

Mobile Geometric Graphs: Detection, Isolation and Percolation

Perla Sousi ¹

Based on joint works with

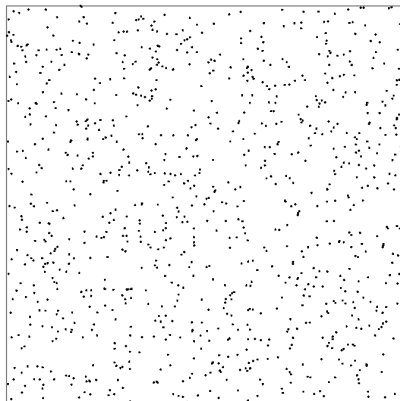
Yuval Peres, Alistair Sinclair, Alexandre Stauffer

¹Emmanuel College, University of Cambridge

Random Geometric Graph (Boolean Model)

Nodes: Poisson point process in \mathbb{R}^d , intensity λ

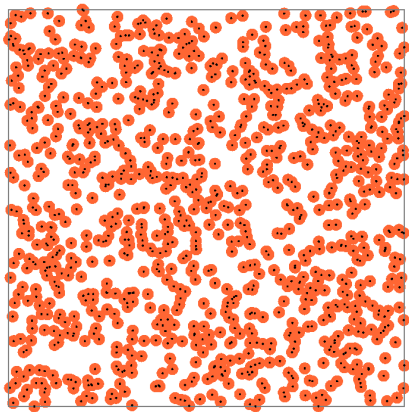
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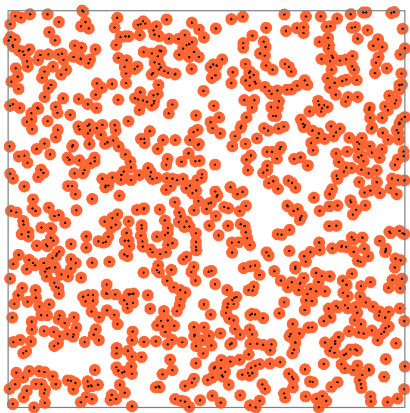
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Obtain stationary sequence of graphs $(G_s)_{s \geq 0}$

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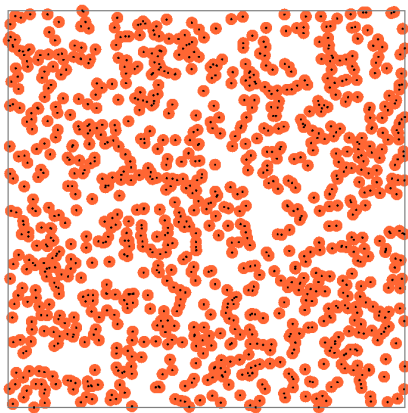


time 0

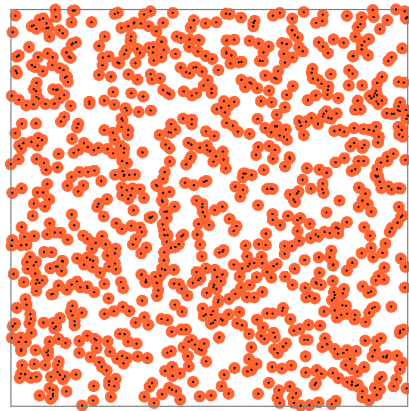
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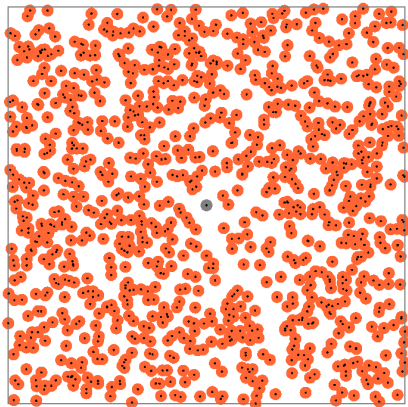
Detection in a mobile geometric graph

