

Comparison of point processes and applications to random geometric networks

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- ▶ **Stationary** : $\Phi + x \stackrel{d}{=} \Phi$.
- ▶ $\Rightarrow E(\Phi(B)) = \lambda |B|$. Assume $\lambda = 1$.

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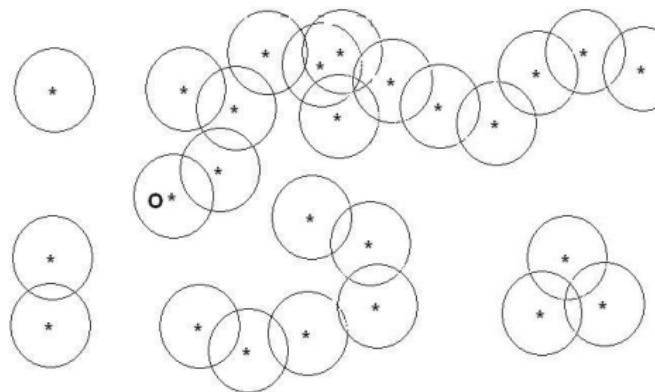
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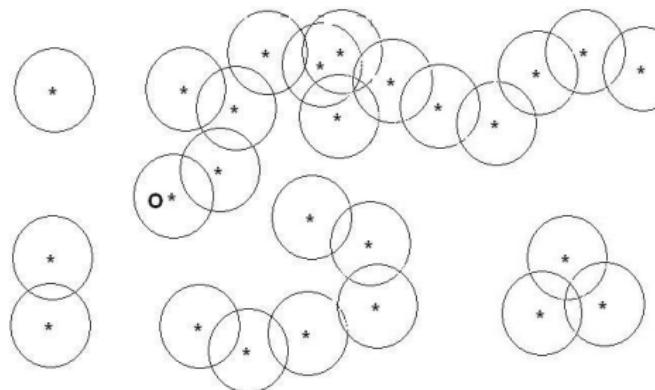
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- ▶ Generic methods ?

