

Lecture 3: Limit theory for statistics of geometric structures via stabilizing score functions

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February 26, 2019

Probabilistic Analysis of Geometric Structures

- **Lecture 1:** Probabilistic analysis of Euclidean optimization problems
- **Lecture 2:** Central limit theorems for statistics of geometric structures
- **Lecture 3:** Limit theory for statistics of geometric structures via stabilizing score functions
- **Lecture 4:** Statistics of random polytopes
- **Lecture 5:** Rates of multivariate normal approximation for statistics of geometric structures

Lecture 3: Limit theory for statistics of geometric structures via stabilizing scores

- **I Examples and Goals**
- **II Stabilization**
- **III Binomial and Poisson Input**
 - WLLN
 - Gaussian fluctuations
 - Variance asymptotics
- **IV More General Input**

I Examples and Goals

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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I Examples and Goals: Statistics of random graphs

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

- Geometric graph: Join two points of \mathcal{X} iff they are at distance at most ρ .
- Vietoris-Rips complex (with parameter ρ) is simplicial complex whose k -simplices correspond to unordered $(k+1)$ -tuples of points in \mathcal{X} all pairwise within ρ of each other.

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- 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, Decreusefond et al., Eichelsbacher, Lachièze-Rey + Peccati, Reitzner + Schulte, Thäle,...

I Examples and Goals: 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 (NN) 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

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

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- Total edge length of NN graph on \mathcal{X} : $\sum_{x \in \mathcal{X}} \xi(x, \mathcal{X})$.
- Chatterjee; Last, Peccati, + Schulte; Steele; Penrose + Y

I Examples and Goals: 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: $\bigcup_{x \in \mathcal{X}} (x \oplus S_x)$.
- Total surface area, volume, 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; Thäle

I Examples and Goals: Random packing (Random sequential adsorption)

- $\mathcal{X} \subset \mathbb{R}^d$ finite. Assign $x \in \mathcal{X}$ a time mark $\tau_x \in [0, 1]$.
- Let B_1, B_2, \dots be a sequence of unit volume d -dimensional Euclidean balls with centers arriving sequentially at points $x_i \in \mathcal{X}$ and at arrival times τ_{x_i} .
- 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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- For $x \in \mathcal{X}$ define packing functional

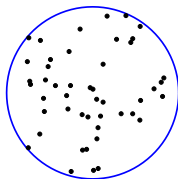
$$\xi_{\text{pack}}(x, \mathcal{X}) := \begin{cases} 1 & \text{if ball arriving at } x \text{ is packed} \\ 0 & \text{otherwise.} \end{cases}$$

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

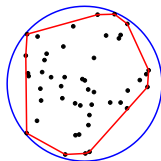
- Rényi, Coffman, Dvoretzky + Robbins; Flory, Itoh + Shepp; Torquato, ...

Examples and Goals: Statistics of random convex hulls

- $\mathcal{X} \subset \mathbb{R}^d$ finite. Let $\text{co}(\mathcal{X})$ denote the convex hull of \mathcal{X} .



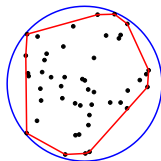
Examples and Goals: Statistics of random convex hulls



· For $x \in \mathcal{X}$, $k \in \{0, 1, \dots, d-1\}$, we put

$$f_k(x, \mathcal{X}) := \frac{1}{k+1} (\text{number of } k\text{-dimensional faces containing } x).$$