Target particle initially at origin

T_{det} = 1st time some node within distance r of target

Want to study $\mathbb{P}(T_{\text{det}} > t)$

$\mathbb{P}(\text{target not detected at fixed } s) = \mathbb{P}(T_{\text{det}} > 0) = e^{-\lambda\pi r^2}$



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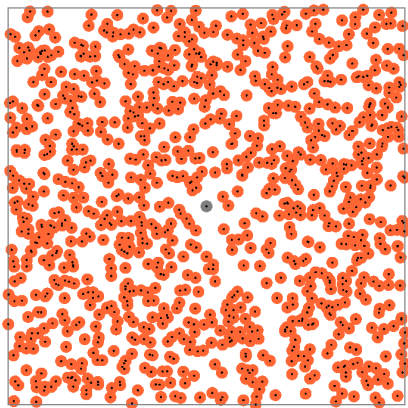
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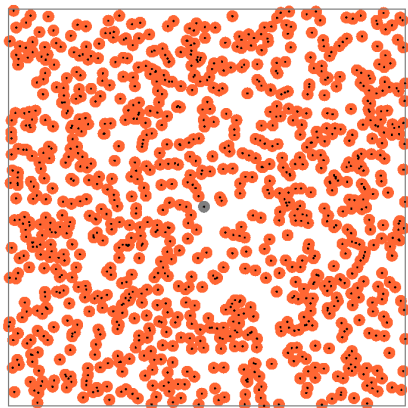
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Detection of a non-mobile target

Lemma (Classical result of stochastic geometry)

Let ξ be a standard Brownian motion and $W_r(t) = \cup_{s \leq t} \mathcal{B}(\xi(s), r)$, the Wiener sausage up to time t . Then

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In dimension 3 and above as $t \rightarrow \infty$

$$\mathbb{P}(T_{\text{det}}^f > t) \leq \exp(-\lambda\alpha(d)c_d r^{d-2} t (1 + o(1))).$$

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The **symmetric rearrangement** of A , denoted A^* , is a ball centered at the origin with $\text{vol}(A^*) = \text{vol}(A)$.

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Theorem (Special case of Brascamp, Lieb, Luttinger (1974))

Let $A_1, \dots, A_n \subset \mathbb{R}^d$ of finite volume and $\psi : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}_+$ a nonincreasing function of distance. Then

$$\begin{aligned} & \int_{\mathbb{R}^d} \dots \int_{\mathbb{R}^d} \prod_{0 \leq i \leq n} \mathbf{1}(x_i \in A_i) \prod_{1 \leq i \leq n} \psi(x_{i-1}, x_i) dx_0 \dots dx_n \\ & \leq \int_{\mathbb{R}^d} \dots \int_{\mathbb{R}^d} \prod_{0 \leq i \leq n} \mathbf{1}(x_i \in A_i^*) \prod_{1 \leq i \leq n} \psi(x_{i-1}, x_i) dx_0 \dots dx_n. \end{aligned}$$

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Let $d \geq 1$ and $f : \mathbb{R}_+ \rightarrow \mathbb{R}^d$ be a deterministic motion of the target.
Then for all t we have

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Note that f does not need to be continuous.

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where r is such that $\text{vol}(\mathcal{B}(0, r)) = c$.

More general result

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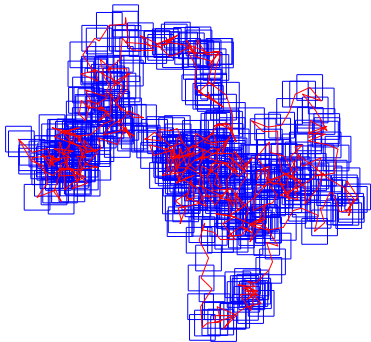
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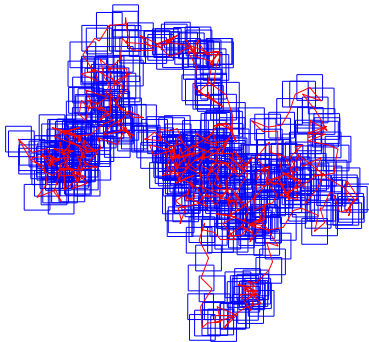
In particular this gives that the expected volume of the Wiener sausage with squares is bigger than the expected volume with balls.

