On estimating the structure factor of a point process, with applications to hyperuniformity

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Contents

- Hyperuniformity
- 2 Motivations
- 3 Estimators assuming stationarity
- 4 Tests: Estimators
- 5 Comparison of the estimators
- 6 Tests: Hyperuniformity
- **7** Code

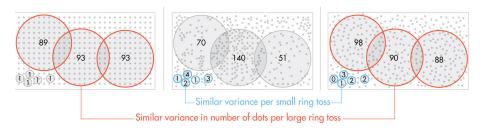
Hyperuniformity

Hyperuniformity

Let $\mathcal X$ be a stationary point process of $\mathbb R^d$ of intensity $ho,\,\mathcal X$ is hyperuniform iff

Variance:

$$\lim_{R\to\infty}\frac{\operatorname{Var}\left(\operatorname{Card}(\mathcal{X}\cap B(0,R))\right)}{|B(0,R)|}=0.$$

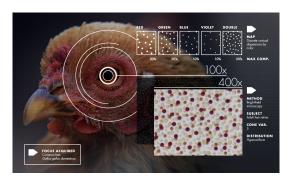


S. Torquato, Hyperuniform States of Matter, 2018.

S. Coste, Order, Fluctuations, Rigidities, 2021.

Bird's-Eye

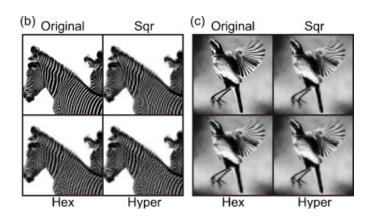
Motivations



Y. Jiao, T. Lau, H. Hatzikirou, M Meyer-Hermann, J. C. Corbo, and S. Torquato, *Avian photoreceptor patterns represent a disordered hyperuniform solution to a multiscale packing problem.* 2014.

Image reconstruction

Motivations



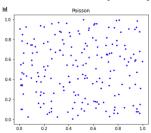
Ming-Jie Sun, Xin-Yu Zhao, and Li-Jing Li, *Imaging using hyperuniform sampling with a single-pixel camera*, 2018.

Motivations

■ Monte Carlo integration:

$$\int f(x)\mu(\mathrm{d}x) \approx \sum_{i=1}^N w_i f(\mathbf{x}_i)$$

■ Rate of convergence with a Poisson point process: $O(1/\sqrt{N})$

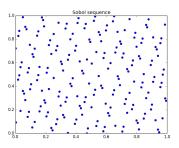


Motivations

■ Monte Carlo integration:

$$\int f(x)\mu(\mathrm{d}x) \approx \sum_{i=1}^{N} w_i f(\mathbf{x}_i)$$

Rate of convergence with Sobol sequence: $O(\log(N)^d/N)$



Let \mathcal{X} be a stationary point process of \mathbb{R}^d of intensity ρ ,

Structure factor:

$$S(\mathbf{k}) = 1 + \rho \mathcal{F}(g-1)(\mathbf{k}),$$

Pair correlation function

$$\mathbb{E}\left[\sum_{\mathbf{x},\mathbf{y}\in\mathcal{X}}^{\neq} f(\mathbf{x},\mathbf{y})\right] = \int_{\mathbb{R}^d \times \mathbb{R}^d} f(\mathbf{x}+\mathbf{y},\mathbf{y}) \rho^2 g(\mathbf{x}) d\mathbf{x} d\mathbf{y},$$

S. Coste, Order, Fluctuations, Rigidities, 2021.

S. Torquato, Hyperuniform States of Matter, 2018.

Structure Factor

Motivations

Let \mathcal{X} be a stationary point process of \mathbb{R}^d of intensity ρ ,

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lacksquare \mathcal{X} is hyperuniform iff

$$S(\mathbf{0}) = 0.$$

S. Coste, Order, Fluctuations, Rigidities, 2021.

S. Torquato, Hyperuniform States of Matter, 2018.

Hyperuniformity class

Motivations

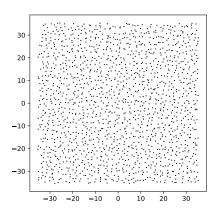
 \mathcal{X} is hyperuniform with $|S(\mathbf{k})| \sim c ||\mathbf{k}||_2^{\alpha}$ in the neighborhood of 0 then,

