

# Localisation and delocalisation in the parabolic Anderson model

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joint works (2006 – 2017) with  
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Stephen Muirhead (Kings), Marcel Ortgiese (Bath), Richard Pymar (Birkbeck),  
Aleksander Twarowski (London)

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4 October 2017

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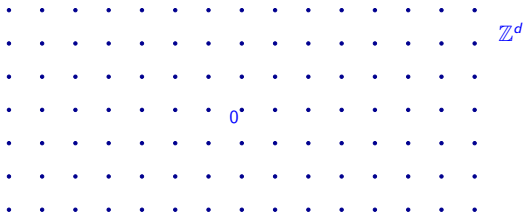
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How does  $u(t, \cdot)$  behave as  $t \rightarrow \infty$ ?

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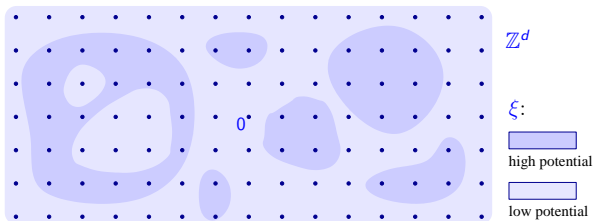
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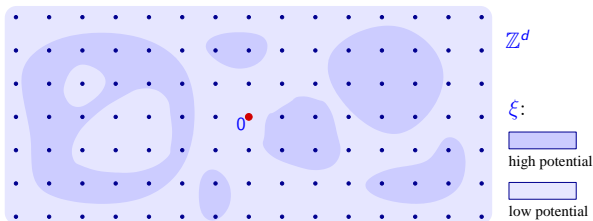
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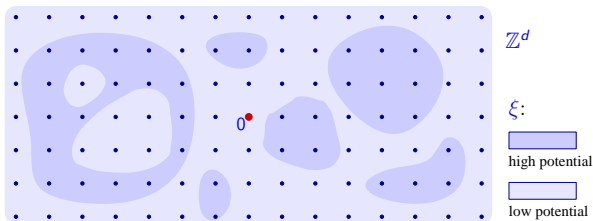
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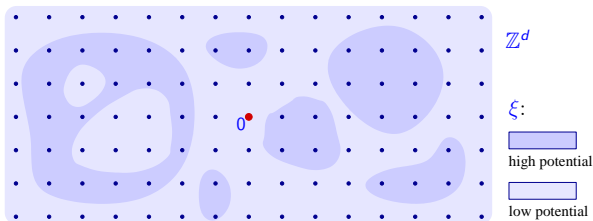
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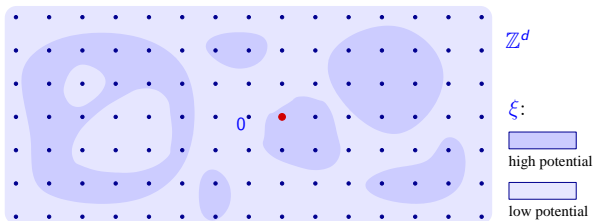
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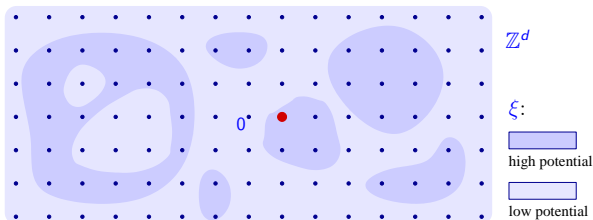
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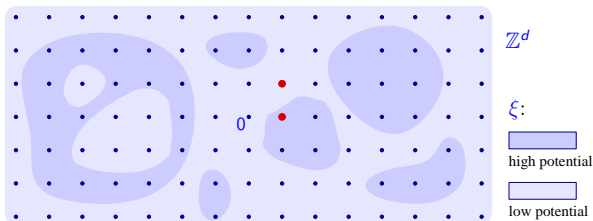
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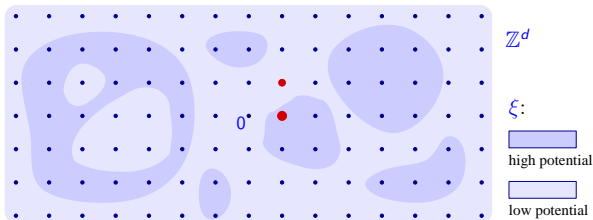
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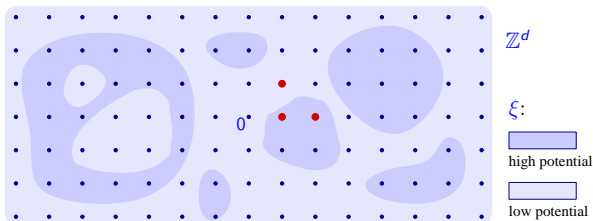
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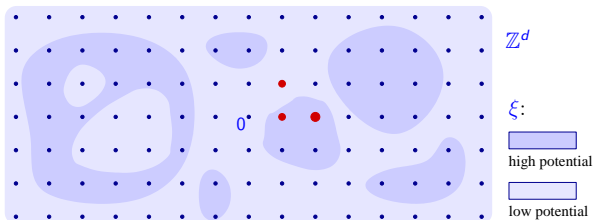
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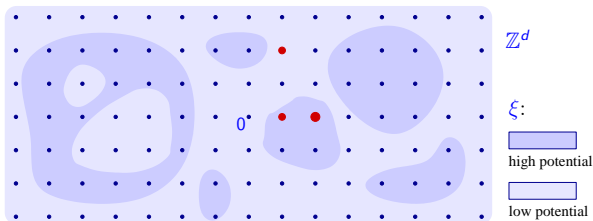