Examples and Goals: Statistics of random convex hulls



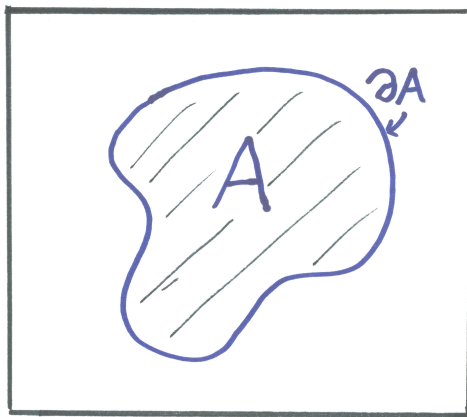
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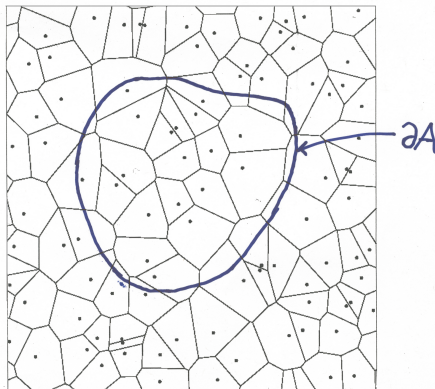
· Total number of k -dimensional faces of $\text{co}(\mathcal{X})$: $\sum_{x \in \mathcal{X}} f_k(x, \mathcal{X})$.

· Rényi+Sulanke; Bárány; Buchta; Calka; Groeneboom, Reitzner, Thäle, Vu, ...

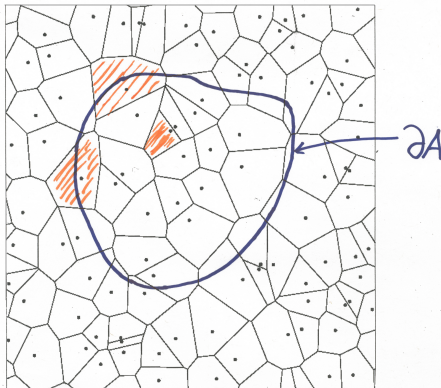
I Examples and Goals: Poisson - Voronoi tessellation



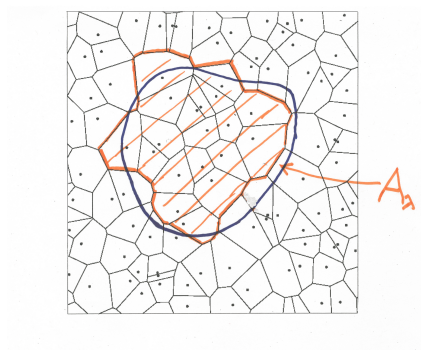
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Examples and Goals: Poisson - Voronoi tessellation



Def. A_λ is the Poisson - Voronoi approximation of A .

Question: What is $\text{Vol}(A_\lambda)$?

Define volume score: $\xi_{Vol}(x, \mathcal{X}) = \text{Vol}(C(x, \mathcal{X}))$ when $x \in A$, otherwise put the score to be zero. Sum of volume scores gives $\text{Vol}(A_\lambda)$.

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 structure.

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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 structure.
- What is the distribution of these sums for large pt configurations \mathcal{X} ?
LLN? CLT?

I Examples and Goals

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

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

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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

$$\sum_{x \in \mathcal{P} \cap Q_\lambda} \xi(x, \mathcal{P} \cap Q_\lambda)$$

and total measure

$$\mu_\lambda^\xi := \sum_{x \in \mathcal{P} \cap Q_\lambda} \xi(x, \mathcal{P} \cap Q_\lambda) \delta_{\lambda^{-1/d}x}.$$

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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 $\xi(x, \mathcal{P} \cap Q_\lambda)$.

II 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 $\mathcal{A} \subset \mathbb{R}^d$.

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for any locally finite $\mathcal{A} \subset \mathbb{R}^d$. ξ is *exponentially stabilizing* wrt \mathcal{P} if there is a constant $c \in (0, \infty)$ such that

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

II Stabilization

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

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

$$\sup_{\lambda \geq 1} \sup_{x, y \in \mathbb{R}^d} \mathbb{E} |\xi(x, (\mathcal{P} \cap Q_\lambda) \cup \{y\})|^p < \infty.$$

II Stabilization

- Let \mathcal{P}_1 be a rate 1 Poisson pt process on \mathbb{R}^d
- $\mathcal{P}_1 \cap Q_\lambda := \mathcal{P}_1 \cap [-\frac{\lambda^{1/d}}{2}, \frac{\lambda^{1/d}}{2}]^d$. Put

$$\mu_\lambda^\xi := \sum_{x \in \mathcal{P}_1 \cap Q_\lambda} \xi(x, \mathcal{P}_1 \cap Q_\lambda) \delta_{\lambda^{-1/d}x}.$$