α	$Var\left[Card(\mathcal{X}\cap B(0,R))\right]$	class
> 1	$O(R^{d-1})$	I
1	$O(R^{d-1}\log(R))$	П
]0, 1[$O(R^{d-\alpha})$	Ш

S. Cost, Order, Fluctuations, Rigidities, 2021.

Ginibre ensemble

Motivations



Ginibre ensemble

Motivations

- Intenity: $\rho_{\text{Ginibre}} = 1/\pi$
- Pair correlation function: $g_{Ginibre}(r) = 1 \exp(-r^2)$
- Structure factor: $S_{\text{Ginibre}}(k) = 1 \exp(-k^2/4)$
- Power decay: $\alpha_{Ginibre} = 2$
- Hyperuniform class: I

Estimators assuming stationarity

 $\mathcal{X}_N = \{\mathbf{x}_i\}_1^N$ a realization of a **stationary** process \mathcal{X} of intensity ρ in $W = [-L/2, L/2]^d$.

Estimator:

$$\widehat{S}_{\mathrm{SI,s}}(\mathbf{k}) \triangleq \frac{1}{N} \left| \sum_{j=1}^{N} e^{-i\langle \mathbf{k}, \mathbf{x}_j \rangle} \right|^2$$

Allowed wavevectors:

$$\mathbf{k} \in \left\{ \left(\frac{2\pi n_1}{L}, \cdots, \frac{2\pi n_d}{L} \right) \text{ with, } \mathbf{n} = (n_1, \cdots, n_d) \in \mathbb{Z}^d \setminus \{\mathbf{0}\} \right\}.$$

¹⁻ S. Torquato, Hyperuniform States of Matter, 2018.

²⁻ M.A. Klatt and G. Last and D. Yogeshwaran, *Hyperuniform and Rigid Stable Matchings*, 2020.

Estimators assuming stationarity

- **Given**: $\mathcal{X}_N = \{\mathbf{x}_i\}_1^N$ a realization of a **stationary** point process \mathcal{X} of intensity ρ in $W = [-L/2, L/2]^d$.
- Need: Use \mathcal{X}_N to approximate $S(\mathbf{k}) = 1 + \rho \int_{\mathbb{R}^d} (g(\mathbf{r}) 1) e^{-i\langle \mathbf{k}, \mathbf{r} \rangle} d\mathbf{r}$.

Estimators assuming stationarity

- **Given**: $\mathcal{X}_N = \{\mathbf{x}_i\}_1^N$ a realization of a **stationary** point process \mathcal{X} of intensity ρ in $W = [-L/2, L/2]^d$.
- Need: Use \mathcal{X}_N to approximate $S(\mathbf{k}) = 1 + \rho \int_{\mathbb{R}^d} (g(\mathbf{r}) 1) e^{-i\langle \mathbf{k}, \mathbf{r} \rangle} d\mathbf{r}$.
- Idea:
 - 1 Use $\alpha_t(\mathbf{r}, W) = \int_{\mathbb{R}^d} t(\mathbf{r} + \mathbf{y}, W) t(\mathbf{y}, W) d\mathbf{y}$ s.t. $\lim_{L \to \infty} \alpha_t(\mathbf{r}, W) = 1$ and $||t||_2 = 1$:

$$S(\mathbf{k}) = 1 + \rho \int_{\mathbb{R}^d} \lim_{L \to \infty} (g(\mathbf{r}) - 1) \alpha_t(\mathbf{r}, W) e^{-i\langle \mathbf{k}, \mathbf{r} \rangle} d\mathbf{r}$$
$$= \lim_{L \to \infty} \mathbb{E}[\widehat{S}(t, \mathbf{k})] - \underbrace{\rho \mathcal{F}(\alpha_t)(\mathbf{k}, W)}_{\epsilon_t(\mathbf{k}, \mathbf{L})}$$

2 Reduce bias: Consider the zeros of $\epsilon_t(\mathbf{k}, \mathbf{L})$ as the set of allowed wavevectors of \widehat{S} , or remove the bias term.

