

# Critical Exponents for Marked Random Connection Models

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# The Marked Random Connection Model

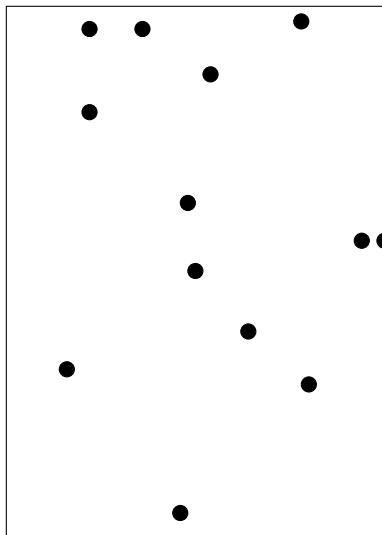
- We produce a random graph on the space  $\mathbb{X} = \mathbb{R}^d \times \mathcal{E}$ , where  $\mathcal{E}$  is the **Mark Space**.
- The **Vertex Set**  $\eta \subset \mathbb{X}$  is a Poisson Point Process with intensity measure  $\lambda\nu$ .  $\lambda > 0$  and  $\nu = \text{Leb} \otimes \mathcal{P}$ , where  $\mathcal{P}$  is a probability measure on  $\mathcal{E}$ .
- Edges form independently according to a given symmetric **Adjacency function**:

$$\varphi(x, y) = \mathbb{P}(x \sim y)$$

where  $x = (\bar{x}, a)$  and  $y = (\bar{y}, b)$ . In order to have spatial translation invariance, we require  $\varphi(x, y) = \varphi(\bar{x} - \bar{y}; a, b)$ .

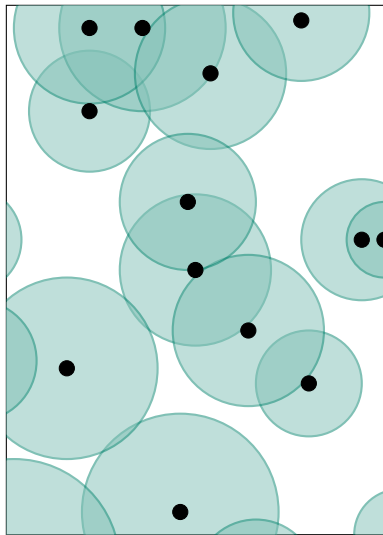
## Example Model: Boolean Hyper-Sphere Model

- First assign vertices to  $\mathbb{R}^d$  according to a PPP with intensity  $\lambda \text{Leb}$ , with  $\lambda > 0$ .



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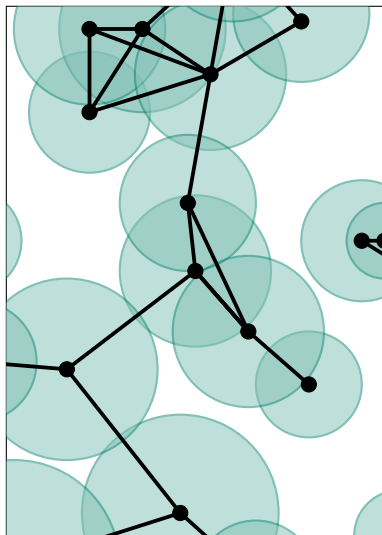
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- Independently assign each vertex a disc with random radius in  $\mathcal{E} = \mathbb{R}_+$  with distribution  $\mathcal{P}$ .
- Edges form between vertices when their discs overlap. This corresponds to

$$\varphi(\bar{x}; a, b) = \mathbb{1} \{|\bar{x}| < a + b\}.$$



## Other Examples

- **Factorisable Models:** Let  $\psi: \mathbb{R}^d \rightarrow [0, 1]$  and  $K: \mathcal{E} \times \mathcal{E} \rightarrow [0, 1]$  be symmetric and measurable. Then let

$$\varphi(\bar{x}; a, b) = \psi(\bar{x}) K(a, b).$$

- **Gaussian Model:** Let  $\Sigma: \mathcal{E}^2 \rightarrow \mathbb{R}^{d \times d}$  be a measurable map where for every  $a, b \in \mathcal{E}$ ,  $\Sigma(a, b)$  is itself a symmetric positive definite covariance matrix. Then let

$$\varphi(\bar{x}; a, b) = (2\pi)^{-d/2} (\det \Sigma(a, b))^{-1/2} \exp\left(-\frac{1}{2} \bar{x}^\top \Sigma(a, b)^{-1} \bar{x}\right).$$