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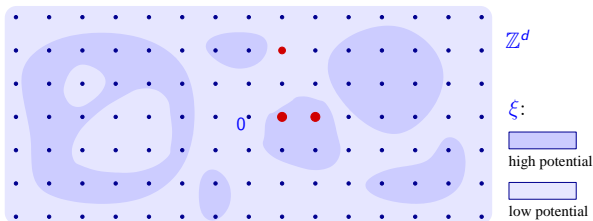
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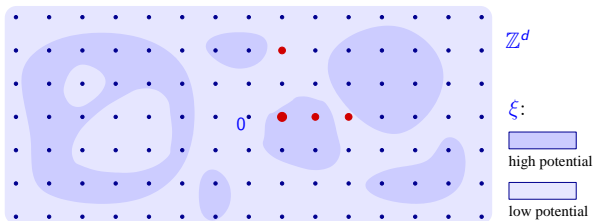
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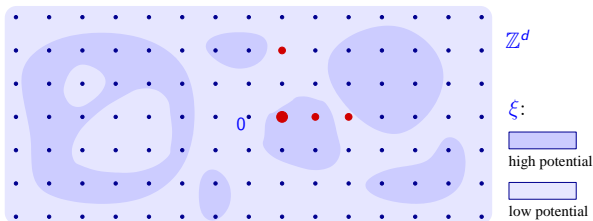
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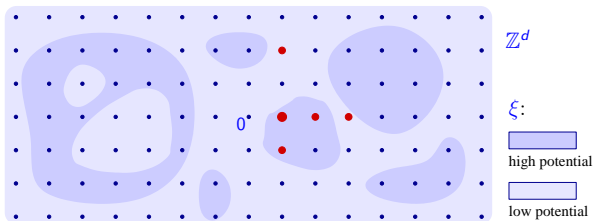
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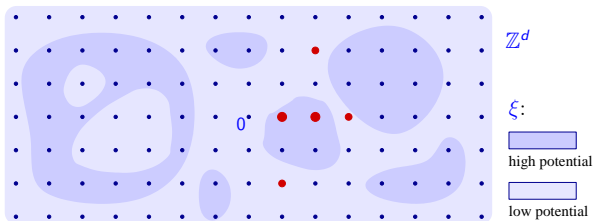
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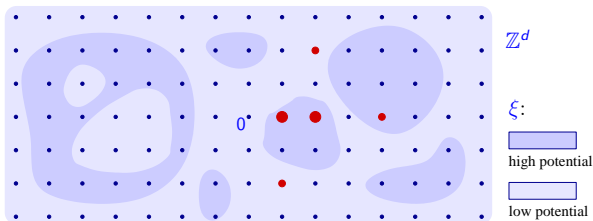
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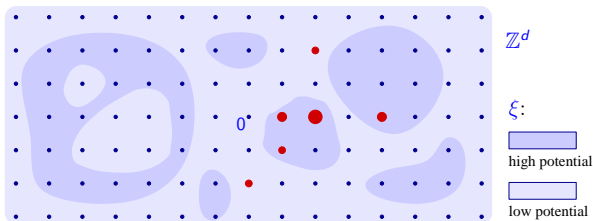
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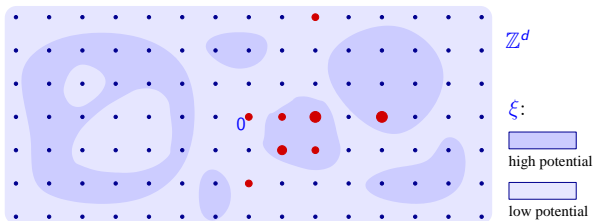
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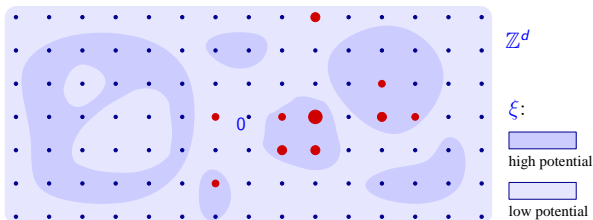
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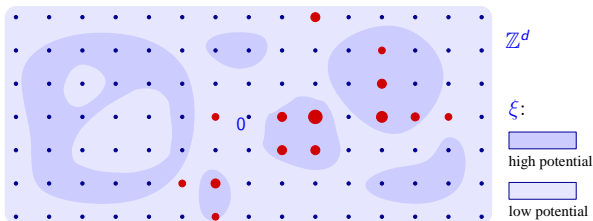
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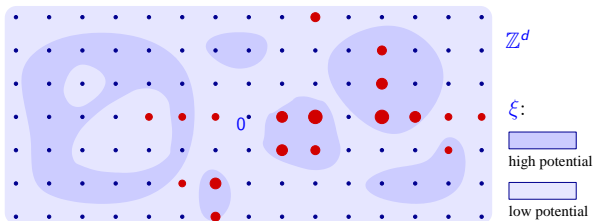
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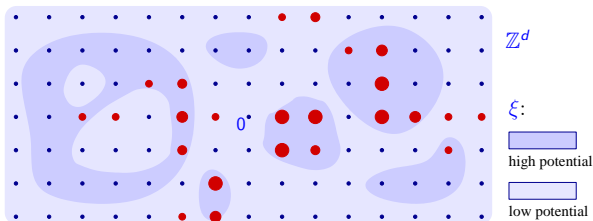
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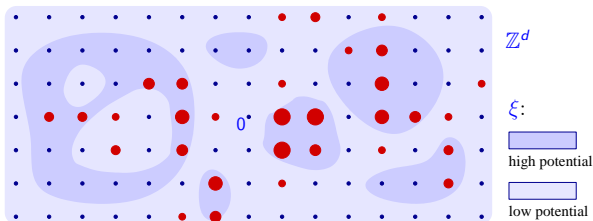
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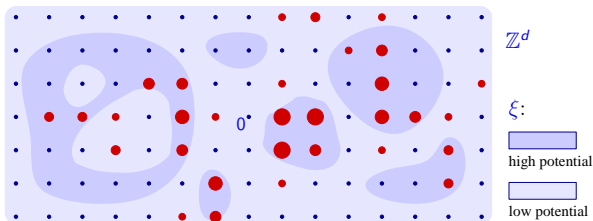
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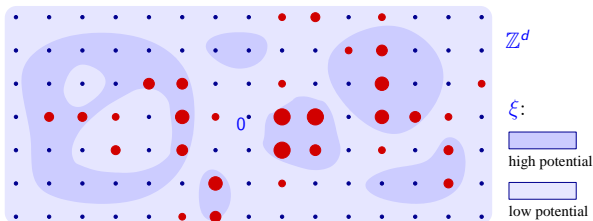
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$u(t, z) = \mathbb{E}N(t, z)$  is the **average** number of particles at time  $t$  at site  $z$ , **still random**.