■ **Taper:**
$$t_0(\mathbf{x}, W) = \frac{1}{\sqrt{|W|}} \mathbb{1}_W(\mathbf{x}).$$

$$S(\mathbf{k}) = \lim_{L \to \infty} \mathbb{E}\left[\underbrace{\frac{1}{\rho|W|} \Big| \sum_{\mathbf{x} \in \mathcal{X} \cap W} e^{-i\langle \mathbf{k}, \mathbf{x} \rangle} \Big|^{2}}_{\widehat{S}_{\mathrm{SI}}(\mathbf{k})}\right] - \rho \underbrace{\left(\prod_{j=1}^{d} \frac{\sin(k_{j}L/2)}{k_{j}\sqrt{L}/2}\right)^{2}}_{\epsilon_{0}(\mathbf{k}, \mathbf{L})}$$

Allowed wavevectors:

$$\mathbb{A}_{L} = \{ (k_1, \dots, k_d) \in (\mathbb{R}^d)^*, \exists j \in \{1, \dots, d\}, n \in \mathbb{Z}^* \text{ s.t. } k_j = \frac{2\pi n}{L} \}$$

1 Estimator:

$$\widehat{S}_{\mathrm{SI}}(\mathbf{k}) = \frac{1}{\rho|\mathcal{W}|} \left| \sum_{\mathbf{x} \in \mathcal{X} \cap \mathcal{W}} e^{-i\langle \mathbf{k}, \mathbf{x} \rangle} \right|^2$$

2 Allowed wavevectors:

$$\mathbb{A}_{\mathbf{L}} = \left\{ (k_1, \cdots, k_d) \in (\mathbb{R}^d)^*, \exists j \in \{1, \cdots, d\}, n \in \mathbb{Z}^* \text{ s.t. } k_j = \frac{2\pi n}{L} \right\}.$$

- Formulation in the literature:
 - 1 Estimator:

$$\widehat{S}_{\mathrm{SI,s}}(\mathbf{k}) \triangleq \frac{1}{N} \left| \sum_{j=1}^{N} e^{-i\langle \mathbf{k}, \mathbf{x}_j \rangle} \right|^2$$

2 Allowed wavevectors:

$$\mathbb{A}_{\mathbf{L}}^{res} = \left\{ \left(\frac{2\pi n_1}{L}, \cdots, \frac{2\pi n_d}{L} \right) \text{ with, } \mathbf{n} = \left(n_1, \cdots, n_d \right) \in \mathbb{Z}^d \setminus \{\mathbf{0}\} \right\}.$$

Tapered estimator

Estimators assuming stationarity

General case

■ Tapered estimator:

$$S(\mathbf{k}) = \lim_{L \to \infty} \mathbb{E}\left[\underbrace{\frac{1}{\rho} \Big| \sum_{j=1}^{N} t(\mathbf{x}_{j}, W) e^{-i\langle \mathbf{k}, \mathbf{x}_{j} \rangle} \Big|^{2}}_{\widehat{S}_{T}(t, \mathbf{k})} - \underbrace{\rho |\mathcal{F}(t)(\mathbf{k}, W)|^{2}}_{\epsilon_{t}(\mathbf{k}, \mathbf{L})}.$$