- **Weight-Dependent Models:** Let  $\rho: \mathbb{R}_+ \rightarrow [0, 1]$  be non-increasing and  $g: (0, 1) \times (0, 1) \rightarrow \mathbb{R}_+$  be non-decreasing in both arguments. Then let

$$\varphi(\bar{x}; a, b) = \rho\left(g(a, b) |\bar{x}|^d\right).$$

## Other Examples

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Different choices of  $\rho$  and  $g$  produce various models in the literature:

- Boolean model, Gilbert disk model [Gilbert '61, Hall '85]
- (Soft) random geometric graph [Penrose '93]
- Ultra-small scale-free geometric networks [Yukich '03]
- Scale-free Gilbert graph [Hirsch '17]
- Continuum scale-free percolation [Deprez-Wüthrich '19]
- Geometric inhomogeneous random graphs [Bringmann-Keusch-Lengler '19]
- Age-dependent random connection model [Gracar-Mönch-Mörters '19].

# Critical Intensities

- The *cluster* of  $x$  is given by

$$\mathcal{C}(x) = \{y \in \eta^x : x \longleftrightarrow y \text{ in } \xi^x\}.$$

- Define *susceptibility*:

$$\chi_\lambda: \mathcal{E} \rightarrow [0, \infty], \quad \chi_\lambda(\mathbf{a}) = \mathbb{E}_\lambda [|\mathcal{C}(\bar{0}, \mathbf{a})|],$$

and the *percolation probability*:

$$\theta_\lambda: \mathcal{E} \rightarrow [0, 1], \quad \theta_\lambda(\mathbf{a}) = \mathbb{P}_\lambda (|\mathcal{C}(\bar{0}, \mathbf{a})| = \infty).$$

- For  $p \in [1, \infty]$  there are the associated critical intensities

$$\lambda_T^{(p)} := \inf \left\{ \lambda > 0 : \|\chi_\lambda\|_p = \infty \right\}, \quad \lambda_c^{(p)} := \inf \left\{ \lambda > 0 : \|\theta_\lambda\|_p > 0 \right\}.$$



# Critical Intensities

- Recall

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- Observe

- ▶ For all  $p \in [1, \infty]$ ,  $\lambda_c^{(p)} = \lambda_c$ .
- ▶ For all  $p \in [1, \infty]$ ,  $\lambda_T^{(p)} \leq \lambda_c$ .
- ▶ For all  $1 \leq p_1 \leq p_2 \leq \infty$ ,  $\lambda_T^{(p_1)} \geq \lambda_T^{(p_2)}$ .

## Lemma (D., Heydenreich '22+ & Caicedo, D. '23+)

$$\operatorname{ess\,sup}_{a,b \in \mathcal{E}} \int_{\mathbb{R}^d} \varphi(\bar{x}; a, b) \, d\bar{x} < \infty \implies \lambda_T^{(\infty)} = \lambda_T^{(1)} = \lambda_T.$$

If furthermore  $\varphi > 0$  on a  $\text{Leb} \times \mathcal{P}^2$ -positive set and  $d \geq 2$ , then

$$0 < \lambda_T \leq \lambda_c < \infty.$$

For comparison, in the single-mark case we have  $\lambda_T = \lambda_c$  [Meester '95], and  $\lambda_c \in (0, \infty)$  iff  $\int_{\mathbb{R}^d} \varphi(\bar{x}) \, d\bar{x} \in (0, \infty)$  (for  $d \geq 2$ ) [Penrose '91].