# Two approaches to study $u(t, z)$

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- **Probabilistic:** use path analysis to analyse the **Feynman–Kac Formula**

$$u(t, z) = \mathbb{E} \left\{ e^{\int_0^t \xi(X_s) ds} \mathbf{1}_{\{X_t=z\}} \right\},$$

where  $(X_s)$  is a continuous-time random walk starting at zero.

# Heat equation

The propagation of temperature  $u(t, x)$  at time  $t$  at the point  $x \in \mathbb{R}$  is described by

$$\frac{\partial u}{\partial t} = \Delta u.$$

If the initial temperature is  $\delta_0$  then

$$u(t, x) = \frac{1}{\sqrt{4\pi t}} e^{-\frac{x^2}{4t}}.$$

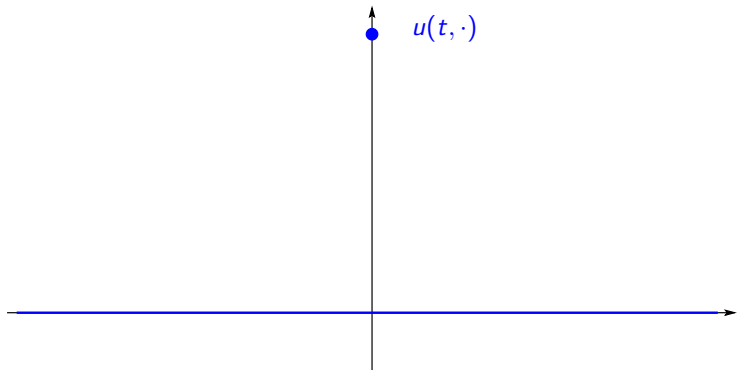
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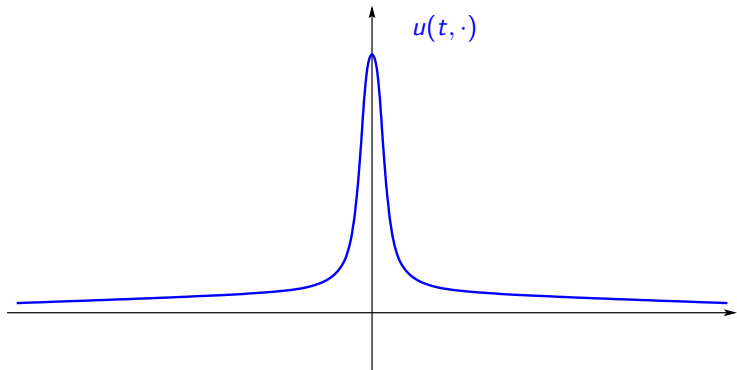
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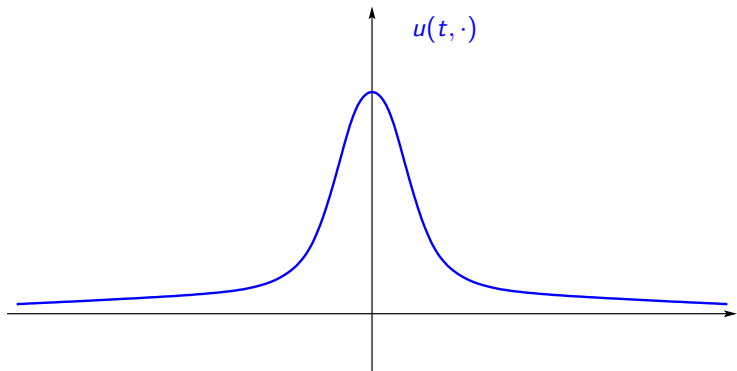
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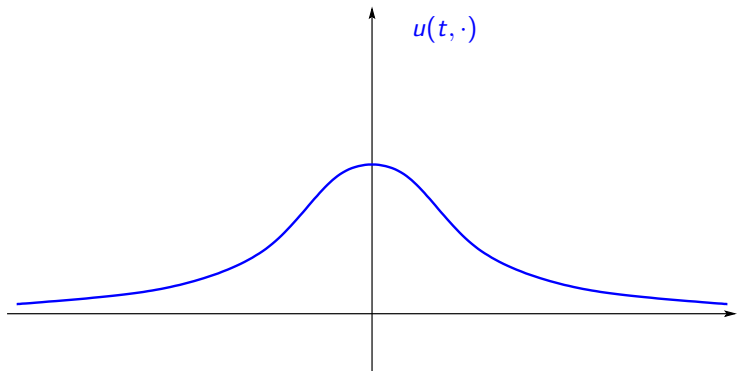
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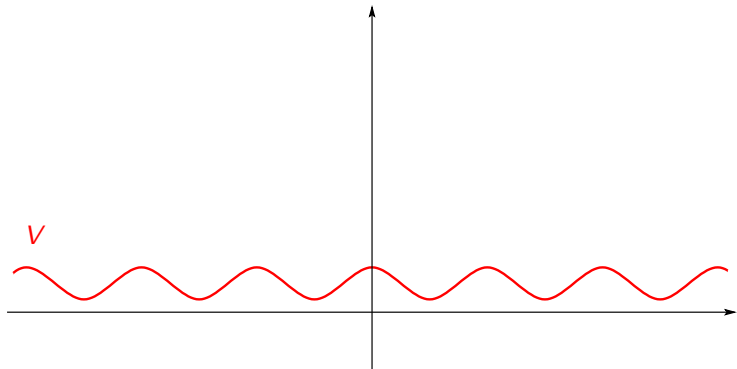


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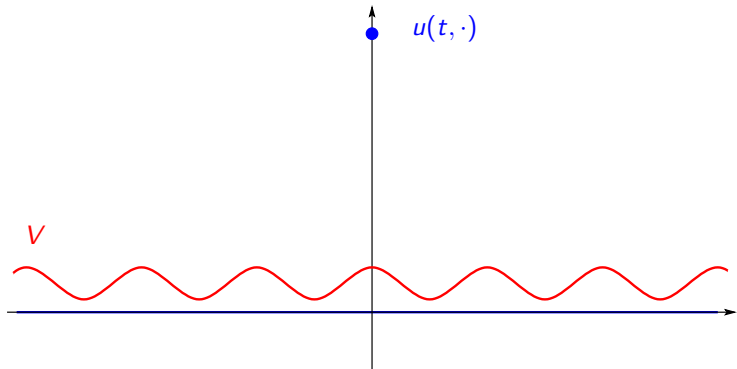
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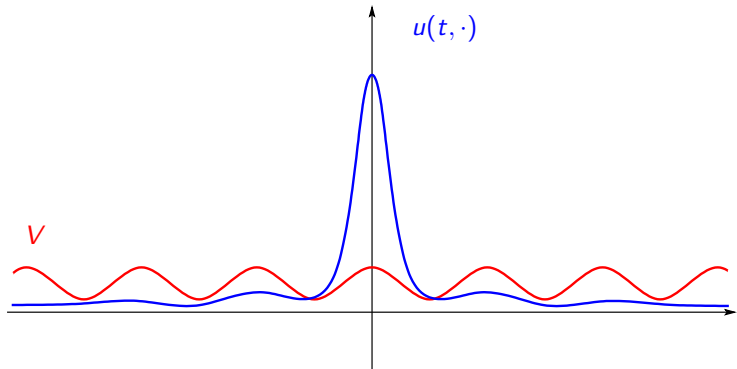
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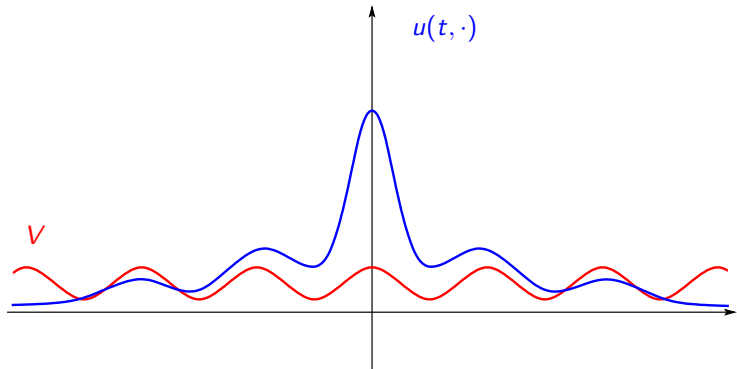
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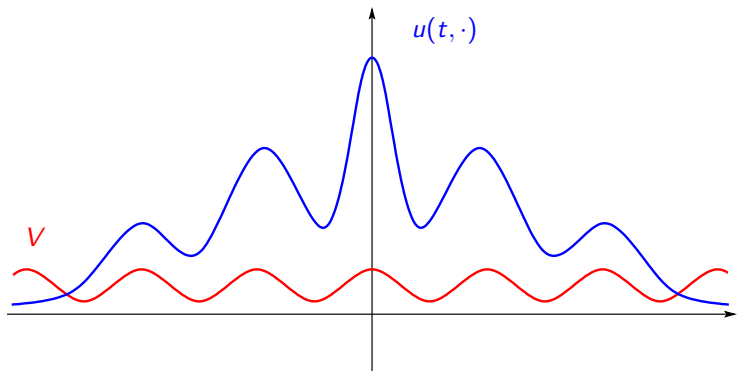
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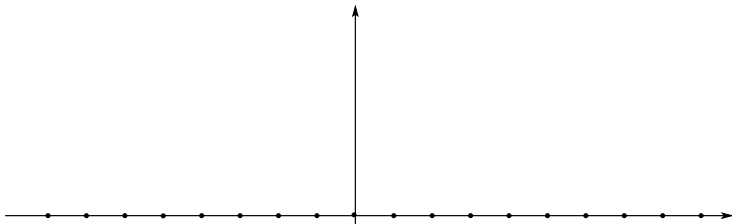


