

# Exploring the Hyperuniformity with Python

Diala Hawat

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- 4 Effective Hyperuniformity
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Let  $\mathcal{X}$  be a point process of  $\mathbb{R}^d$  of intensity  $\rho$ ,  $\mathcal{X}$  is hyperuniform iff<sup>1</sup>

■ **Variance:**

$$\lim_{R \rightarrow \infty} \frac{\text{Var}(\text{Card}(\mathcal{X} \cap \mathbf{B}(0, R)))}{\mathcal{L}^d(\mathbf{B}(0, R))} = 0,$$

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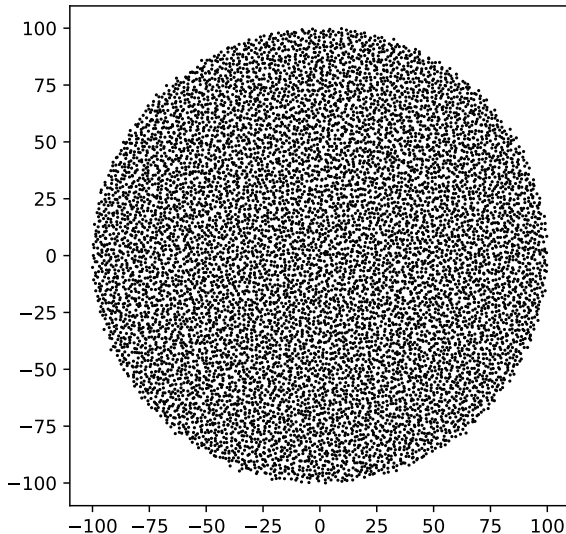
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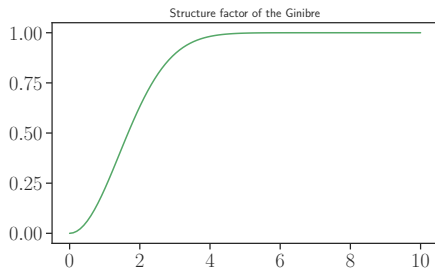
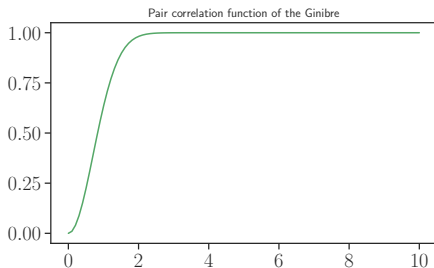
■ **Structure Factor:**

$$S(\mathbf{k}) = 1 + \rho \mathcal{F}(g - 1)(\mathbf{k}) \xrightarrow{|\mathbf{k}| \rightarrow 0} 0$$

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<sup>1</sup>Tor:18.





Let  $W = [-L/2, L/2]^d$  and  $\mathcal{X} \cap W = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$ ,

- Scattering intensity<sup>2</sup>

$$\hat{S}_{\text{SI}}(\mathbf{k}) \triangleq \frac{1}{N} \left| \sum_{j=1}^N e^{-i\langle \mathbf{k}, \mathbf{x}_j \rangle} \right|^2, \mathbf{k} \in \mathbb{R}^d.$$

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## ■ Allowed wavevectors

$$\mathbf{k} \in \left\{ \frac{2\pi}{L} \mathbf{n}, \mathbf{n} \in (\mathbb{Z}^d)^* \right\}.$$

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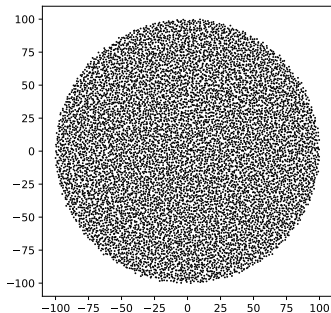


# Test the scattering intensity

structure-factor 1.0.1

`pip install structure-factor`

Estimators of the structure factor

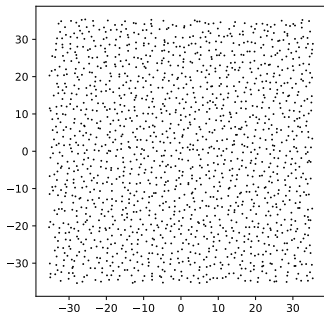


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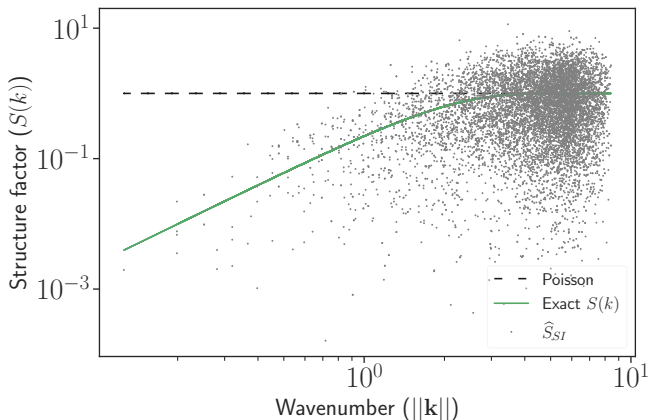