Squares vs disks

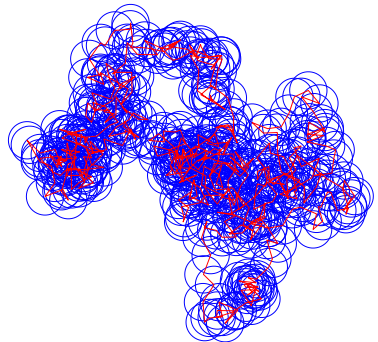


Wiener sausage with squares

Squares vs disks



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A connection to capacity

Spitzer and Whitman(1964) proved that in $d \geq 3$, if $A \subset \mathbb{R}^d$ is an open set with finite volume, then

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Our theorem is a refinement of a classical inequality due to Pólya and Szëgo:

In $d \geq 3$ among all open sets of fixed volume, the ball has the smallest Newtonian capacity.

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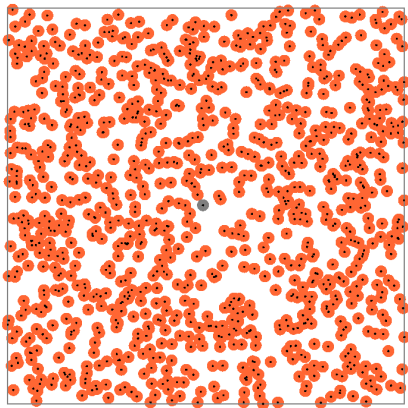
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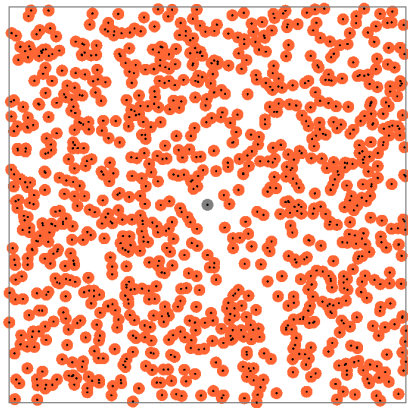
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time 0



time T_{isol}

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$$\Psi_d(t) = \begin{cases} \sqrt{t}, & \text{for } d = 1 \\ \log t, & \text{for } d = 2 \\ 1, & \text{for } d \geq 3. \end{cases} \quad (1)$$

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Theorem (Peres, S., Stauffer (2011))

For all $d \geq 1$ as $t \rightarrow \infty$

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Lower bound matches upper bound in $d \geq 3$ and up to logarithmic factors in the exponent in $d = 2$.

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Theorem (Peres, S., Stauffer (2012))

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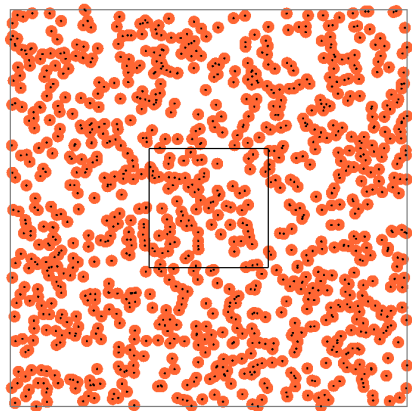
Proof uses rearrangement inequalities of Brascamp, Lieb, Luttinger ('74) and a new decoupling idea.

Coverage

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$T_{\text{cov}}(Q_R) =$ 1st time all points of Q_R have been detected

Open problem proposed in Konstantopoulos'09.