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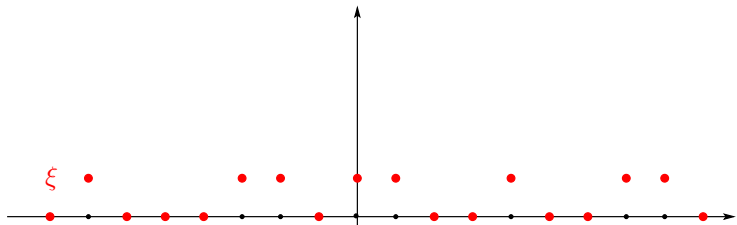


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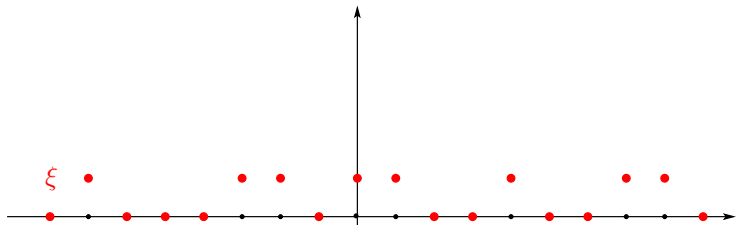


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where  $\xi : \mathbb{Z}^d \rightarrow \mathbb{R}$  is a **random i.i.d. potential**.



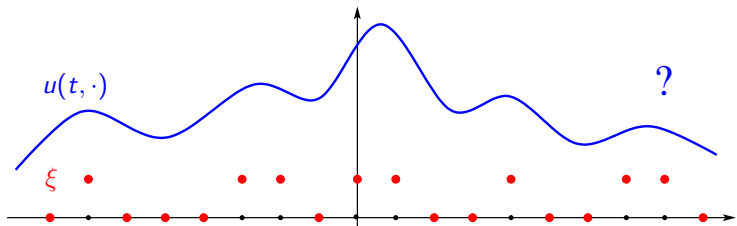
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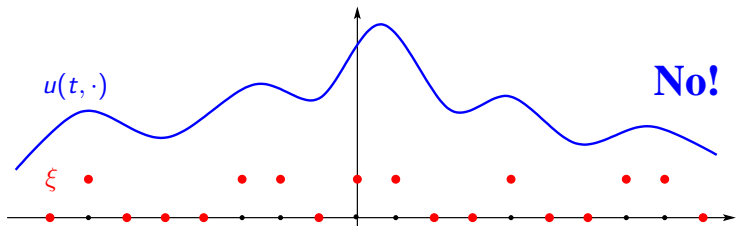
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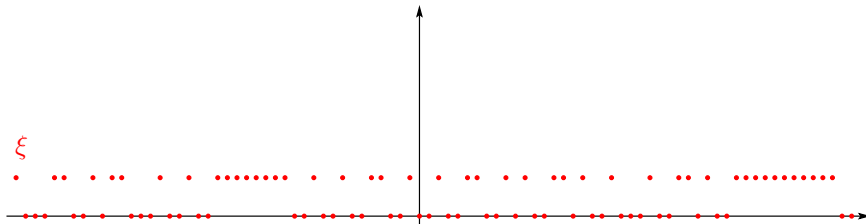
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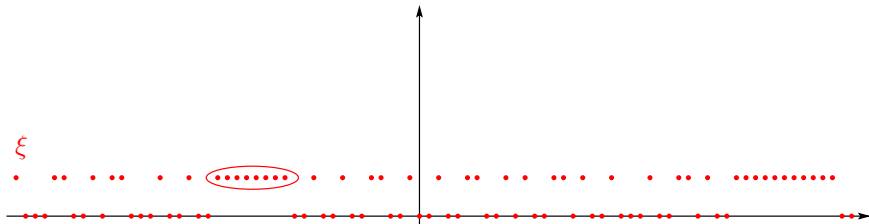
# Why not?

Bernoulli potential:



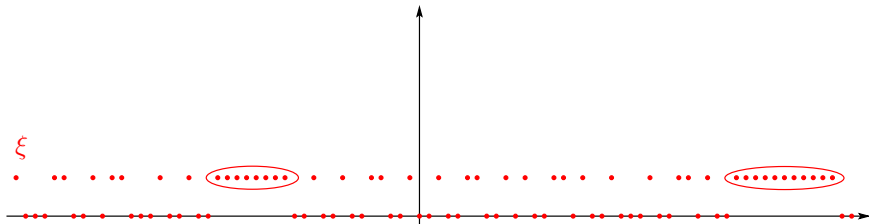
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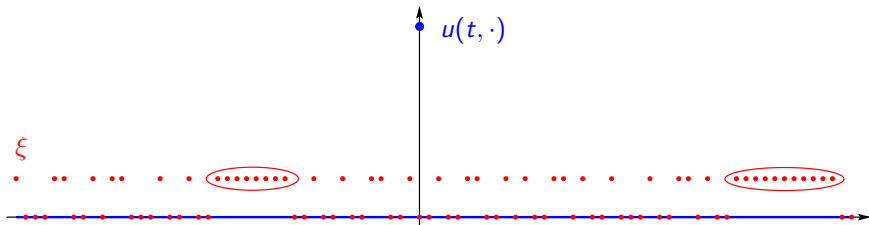
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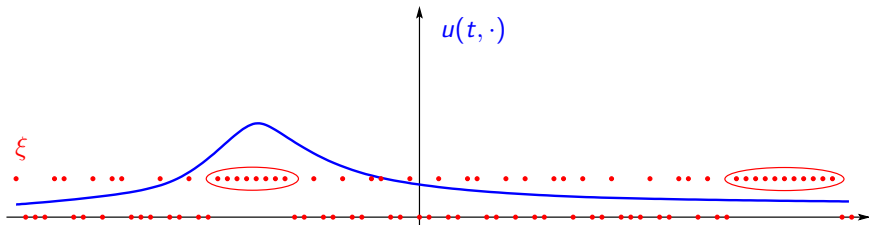
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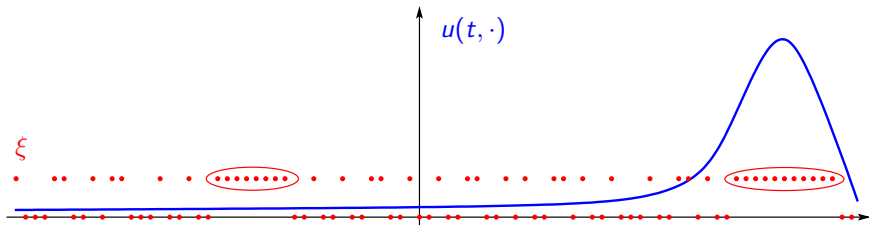
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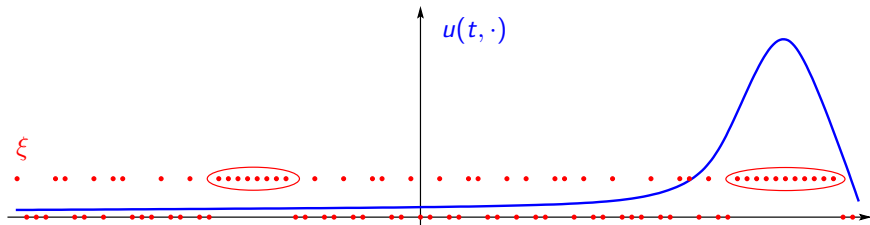
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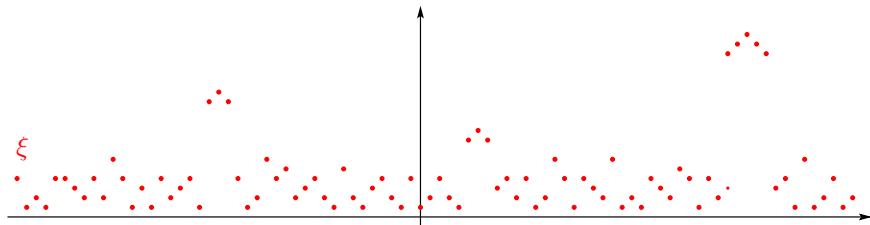


