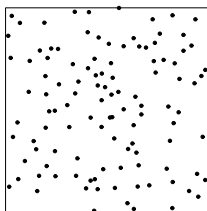


# DPPs, a class of inhibitive point processes

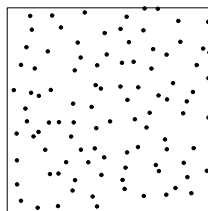
Determinantal point processes (DPPs) are adapted to inhibitive (or repulsive, or regular) point patterns.



Poisson



DPP with  
intermediate repulsion



DPP with  
stronger repulsion

# Notation

- $\mathbf{X}$  is a spatial point process on  $\mathbb{R}^d$ .
- For any integer  $n > 0$ ,  $\rho^{(n)}$  denotes the  $n$ -th joint intensity (or product density function) of  $\mathbf{X}$ .

Intuitively,

$$\rho^{(n)}(x_1, \dots, x_n) dx_1 \cdots dx_n$$

is the probability that for each  $i = 1, \dots, n$ ,  $\mathbf{X}$  has a point in a region around  $x_i$  of volume  $dx_i$ .

- In particular  $\rho = \rho^{(1)}$  is the intensity function.

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# Stationary DPPs

For a function  $C$  from  $\mathbb{R}^d$  into  $\mathbb{R}$ , denote  $[C](x_1, \dots, x_n)$  the matrix  $(C(x_i - x_j))_{1 \leq i, j \leq n}$ .

For instance:  $[C](x_1) = C(0)$ ,  $[C](x_1, x_2) = \begin{pmatrix} C(0) & C(x_1 - x_2) \\ C(x_2 - x_1) & C(0) \end{pmatrix}$

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## Definition

A point process  $\mathbf{X}$  is a stationary determinantal point process with kernel  $C$ , denoted by  $DPP(C)$ , if for all  $n \in \mathbb{N}$ ,

$$\rho^{(n)}(x_1, \dots, x_n) = \det[C](x_1, \dots, x_n).$$

- In particular,  $\rho = C(0)$ ,  $\rho^{(2)}(x_1, x_2) = C(0)^2 - C(x_1 - x_2)C(x_2 - x_1)$ .



# Existence and uniqueness

Theorem (Hough, Perez, Krishnapour, Virag, 09)

*A function  $C$  defines at most one DPP.*

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Theorem (Macchi, 75 and Lavancier, Møller, Rubak, 15)

*A stationary determinantal point process with kernel  $C$  exists if  $C$  verifies the following assumptions,*

- *$C$  is real valued, symmetric and continuous,*
- *$C \in L^2(\mathbb{R}^d)$ ,*
- *$0 \leq \mathcal{F}(C) \leq 1$ .*

We denote by  $\mathcal{H}$  the set of functions that verify the last three assumptions.

- Up to a re-normalization, all continuous square-integrable covariance functions belong to  $\mathcal{H}$ .
- There already exist many functions of this kind in the literature.

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For instance, for  $\nu > 0$  and  $\alpha > 0$ ,

- the Whittle-Matérn functions

$$C(x) = \rho \frac{2^{1-\nu}}{\Gamma(\nu)} \left| \frac{x}{\alpha} \right| K_\nu \left( \left| \frac{x}{\alpha} \right| \right), \quad x \in \mathbb{R}^d,$$

define DPPs with intensity  $\rho$  if and only if  $\rho \leq \frac{\Gamma(\nu)}{\Gamma(\nu+d/2)(2\sqrt{\pi}\alpha)^d}$ ;

- the Generalized Cauchy functions

$$C(x) = \frac{\rho}{\left(1 + |x/\alpha|^2\right)^{\nu+d/2}}, \quad x \in \mathbb{R}^d,$$

define DPPs with intensity  $\rho$  if and only if  $\rho \leq \frac{\Gamma(\nu+d/2)}{\Gamma(\nu)(\sqrt{\pi}\alpha)^d}$ .

# First properties

DPPs have several advantages:

- By definition, their moments of any order exist and are known.
- They can be easily simulated (perfect simulation).
- On all bounded sets, the expression of the density is known.
- Parametric estimation is feasible:
  - by maximum likelihood,
  - by minimum contrast, for instance  $\int (\widehat{K}(t) - K_\theta(t))^2 dt$ .

For Gibbs point processes, none of these properties hold.