Thm (WLLN): If ξ is stabilizing wrt \mathcal{P}_1 and satisfies the p moment condition for some $p \in (1, \infty)$, then for all $f \in B([- \frac{1}{2}, \frac{1}{2}]^d)$ we have

$$|\lambda^{-1} \mathbb{E} \langle \mu_\lambda^\xi, f \rangle - \mathbb{E} \xi(\mathbf{0}, \mathcal{P}_1 \cup \{\mathbf{0}\}) \int_{[-\frac{1}{2}, \frac{1}{2}]^d} f(x) dx| \leq \epsilon_\lambda.$$

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

Lachièze-Rey, Schulte, + Y (2017): $\epsilon_\lambda = O(\lambda^{-1/d})$ if ξ is exponentially stabilizing wrt \mathcal{P}_1 .

II Stabilization

What about weak laws of large numbers on non-uniform input?

It is useful to consider ξ_λ defined as follows. For all $\lambda > 0$ define the λ *re-scaled version* of ξ by

$$\xi_\lambda(x, \mathcal{X}) := \xi(\lambda^{1/d}x, \lambda^{1/d}\mathcal{X}).$$

Re-scaling is natural when considering point sets \mathcal{X} in compact sets K having cardinality roughly λ ; dilation by $\lambda^{1/d}$ means that unit volume subsets of $\lambda^{1/d}K$ host on the average one point.

II Stabilization

$\mathcal{P}_{\lambda\kappa}$: PPP on \mathbb{R}^d with intensity density $\lambda\kappa(x)dx$.

One may show that $\lambda^{1/d}(\mathcal{P}_{\lambda\kappa} - x_0) \xrightarrow{\mathcal{D}} \mathcal{P}_{\kappa(x_0)}$ as $\lambda \rightarrow \infty$, where convergence is in the sense of weak convergence of point processes.

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If $\xi(\cdot, \cdot)$ is a functional defined on $\mathbb{R}^d \times \mathbf{N}$, where we recall \mathbf{N} is the space of locally finite point sets in \mathbb{R}^d , one might hope that ξ is *continuous* on the pairs $(\mathbf{0}, \lambda^{1/d}(\mathcal{P}_{\lambda\kappa} - x_0))$ in the sense that $\xi(\mathbf{0}, \lambda^{1/d}(\mathcal{P}_{\lambda\kappa} - x_0))$ converges in distribution to $\xi(\mathbf{0}, \mathcal{P}_{\kappa(x_0)})$ as $\lambda \rightarrow \infty$.

This turns out to be the case whenever ξ is stabilizing wrt to $\mathcal{P}_{\kappa(x_0)}$ and if x_0 is a Lebesgue point of κ .

II Stabilization

Almost every $x \in \mathbb{R}^d$ is a *Lebesgue point* of κ , that is to say for almost all $x \in \mathbb{R}^d$ we have

$$\lim_{\epsilon \rightarrow 0} \epsilon^{-d} \int_{B_\epsilon(x)} |\kappa(y) - \kappa(x)| dy = 0.$$

Lemma (convergence of re-scaled binomial pt process) Let $x \in \mathbb{R}^d$ be a Lebesgue point for κ . Then

$$n^{1/d}(-x + \mathcal{X}_n) \xrightarrow{\mathcal{D}} \mathcal{P}_{\kappa(x)}, \quad n \rightarrow \infty.$$

Lemma (convergence of re-scaled binomial pt process) Let $x \in \mathbb{R}^d$ be a Lebesgue point for κ . Then

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Key ‘Continuity’ Lemma. Let $x \in \mathbb{R}^d$ be a Lebesgue point for κ and assume that $R^\xi(x, \mathcal{P}_{\kappa(x)}) < \infty$ a.s. where $R^\xi(x, \mathcal{P}_{\kappa(x)})$ is the radius of stabilization for ξ at x wrt $\mathcal{P}_{\kappa(x)}$. Then

- (a) $\xi_\lambda(x, \mathcal{P}_{\lambda\kappa}) \xrightarrow{\mathcal{D}} \xi(\mathbf{0}, \mathcal{P}_{\kappa(x)}), \quad \lambda \rightarrow \infty,$
- (b) $\xi_n(x, \mathcal{X}_n) \xrightarrow{\mathcal{D}} \xi(\mathbf{0}, \mathcal{P}_{\kappa(x)}), \quad n \rightarrow \infty.$

So stabilization of a score function acts as a surrogate for continuity.