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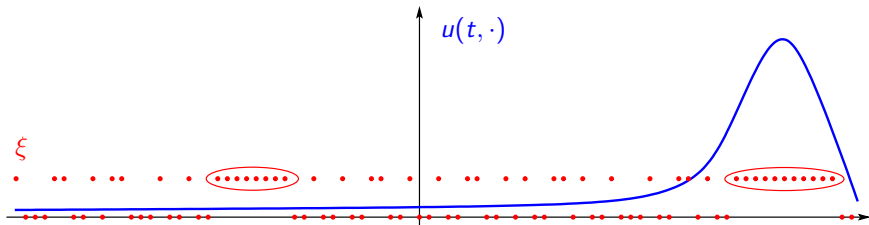


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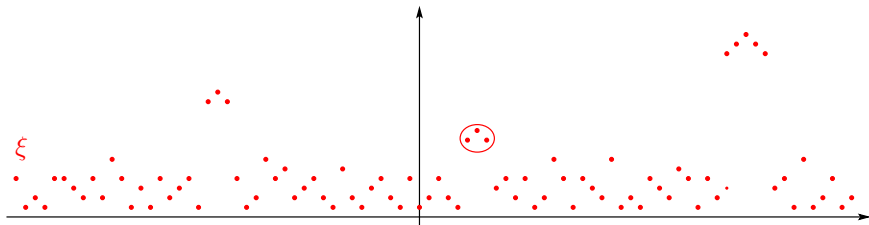


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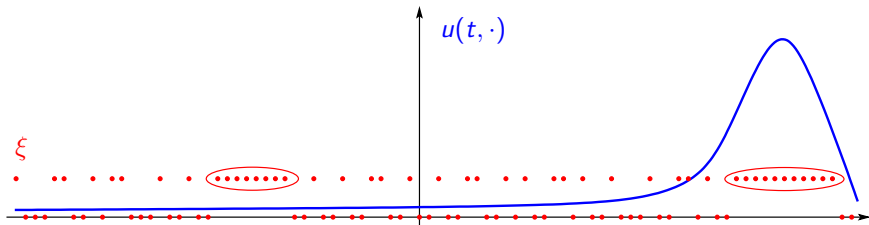


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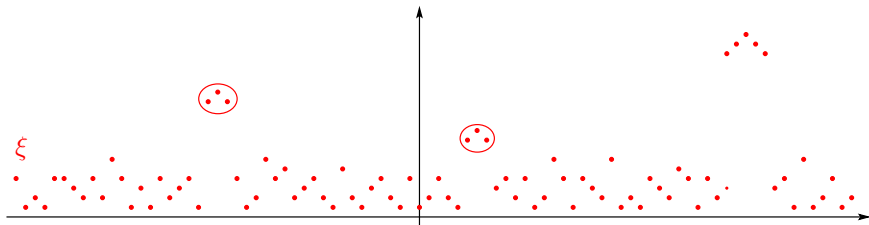


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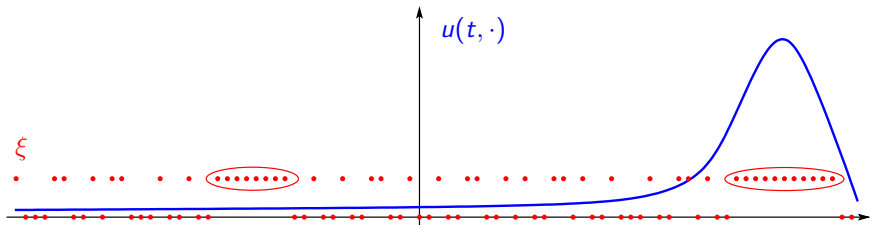


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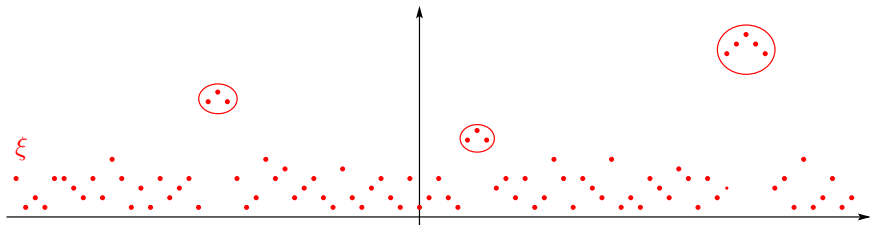


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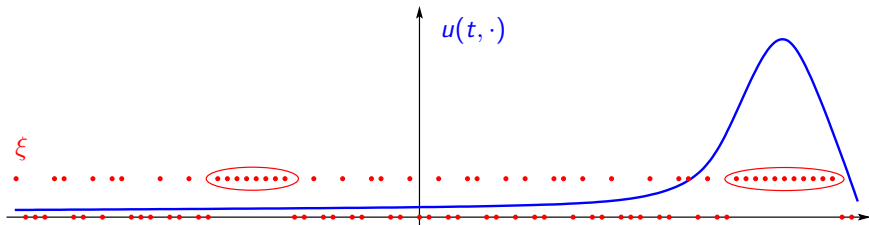


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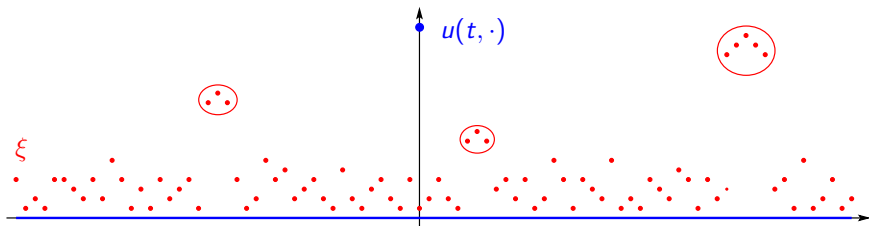


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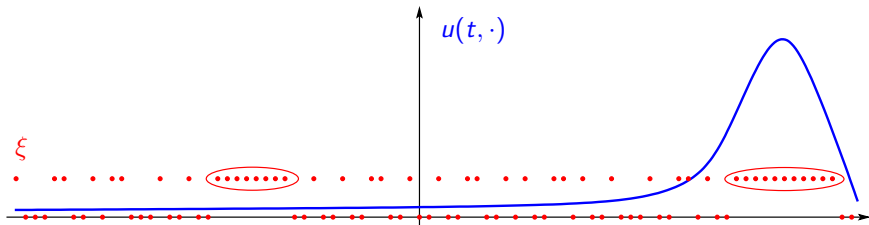
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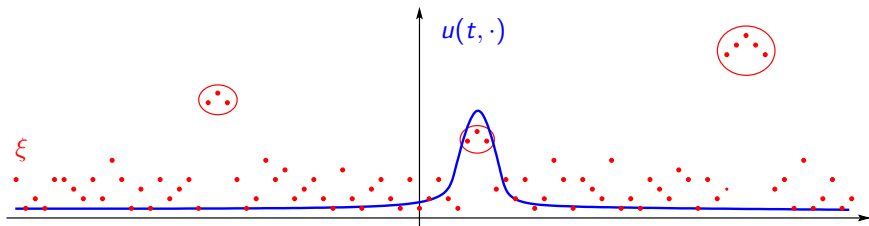


