

Limit Theory for Statistics of Random Geometric Structures

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Stochastic Geometry and Its Applications, Nantes, April 4-8, 2016

Talk is based on joint work with B. Błaszczyszyn and D. Yogeshwaran

Introduction

Questions pertaining to geometric structures on random input $\mathcal{X} \subset \mathbb{R}^d$ often involve analyzing sums of spatially correlated terms

$$\sum_{x \in \mathcal{X}} \xi(x, \mathcal{X}),$$

where the \mathbb{R} -valued score function ξ , defined on pairs (x, \mathcal{X}) , represents the interaction of x with respect to \mathcal{X} .

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Ex. 1: Statistics of random graphs

Clique counts. $\mathcal{X} \subset \mathbb{R}^d$ finite, $r \in (0, \infty)$.

- Join two points of \mathcal{X} iff they are at distance at most r . Vietoris-Rips complex (with parameter r) is simplicial complex whose k -simplices correspond to unordered $(k+1)$ -tuples of points in \mathcal{X} all pairwise within r of each other.
- For $k \in \mathbb{N}$ and $x \in \mathcal{X}$, put $\sigma_k(x, \mathcal{X}) := \frac{\text{number of } k\text{-simplices containing } x}{k+1}$

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- Total number of k -simplices in Vietoris-Rips complex: $\sum_{x \in \mathcal{X}} \sigma_k(x, \mathcal{X})$.

Chatterjee, Decreasefond et al., Eichelsbacher, Lachièze-Rey + Peccati, Reitzner + Schulte, Penrose + Y

Ex. 1: Statistics of random graphs

Total edge length of graphs. $\mathcal{X} \subset \mathbb{R}^d$ finite. Given $x \in \mathcal{X}$, let x_{NN} be the nearest neighbor of x .

- Undirected nearest neighbor graph on \mathcal{X} : include an edge $\{x, y\}$ if $y = x_{NN}$ and/or $x = y_{NN}$.
- For $x \in \mathcal{X}$, put

$$\xi(x, \mathcal{X}) := \begin{cases} \frac{1}{2} \|x - x_{NN}\| & \text{if } x, x_{NN} \text{ are mutual n.n.} \\ \|x - x_{NN}\| & \text{otherwise.} \end{cases}$$

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· Total edge length of n.n. graph on \mathcal{X} : $\sum_{x \in \mathcal{X}} \xi(x, \mathcal{X})$.

Chatterjee; Last, Peccati, + Schulte; Steele; Penrose + Y

Ex. 2: Germ-grain models

- $\mathcal{X} \subset \mathbb{R}^d$ a collection of 'germs'.
- $S_x, x \in \mathcal{X}$, a collection of 'grains' (closed bounded sets).
- Germ-grain model: $\bigcup_{x \in \mathcal{X}} (x \oplus S_x)$.
- Surface area, Euler characteristic, clump count,... may be expressed as $\sum_{x \in \mathcal{X}} \xi(x, \mathcal{X})$ for appropriate ξ . For example, for $x \in \mathcal{X}$ we put $\xi_{\text{clump}}(x, \mathcal{X}) := (\text{size of clump of germ-grain model containing } x)^{-1}$.

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- Clump count in germ-grain model equals $\sum_{x \in \mathcal{X}} \xi_{\text{clump}}(x, \mathcal{X})$.
- Baddeley; Hall; Hug, Last + Schulte; Molchanov; Penrose + Y; Schneider + Weil; Stoyan; ...

Ex. 3: Random packing (Random sequential adsorption)

- $\mathcal{X} \subset \mathbb{R}^d$ finite. Assign elements $x \in \mathcal{X}$ time marks $\tau_x \in [0, 1]$.
- Let B_1, B_2, \dots be a sequence of unit volume d -dimensional Euclidean balls with centers arriving sequentially at points $x \in \mathcal{X}$ and at arrival times τ_x .
- The first ball B_1 to arrive is packed. Recursively, for $i = 2, 3, \dots$, the i th ball is packed if it does not overlap any ball in B_1, B_2, \dots, B_{i-1} which has already been packed.