II Stabilization

Theorem (Campbell Formula). Let \mathcal{P} be a point process on \mathbb{R}^d with intensity $\kappa(x)$ and let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be a measurable function. Then the random sum

$$\sum_{x \in \mathcal{P}} f(x)$$

has expected value

$$\mathbb{E} \sum_{x \in \mathcal{P}} f(x) = \int_{\mathbb{R}^d} f(x) \kappa(x) dx.$$

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Theorem (Mecke Formula). The random sum

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$$\mathbb{E} \sum_{x \in \mathcal{P}} f(x, \mathcal{P}) = \int_{\mathbb{R}^d} \mathbb{E} f(x, \mathcal{P} \cup \{x\}) \kappa(x) dx.$$

II Stabilization

Let $\mathbb{B}(K)$ denote the class of all bounded $f : K \rightarrow \mathbb{R}$ and for all measures μ on \mathbb{R}^d let $\langle f, \mu \rangle := \int f d\mu$. Put $\bar{\mu} := \mu - \mathbb{E} \mu$.

For all $f \in \mathbb{B}(\mathbb{R}^d)$ we have by Mecke formula that

$$\mathbb{E} [\langle f, \mu_\lambda \rangle] = \lambda \int_{\mathbb{R}^d} f(x) \mathbb{E} [\xi_\lambda(x, \mathcal{P}_{\lambda\kappa})] \kappa(x) dx.$$

If the moment condition

$$\sup_{\lambda} \sup_{x, y \in \mathbb{R}^d} \mathbb{E} |\xi_\lambda(x, (\mathcal{P}_{\lambda\kappa}) \cup \{y\})|^p < \infty$$

holds for some $p > 1$, then uniform integrability and the ‘continuity’ Lemma show that for all Lebesgue points x of κ one has $\mathbb{E} \xi_\lambda(x, \mathcal{P}_{\lambda\kappa}) \rightarrow \mathbb{E} \xi(\mathbf{0}, \mathcal{P}_{\kappa(x)})$ as $\lambda \rightarrow \infty$.

II Stabilization

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$\mathbb{E} \xi_{\lambda}(x, \mathcal{P}_{\lambda\kappa}) \rightarrow \mathbb{E} \xi(\mathbf{0}, \mathcal{P}_{\kappa(x)})$ as $\lambda \rightarrow \infty$.

- The set of points failing to be Lebesgue points has measure zero and so when the moment condition holds for some $p > 1$, the bounded convergence theorem gives

$$\lim_{\lambda \rightarrow \infty} \lambda^{-1} \mathbb{E} [\langle f, \mu_{\lambda} \rangle] = \int_{\mathbb{R}^d} f(x) \mathbb{E} [\xi(\mathbf{0}, \mathcal{P}_{\kappa(x)})] \kappa(x) dx.$$

II Stabilization

Convergence of means $\mathbb{E}[\langle f, \mu_\lambda \rangle]$ is now upgraded to convergence in L^q , $q = 1$ or 2 .

We also prove LLN for

$$\mu_n^\xi := \sum_{i=1}^n \xi_n(X_i, \mathcal{X}_n) \delta_{X_i}$$

where $\mathcal{X}_n := \{X_i\}_{i=1}^n$, $X_i, i \geq 1$, i.i.d. with density κ .