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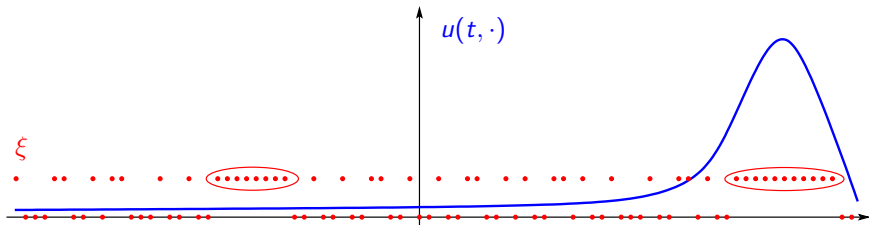


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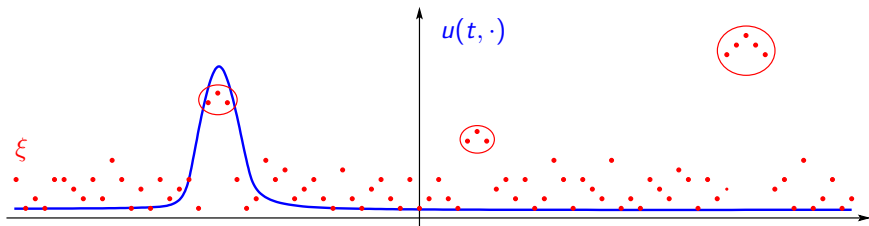


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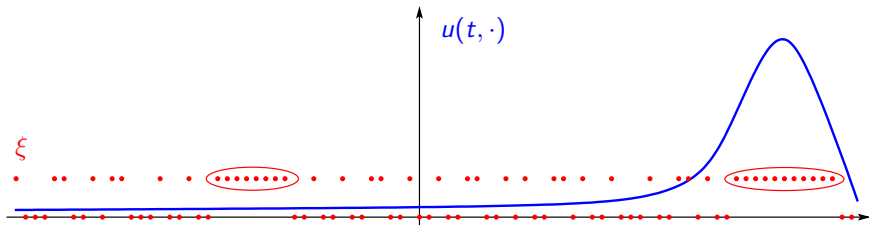


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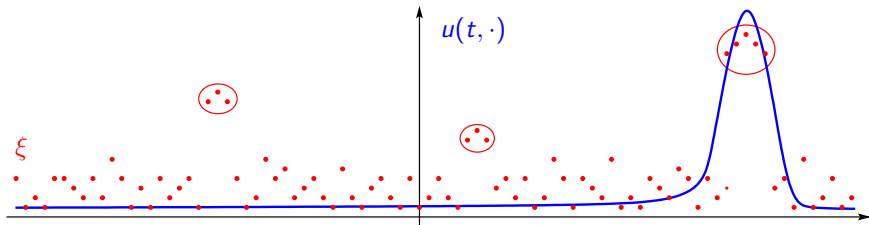


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What can we say about **unbounded** potentials?

- **Pareto**:  $P(\xi(0) > x) = x^{-\alpha}$ ,  $\alpha > d$
- **Weibull**:  $P(\xi(0) > x) = \exp\{-x^\gamma\}$ ,  $\gamma > 0$
- **Double-exponential**:  $P(\xi(0) > x) = \exp\{-e^{x/\rho}\}$ ,  $\rho > 0$
- 'Almost bounded' — quite different, not in this talk



## Theorem 1

[König, Mörters, S. '06] Pareto

[S., Twarowski '12] Weibull with  $\gamma < 2$

[Fiodorov, Muirhead '13] Weibull with any  $\gamma$

There exists a process  $Z_t$  with values in  $\mathbb{Z}^d$  such that

$$\lim_{t \rightarrow \infty} \frac{u(t, Z_t)}{\sum_{z \in \mathbb{Z}^d} u(t, z)} = 1 \quad \text{in probability.}$$

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- The mass is concentrated at the maximiser  $Z_t$  of

$$\Psi_t(z) = \xi(z) - \frac{|z|}{t} \log \xi(z)$$

in the Pareto case, and of a similarly shaped functional  $\Psi_t$  in the Weibull case.

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- For **double-exponential potentials** the solution  $u(t, \cdot)$  is concentrated on **one bounded ball**. [Biskup, König, dos Santos, '16]

## Theorem 2

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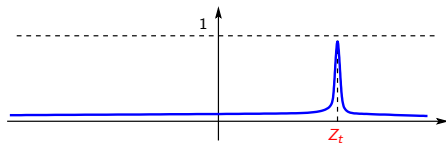
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$$r_t = \begin{cases} \left(\frac{t}{\log t}\right)^{\frac{\alpha}{\alpha-d}} & \text{in the Pareto case,} \\ \frac{t(\log t)^{1/\gamma-1}}{\log \log t} & \text{in the Weibull case.} \end{cases}$$

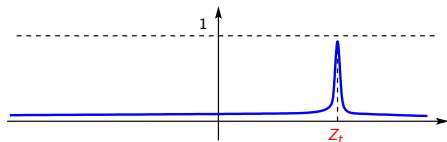




# Ageing

Waiting time until next **change of state**:

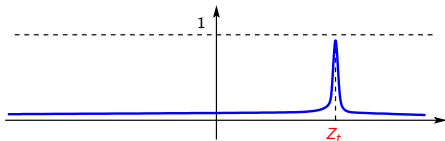
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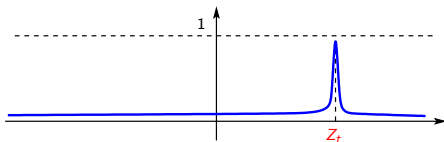
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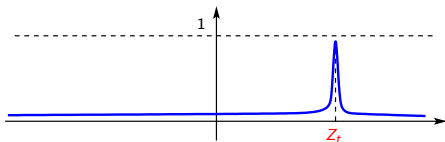
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The **scaling limit of the whole process** ( $Z_t$ ) can be described in terms of a Poisson point process [Mörters, Ortgiese, S.'11, Pareto].

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Recall that (for Pareto and Weibull) we have

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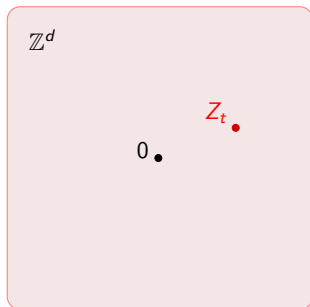
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In the Weibull case this is an open question but is likely to be true.

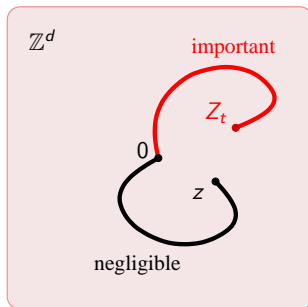
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$$u(t, z) = \mathbb{E} \left\{ e^{\int_0^t \xi(X_s) ds} \mathbf{1}_{\{\text{all paths from } 0 \text{ to } z\}} \right\}$$



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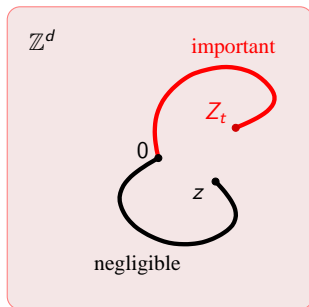
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Contribution of paths from 0 to all  $z \neq Z_t$  is negligible.