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- The first ball B_1 to arrive is packed. Recursively, for $i = 2, 3, \dots$, the i th ball is packed if it does not overlap any ball in B_1, B_2, \dots, B_{i-1} which has already been packed.
- For $x \in \mathcal{X}$ define packing functional

$$\rho(x, \mathcal{X}) := \begin{cases} 1 & \text{if ball arriving at } x \text{ is packed} \\ 0 & \text{otherwise} \end{cases},$$

Then total number of packed balls equals $\sum_{x \in \mathcal{X}} \rho(x, \mathcal{X})$.

- Rényi, Coffman, Dvoretzky + Robbins; Flory, Itoh + Shepp; Torquato,...

Ex. 4: Statistics of random convex hulls

- $\mathcal{X} \subset \mathbb{R}^d$ finite. Let $\text{co}(\mathcal{X})$ denote the convex hull of \mathcal{X} .
 - For $x \in \mathcal{X}$, $k \in \{0, 1, \dots, d - 1\}$, we put
- $$f_k(x, \mathcal{X}) := \frac{1}{k+1} (\text{number of } k\text{-dimensional faces containing } x).$$

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$$f_k(x, \mathcal{X}) := \frac{1}{k+1}(\text{number of } k\text{-dimensional faces containing } x).$$
- Total number of k -dimensional faces of $\text{co}(\mathcal{X})$ equals $\sum_{x \in \mathcal{X}} f_k(x, \mathcal{X})$.
- Rényi + Sulanke; Bárány; Buchta; Calka, Schreiber + Y; Groeneboom, Reitzner, Vu,...

General questions

- When $\mathcal{X} \subset \mathbb{R}^d$ is a random pt configuration, the sums $\sum_{x \in \mathcal{X}} \xi(x, \mathcal{X})$ describe a global feature of some spatial random system.

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- When $\mathcal{X} \subset \mathbb{R}^d$ is a random pt configuration, the sums $\sum_{x \in \mathcal{X}} \xi(x, \mathcal{X})$ describe a global feature of some spatial random system.
- **Question.** What is the distribution of these sums for large pt configurations \mathcal{X} ? LLN? CLT?

Goals

\mathcal{P} : stationary pt process on \mathbb{R}^d

Restrict to windows: $\mathcal{P}_n := \mathcal{P} \cap [-\frac{n^{1/d}}{2}, \frac{n^{1/d}}{2}]^d$.

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Goal. Given a score function $\xi(\cdot, \cdot)$ defined on pairs (x, \mathcal{X}) , given a pt process \mathcal{P} , we seek the limit theory (LLN, CLT, variance asymptotics) for the total score

$$\sum_{x \in \mathcal{P}_n} \xi(x, \mathcal{P}_n)$$

and total measure

$$\mu_n^\xi := \sum_{x \in \mathcal{P}_n} \xi(x, \mathcal{P}_n) \delta_{n^{-1/d}x}.$$

Tractable problems must be *local* in the sense that points far away from x should not play a role in the evaluation of the score $\xi(x, \mathcal{P}_n)$.

Stabilization

We assume translation invariant scores: $\xi(x, \mathcal{X}) = \xi(\mathbf{0}, \mathcal{X} - x)$.

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Key Definition. ξ is *stabilizing* wrt pt process \mathcal{P} on \mathbb{R}^d if for all $x \in \mathcal{P}$ there is $R := R^\xi(x, \mathcal{P}) < \infty$ a.s. (a 'radius of stabilization') such that

$$\xi(x, \mathcal{P} \cap B_R(x)) = \xi(x, \mathcal{P} \cap B_R(x) \cup (\mathcal{A} \cap B_R^c(x))).$$

for any locally finite $\mathcal{A} \subset \mathbb{R}^d$. ξ is *exponentially stabilizing* wrt \mathcal{P} if there is a constant c such that

$$\sup_{x \in \mathbb{R}^d} \sup_n P[R^\xi(x, \mathcal{P}_n) \geq r] \leq c \exp(-\frac{r}{c}), \quad r \in [1, \infty).$$

Moment condition

\mathcal{P} : a pt process on \mathbb{R}^d ; $\mathcal{P}_n := \mathcal{P} \cap [-\frac{n^{1/d}}{2}, \frac{n^{1/d}}{2}]^d$.