III Binomial and Poisson Input: WLLN

Theorem (WLLN for sums of translation invariant stabilizing functionals)
Let $q = 1$ or $q = 2$. Assume that ξ is translation invariant and stabilizing, so that $\xi(\mathbf{0}, \mathcal{P}_\tau) := \lim_{r \rightarrow \infty} \xi(\mathbf{0}, \mathcal{P}_\tau \cap B_r(\mathbf{0}))$ exists for all $\tau > 0$. If $\sup_n \mathbb{E} |\xi_n(X_1, \mathcal{X}_n)|^p < \infty$ for some $p \in (q, \infty)$, then for all $f \in \mathbb{B}(\mathbb{R}^d)$ we have

$$\begin{aligned} \lim_{n \rightarrow \infty} n^{-1} \langle f, \mu_n \rangle &= \lim_{n \rightarrow \infty} n^{-1} \sum_{i=1}^n \xi_n(X_i, \mathcal{X}_n) f(X_i) \\ &= \int f(x) \mathbb{E} [\xi(\mathbf{0}, \mathcal{P}_{\kappa(x)})] \kappa(x) dx \text{ in } L^q. \end{aligned}$$

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If $\sup_\lambda \mathbb{E} |\xi_\lambda(\mathbf{0}, \mathcal{P}_{\lambda\kappa})|^p < \infty$ for some $p \in (q, \infty)$, then for all $f \in \mathbb{B}(\mathbb{R}^d)$ we have

$$\lim_{\lambda \rightarrow \infty} \lambda^{-1} \langle f, \mu_\lambda \rangle = \int f(x) \mathbb{E} [\xi(\mathbf{0}, \mathcal{P}_{\kappa(x)})] \kappa(x) dx \text{ in } L^q.$$

III Binomial and Poisson Input: WLLN

Corollaries of WLLN. We can deduce a weak law of large numbers for the following statistics:

- clique counts in the random geometric graph on $\mathcal{P}_{\lambda\kappa}$
- total edge length of nearest neighbors graph on $\mathcal{P}_{\lambda\kappa}$
- clump count in the germ grain model on $\mathcal{P}_{\lambda\kappa}$
- number of balls accepted in RSA model on $\mathcal{P}_{\lambda\kappa}$

III Binomial and Poisson Input: Gaussian fluctuations

Recall $\mu_\lambda^\xi := \sum_{x \in \mathcal{P}_1 \cap Q_\lambda} \xi(x, \mathcal{P}_1 \cap Q_\lambda) \delta_{\lambda^{-1/d}x}$.

Thm (CLT): Assume ξ is exponentially stabilizing wrt \mathcal{P}_1 and satisfies the p moment condition for some $p \in (5, \infty)$. If $f \in B([-1/2, 1/2]^d)$ satisfies $\text{Var}\langle \mu_\lambda^\xi, f \rangle = \Omega(\lambda)$, then

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

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

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

Lachièze-Rey, Schulte, + Y (2017): $\epsilon_\lambda = O(\lambda^{-1/2})$ (Stein's method)

III Binomial and Poisson Input: Gaussian fluctuations

The gaussian fluctuation result may be extended to treat:

- binomial input
- stabilizing functionals on input on general metric spaces
- stabilizing functionals on input on manifolds

III Poisson Input: Variance asymptotics

Lemma (continuity lemma for pairs) Let x be a Lebesgue point for κ . If ξ is stabilizing w.r.t. $\mathcal{P}_{\kappa(x)}$, then for all $z \in \mathbb{R}^d$, we have as $\lambda \rightarrow \infty$

$$(\xi_\lambda(x, \mathcal{P}_{\lambda\kappa}), \xi_\lambda(x + \lambda^{-1/d}z, \mathcal{P}_{\lambda\kappa})) \xrightarrow{\mathcal{D}} (\xi(\mathbf{0}, \mathcal{P}_{\kappa(x)}), \xi(z, \mathcal{P}_{\kappa(x)})).$$

We use this lemma to prove variance asymptotics. (Remember it for the next slide.)

III Poisson Input: Variance asymptotics

By Mecke's Formula for the Poisson process $\mathcal{P}_{\lambda\kappa}$ we have

$$\begin{aligned} & \lambda^{-1} \text{Var}[\langle f, \mu_\lambda \rangle] \\ &= \lambda \int_K \int_K f(x) f(y) \{ \mathbb{E} [\xi_\lambda(x, \mathcal{P}_{\lambda\kappa} \cup \{y\}) \xi_\lambda(y, \mathcal{P}_{\lambda\kappa} \cup \{x\})] \\ & \quad - \mathbb{E} [\xi_\lambda(x, \mathcal{P}_{\lambda\kappa})] \mathbb{E} [\xi_\lambda(y, \mathcal{P}_{\lambda\kappa})] \} \kappa(x) \kappa(y) dx dy \\ & \quad + \int_K f(x)^2 \mathbb{E} [\xi_\lambda^2(x, \mathcal{P}_{\lambda\kappa})] \kappa(x) dx. \end{aligned}$$