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**How much DPPs are flexible (repulsive)?**

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# The pair correlation function

The pair correlation function (pcf) is

$$g(x, y) = \frac{\rho^{(2)}(x, y)}{\rho(x)\rho(y)}, \quad \forall (x, y) \in \mathbb{R}^d \times \mathbb{R}^d.$$

- For a stationary and isotropic point process,  $g(x, y) = g_0(r)$  where  $r = |x - y|$ ;
- $g_0(r) < 1$  represents an inhibitive behaviour;
- $g_0(r) > 1$  represents a clustering behaviour.



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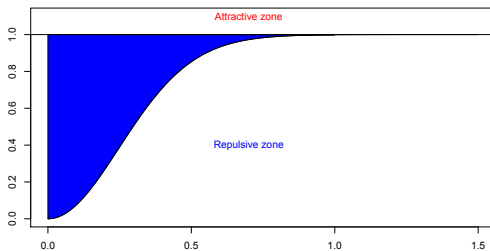
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- $g_0(r) < 1$  represents an inhibitive behaviour;
- $g_0(r) > 1$  represents a clustering behaviour.

For a stationary and isotropic DPP,  $C(x) = C_0(|x|)$  and

$$g_0(r) = 1 - \left( \frac{C_0(r)}{C_0(0)} \right)^2 \leq 1$$

# Repulsiveness



We consider only processes with given intensity  $\rho > 0$ . Let  $\mathbf{X}$  and  $\mathbf{Y}$  be two stationary DPPs with pcfs  $g_{\mathbf{X}}$  and  $g_{\mathbf{Y}}$  respectively.

## Global repulsiveness

$\mathbf{X}$  is more globally repulsive than  $\mathbf{Y}$  if  $g_{\mathbf{X}}$  has a larger “blue zone” than  $g_{\mathbf{Y}}$ , i.e.  $\int_{\mathbb{R}^d} (1 - g_{\mathbf{X}}) \geq \int_{\mathbb{R}^d} (1 - g_{\mathbf{Y}})$ .

# The most globally repulsive DPPs in the global sense

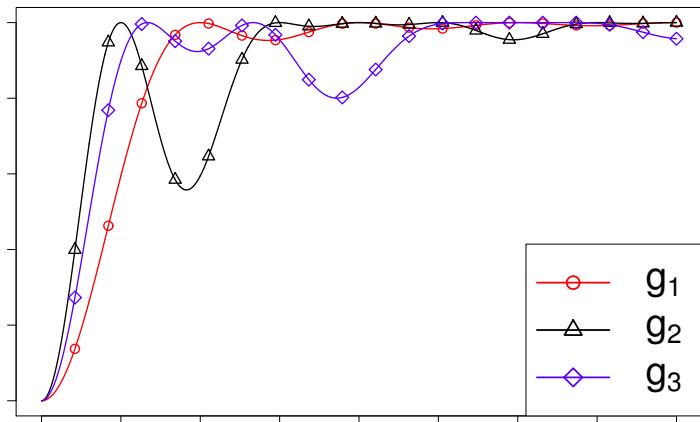
**Theorem** (Lavancier, Møller, Rubak, 15)

*For a given  $\rho > 0$ , a DPP with kernel  $C \in \mathcal{H}$  is the most globally repulsive if and only if there exists a set  $A \subset \mathbb{R}^d$ , with volume  $\rho$ , centred at 0 such that*

$$\mathcal{F}(C)(x) = \mathbf{1}_A(x) \quad a.e.$$

# Examples in dimension 1

- $C_1 = \mathcal{F}(\mathbf{1}_{[-\frac{1}{2}, \frac{1}{2}]})$  ;
- $C_2 = \mathcal{F}(\mathbf{1}_{[-\frac{3}{4}, -\frac{1}{4}]} + \mathbf{1}_{[\frac{1}{4}, \frac{3}{4}]})$  ;
- $C_3 = \mathcal{F}(\mathbf{1}_{[-\frac{2}{3}, -\frac{1}{3}]} + \mathbf{1}_{[-\frac{1}{6}, \frac{1}{6}]} + \mathbf{1}_{[\frac{1}{3}, \frac{2}{3}]})$ .

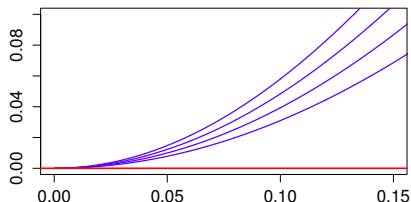


# Repulsiveness: an other definition

Let  $\mathbf{X}$  and  $\mathbf{Y}$  be two stationary DPPs with pcf  $g_{\mathbf{X}}$  and  $g_{\mathbf{Y}}$  respectively.