- Debiased tapered estimator:
 - 1 Directly debiased:

$$\widehat{S}_{\mathrm{DDT}}(t,\mathbf{k}) \triangleq \frac{1}{
ho} \left| \sum_{j=1}^{N} t(\mathbf{x}_{j},W) e^{-i\langle \mathbf{k},\mathbf{x}_{j} \rangle} -
ho \mathcal{F}(t)(\mathbf{k},W) \right|^{2}.$$

2 Undirectly debiased:

$$\widehat{S}_{\mathrm{UDT}}(t,\mathbf{k}) \triangleq \frac{1}{\rho} \left| \sum_{j=1}^{N} t(\mathbf{x}_{j},W) e^{-i\langle \mathbf{k},\mathbf{x}_{j} \rangle} \right|^{2} - \rho \left| \mathcal{F}(t)(\mathbf{k},W) \right|^{2}.$$

Preprint: T. Rajala and S. C. Olhede and D. John Murrell *Spectral estimation for spatial point patterns, 2020.*

More generally,

- Family of orthogonal tapers: $(t_q)_{q=1}^P$
- Multitapered estimator:

$$\widehat{S}_{\mathrm{MT}}((t_q)_{q=1}^P,\mathbf{k}) = rac{1}{P}\sum_{q=1}^P \widehat{S}_{\mathrm{T}}(t_q,\mathbf{k}).$$

Preprint: T. Rajala and S. C. Olhede and D. John Murrell, *Spectral estimation for spatial point patterns*. 2020.

Estimator assuming stationarity

Tests: Estimators

■ Tapered estimator:

$$\widehat{S}_{\mathrm{T}}(\mathbf{k}) \triangleq \frac{1}{\rho} \big| \sum_{j=1}^{N} t(\mathbf{x}_{j}, W) e^{-i\langle \mathbf{k}, \mathbf{j} \rangle} \big|^{2}.$$

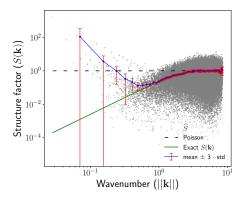
- Debiased tapered estimator:
 - 1 Directly debiased:

$$\widehat{S}_{\mathrm{DDT}}(t,\mathbf{k}) \triangleq \frac{1}{\rho} \left| \sum_{j=1}^{N} t(\mathbf{x}_{j},W) e^{-i\langle \mathbf{k},\mathbf{x}_{j} \rangle} - \rho \mathcal{F}(t)(\mathbf{k},W) \right|^{2}.$$

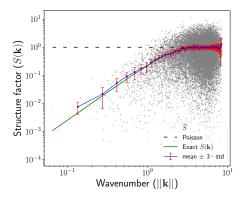
2 Undirectly debiased:

$$\widehat{S}_{\mathrm{UDT}}(t,\mathbf{k}) \triangleq \frac{1}{\rho} \left| \sum_{j=1}^{N} t(\mathbf{x}_{j},W) e^{-i\langle \mathbf{k},\mathbf{x}_{j} \rangle} \right|^{2} - \rho \left| \mathcal{F}(t)(\mathbf{k},W) \right|^{2}.$$

■ Multitapered estimators $\widehat{S}_{\mathrm{MT}}((t_q)_{q=1}^P, \mathbf{k}) = \frac{1}{P} \sum_{q=1}^P \widehat{S}(t_q, \mathbf{k}).$



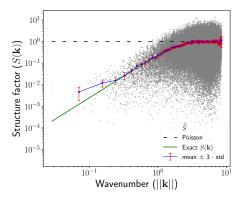
Scattering intensity on arbitrary wavevectors



Scattering intensity on allowed wavevectors

https://github.com/For-a-few-DPPs-more/structure-factor

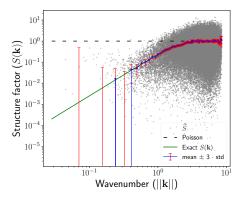
Tests: Estimators



Scattering intensity directly debiased

17

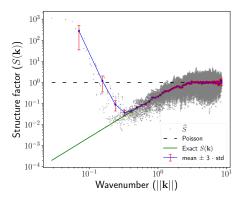
https://github.com/For-a-few-DPPs-more/structure-factor