Put $y = x + \lambda^{-1/d}z$ in the right-hand side of the above (so $\lambda dy = dz$). Then the two point correlation function $\{\dots\}$ becomes

$$\begin{aligned} \{\dots\} &:= \{ \mathbb{E} [\xi_\lambda(x, \mathcal{P}_{\lambda\kappa} \cup \{x + \lambda^{-1/d}z\}) \xi_\lambda(x + \lambda^{-1/d}z, \mathcal{P}_{\lambda\kappa} \cup \{x\})] \\ & \quad - \mathbb{E} [\xi_\lambda(x, \mathcal{P}_{\lambda\kappa})] \mathbb{E} [\xi_\lambda(x + \lambda^{-1/d}z, \mathcal{P}_{\lambda\kappa})] \}. \end{aligned}$$

Now use $\xi_\lambda(x, \mathcal{P}_{\lambda\kappa}) \xi_\lambda(x + \lambda^{-1/d}z, \mathcal{P}_{\lambda\kappa}) \xrightarrow{\mathcal{D}} \xi(\mathbf{0}, \mathcal{P}_{\kappa(x)}) \xi(z, \mathcal{P}_{\kappa(x)})$.

III Poisson Input: Variance asymptotics

- Assuming exponential stabilization, the integrand in the above is dominated by an integrable function of z over \mathbb{R}^d .
- For simplicity we assume that f is a.e. continuous.
- The double integral in the above thus converges to

$$\int_K \int_{\mathbb{R}^d} [\mathbb{E} [\xi(\mathbf{0}, \mathcal{P}_{\kappa(x)} \cup \{z\}) \xi(z, \mathcal{P}_{\kappa(x)} \cup \mathbf{0})] \\ - (\mathbb{E} \xi(\mathbf{0}, \mathcal{P}_{\kappa(x)}))^2] f(x)^2 \cdot \kappa(x)^2 dz dx$$

by dominated convergence, the a.e. continuity of f , and the assumed moment bounds.

III Poisson Input: Variance asymptotics

Given homogenous rate 1 Poisson input \mathcal{P}_1 on \mathbb{R}^d , and a score ξ , put

$$\begin{aligned}\sigma^2(\xi) := & \mathbb{E} \xi^2(\mathbf{0}, \mathcal{P}_1) + \int_{\mathbb{R}^d} [\mathbb{E} \xi(\mathbf{0}, \mathcal{P}_1 \cup \{x\}) \xi(x, \mathcal{P}_1 \cup \{\mathbf{0}\}) \\ & - \mathbb{E} \xi(\mathbf{0}, \mathcal{P}_1) \mathbb{E} \xi(x, \mathcal{P}_1)] dx.\end{aligned}$$

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Thm (variance asymptotics): If ξ is exponentially stabilizing wrt \mathcal{P}_1 and satisfies the p moment condition for some $p \in (2, \infty)$, then for all $f \in B([- \frac{1}{2}, \frac{1}{2}]^d)$ we have

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

Baryshnikov + Y (2005); Penrose (2007)

IV General input

- **Question.** If the input pt process is neither Poisson nor binomial, when do we get results which are qualitatively similar?
- Soshnikov (2002): establishes asymptotic normality of the *count statistic*

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

where \mathcal{P} is determinantal pt process, $\mathcal{P} \cap Q_n := \mathcal{P}_1 \cap [-\frac{1}{2}n^{1/d}, \frac{1}{2}n^{1/d}]^d$.

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- Nazarov and Sodin (2012): establish asymptotic normality of the *count statistic*

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

where \mathcal{P} is zero set of Gaussian analytic function.

- We want to extend these results to more general statistics

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

IV General input

Def (correlation functions). 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

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

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

Rks.