## Local repulsiveness

$\mathbf{X}$  is more locally repulsive than  $\mathbf{Y}$  if  $g_{\mathbf{X}}$  is more “flat” at 0 than  $g_{\mathbf{Y}}$ , i.e.  $g_{\mathbf{X}}(0) = g_{\mathbf{Y}}(0) = 0$ ,  $\nabla g_{\mathbf{X}}(0) = \nabla g_{\mathbf{Y}}(0) = 0$  and  $\Delta g_{\mathbf{X}}(0) \leq \Delta g_{\mathbf{Y}}(0)$ .



Note that for a hardcore point process,  $g(0) = \nabla g(0) = \Delta g(0) = 0$ .

# The most locally repulsive DPP

## Theorem (Biscio, Lavancier, 15)

*For a given  $\rho > 0$ , there exists a unique DPP with kernel  $C$  that is the most locally repulsive among all DPPs with kernels belonging to  $\mathcal{H}$ . This kernel is given by*

$$C(x) = \frac{\sqrt{\rho\Gamma(\frac{d}{2} + 1)}}{\pi^{d/4}} \frac{J_{\frac{d}{2}}\left(2\sqrt{\pi}\Gamma(\frac{d}{2} + 1)^{\frac{1}{d}}\rho^{\frac{1}{d}}|x|\right)}{|x|^{\frac{d}{2}}}, \quad \forall x \in \mathbb{R}^d,$$

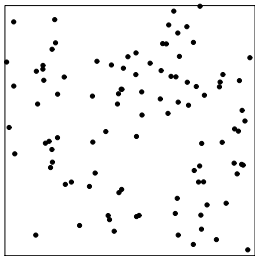
*where  $J_{\frac{d}{2}}$  denotes the Bessel function of the first kind. Moreover,*

$$\mathcal{F}(C)(x) = \mathbf{1}_{B(0, \sqrt[d]{\rho/\omega_d})}, \quad \forall x \in \mathbb{R}^d,$$

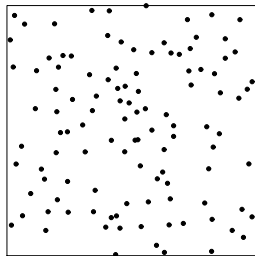
*where  $\omega_d$  denotes the volume of the unit ball in  $\mathbb{R}^d$ .*

# Summary

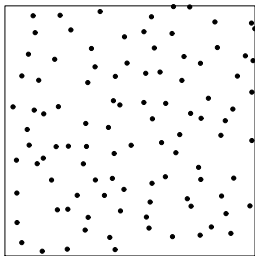
- There exists a unique DPP that is the most locally repulsive.
- Further, it is one of the most globally repulsive,
  - for  $d = 1$ ,  $C(x) = \text{sinc}(x) = \frac{\sin(\pi\rho|x|)}{\pi|x|}$ ,
  - for  $d = 2$ ,  $C(x) = \sqrt{\rho} \frac{J_1(2\sqrt{\pi\rho}|x|)}{\sqrt{\pi}|x|} := \text{Jinc}(x)$ .
- The inhibition of DPPs is limited, hardcore inhibition is impossible.



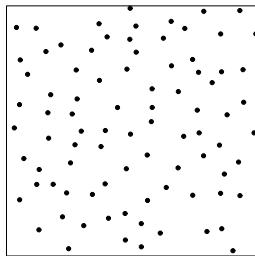
Poisson



DPP with  
intermediate repulsion



The most repulsive DPP



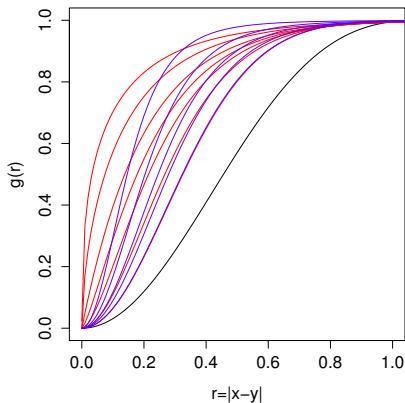
Hardcore



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# Pcfs for usual models of DPPs in dimension $d = 2$

- In blue, pcfs of DPPs with generalized Cauchy kernels,  $\alpha = \alpha_{max}(\nu)$  and different values of  $\nu$ .
- In red, pcfs of DPPs with Whittle-Matérn kernel,  $\alpha = \alpha_{max}(\nu)$  and different values of  $\nu$ .
- In black, the pcf of the most repulsive DPP,  $DPP(Jinc)$ .