Percolation

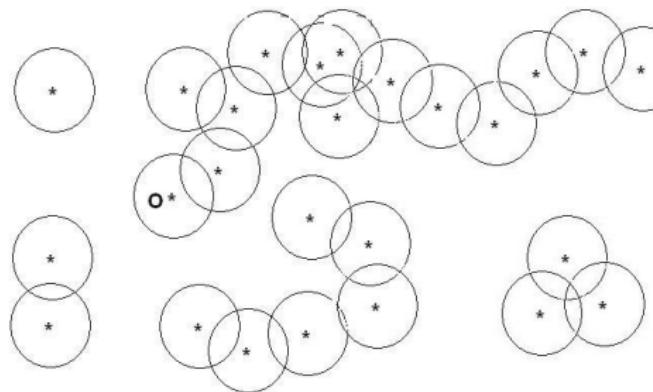


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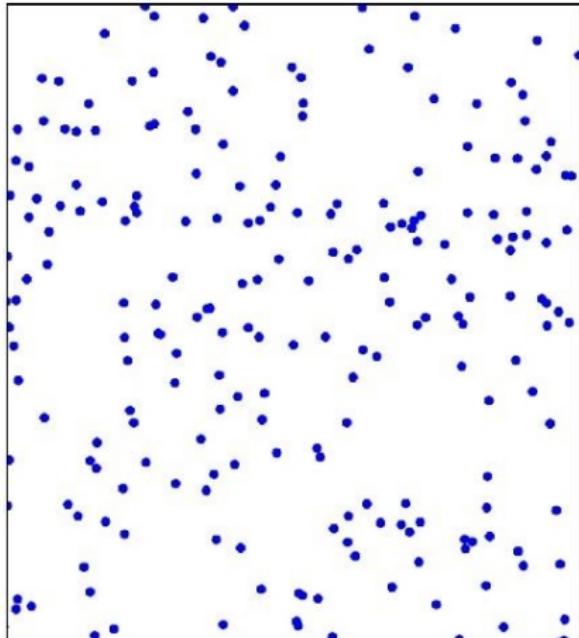
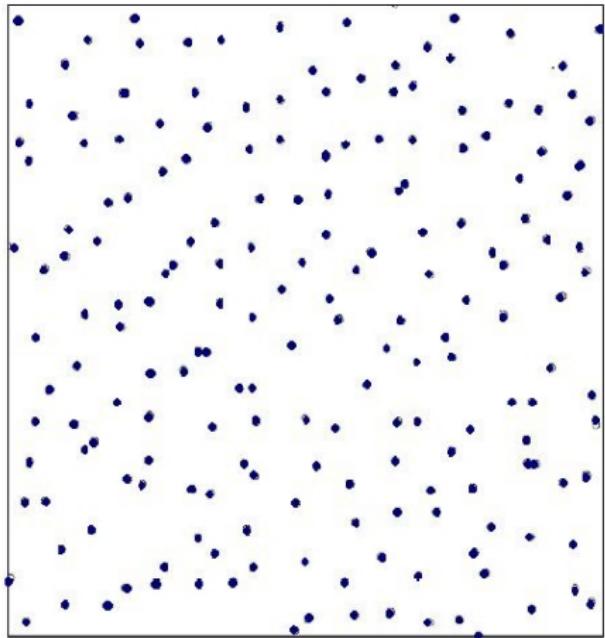
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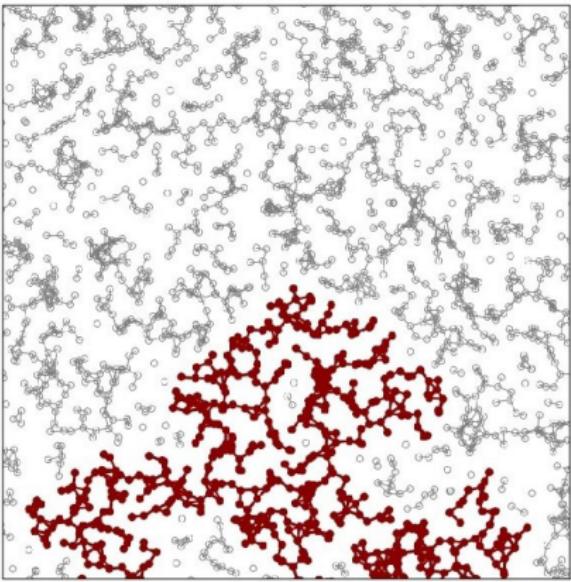
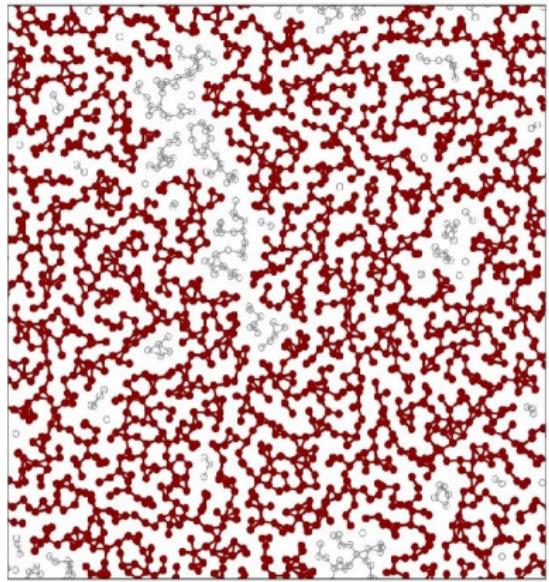


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- ▶ $r_c(\Phi) := \inf\{r : P(0 \text{ percolates in } C(\Phi, r)) > 0\}$.