Definition. ξ satisfies the p moment condition wrt \mathcal{P} if

$$\sup_n \sup_{x,y \in \mathbb{R}^d} \mathbb{E} |\xi(x, \mathcal{P}_n \cup \{y\})|^p < \infty.$$

Weak law of large numbers for Poisson input \mathcal{H}

Let \mathcal{H} be a rate 1 Poisson pt process on \mathbb{R}^d ; $\mathcal{H}_n := \mathcal{H} \cap [-\frac{n^{1/d}}{2}, \frac{n^{1/d}}{2}]^d$.

$$\mu_n^\xi := \sum_{x \in \mathcal{H}_n} \xi(x, \mathcal{H}_n) \delta_{n^{-1/d}x}.$$

Thm (WLLN): If ξ is stabilizing wrt \mathcal{H} , if ξ satisfies the p moment condition for some $p \in (1, \infty)$, then for all $f \in B([-1/2, 1/2]^d)$ we have

$$|n^{-1} \mathbb{E} \langle \mu_n^\xi, f \rangle - \mathbb{E} \xi(\mathbf{0}, \mathcal{H} \cup \{\mathbf{0}\}) \int_{[-1/2, 1/2]^d} f(x) dx| \leq \epsilon_n.$$

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Penrose and Y (2003): $\epsilon_n = o(1)$.

Schulte + Y (2016): $\epsilon_n = O(n^{-1/d})$ if ξ is exponentially stabilizing wrt \mathcal{H} .

Gaussian fluctuations for Poisson input \mathcal{H} on \mathbb{R}^d

Recall $\mu_n^\xi := \sum_{x \in \mathcal{H}_n} \xi(x, \mathcal{H}_n) \delta_{n^{-1/d}x}$.

Thm (CLT): Assume ξ is exponentially stabilizing wrt \mathcal{H} and that ξ satisfies the p moment condition for some $p \in (5, \infty)$. If $f \in B([-\frac{1}{2}, \frac{1}{2}]^d)$ satisfies $\text{Var}\langle \mu_n^\xi, f \rangle = \Omega(n)$, then

$$\sup_{t \in \mathbb{R}} \left| P \left[\frac{\langle \mu_n^\xi, f \rangle - \mathbb{E} \langle \mu_n^\xi, f \rangle}{\sqrt{\text{Var} \langle \mu_n^\xi, f \rangle}} \leq t \right] - P[N(0, 1) \leq t] \right| \leq \epsilon_n.$$

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Penrose + Y (2005), Penrose (2007): $\epsilon_n = O((\log n)^{3d} n^{-1/2})$.

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Variance asymptotics for Poisson input; volume order fluctuations

Given homogenous rate 1 Poisson input \mathcal{H} on \mathbb{R}^d , and a score ξ , put

$$\sigma^2(\xi) := \mathbb{E} \xi^2(\mathbf{0}, \mathcal{H}) + \int_{\mathbb{R}^d} \mathbb{E} \xi(\mathbf{0}, \mathcal{H} \cup \{x\}) \xi(x, \mathcal{H} \cup \{\mathbf{0}\}) - \mathbb{E} \xi(\mathbf{0}, \mathcal{H}) \mathbb{E} \xi(x, \mathcal{H}) dx$$