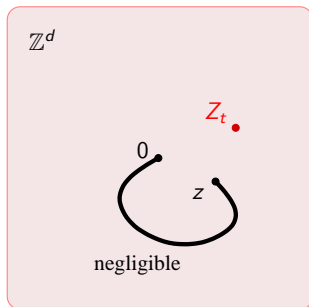
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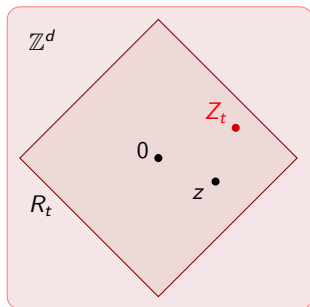
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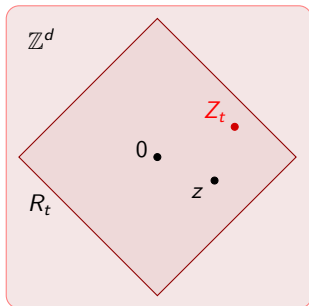
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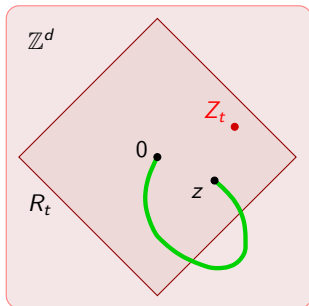
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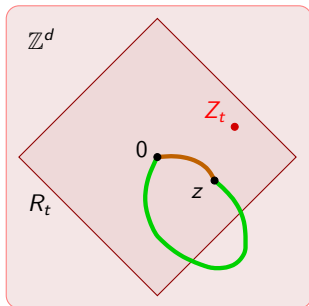
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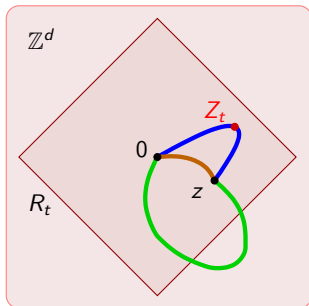
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Localisation at  $Z_t$

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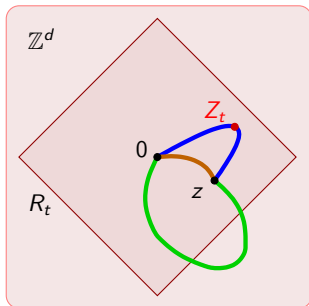
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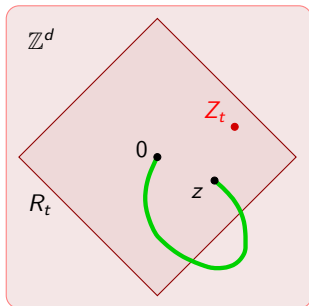
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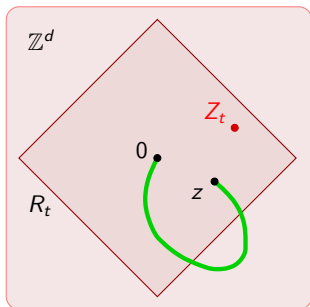
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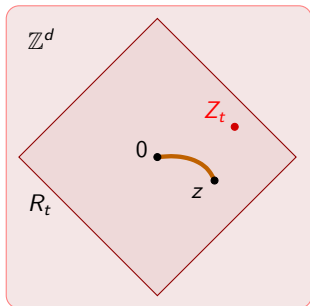
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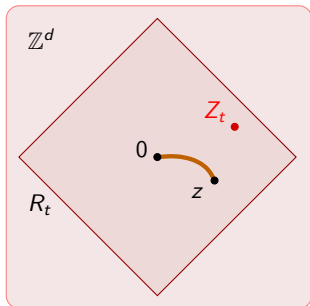
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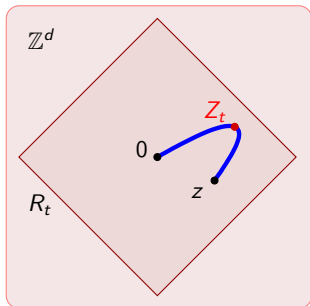
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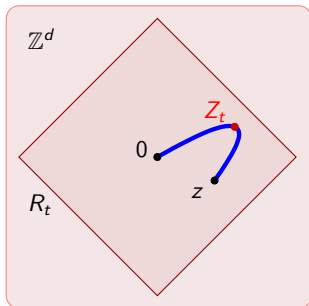
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main part: spectral theory



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# PAM with duplication

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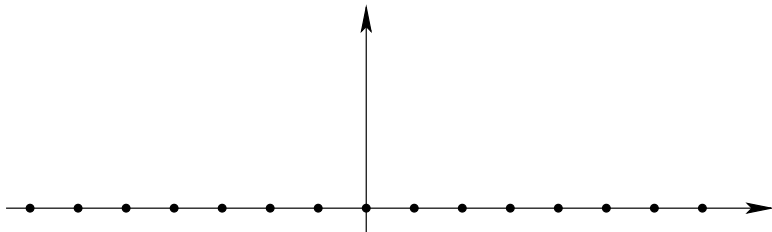
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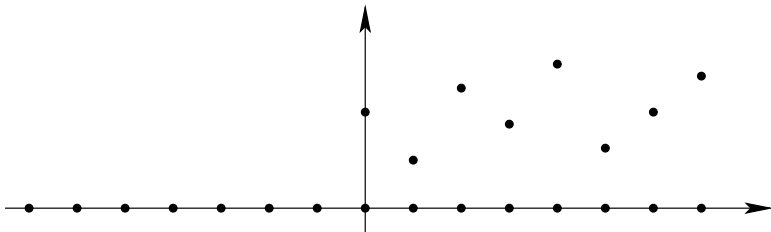
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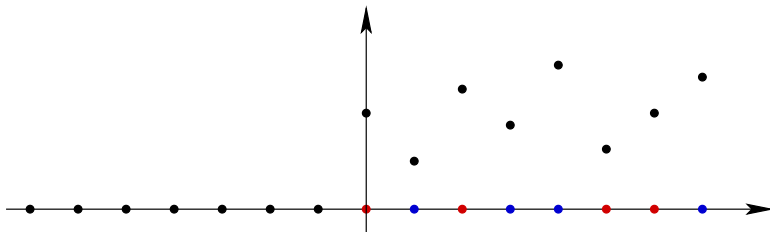
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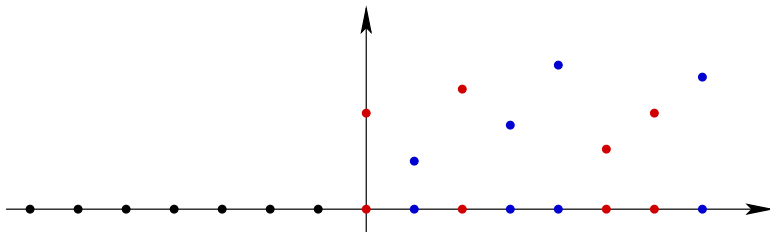
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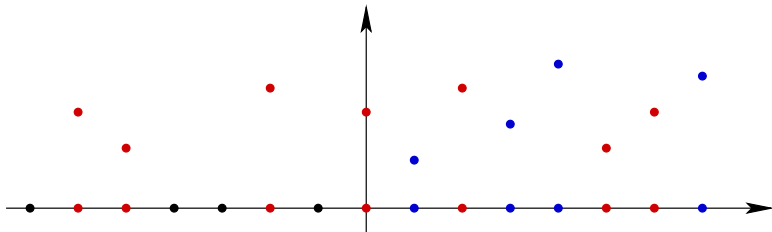
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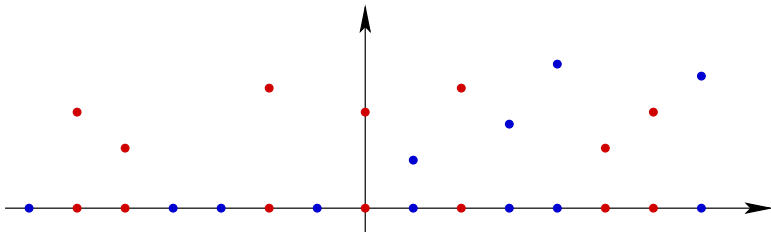