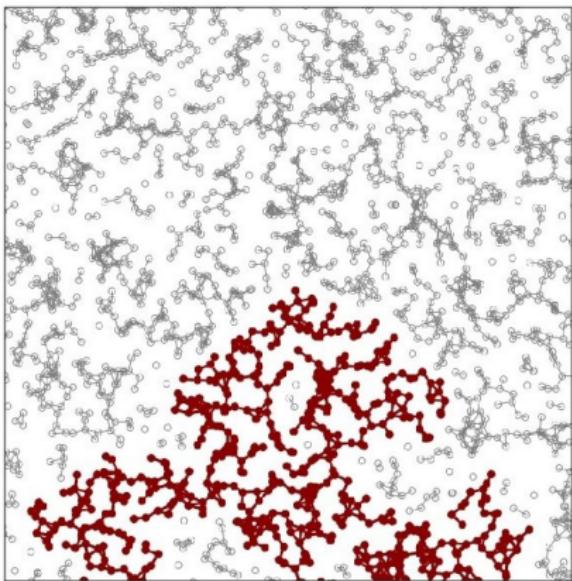
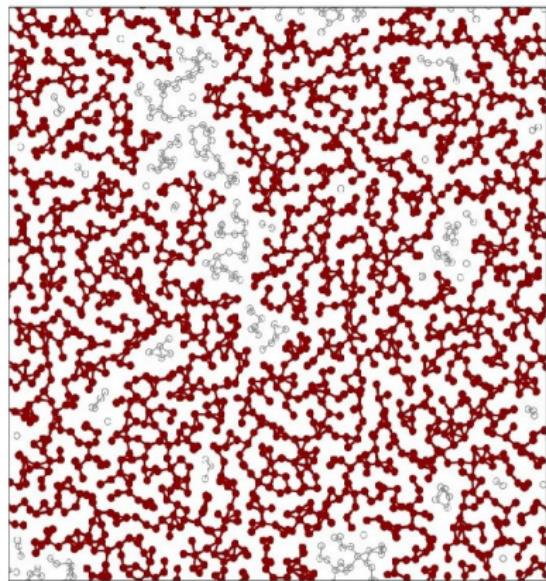
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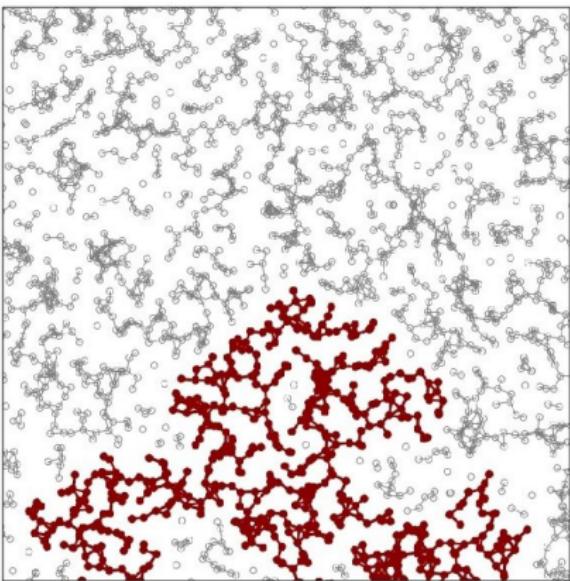
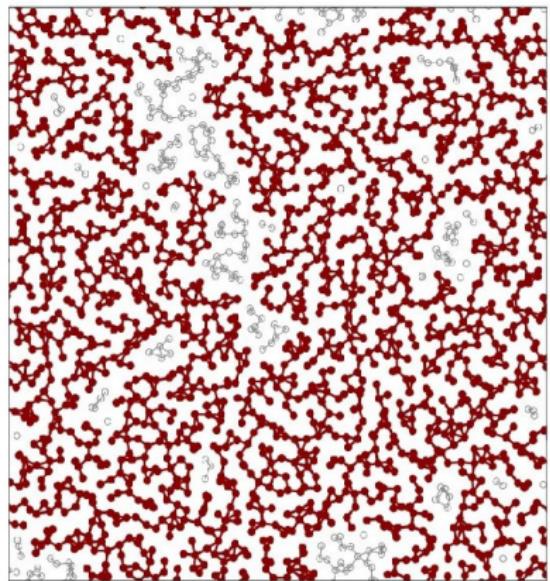


Percolation and clustering



- ▶ $G(\Phi, r) : (X, Y)$ an edge if $|X - Y| \leq 2r$. Percolation = infinite component.

Percolation and clustering



- ▶ $\Phi_1 \leq_{\text{clustering}} \Phi_2 \Rightarrow r_c(\Phi_1) \leq r_c(\Phi_2)$!

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 - ▶ In other words, a **simple but not simple enough** partial order !

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 - ▶ $P(\Phi(B) = 0) \leq e^{-|B|} = P(\Phi_{(1)}(B) = 0)$.
- ▶ Can be extended to a Partial order on point processes.

Ordering of Laplace transforms

- ▶ For $f \geq 0$ or $f \leq 0$,

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- ▶ Setting $|B_n| = n$, $f(x) = \mathbf{1}[x \in B_n] \Rightarrow$

- ▶ Concentration inequality :

$$P(|\Phi(B_n) - n| \geq n^a) \leq 2 \exp[-n^{2a-1}/9], \quad a > \frac{1}{2}.$$

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- ▶ i.e., $\forall f$ dcx,

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- ▶ **sub-Poisson : Perturbed lattices, Ginibre Ensemble:**
Eigenvalues of $N \times N$ matrix with i.i.d. standard complex Gaussian entries as $N \rightarrow \infty$.

Negative Association

- Φ - **negatively associated** if for f, g increasing functions and A_1, \dots, A_n disjoint

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- ▶ **Φ is NA,** $\Phi(A) \leq_{convex} Poi(\lambda|A|) \Rightarrow \Phi \leq_{dcx} \Phi_{(\lambda)}$.
- ▶ **NA point processes :** Simple perturbed lattice, Some determinantal point processes.

Recap

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- ▶ $NA+ \Rightarrow DCX$ sub-Poisson \Rightarrow weak sub-Poisson \Rightarrow Laplace transform ordering.

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- ▶ Comparison of SINR coverage and capacity under *dcx* assumption.

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- ▶ More concentration inequalities ?
- ▶ Other functionals, Eg. Capacity ?
- ▶ Where do Gibbs point processes fit in ?

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 $(V_{\Phi_1}(y_1), \dots, V_{\Phi_1}(y_n)) \leq_{dcx} (V_{\Phi_2}(y_1), \dots, V_{\Phi_2}(y_n)).$

Some References

- ▶ Clustering Comparison of Point Processes, with Applications to Random Geometric Models - Book Chapter in *Springer Lecture Notes in Mathematics on Stochastic Geometry, Spatial Statistics and Random Fields.* B. B., D. Y.
- ▶ More detailed slides on Bartek Błaszczyzyn's webpage.