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Thm (variance asymptotics): If ξ is exponentially stabilizing wrt \mathcal{H} , if ξ satisfies the p moment condition for some $p \in (2, \infty)$, then for all $f \in B([-1/2, 1/2]^d)$ we have

$$\lim_{n \rightarrow \infty} n^{-1} \text{Var} \langle \mu_n^\xi, f \rangle = \sigma^2(\xi) \int_{[-1/2, 1/2]^d} f^2(x) dx \in [0, \infty).$$

Baryshnikov + Y. (2005); Penrose (2007)

- **Question.** If the input pt process is not Poisson, when do we get results which are qualitatively similar?
- Soshnikov (2002): establishes asymptotic normality of the *linear* statistics

$$\sum_{x \in \mathcal{P}_n} \delta_{n^{-1/d}x}$$

where \mathcal{P} is determinantal pt process, $\mathcal{P}_n := \mathcal{P} \cap W_n$.

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where \mathcal{P} is determinantal pt process, $\mathcal{P}_n := \mathcal{P} \cap W_n$.

- Nazarov and Sodin (2012): establish asymptotic normality of the *linear* statistics

$$\sum_{x \in \mathcal{P}_n} \delta_{n^{-1/d}x}$$

where \mathcal{P} is zero set of Gaussian analytic function, $\mathcal{P}_n := \mathcal{P} \cap W_n$.

- We want to extend these results to non-linear statistics

$$\mu_n^\xi := \sum_{x \in \mathcal{P}_n} \xi(x, \mathcal{P}_n) \delta_{n^{-1/d}x}.$$

Clustering pt processes

Def. Given a simple pt process \mathcal{P} on \mathbb{R}^d , the k pt correlation function $\rho^{(k)} : (\mathbb{R}^d)^k \rightarrow [0, \infty)$ is defined via

$$\mathbb{E} [\prod_{i=1}^k \text{card}(\mathcal{P} \cap B_i)] = \int_{B_1} \dots \int_{B_k} \rho^{(k)}(x_1, \dots, x_k) dx_1 \dots dx_k,$$

where B_1, \dots, B_k are disjoint subsets of \mathbb{R}^d .

Rk. $\rho^{(k)}(x_1, \dots, x_k) = \prod_{i=1}^k \rho^{(1)}(x_i)$ characterizes the Poisson pt process

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Key Definition A pt process \mathcal{P} *clusters* if there is a fast decreasing function $\phi : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ such that for all $p, q \in \mathbb{N}$ there are constants $c_{p,q}$ and $C_{p,q}$ such that for all $x_1, \dots, x_{p+q} \in \mathbb{R}^d$,

$$|\rho^{(p+q)}(x_1, \dots, x_{p+q}) - \rho^{(p)}(x_1, \dots, x_p)\rho^{(q)}(x_{p+1}, \dots, x_{p+q})| \leq C_{p,q}\phi(-c_{p,q}s),$$

where $s := \inf_{i \in \{1, \dots, p\}, j \in \{p+1, \dots, p+q\}} |x_i - x_j|$.

(ϕ 'fast decreasing' means ϕ decaying faster than any power)

Ex. 1: Determinantal pt process

A pt process is determinantal (DPP) if its correlation functions satisfy

$$\rho^{(k)}(x_1, \dots, x_k) = \det(K(x_i, x_j))_{1 \leq i \leq j \leq k},$$

where $K(\cdot, \cdot)$ is Hermitian kernel of integral operator from $L^2(\mathbb{R}^d)$ to itself.

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Fact (Błaszczyszyn, Yogeshwaran, + Y (2016)). If

$|K(x, y)| \leq \phi(\|x - y\|)$, with ϕ fast decreasing, then the DPP clusters.

Ex. Infinite Ginibre ensemble on complex plane clusters with kernel

$$K(z_1, z_2) = \exp(i \operatorname{Im}(z_1 \bar{z}_2) - \frac{1}{2}|z_1 - z_2|^2).$$

Ex. 2: Zero set of Gaussian entire function

- Let $X_j, j \geq 1$, be i.i.d. standard complex Gaussians. Consider the Gaussian entire function

$$F(z) := \sum_{j=1}^{\infty} \frac{X_j}{\sqrt{j!}} z^j.$$

- Zero set $Z_F := F^{-1}(\{0\})$ is stationary.