# Critical Exponents

## Recall

$$\chi_\lambda(\mathbf{a}) = \mathbb{E}_\lambda [|\mathcal{C}(\bar{0}, \mathbf{a})|], \quad \theta_\lambda(\mathbf{a}) = \mathbb{P}_\lambda (|\mathcal{C}(\bar{0}, \mathbf{a})| = \infty).$$

- How do  $\chi_\lambda$  and  $\theta_\lambda$  behave near  $\lambda_T$  and  $\lambda_c$ ? Do there exist  $\gamma, \beta$  such that (in a bounded ratio sense)

$$\begin{aligned} \|\chi_\lambda\|_p &\asymp \frac{1}{(\lambda_T - \lambda)^\gamma}, & \text{as } \lambda \nearrow \lambda_T, \\ \|\theta_\lambda\|_p &\asymp (\lambda - \lambda_c)^\beta, & \text{as } \lambda \searrow \lambda_c? \end{aligned}$$

- If you were to consider a spatial branching process with offspring kernel  $\lambda\varphi$ , the analogous quantities would have exponents  $\gamma = 1$  and  $\beta = 1$ . These are called the *mean-field* exponents.

## Some Assumptions ...

Given  $a, b \in \mathcal{E}$  and  $n \geq 1$ , let us define

$$D(a, b) := \int_{\mathbb{R}^d} \varphi(\bar{x}; a, b) \, d\bar{x},$$

$$D^{(n)}(a, b) := \int_{\mathcal{E}^{n-1}} \left( \prod_{j=1}^n D(c_{j-1}, c_j) \right) \mathcal{P}^{\otimes(n-1)}(d\vec{c}_{[1, \dots, n-1]}),$$

where  $c_0 = a$  and  $c_k = b$ .  $D^{(n)}$  is the “matrix product” of  $n$  copies of  $D$ .

### Assumptions (D)

**(D.1)** “Every mark has bounded expected degree with every other mark”

$$\operatorname{ess\,sup}_{a, b \in \mathcal{E}} D(a, b) < \infty,$$

**(D.2)** “Some mark can be connected to every other mark in exactly  $k$  steps for some  $k$ ”

$$\operatorname{ess\,sup}_{a \in \mathcal{E}} \operatorname{ess\,sup}_{k \geq 1} \operatorname{ess\,inf}_{b \in \mathcal{E}} D^{(k)}(a, b) > 0.$$

# Mean Field Bounds

## Theorem (Caicedo, D. '23+)

If Assumptions **(D.1)** and **(D.2)** hold, then there exist  $\varepsilon > 0$  and  $C > 0$  such that

$$\begin{aligned}\|\chi_\lambda\|_p &\geq C(\lambda_T - \lambda)^{-1} && \text{for } \lambda < \lambda_T, \\ \|\theta_\lambda\|_p &\geq C(\lambda - \lambda_T)_+ && \text{for } \lambda < \lambda_T + \varepsilon,\end{aligned}$$

for all  $p \in [1, \infty]$ .

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Oh look!

$$\lambda_T = \lambda_c$$

This theorem had already been proven for the Boolean Hyper-Sphere model [Dembin, Tassion '22] if the radius distribution has finite  $d$ -moments. This is a weaker radius condition than **(D.1)**, but our result can be applied to a wider class of models.

# Mean-Field Behaviour

## Theorem (Caicedo, D. '23+)

If Assumptions **(D.1)**, **(D.2)**, and **(T)** hold, then there exist  $\varepsilon > 0$  and  $C' > 0$  such that

$$\|\chi_\lambda\|_p \leq C' (\lambda_T - \lambda)^{-1} \quad \text{for } \lambda < \lambda_T,$$

$$\|\theta_\lambda\|_p \leq C' (\lambda - \lambda_T)_+ \quad \text{for } \lambda < \lambda_T + \varepsilon,$$

for all  $p \in [1, \infty]$ .

That is,  $\gamma = 1$  and  $\beta = 1$  (they take their mean-field values).

What is **(T)**?

## What is **(T)**?

Define the *two-point function*:

$$\tau_\lambda(x, y) := \mathbb{P}_\lambda(x \longleftrightarrow y \text{ in } \xi^{x,y}).$$

For  $\lambda \geq 0$ , the “triangle diagram” is defined as

$$\Delta_\lambda := \lambda^2 \operatorname{ess\,sup}_{x,y \in \mathbb{X}} \int \tau_\lambda(x, u) \tau_\lambda(u, v) \tau_\lambda(v, y) \nu^{\otimes 2}(du, dv).$$

### Triangle Condition

**(T)** We have

$$\Delta_{\lambda_T} < C_\Delta,$$

where  $C_\Delta > 0$  is a specific constant.

When does **(T)** hold?