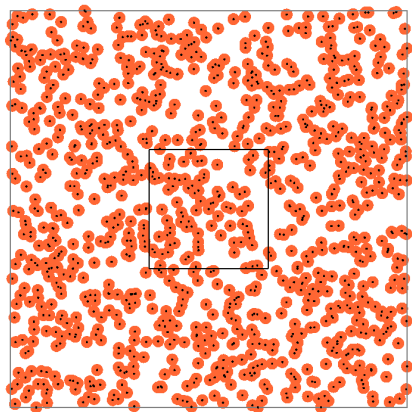
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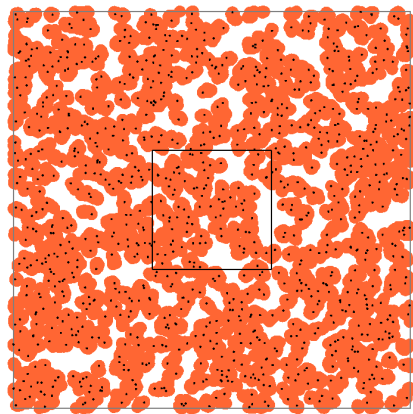
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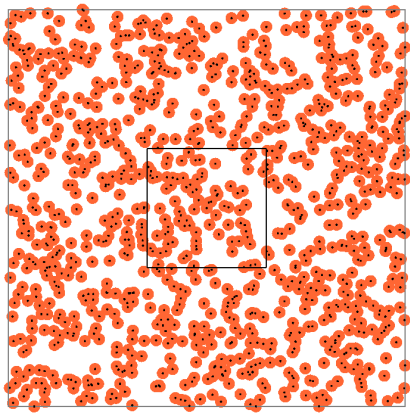


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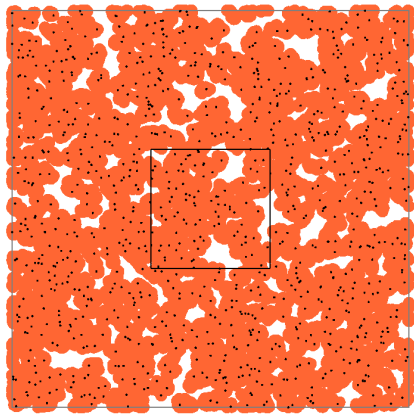
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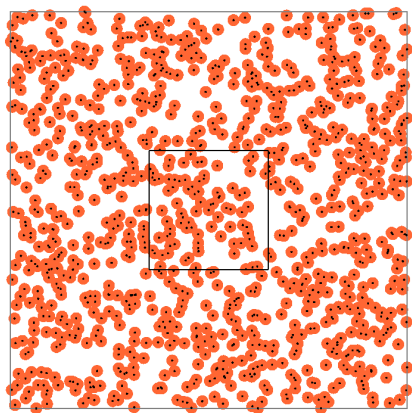


Coverage

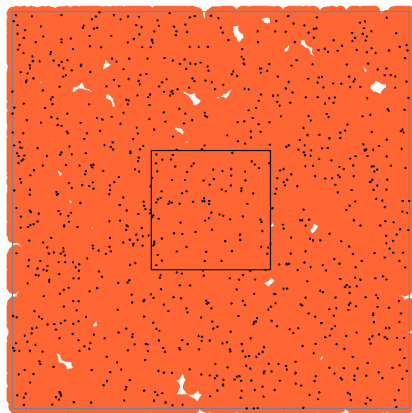
Q_R = cube of side length R

$T_{\text{cov}}(Q_R)$ = 1st time all points of Q_R have been detected

Open problem proposed in Konstantopoulos'09.



time 0



time $T_{\text{cov}}(Q_R)$

Theorem (Peres, Sinclair, S., Stauffer)

