Tail estimate for random walk in random scenery

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Joint work with J.-D. Deuschel (TU Berlin).

Random walk in random scenery (RWRS)

- $(\{z(x)\}_{x\in\mathbb{Z}^d},\mathbb{P})$: IID random variables,
- $(S_n)_{n \in \mathbb{Z}_+}$: Random walk on \mathbb{Z}^d .

Random walk in random scenery:

$$W_n := \sum_{k=1}^n z(S_k).$$

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- Introduced by Borodin and Kesten-Spitzer in 1979.
- Scaling limit (under P ⊗ P₀) yields a self-similar process.
 d = 1, z: α-stable, S: β>1-stable ⇒ index = 1 − ¹/_β + ¹/_{αβ}.
- Central limit theorem hold if S is transient and $Var(z) < \infty$.
- ► d = 2, S = SRW, $Var(z) < \infty$, $\frac{1}{\sqrt{n \log n}} W_n \rightarrow \mathcal{N}(0, \sigma^2)$ (Bolthausen 1989).

RWRS: continuous time

In this talk,

- ► $(\{z(x)\}_{x\in\mathbb{Z}^d},\mathbb{P})$: IID, ≥ 0 with $\mathbb{P}(z(x)\geq r)=r^{-\alpha+o(1)}$,
- ► $((S_t)_{t\geq 0}, (P_x)_{x\in\mathbb{Z}^d})$: continuous time simple random walk. Continuous time version of RWRS:

$$A_t := \int_0^t z(S_u) \mathrm{d} u.$$

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Naturally appears in random media models:

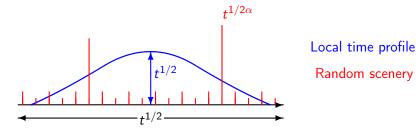
- $E_x[f(S_t)e^{A_t}]$ is a solution of $\partial_t u = \Delta u + zu$, u(0, x) = f(x).
- $(S_t^1, S_t^2 + A_t^1)_{t \ge 0}$: diffusion in random shear flow.
- ► (S_{A_t⁻¹})_{t≥0}: random hopping time dynamics.
- $(S^1_{A^2_t}, S^2_t)_{t \ge 0}$: random walk in layered conductance.

Scaling and strategy

The typical behavior of RWRS is

$$A_t = t^{s(d,\alpha)+o(1)} \text{ with } s(d,\alpha) = \begin{cases} \frac{\alpha+1}{2\alpha} \vee 1 & \text{if } d = 1, \\ \frac{1}{\alpha} \vee 1 & \text{if } d \geq 2. \end{cases}$$

Schematic picture for d = 1 and $\alpha < 1$:

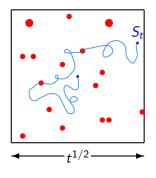


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Schematic picture for $d \ge 3$ and $\alpha < 1$:



RW trajectory

• = $t^{1/\alpha}$ high points

• =
$$t^{d/2\alpha}$$
 high points

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Known tail estimates for RWRS

Many annealed results: $\mathbb{P} \otimes P_0(A_t \ge t^{\rho})$.

- Asselah, Castell, Csáki, Fleischman, Gantert, van der Hofstad, Khoshnevisan, König, Lewis, Li, Mörters, Pradeilis, Remillard, Shi, Wachtel...
- ▶ Related to law of iterated logarithm, intersection local time.

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- Related to law of iterated logarithm, intersection local time.
- Few quenched results: $P_0(A_t \ge t^{\rho})$ for typical z.
 - Brownian motion in Gaussian scenery,
 - Large deviation for $\frac{1}{t_1/\log t}A_t$: Asselah-Castell (2003),
 - Moderate deviations: Castell (2004),
 - Brownian motion in bounded scenery,
 - Large deviation for $\frac{1}{t}A_t$: Asselah-Castell (2003).

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In particular, no results in Borodin and Kesten-Spitzer setting.

Upper tail — stretched exponential decay

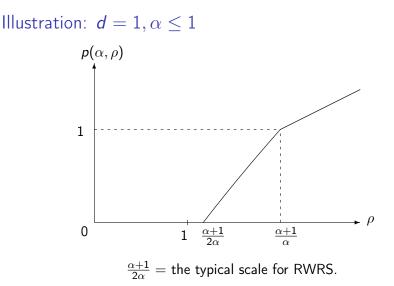
Theorem (Deuschel–F. 2019) Assume $\mathbb{P}(z(x) \ge r) = r^{-\alpha+o(1)}$ and let $\rho > 0$. Then $P_0(A_t \ge t^{\rho}) = \exp\left\{-t^{p(\alpha,\rho)+o(1)}\right\}, \quad \mathbb{P} ext{-almost surely}$