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- Zero set $Z_F := F^{-1}(\{0\})$ is stationary.
- Z_F exhibits local repulsivity.
- Z_F strongly clusters (Nazarov and Sodin (2012)).

Ex. 3: Gibbs pt processes

Consider the class Ψ of Hamiltonians consisting of:

- pair potentials without negative part,
 - area interaction Hamiltonians, and
 - hard core Hamiltonians.
-
- For $\Psi \in \Psi$, let $\mathcal{P}^{\beta\Psi}$ be the Gibbs pt process having Radon-Nikodym derivative $\exp(-\beta\Psi(\cdot))$ with respect to a reference homogeneous Poisson pt process \mathcal{H}_τ on \mathbb{R}^d of intensity τ .
 - There is a range of inverse temperature and activity parameters (β and τ) such that $\mathcal{P}^{\beta\Psi}$ clusters (Schreiber and Y, 2013).

Weak law of large numbers for clustering input

Let \mathcal{P} be clustering pt process on \mathbb{R}^d . Recall $\mathcal{P}_n := \mathcal{P} \cap [-\frac{n^{1/d}}{2}, \frac{n^{1/d}}{2}]^d$ and

$$\mu_n^\xi := \sum_{x \in \mathcal{P}_n} \xi(x, \mathcal{P}_n) \delta_{n^{-1/d}x}.$$

Thm (BYY '16): If ξ is stabilizing wrt \mathcal{P} , if ξ satisfies the p moment condition for some $p \in (1, \infty)$, then for all $f \in B([-1/2, 1/2]^d)$ we have

$$\lim_{n \rightarrow \infty} n^{-1} \mathbb{E} \langle \mu_n^\xi, f \rangle = \mathbb{E} \xi(\mathbf{0}, \mathcal{P} \cup \{\mathbf{0}\}) \int_{[-1/2, 1/2]^d} f(x) dx \cdot \rho^{(1)}(\mathbf{0}).$$

Gaussian fluctuations for clustering input \mathcal{P}

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- \mathcal{P} clusters,
- ξ has deterministic radius of stabilization wrt \mathcal{P} ,
- ξ satisfies the p moment condition for some $p \in (2, \infty)$, and
- $\text{Var}\langle \mu_n^\xi, f \rangle = \Omega(n^\alpha)$ for some $\alpha \in (0, 1)$, $f \in B([-1/2, 1/2]^d)$. Then

$$\frac{\langle \mu_n^\xi, f \rangle - \mathbb{E} \langle \mu_n^\xi, f \rangle}{\sqrt{\text{Var}\langle \mu_n^\xi, f \rangle}} \xrightarrow{\mathcal{D}} N(0, 1).$$

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- $\text{Var}\langle \mu_n^\xi, f \rangle = \Omega(n^\alpha)$ for some $\alpha \in (0, 1)$, $f \in B([-1/2, 1/2]^d)$. Then

$$\frac{\langle \mu_n^\xi, f \rangle - \mathbb{E} \langle \mu_n^\xi, f \rangle}{\sqrt{\text{Var}\langle \mu_n^\xi, f \rangle}} \xrightarrow{\mathcal{D}} N(0, 1).$$

Remarks. If \mathcal{P} is determinantal with fast decreasing kernel then this extends Soshnikov (2002), who restricts to linear statistics $\sum_{x \in \mathcal{P}_n} \delta_{n^{-1/d}x}$, that is he puts $\xi \equiv 1$.

- If \mathcal{P} is zero set of Gaussian entire function, this extends Nazarov and Sodin (2012), who also restrict to $\sum_{x \in \mathcal{P}_n} \delta_{n^{-1/d}x}$.