As $R \rightarrow \infty$, we have that

$$\mathbb{E} T_{\text{cov}}(Q_R) \sim \frac{2}{2\pi\lambda} \log R \log \log R \quad \text{and} \quad \frac{T_{\text{cov}}(Q_R)}{\mathbb{E} T_{\text{cov}}(Q_R)} \rightarrow 1 \text{ in probability}$$

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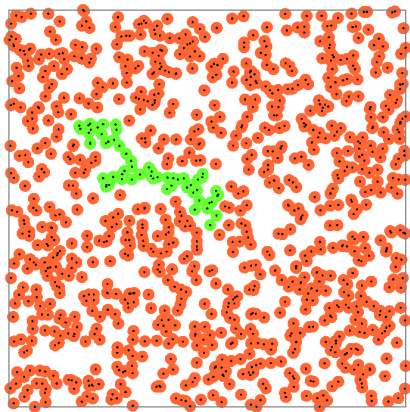
Theorem ((General result), Peres, Sinclair, S., Stauffer)

For a set A and $R > 0$, let $RA = \{Ra : a \in A\}$. If A has Minkowski dimension α , then as $R \rightarrow \infty$

$$\mathbb{E} T_{\text{cov}}(RA) \sim \frac{\alpha}{2\pi\lambda} \log R \log \log R \quad \text{and} \quad \frac{T_{\text{cov}}(RA)}{\mathbb{E} T_{\text{cov}}(RA)} \rightarrow 1 \text{ in probability}$$

Percolation on Mobile Geometric Graph

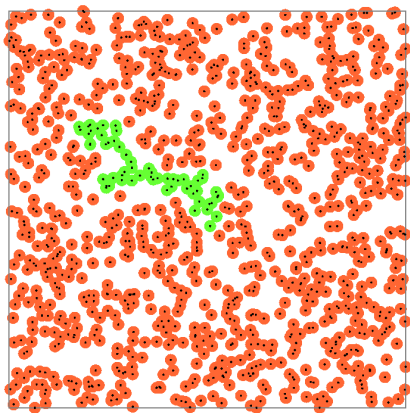
$\exists \lambda_c$ s.t. $\lambda > \lambda_c \Rightarrow$ a.s. \exists infinite component at fixed time s



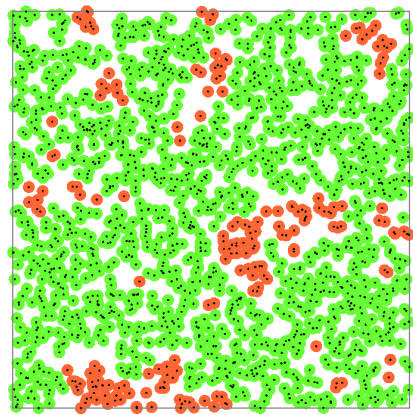
$\lambda < \lambda_c$

Percolation on Mobile Geometric Graph

$\exists \lambda_c$ s.t. $\lambda > \lambda_c \Rightarrow$ a.s. \exists infinite component at fixed time s



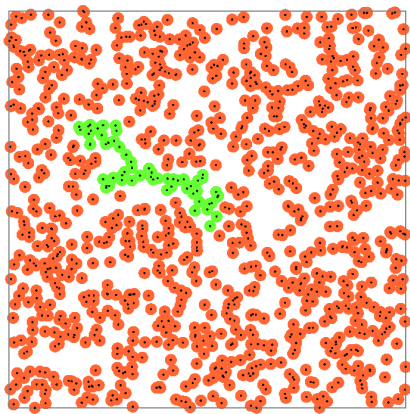
$\lambda < \lambda_c$



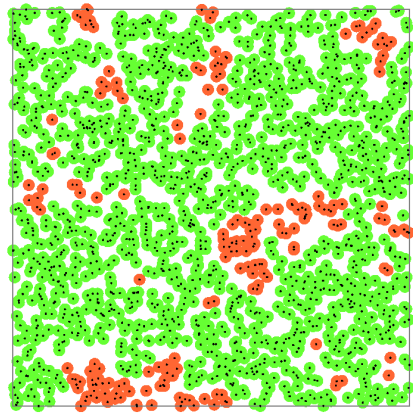
$\lambda > \lambda_c$

Percolation on Mobile Geometric Graph

$\lambda > \lambda_c \Rightarrow$ a.s. \exists infinite component for every s (van den Berg, Meester, White'97)