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

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

$\rho^{(k)}(x_1, \dots, x_k) \geq \Pi_{i=1}^k \rho^{(1)}(x_i)$ implies \mathcal{P} is attractive

$\rho^{(k)}(x_1, \dots, x_k) \leq \Pi_{i=1}^k \rho^{(1)}(x_i)$ implies \mathcal{P} is repulsive

IV General input

Key Definition (weak decay of correlations). A pt process \mathcal{P} has *weak decay of correlations (w.d.c.)* 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 $s := \inf_{i \in \{1, \dots, p\}, j \in \{p+1, \dots, p+q\}} \|x_i - x_j\|$.

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Note: 'weak decay of correlations' is called 'clustering' in physics literature.

IV General input

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 non-negative definite kernel of locally trace class integral operator from $L^2(\mathbb{R}^d)$ to itself.

DPP is repulsive

Fact If $|K(x, y)| \leq \phi(\|x - y\|)$, with ϕ fast decreasing, then the DPP has weak decay of correlations.

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Fact If $|K(x, y)| \leq \phi(\|x - y\|)$, with ϕ fast decreasing, then the DPP has weak decay of correlations.

Ex. Infinite Ginibre ensemble on complex plane clusters with kernel

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

IV General input

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 trans. invariant (in the class of Gaussian power series, it is the only one which is trans. inv.).
- Z_F exhibits local repulsivity.
- Z_F has weak decay of correlations (Nazarov and Sodin (2012)).

IV General input

Other examples of pt processes with weak decay of correlations.

- Permanental pt processes with fast decreasing kernel,
- Certain Gibbs pt processes.

IV General input: WLLN

Let \mathcal{P} be a pt process on \mathbb{R}^d with weak decay of correlations (wdc). Recall $\mathcal{P} \cap Q_n := \mathcal{P} \cap [-\frac{n^{1/d}}{2}, \frac{n^{1/d}}{2}]^d$ and

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

Thm (BYY '19): If ξ is stabilizing wrt \mathcal{P} and satisfies the p moment condition for some $p \in (1, \infty)$, then for all $f \in B([- \frac{1}{2}, \frac{1}{2}]^d)$ we have

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

IV General input: Gaussian fluctuations

Thm (BYY '19) $\mu_n^\xi := \sum_{x \in \mathcal{P} \cap Q_n} \xi(x, \mathcal{P} \cap Q_n) \delta_{n^{-1/d}x}$. Assume

- \mathcal{P} has wdc
- 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 $\alpha \in (0, 1)$, $f \in B([- \frac{1}{2}, \frac{1}{2}]^d)$.

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Remarks. When \mathcal{P} is determinantal with fast decreasing kernel, this extends Soshnikov (2002) and Shirai + Takahashi (2003) who restrict to the count statistics $\sum_{x \in \mathcal{P}_n} \delta_{n^{-1/d}x}$, i.e., they put $\xi \equiv 1$.

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

IV General input: Gaussian fluctuations

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

IV General input: Variance asymptotics

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

$$\begin{aligned}\sigma^2(\xi) &:= \mathbb{E} \xi^2(\mathbf{0}, \mathcal{P}) \rho^{(1)}(\mathbf{0}) \\ &+ \int_{\mathbb{R}^d} [\mathbb{E} \xi(\mathbf{0}, \mathcal{P} \cup x) \xi(x, \mathcal{P} \cup \mathbf{0}) \rho^{(2)}(\mathbf{0}, x) \\ &\quad - \mathbb{E} \xi(\mathbf{0}, \mathcal{P}) \rho^{(1)}(\mathbf{0}) \mathbb{E} \xi(x, \mathcal{P}) \rho^{(1)}(x)] dx.\end{aligned}$$

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- Thm (BYY '19):** If ξ is exponentially stabilizing wrt \mathcal{P} , if ξ satisfies the p moment condition for some $p \in (2, \infty)$, then for all $f \in B([- \frac{1}{2}, \frac{1}{2}]^d)$ we have

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

IV General input: Proof of CLT

Cumulants. For a random variable Y with all finite moments, expanding the logarithm of the Laplace transform in a formal power series gives

$$\log \mathbb{E}(e^{tY}) = \log\left(1 + \sum_{k=1}^{\infty} \frac{M_k t^k}{k!}\right) = \sum_{k=1}^{\infty} \frac{S_k t^k}{k!},$$

where $M^k = \mathbb{E}(Y^k)$ is the k th moment of Y and $S_k = S_k(Y)$ denotes the k th cumulant of Y .