Gaussian fluctuations for clustering input \mathcal{P}

- Thm (BYY '16)** $\mu_n^\xi := \sum_{x \in \mathcal{P}_n} \xi(x, \mathcal{P}_n) \delta_{n^{-1/d}x}$. Assume
- \mathcal{P} clusters and clustering coeff. satisfy mild growth condition
 - ξ exponentially stabilizing wrt \mathcal{P} ,
 - ξ satisfies the p moment condition for some $p \in (2, \infty)$, and
 - $\text{Var}\langle \mu_n^\xi, f \rangle = \Omega(n^\alpha)$ for some $\alpha \in (0, 1)$, $f \in B([-1/2, 1/2]^d)$. Then

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Remark. If \mathcal{P} is determinantal with fast decreasing kernel (e.g. Ginibre) then \mathcal{P} satisfies stated condition.

Variance asymptotics for clustering input \mathcal{P}

- Given clustering input \mathcal{P} and a score ξ , put

$$\sigma^2(\xi) := \mathbb{E} \xi^2(\mathbf{0}, \mathcal{P}) \rho^{(1)}(\mathbf{0}) +$$

$$\int_{\mathbb{R}^d} \mathbb{E} \xi(\mathbf{0}, \mathcal{P} \cup x) \xi(x, \mathcal{P} \cup \mathbf{0}) \rho^{(2)}(\mathbf{0}, x) - \mathbb{E} \xi(\mathbf{0}, \mathcal{P}) \rho^{(1)}(\mathbf{0}) \mathbb{E} \xi(x, \mathcal{P}) \rho^{(1)}(\mathbf{x}) dx.$$

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- Thm (BYY '16):** If ξ is exponentially stabilizing wrt \mathcal{P} , if ξ satisfies the p moment condition for some $p \in (2, \infty)$, then for all $f \in B([-1/2, 1/2]^d)$ we have

$$\lim_{n \rightarrow \infty} n^{-1} \text{Var} \langle \mu_n^\xi, f \rangle = \sigma^2(\xi) \int_{[-1/2, 1/2]^d} f^2(x) dx \in [0, \infty).$$

- Rk.** When \mathcal{P} is determinantal with fast decreasing kernel this extends Soshnikov (2002), who assumes $\xi \equiv 1$.

Proof idea for CLT

- Given ξ , consider k mixed moment functions $m_{(k)} : (\mathbb{R}^d)^k \rightarrow \mathbb{R}$ given by

$$m_{(k)}(x_1, \dots, x_k; \mathcal{P}_n) := \mathbb{E} \prod_{i=1}^k \xi(x_i, \mathcal{P}_n) \rho^{(k)}(x_1, \dots, x_k).$$

- We show that the mixed moments cluster, that is for all $p, q \in \mathbb{N}$ there are constants $c_{p,q}$ and $C_{p,q}$ s.t. for all $x_1, \dots, x_{p+q} \in \mathbb{R}^d$,

$$|m_{(p+q)}(x_1, \dots, x_{p+q}) - m_{(p)}(x_1, \dots, x_p) m_{(q)}(x_{p+1}, \dots, x_{p+q})| \leq C_{p,q} \varphi(-c_{p,q} s),$$

where

$$s := \inf_{i \in \{1, \dots, p\}, j \in \{p+1, \dots, p+q\}} |x_i - x_j|$$

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- \mathcal{P} clusters and ξ exp. stabilizing \Rightarrow mixed moments cluster
- cumulants of $\frac{\langle \mu_n^\xi, f \rangle - \mathbb{E} \langle \mu_n^\xi, f \rangle}{\sqrt{\text{Var} \langle \mu_n^\xi, f \rangle}}$ converge to cumulants of $N(0, 1)$.

Applications

General results yield WLLN, Gaussian fluctuations, variance asymptotics for statistics of geometric structures on clustering pt processes (CPP):

(i) Vietoris-Rips clique count on any CPP, including DPP with fast decreasing kernel, zero set of Gaussian entire function.

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