$\lambda < \lambda_c$



$\lambda > \lambda_c$

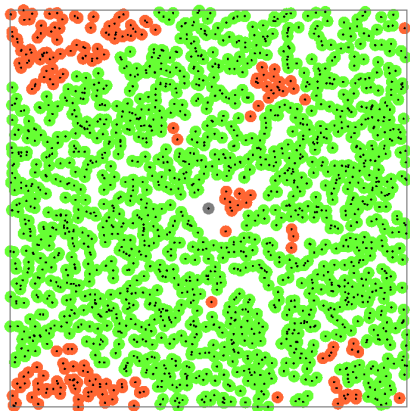
Percolation

Target particle initially at origin

We assume $\lambda > \lambda_c$

T_{perc} = 1st time target belongs to infinite component

Want to study $\mathbb{P}(T_{\text{perc}} > t)$



time 0

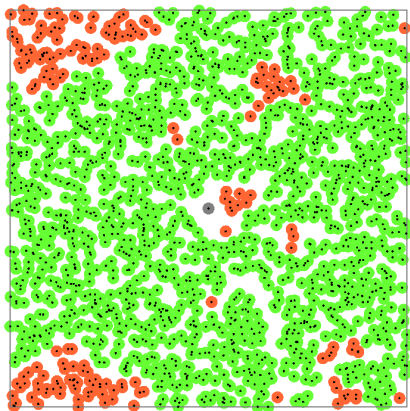
Percolation

Target particle initially at origin

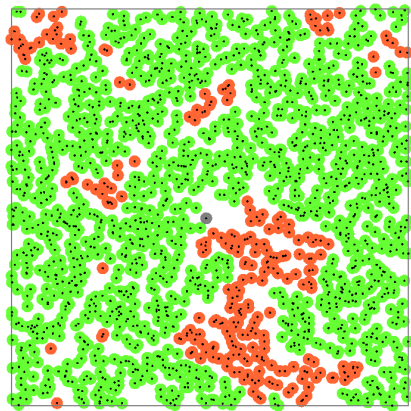
We assume $\lambda > \lambda_c$

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time 0



time T_{perc}

Lower bound in discrete time via FKG (extends to continuous time):

$$\mathbb{P}(\text{target} \notin \text{infinite component at time } s) = \mathbb{P}(T_{\text{perc}} > 0) = e^{-c}$$

$$\text{FKG} \Rightarrow \mathbb{P}(T_{\text{perc}} > t) \geq e^{-ct}$$

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Lower bound via detection:

$$\mathbb{P}(T_{\text{perc}} > t) \geq \mathbb{P}(T_{\text{det}} > t) \geq e^{-c''t/\log t}$$

Upper bound:

$$\mathbb{P}(T_{\text{perc}} > t) \leq \exp(-c\sqrt{t})$$

(Sinclair, Stauffer 2010)

Upper bound:

$$\mathbb{P}(T_{\text{perc}} > t) \leq \exp(-c\sqrt{t}) \quad (\text{Sinclair, Stauffer 2010})$$

Theorem (Peres, Sinclair, S., Stauffer (2010))

If $\lambda > \lambda_c$, then \exists constant c s.t.

$$\mathbb{P}(T_{\text{perc}} > t) \leq \exp(-ct/\log^6 t), \text{ for all } t \text{ large enough}$$

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Proof uses coupling and multiscale analysis.



Y. Peres, A. Sinclair, P. Sousi, and A. Stauffer.

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The isolation time of Poisson Brownian motions.
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