# Bessel type family

## Bessel-type family

For  $\sigma \geq 0$  and  $0 \leq \alpha \leq \alpha_{\max}(d, \rho, \sigma)$ , the functions

$$C(x) = \rho 2^{\frac{\sigma+d}{2}} \Gamma\left(\frac{\sigma+d+2}{2}\right) \frac{J_{\frac{\sigma+d}{2}}\left(2\left|\frac{x}{\alpha}\right|\sqrt{\frac{\sigma+d}{2}}\right)}{\left(2\left|\frac{x}{\alpha}\right|\sqrt{\frac{\sigma+d}{2}}\right)^{\frac{\sigma+d}{2}}},$$

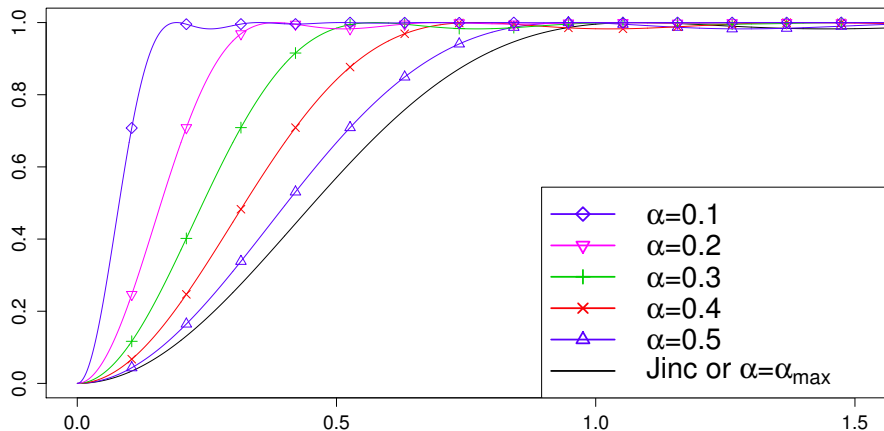
with Fourier transforms

$$\mathcal{F}(C)(x) = \frac{\rho(2\pi)^{\frac{d}{2}} \alpha^d \Gamma(\frac{\sigma+d+2}{2})}{(\sigma+d)^{\frac{d}{2}} \Gamma(\frac{\sigma+2}{2})} \left(1 - \frac{2(\pi|\alpha x|)^2}{\sigma+d}\right)_+^{\frac{\sigma}{2}}$$

define DPPs with intensity  $\rho$ .

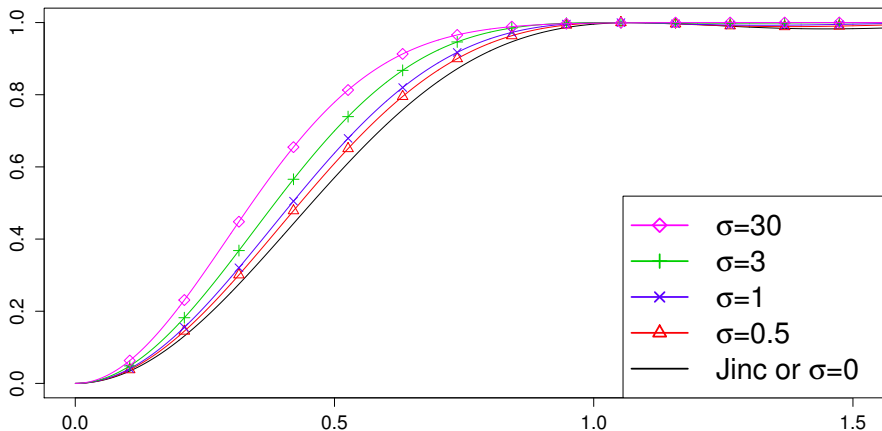
# Pcfs of the Bessel type family

Associated pcfs in dimension  $d = 2$  with  $\rho = 1$ ,  $\sigma = 0$  and different values of  $\alpha$ .



# Pcfs of the Bessel type family

Associated pcfs in dimension  $d = 2$  with  $\rho = 1$ ,  $\alpha = \alpha_{\max}(d, \rho, \sigma)$  and different values of  $\sigma$ .