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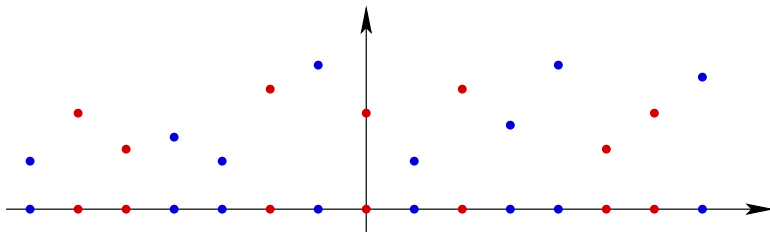
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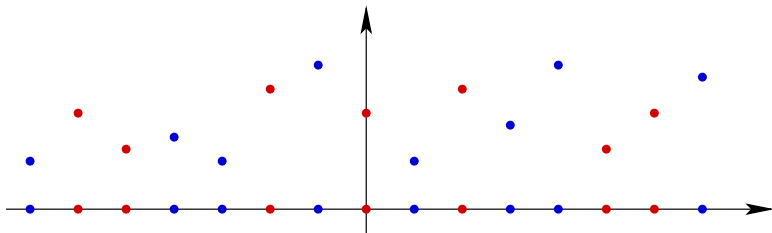
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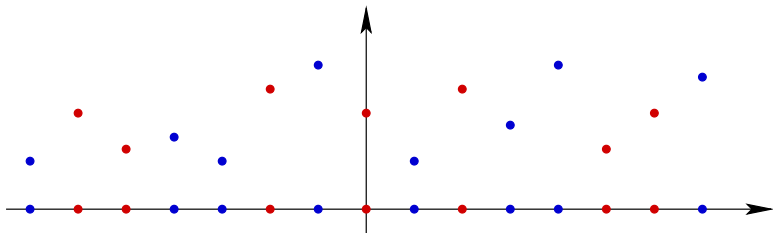


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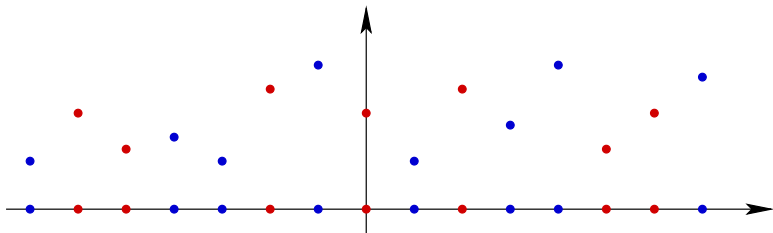
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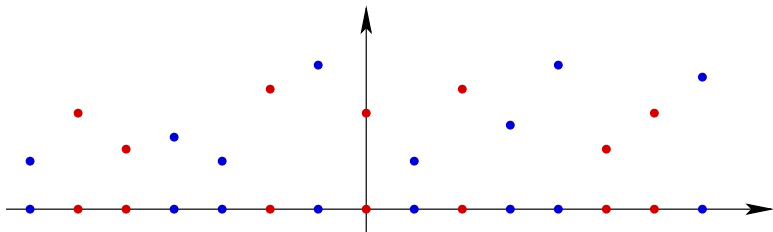
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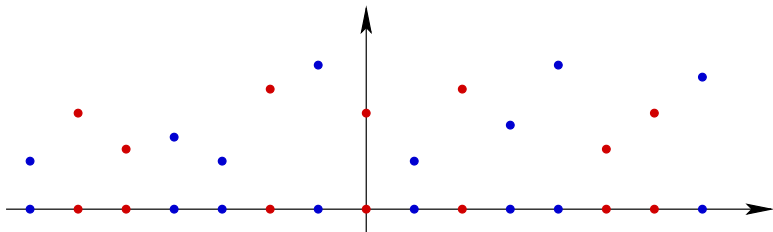
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Denote the total mass of the solution by

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# Answers

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Let  $1 < \alpha < 2$ .

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where  $\Upsilon$  is a random variable with positive density on  $(0, \infty)$ .

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$$\frac{u(t, Z_t)}{U(t)} \rightarrow 1 \quad \text{in probability.}$$

# Answers

## Theorem 1 (Muirhead, Pymar, S. '16)

Let  $1 < \alpha < 2$ . Conditionally on **no duplication at  $Z_t$** , as  $t \rightarrow \infty$ , **one point**

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Conditionally on the **duplication at  $Z_t$** , as  $t \rightarrow \infty$ , **two points, each with a random amount of mass**

$$\frac{u(t, Z_t) + u(t, -Z_t)}{U(t)} \rightarrow 1 \quad \text{in probability}$$

and

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where  $\mathcal{P}_t^\pm$  are the sets of paths on  $\mathbb{Z}$  starting at 0 and ending at  $\pm Z_t$ .

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In particular, for  $1 < \alpha < 2$  we have

$$u(t, \pm Z_t) \sim e^{t\xi(Z_t) - 2t} \prod_{k=0}^{Z_t} \frac{1}{\xi(Z_t) - \xi(\pm k)}$$

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↑  
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$$- \sum_{k:\text{non-dupl}} \log \left( 1 - \frac{\xi(\pm k)}{\xi(Z_t)} \right) \approx \frac{1}{\xi(Z_t)} \sum_{k:\text{non-dupl}} \xi(\pm k) \approx$$

$$1 < \alpha < 2$$

$$\frac{u(t, Z_t)}{u(t, -Z_t)} \sim \prod_{k=1}^{Z_t} \frac{1}{\xi(Z_t) - \xi(k)} : \prod_{k=1}^{Z_t} \frac{1}{\xi(Z_t) - \xi(-k)}$$
$$= \exp \left\{ - \sum_{k:\text{non-dupl}} \log \left( 1 - \frac{\xi(k)}{\xi(Z_t)} \right) + \sum_{k:\text{non-dupl}} \log \left( 1 - \frac{\xi(-k)}{\xi(Z_t)} \right) \right\}$$

$\sum_{i=1}^n X_i \approx n\mu + n^{1/\alpha} \mathcal{N}$
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same for  $\pm Z_t$

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$$\frac{|Z_t|^{1/\alpha}}{\xi(Z_t)} \asymp$$



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