For the single-mark RCM, (Heydenreich, van der Hofstad, Last, Matzke '19) gave conditions under which there exists  $d^*$  such that the triangle condition holds for  $d > d^*$ . (It is expected that  $d^* = 6$ . This is not proven.)



## When does **(T)** hold?

Let  $\{\varphi_d\}_{d \geq 1}$  be a sequence of adjacency functions, each on  $(\mathbb{R}^d \times \mathcal{E})^2$ .

### Theorem (D., Heydenreich '22+)

*Given conditions on  $\{\varphi_d\}_{d \geq 1}$  (to be seen shortly), there exists a critical dimension  $d^* \in \mathbb{N}$ , a constant  $C > 0$ , and  $\alpha = \alpha(d)$  such that for  $d > d^*$  and all  $\lambda \in [0, \lambda_T]$ ,*

$$\Delta_\lambda \leq C\alpha.$$

The 'lace expansion' proof relies on deriving a linear operator equation (an Ornstein-Zernike Equation). We therefore need to introduce our operator formalism (relevant for the conditions).

# Operator Notation

- For all  $k \in \mathbb{R}^d$ , let  $\widehat{\varphi}(k; a, b)$  is the Fourier transform of  $\varphi(\bar{x}; a, b)$  and define

$$\widehat{\Phi}(k) : L^2(\mathcal{E}) \rightarrow L^2(\mathcal{E}), \quad \left(\widehat{\Phi}(k) f\right)(a) = \int \widehat{\varphi}(k; a, b) f(b) \mathcal{P}(db).$$

- The important properties of these operators are encoded in their spectra. We have the spectral radius:

$$\rho\left(\widehat{\Phi}(k)\right) = \sup \left\{ |z| : z \in \sigma\left(\widehat{\Phi}(k)\right) \right\}.$$

Since  $\widehat{\Phi}(k)$  is self-adjoint, we can also define the *spectral supremum*:

$$\mathbb{S}\left(\widehat{\Phi}(k)\right) = \sup \left\{ z : z \in \sigma\left(\widehat{\Phi}(k)\right) \subset \mathbb{R} \right\}.$$

- Sometimes easier to work with

$$\left\| \widehat{\Phi}(k) \right\|_{\infty, \infty} = \operatorname{ess\,sup}_{a, b} |\widehat{\varphi}(k; a, b)|.$$

# Marked RCM Assumptions

## Assumption 1

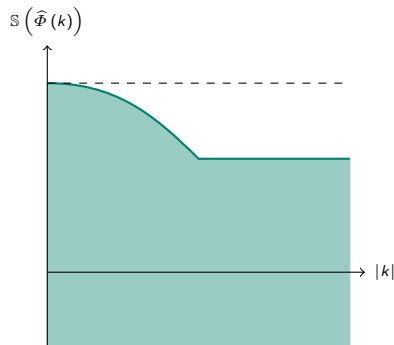
For all dimensions  $d$ , there exists a  $d$ -independent constant  $C > 0$  such that:

$$\mathbb{S}(\widehat{\Phi}(0)) < \infty, \quad \|\widehat{\Phi}(0)\|_{\infty, \infty} \leq C \mathbb{S}(\widehat{\Phi}(0)),$$
$$\|\widehat{\Phi}(0) - \widehat{\Phi}(k)\|_{\infty, \infty} \leq C \left( \mathbb{S}(\widehat{\Phi}(0)) - \mathbb{S}(\widehat{\Phi}(k)) \right).$$

## Assumption 2

There exist  $d$ -independent constants  $C_1 \in (0, 1)$  and  $C_2 > 0$  such that

$$\mathbb{S}(\widehat{\Phi}(k)) \leq [C_1 \vee (1 - C_2 |k|^2)] \mathbb{S}(\widehat{\Phi}(0)).$$



# Marked RCM Assumptions

By a spatial scaling argument, w.l.o.g.  $\mathbb{S}(\widehat{\Phi}(0)) = 1$ .