# Laguerre-Gauss Family

The Laguerre polynomials are defined by

$$L_m^\alpha(x) = \sum_{k=0}^m \binom{m+\alpha}{m-k} \frac{(-x)^k}{k!}, \quad \forall x \in \mathbb{R}, \forall m \in \mathbb{N}, \alpha \in \mathbb{R}^+.$$

## Laguerre-Gauss Family

For  $m \in \mathbb{N}^*$  and  $0 \leq \alpha \leq \alpha_{\max}(d, \rho, m)$ , the functions

$$C(x) = \rho \frac{\Gamma(m)\Gamma\left(\frac{d}{2} + 1\right)}{\Gamma\left(m + \frac{d}{2}\right)} L_{m-1}^{\frac{d}{2}} \left( \frac{1}{m} \left| \frac{x}{\alpha} \right|^2 \right) e^{-\frac{1}{m} \left| \frac{x}{\alpha} \right|^2},$$

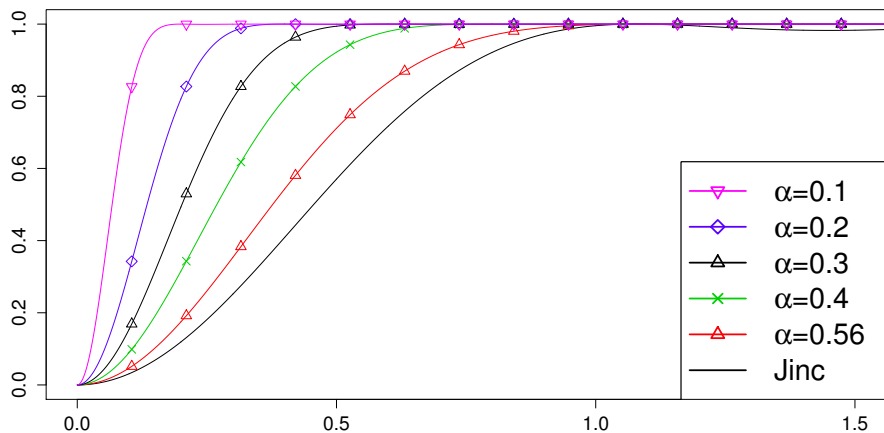
with Fourier transforms

$$\mathcal{F}(C)(x) = \rho \frac{\Gamma(m)\Gamma\left(\frac{d}{2} + 1\right)}{\Gamma\left(m + \frac{d}{2}\right)} \alpha^d (m\pi)^{\frac{d}{2}} e^{-m(\pi\alpha|x|)^2} \sum_{k=0}^{m-1} \frac{(\pi\sqrt{m}|\alpha x|)^{2k}}{k!}$$

define DPPs with intensity  $\rho$ .

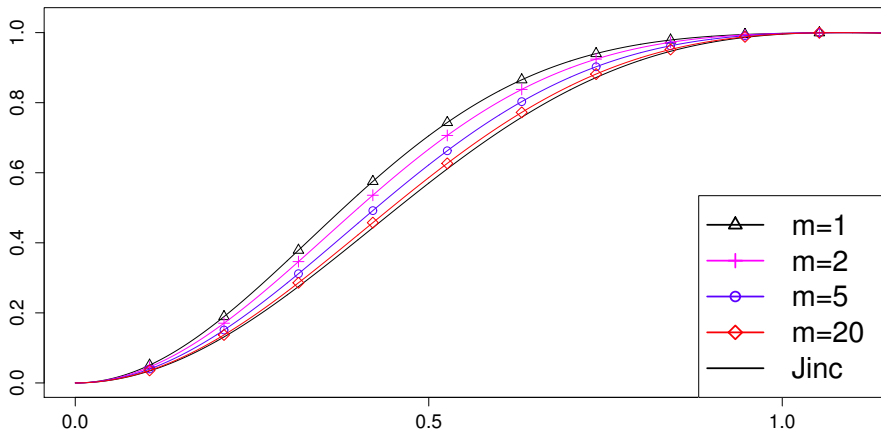
# Pcf of the Laguerre-Gauss family

Associated pcfs in dimension  $d = 2$  for  $\rho = 1$ ,  $m = 1$  and different values of  $\alpha$ .



# Pcf of the Laguerre-Gauss family

Associated pcfs in dimension  $d = 2$  for  $\rho = 1$ ,  $\alpha = \alpha_{max}(d, \rho, m) \approx 0.56$  and different values of  $m$ .





# Conclusion

- DPPs have some appealing properties: Their moments and density are known, inference is feasible.
- They are adapted to model a wide variety of repulsive points patterns,
- but they are not as flexible as Gibbs point processes, in particular they can not model hardcore phenomenon.
- There exist several parametric families that cover all the range of repulsiveness allowed by stationary DPPs.



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Thank you for your attention.