

Limit theorems for random geometric complexes in the thermodynamic regime

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Indian Statistical Institute, Bangalore.

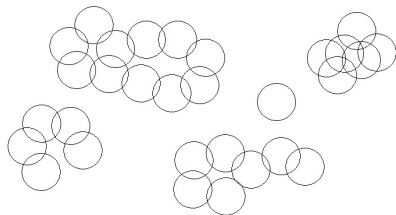
Joint work with: E. Subag & R. J. Adler

Weizmann Institute & Technion, Israel.

ISID, Nov 2015.

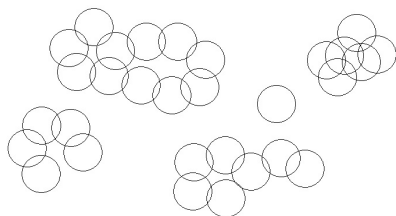
Boolean Model

- ▶ $C_B(\mathcal{X}, r) := \bigcup_{x \in \mathcal{X}} B_x(r)$; $\mathcal{X} \subset \mathbb{R}^d$; $d \geq 2$.



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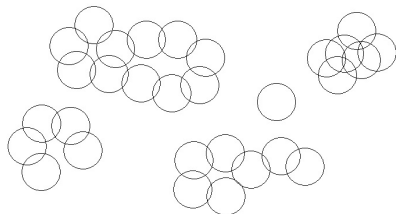
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- ▶ **Geometric properties** : Volume, Surface measures, Intrinsic volumes.

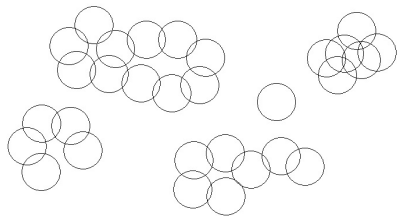
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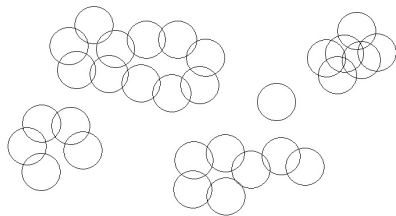


- ▶ **Geometric properties** : Volume, Surface measures, Intrinsic volumes.
- ▶ **Combinatorial properties** : Subgraph counts, Component counts.

Algebraic Topology Viewpoint

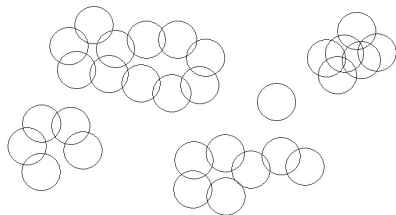


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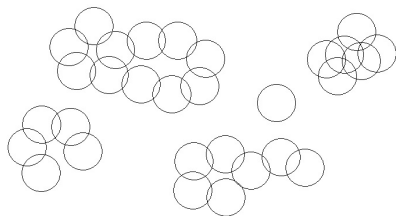
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- ▶ What about the holes ?

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Figure: $\beta_0(T) = 1, \beta_1(T) = 2, \beta_2(T) = 1$.

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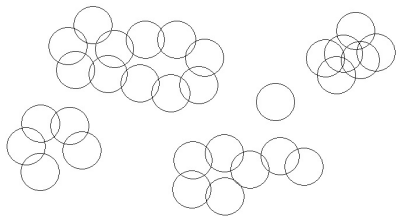
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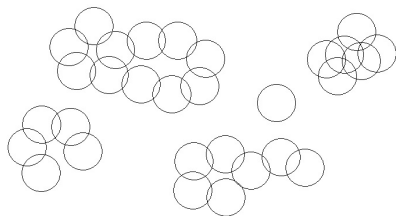
Figure: $\beta_0(S) = 1, \beta_1(S) = 0, \beta_2(S) = 1.$

- ▶ Alexander's duality : $\beta_{d-1}(A) = \beta_0(\mathbb{R}^d \setminus A) - 1.$