Both of the above series can be considered as formal ones and no additional condition (on exponential moments of Y) are required for the cumulants to exist.

IV General input: Proof of CLT

Cumulants.

$$\log \mathbb{E}(e^{tY}) = \log\left(1 + \sum_{k=1}^{\infty} \frac{M^k t^k}{k!}\right) = \sum_{k=1}^{\infty} \frac{S_k t^k}{k!},$$

We have

$$S_k = \sum_{\gamma \in \Pi[k]} (-1)^{|\gamma|-1} (|\gamma| - 1)! \prod_{i=1}^{|\gamma|} M^{|\gamma(i)|},$$

where $\Pi[k]$ is the set of all unordered partitions of the set $\{1, \dots, k\}$, and for a partition $\gamma = \{\gamma(1), \dots, \gamma(l)\} \in \Pi[k]$, $|\gamma|$ denotes the number of its elements (in this case $|\gamma| = l$), while $|\gamma(i)|$ the number of elements of subset $\gamma(i)$. In view of the above, the existence of the k th cumulant S_k follows from the finiteness of the moment M^k .

First cumulant is the mean, second cumulant is the variance.

IV General input: Proof of CLT

Proof idea for CLT.

- Let $X_n, n \geq 1$, be mean zero random variables, $\text{Var}X_n = 1$.
- Put $c_n^k := c^k(X_n)$, $k \in \mathbb{N}$, to be k th order cumulants for X_n .
- Recall $c_n^1 = \mathbb{E} X_n = 0$, $c_n^2 = \text{Var}X_n$.
- **Classic Theorem.** If $\lim_{n \rightarrow \infty} c_n^k = 0$ for all k large, then $X_n \xrightarrow{\mathcal{D}} N(0, 1)$ as $n \rightarrow \infty$.

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- Let $X_n, n \geq 1$, be mean zero random variables, $\text{Var}X_n = 1$.
- Put $c_n^k := c^k(X_n)$, $k \in \mathbb{N}$, to be k th order cumulants for X_n .
- Recall $c_n^1 = \mathbb{E} X_n = 0$, $c_n^2 = \text{Var}X_n$.
- **Classic Theorem.** If $\lim_{n \rightarrow \infty} c_n^k = 0$ for all k large, then $X_n \xrightarrow{\mathcal{D}} N(0, 1)$ as $n \rightarrow \infty$.

The next corollary gives a CLT when the cumulants have linear growth.

- **Corollary.** If $Y_n, n \geq 1$, are mean zero random variables with $c_n^k = O(n)$ for all k large, $\text{Var}Y_n \geq n^\alpha$ for some $\alpha \in (0, \infty)$, then $Y_n / \sqrt{\text{Var}Y_n} \xrightarrow{\mathcal{D}} N(0, 1)$ as $n \rightarrow \infty$.

IV General input: Proof of CLT

Proof idea for CLT

- To show $\langle \mu_n^\xi, f \rangle / \sqrt{\text{Var} \langle \mu_n^\xi, f \rangle} \xrightarrow{\mathcal{D}} N(0, 1)$, by the previous Corollary it suffices to show that k th order cumulant for $\langle \mu_n^\xi, f \rangle$ is $O(n)$.
- Given ξ , consider k mixed moment functions $m_{(k)} : (\mathbb{R}^d)^k \rightarrow \mathbb{R}$ given by

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

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- Need to show that the mixed moments 'cluster', that is for all $k \in \mathbb{N}$ there are constants c_k and C_k 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 φ is fast decreasing and

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

- \mathcal{P} has wdc and ξ exp. stabilizing \Rightarrow mixed moments cluster.

IV General input: Applications

These general results immediately yield limit theory (WLLN, Gaussian fluctuations, variance asymptotics) for statistics of geometric structures on pt processes with wdc. This includes:

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THANK YOU