Scattering intensity undirectly debiased

https://github.com/For-a-few-DPPs-more/structure-factor

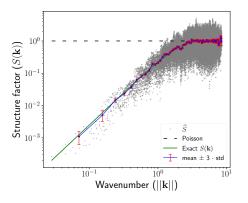
Multitapered estimator



Multitapered estimator

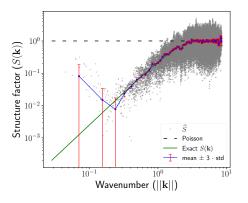
https://github.com/For-a-few-DPPs-more/structure-factor

Multitapered estimator



Multitapered estimator directly debiased

Multitapered estimator



Multitapered estimator undirectly debiased

https://github.com/For-a-few-DPPs-more/structure-factor

Integrated mean square error

Comparison of the estimators

Estimators	iVar	CI[iMSE]	
$\widehat{S}_{\mathrm{SI}}(2\pi\mathbf{n}/L)$	0.32	0.32 ± 0.02	
$\widehat{\mathcal{S}}_{\mathrm{DDT}}(t_0)$	0.32	0.33 ± 0.03	
$\widehat{S}_{\mathrm{DDT}}(t_1)$	0.34	0.35 ± 0.06	
$\widehat{S}_{ ext{DDMT}}((t_q)_1^4)$	0.08	0.08 ± 0.007	
	Ginibre ensemble		

Sample integrated variance and MSE for the variants of the scattering intensity across 50 samples from the Ginibre ensemble.

Integrated mean square error

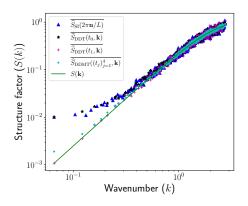
Comparison of the estimators

Estimators	T-score	<i>p</i> -value
$\widehat{S}_{\mathrm{DDMT}}((t_q)_1^4), \ \widehat{S}_{\mathrm{SI}}(2\pi\mathbf{n}/L)$	-29.53	3×10^{-33}
$\widehat{S}_{ ext{DDMT}}((t_q)_1^4), \ \widehat{S}_{ ext{DDT}}(t_0)$	-22.40	10^{-27}
$\widehat{S}_{\mathrm{DDMT}}((t_q)_1^4), \ \widehat{S}_{\mathrm{DDT}}(t_1)$	-12.18	9×10^{-17}
	Ginibre ensemble	

Paired *t*-tests for the variants of the scattering intensity.

Integrated mean square error

Comparison of the estimators



Means of the estimators across 50 samples from the Ginibre ensemble.

Tests: Hyperuniformity

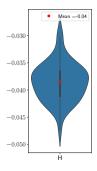
$$\mathcal{X}$$
 is effectively hyperuniform $\iff H = \frac{\widehat{S}(0)}{\widehat{S}(k_{peak})} \le 10^{-3}$,

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

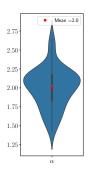
S. Torquato, Hyperuniform States of Matter, 2018.

Hyperuniformity

Tests: Hyperuniformity



(a) H index



(b) Power decay

Python Package

Code

- 1 Open-source Python toolbox called structure_factor 1
- 2 Available on Github and PyPI ²
- 3 Detailed documentation ³
- 4 Jupyter notebook tutorial 4

https://github.com/For-a-few-DPPs-more/structure-factor

²https://pypi.org/project/structure-factor/

³https://for-a-few-dpps-more.github.io/structure-factor/

⁴https://github.com/For-a-few-DPPs-more/structure-factor/tree/main/notebooks

THANK YOU







Documentation



Preprint

https://github.com/For-a-few-DPPs-more/structure-factor https://for-a-few-dpps-more.github.io/structure-factor/

https://arxiv.org/abs/2203.08749