## Assumption 3

There exists a function  $g: \mathbb{N} \rightarrow \mathbb{R}_{\geq 0}$  with the following three properties:

- 1 that  $g(d) \rightarrow 0$  as  $d \rightarrow \infty$ ,
- 2 that

$$\operatorname{ess\,sup}_{\bar{x} \in \mathbb{R}^d, a_1, \dots, a_6 \in \mathcal{E}} (\varphi(\cdot; a_1, a_2) \star \varphi(\cdot; a_3, a_4) \star \varphi(\cdot; a_5, a_6))(\bar{x}) \leq g(d),$$

- 3 and that the family of sets  $\{B(x)\}_{x \in \mathbb{X}}$  given by

$$B(x) := \left\{ y \in \mathbb{R}^d \times \mathcal{E} : \int \varphi(x, u) \varphi(u, y) \nu(du) > g(d) \right\}$$

satisfy  $\operatorname{ess\,sup}_{x \in \mathbb{R}^d \times \mathcal{E}} \nu(B(x)) \leq g(d)$ .

# Proof Outline

- Recall the *two-point function*:

$$\tau_\lambda(x, y) := \mathbb{P}_\lambda(x \longleftrightarrow y \text{ in } \xi^{x,y}),$$

and define the associated  $\widehat{\tau}_\lambda(k; a, b)$  and  $\widehat{\mathcal{T}}_\lambda(k)$ .

- Lace Expansion:** For  $\lambda \in [0, \lambda_T)$ ,

$$\widehat{\mathcal{T}}_\lambda(k) = \widehat{\Phi}(k) + \widehat{\Pi}_{\lambda,n}(k) + \lambda \widehat{\mathcal{T}}_\lambda(k) \left( \widehat{\Phi}(k) + \widehat{\Pi}_{\lambda,n}(k) \right) + \widehat{R}_{\lambda,n}(k).$$

These  $\widehat{\Pi}_{\lambda,n}(k)$  are constructed by counting configurations with  $\leq n$  pivotal points.

- Bounding  $\widehat{\Pi}_{\lambda,n}(k)$  with triangles:** We can count these configurations using thinnings, Mecke's formula, and BK inequality to get bounds in terms of integrals. By supremum bounds, we can extract triangles and other similar shapes.

# Proof Outline

- **Compare to Random walk:** Define

$$\widehat{G}_{\mu_\lambda}(k) := \frac{1}{1 - \mu_\lambda \mathbb{S}(\widehat{\Phi}(k))}, \quad f(\lambda) := \operatorname{ess\,sup}_{k \in \mathbb{R}^d} \frac{\rho(\widehat{\mathcal{T}}_\lambda(k))}{\widehat{G}_{\mu_\lambda}(k)}.$$

In the single-mark model,  $\widehat{G}_{\mu_\lambda}(k)$  is the Fourier transform of the Green's function of a random walk with jump density  $\varphi$ . We can use  $f(\lambda)$  to replace factors of the 'unknown'  $\tau_\lambda$  in the triangles with the 'known'  $\varphi$ .

- **Sub-critical Convergence:** For  $d$  sufficiently large, we can show that the  $\widehat{G}_{\mu_\lambda}$ -triangle (and the original  $\tau_\lambda$ -triangle) are small, and therefore the expansion converges for  $\lambda < \lambda_T$ .

$$\widehat{\mathcal{T}}_\lambda(k) = \widehat{\Phi}(k) + \widehat{\Pi}_\lambda(k) + \lambda \widehat{\mathcal{T}}_\lambda(k) \left( \widehat{\Phi}(k) + \widehat{\Pi}_\lambda(k) \right). \quad (\text{OZE})$$

- **Uniform Sub-critical Convergence:** Using this expansion, we show that  $f(\lambda)$  is uniformly bounded on the entire sub-critical regime (by a forbidden range argument). This also gives a uniform bound  $\Delta_\lambda \leq C\alpha$  for  $\lambda < \lambda_T$ .
- **Extend (OZE) to Criticality:** By Monotone and Dominated convergence arguments, (OZE) holds at  $\lambda = \lambda_T$  and  $\Delta_{\lambda_T} \leq C\alpha$ .

# References

- Alejandro Caicedo and Matthew Dickson. *Critical exponents for marked random connection models*. Preprint arXiv:2305.07398 [math.PR].
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- Markus Heydenreich, Remco van der Hofstad, Günter Last, and Kilian Matzke. *Lace expansion and mean-field behavior for the random connection model*, Preprint arXiv:1908.11356 [math.PR].