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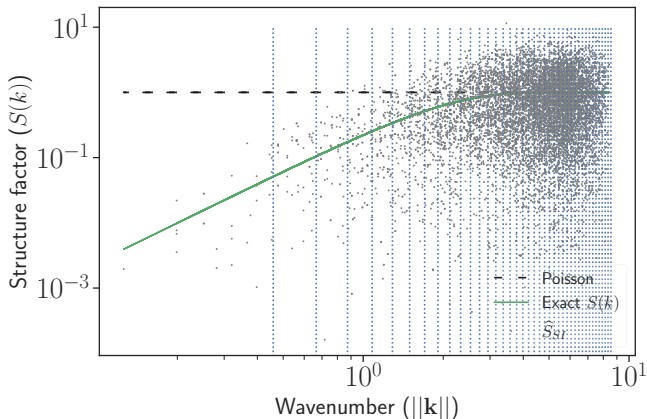


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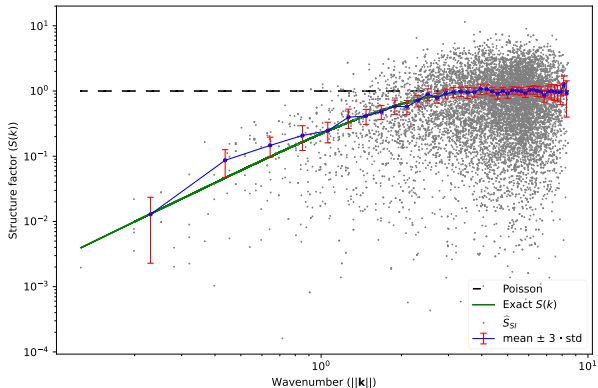


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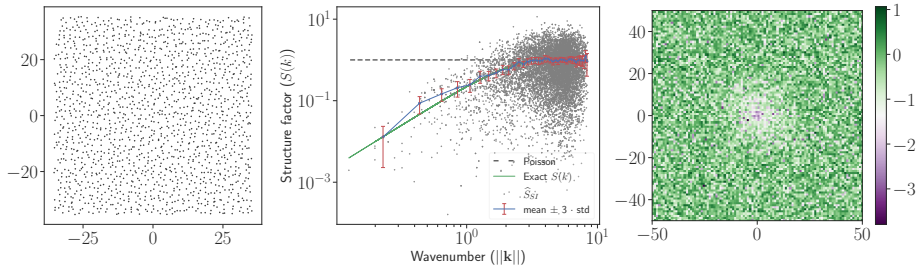


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## Estimators of the structure factor



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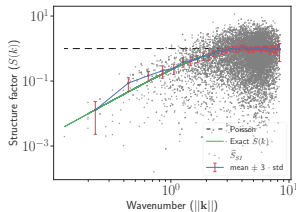


Figure: Box window and allowed wavevectors.

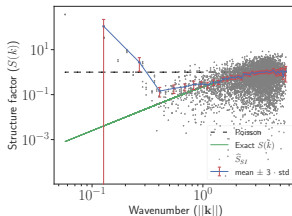


Figure: Box window and **non** allowed wavevectors.

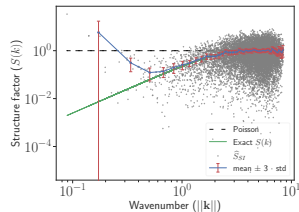


Figure: **Ball** window.