The example of Boolean Model

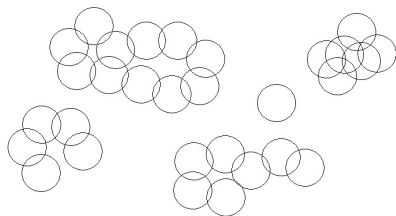


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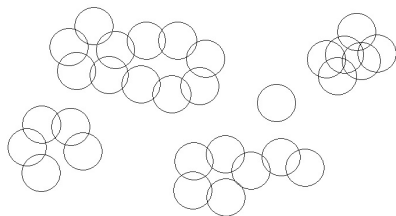
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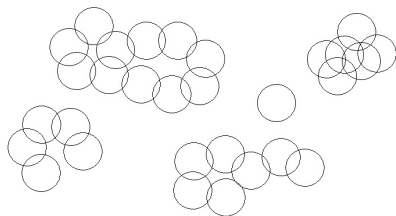
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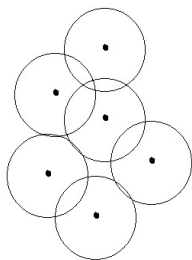
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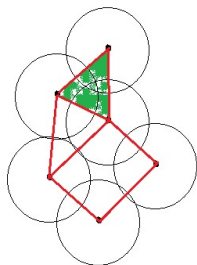


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- ▶ $\chi(C_B(\mathcal{X}, r)) := \sum_{k \geq 0} (-1)^k \beta_k(C_B(\mathcal{X}, r)) = 2.$

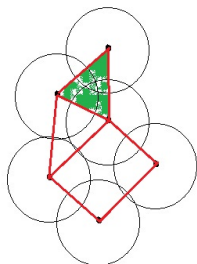
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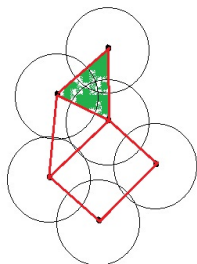


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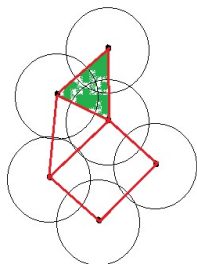
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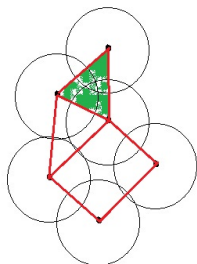


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Cech complex $C(\Phi, r) := \bigcup_{k=0}^{\infty} C_k(\Phi, r) \subset 2^{\Phi}$.

Nerve Theorem

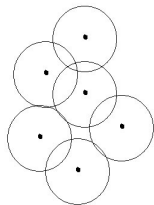
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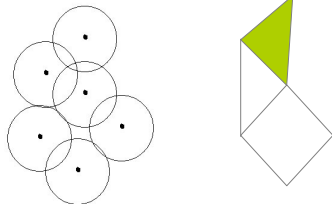


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Nerve theorem : Čech complex $\equiv \cup_i B_r(X_i)$, Boolean model.



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- ▶ $\beta_k(C(\mathcal{P}_n, r_n)), \beta_k(C(\mathcal{X}_n, r_n))$ as $n \rightarrow \infty, nr_n^d \rightarrow r$?

Variance Bounds

- ▶ Add-one cost or difference operator : \mathcal{X} finite set, $x \in \mathbb{R}^d$

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- ▶ Poincaré or Efron-Stein inequalities

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- ▶ Variance bounds of **Last-Peccati-Schulte (2015)**:

$$\text{VAR}(\beta_{d-1}(C(\mathcal{P}_n, r_n))) = \Omega(n).$$

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- ▶ Strong and weak laws hold for Ergodic point processes under appropriate asymptotics. Proof via sub-additive arguments.

Central Limit Theorem

- ▶ \mathcal{P} - Poisson (1) pp in \mathbb{R}^d ; $\mathcal{P}_n = \mathcal{P} \cap W_n$,
 $W_n := \left[-\frac{n^{1/d}}{2}, \frac{n^{1/d}}{2}\right]^d$.

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