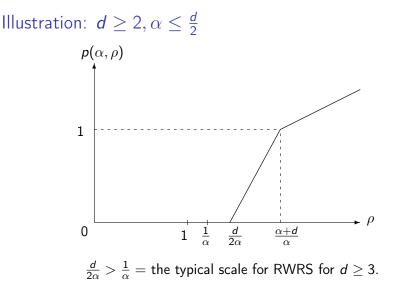
as $t \to \infty$, where for d = 1,

$$p(\alpha, \rho) = \begin{cases} \frac{2\alpha\rho}{\alpha+1} - 1, & \rho \in \left(\frac{\alpha+1}{2\alpha} \vee 1, \frac{\alpha+1}{\alpha}\right], \\ \alpha(\rho - 1), & \rho > \frac{\alpha+1}{\alpha} \end{cases}$$

and for d = 2,

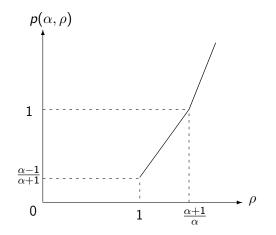
$$p(\alpha, \rho) = \begin{cases} \frac{2\alpha\rho - d}{2\alpha + d}, & \rho \in \left(\frac{d}{2\alpha} \vee 1, \frac{\alpha + d}{\alpha}\right], \\ \frac{\alpha(\rho - 1)}{d}, & \rho > \frac{\alpha + d}{\alpha}. \end{cases}$$





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Illustration: $d = 1, \alpha > 1$ ($d \ge 2, \alpha > \frac{d}{2}$ is similar)

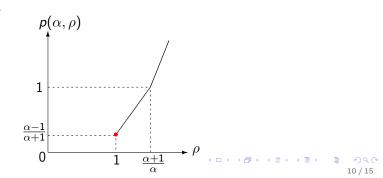


Large deviation

Theorem (Deuschel–F. 2019) Assume $\mathbb{P}(z(x) \ge r) = r^{-\alpha+o(1)}$ and let d = 1 and $\alpha > 1$ or $d \ge 2$ and $\alpha > \frac{d}{2}$. Then for any $c > \mathbb{E}[z(x)]$, \mathbb{P} -almost surely,

$$P_0\left(A_t \ge ct\right) = \begin{cases} \exp\left\{-t^{\frac{\alpha-1}{\alpha+1}+o(1)}\right\}, & d = 1, \\ \exp\left\{-t^{\frac{2\alpha-d}{2\alpha+d}+o(1)}\right\}, & d \ge 2 \end{cases}$$

as $t \to \infty$.

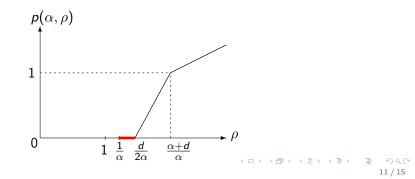


Upper tail — power law decay

Theorem (Deuschel–F. 2019+) Assume $\mathbb{P}(z(x) \ge r) = r^{-\alpha+o(1)}$ and let $d \ge 3$ and $\alpha \le \frac{d}{2}$. Then for any $\rho \in (\frac{1}{\alpha} \lor 1, \frac{d}{2\alpha})$, \mathbb{P} -almost surely,

$$P_0(A(t) \geq t^
ho) = t^{-lpha
ho + 1 + o(1)}$$

as $t \to \infty$.



Lower tail estimate

Theorem (Deuschel–F. 2019+) Let $d \ge 1$ and $\epsilon > 0$. Then \mathbb{P} -almost surely,

$$P_0\left(A(t) \leq t^{s(d,\alpha)-\epsilon}\right) \leq \exp\{-t^{c(\epsilon)}\}.$$

Moreover, if $\mathbb{E}[z(0)] < \infty$,

$$\mathsf{P}_0\left(\mathsf{A}(t) \leq t(\mathbb{E}[z(0)] - \epsilon)
ight) \leq \exp\{-t^{c(\epsilon)}\}.$$

Remark

We only know $c(\epsilon) > 0$. More information as a function of ϵ is desirable.

Random layered conductance model

Let $((X_t)_{t\geq 0}, (P_x^{\omega})_{x\in\mathbb{Z}^{1+d}})$ be a continuous time Markov chain on \mathbb{Z}^2 with jump rates

$$\omega(x, x \pm \mathbf{e}_i) = egin{cases} z(x_2), & i=1, \ 1, & i=2. \end{cases}$$

By using CTSRW (S^1, S^2) on \mathbb{Z}^2 ,

$$(X_t^1, X_t^2)_{t\geq 0} = (S_{A_t^2}^1, S_t^2)_{t\geq 0}$$
 with $A_t^2 = \int_0^t z(S_u^2) du$.

Transition probability:

$$P_0^{\omega} (X_t = (x, y)) = P_0 \left(S_{A_t^2}^1 = x, S_t^2 = y \right)$$
$$= E_0 \left[p_{A_t^2}(0, x) \colon S_t^2 = y \right].$$

On-diagonal estimate

Theorem If $\alpha \leq 1$ and $\mathbb{E}[z(0)] = \infty$, then \mathbb{P} -almost surely,

$$P_0^{\omega}(X_t = 0) = t^{-rac{3lpha + 1}{4lpha} + o(1)}$$

as $t \to \infty.$ If $\mathbb{E}[z(0)] < \infty,$ then $\mathbb{P}\text{-almost surely,}$

$$P_0^{\omega}(X_t=0) = \left((4\pi)^{-rac{d+1}{2}}\mathbb{E}[z(0)]^{-rac{1}{2}} + o(1)
ight)t^{-1}$$

as $t \to \infty$. In particular, $(X_t)_{t \ge 0}$ is transient if $\alpha < 1$ and recurrent if $\mathbb{E}[z(0)] < \infty$.

Remark

There are higher dimensional analogues and off-diagonal estimates.

Thank you!