For isotropic point processes:

$$\blacksquare S(\mathbf{k}) = 1 + \rho \underbrace{\mathcal{F}(g - 1)}_{g(\mathbf{r})=g(\|\mathbf{r}\|)}(\mathbf{k}), \quad \mathbf{k} \in \mathbb{R}^d.$$

Symmetric Fourier transform

$$\blacksquare S(k) = 1 + \rho \mathcal{F}_s(g - 1)(k), \quad k \in \mathbb{R}.$$

$$\blacksquare \mathcal{F}_s(f)(k) = \frac{(2\pi)^{d/2}}{k^{d/2-1}} \mathcal{H}_{d/2-1}(\tilde{f})(k), \quad \tilde{f} : x \mapsto f(x)x^{d/2-1}.$$

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## Method

Estimating the pcf  $\rightarrow$  Interpolation  $\rightarrow$  Estimating the Hankel transform

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Estimators of the structure factor

For isotropic point processes:

- R package `spatstat` .

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A. Baddeley and E. Rubak and R. Turner, *Spatial Point Patterns Methodology and Applications with R*.

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- `pcf.ppp`: Direct kernel estimation.

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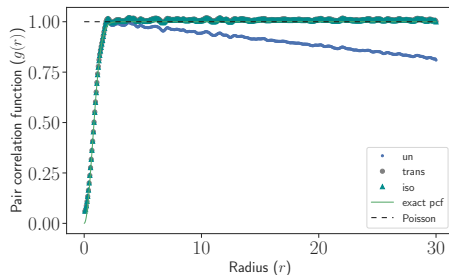
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`pcf.ppp`

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## Estimators of the structure factor

For isotropic point processes:

- R package `spatstat` .
- `pcf.ppp`: Direct kernel estimation.
- `pcf.fv`:  $\hat{g}(r) = \frac{K'(r)}{2\pi r}$ .

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## Estimators of the structure factor

For isotropic point processes:

- R package `spatstat` .
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- `pcf.fv`: Using the derivative of  $K$  .

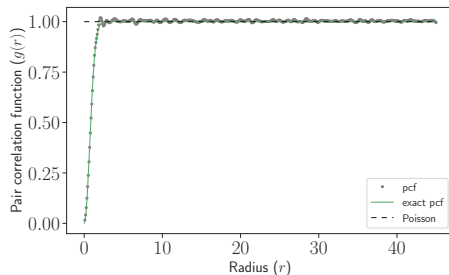
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pcf.fv

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## Method

Estimate the pcf  $\rightarrow$  Clean and Interpolate  $\rightarrow$  Estimate the Hankel transform

	r	un	trans	iso
0	0.000000	inf	inf	inf
1	0.060120	0.060690	0.060690	0.060690
2	0.120240	0.068330	0.068330	0.068354
3	0.180361	0.086678	0.086678	0.086850
4	0.240481	0.108363	0.108363	0.108717
...	...	...	...	...
495	29.759519	0.816099	1.006761	1.004460
496	29.819639	0.815444	1.006340	1.004486
497	29.879760	0.815478	1.006760	1.005236
498	29.939880	0.815336	1.006956	1.005530
499	30.000000	0.809902	1.000599	0.999123

Figure: pcf.ppp

	r	pcf
0	0.000000	NaN
1	0.087891	0.016679
2	0.175781	0.041919
3	0.263672	0.077902
4	0.351562	0.124654
...	...	...
508	44.648438	1.005216
509	44.736328	1.003781
510	44.824219	1.001746
511	44.912109	0.999059
512	45.000000	0.995767

Figure: pcf.fv

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Estimate the pcf  $\rightarrow$  Clean and Interpolate  $\rightarrow$  Estimate the Hankel transform

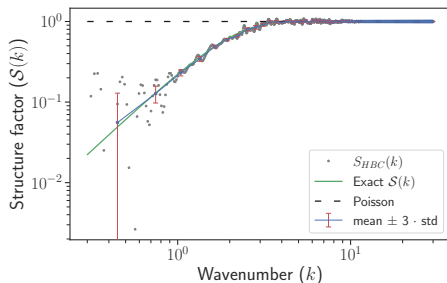
- Using the Discret Hankel Transform.

$$\mathcal{H}_\nu(f)(k_m) \approx \alpha \sum_{j=1}^{N-1} \frac{2}{\eta_{\nu N} J_{\nu+1}^2(\eta_{\nu j})} J_\nu \left( \frac{\eta_{\nu m} \eta_{\nu j}}{\eta_{\nu N}} \right) f(r_j).$$

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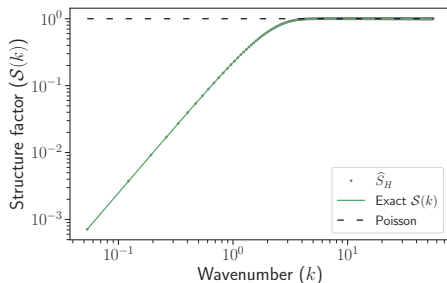
N. Baddour and U. Chouinard, *Theory and operational rules for the discrete Hankel transform*.

- Using the Discret Hankel Transform.



Approximation using the DHT.

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Approximation using the DHT.

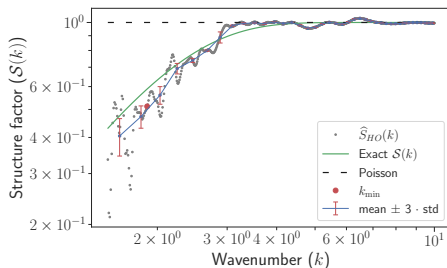
- Using the Discret Hankel Transform.
- Using Ogata quadrature.

$$\mathcal{H}_\nu(f)(k) \approx \pi \sum_{j=1}^{\infty} w_{\nu j} \frac{\pi}{k^2 h} \psi(h\xi_{\nu j}) f\left(\frac{\pi}{kh} \psi(h\xi_{\nu j})\right) J_\nu\left(\frac{\pi}{h} \psi(h\xi_{\nu j})\right) \psi'(h\xi_{\nu j}).$$

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H. Ogata, *A Numerical Integration Formula Based on the Bessel Functions*.

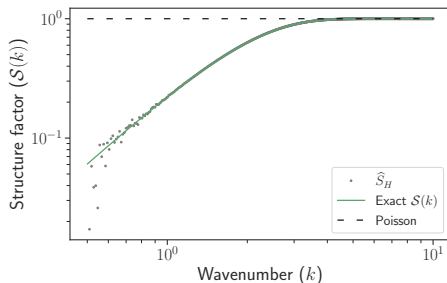
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Approximation using Ogata quadrature.



- Using the Discret Hankel Transform.
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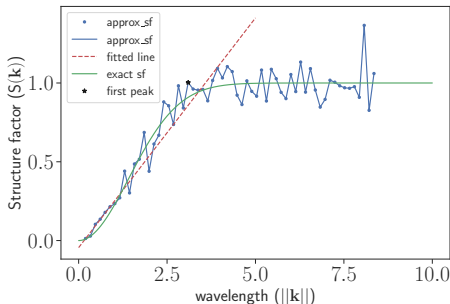


Approximation using Ogata quadrature.

$$\mathcal{X} \text{ is effectively hyperuniform} \iff H = \frac{\hat{S}(0)}{\hat{S}(k_{peak})} \leq 10^{-3},$$

- $\hat{S}(0)$  is a linear extrapolation of the estimated structure factor  $\hat{S}$  in  $k = 0$ .
- $k_{peak}$  is the location of the first dominant peak value of  $\hat{S}$ .

$$\mathcal{X} \text{ is effectively hyperuniform} \iff H = \frac{\hat{S}(0)}{\hat{S}(k_{peak})} \leq 10^{-3},$$



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S. Torquato, *Hyperuniform States of Matter*.

$\mathcal{X}$  is hyperuniform with  $|S(\mathbf{k})| \sim c\|\mathbf{k}\|^\alpha$  in the neighborhood of 0 then,

$\alpha$	$\text{Var} [\text{Card}(\mathcal{X} \cap B(0, R))]$	class
$> 1$	$O(R^{d-1})$	I
1	$O(R^{d-1} \log(R))$	II
$]0, 1[$	$O(R^{d-\alpha})$	III

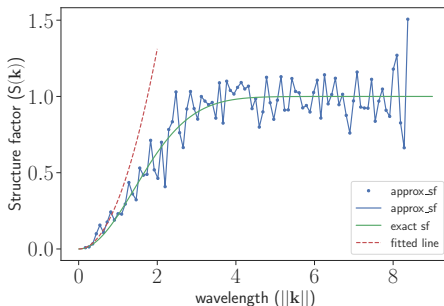
# Power decay of the structure factor

structure-factor 1.0.1

[pip install structure-factor](#)

Hyperuniformity's class

$\alpha$	$\text{Var} [\text{Card}(\mathcal{X} \cap B(0, R))]$	class
$> 1$	$O(R^{d-1})$	I
1	$O(R^{d-1} \log(R))$	II
$]0, 1[$	$O(R^{d-\alpha})$	III



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S. Cost, *Order, Fluctuations, Rigidities*.

```
In [1]: !pip install structure-factor
```

**Rajala2020SpectralEF.**

# THANK YOU.

structure-factor 1.0.1

`pip install structure-factor`



Github



Documentation



Personal webpage