

# Self-interacting random walks

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## Abstract

Let  $\mu_1, \dots, \mu_k$  be  $d$ -dimensional probability measures in  $\mathbb{R}^d$  with mean 0. At each step we choose one of the measures based on the history of the process and take a step according to that measure. We give conditions for transience of such processes and also construct examples of recurrent processes of this type. In particular, in dimension 3 we give the complete picture: every walk generated by two measures is transient and there exists a recurrent walk generated by three measures.

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## 1 Introduction

Let  $\mu_1$  and  $\mu_2$  be two zero mean measures in  $\mathbb{R}^4$  with finite supports that span the whole space. On the first visit to a site the jump of the process has law  $\mu_1$  and at further visits it has law  $\mu_2$ . The following question was posed in [2]: Is the resulting walk transient?

More generally, one can consider any adapted rule (i.e., a rule depending on the history of the process) for choosing between  $\mu_1$  and  $\mu_2$ , and ask the same question. It turns out that the answer to this question is positive, even in  $\mathbb{R}^3$ , as proved in Theorem 1.2 below. Moreover, in 3 dimensions this result is sharp, in the sense that one can construct an example of a recurrent walk with three measures, as shown in Theorem 1.5.

This naturally fits into the wider context of random walks that are not Markovian, namely where the next step the walk takes also depends on the past. Recently there has been a lot of interest in random walks of this kind. A large class of such walks are the so-called vertex (or edge) reinforced random walks, where the walker chooses the next vertex to jump to with weight proportional to the number of visits to that vertex up to that time; see e.g. [1, 9, 10, 11, 13]. Another class of such walks is the so-called excited random walks, when the transition probabilities depend on whether it is the first visit to a site or not, see e.g. [3, 4, 8, 12, 14].

In this paper we study transience and recurrence for walks in dimensions 3 and above that are generated by a finite collection of step distributions. We now give the precise definition of the walks we will be considering.

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**Definition 1.1.** Let  $\mu_1, \dots, \mu_k$  be  $k$  probability measures in  $\mathbb{R}^d$  and for each  $j = 1, \dots, k$ , let  $\xi_1^j, \xi_2^j, \dots$  be i.i.d. with law  $\mu_j$ . Define an *adapted rule*  $\ell = (\ell(i))_i$  with respect to a filtration  $(\mathcal{F}_i)$  to be a process such that  $\ell(i) \in \{1, \dots, k\}$  and is  $\mathcal{F}_i$  measurable for all  $i$ . We will say that the walk  $X$ , with  $X_0 = 0$ , is generated by the measures  $\mu_1, \dots, \mu_k$  and the rule  $\ell$  if

$$X_{i+1} = X_i + \xi_{i+1}^{\ell(i)}.$$

We say that a measure  $\mu$  in  $\mathbb{R}^d$  has mean 0 if  $\int_{\mathbb{R}^d} x \mu(dx) = 0$ . Also we write that a measure  $\mu$  has  $\beta$  moments, if  $\mathbb{E}[\|Z\|^\beta] < \infty$ , where  $Z \sim \mu$ . We define the covariance matrix of  $\mu$  as follows:  $\text{Cov}(\mu) = (\mathbb{E}[Z_i Z_j])_{i,j=1}^d$ .

Note that if  $\mu$  is a measure in  $\mathbb{R}^d$ , then it has an invertible covariance matrix if and only if its support contains  $d$  linearly independent vectors of  $\mathbb{R}^d$ . We will call such measures  $d$ -dimensional.

In this paper we are mainly interested in the following two questions:

- Let  $\mu_1, \dots, \mu_k$  be mean 0 probability measures in  $\mathbb{R}^d$ . What are the conditions on the measures so that for every adapted rule  $\ell$  the resulting walk is transient?
- For a given dimension  $d$ , how do we construct examples of recurrent walks generated by  $k$   $d$ -dimensional mean 0 measures? How small can this number  $k$  be made?

In Section 1.1 we state our results concerning the first question and in Section 1.2 about the second one. Observe that Theorems 1.2 and 1.5 give a complete picture in dimension 3: any two mean 0 measures with  $2 + \beta$  moments, for some  $\beta > 0$ , always generate a transient walk, while there is an example of a recurrent walk generated by three 3-dimensional measures of mean 0 with a suitable adapted rule.

## 1.1 Conditions for transience

**Theorem 1.2.** *Let  $\mu_1, \mu_2$  be  $d$ -dimensional measures in  $\mathbb{R}^d$ ,  $d \geq 3$ , with zero mean and  $2 + \beta$  moments, for some  $\beta > 0$ . If  $X$  is a random walk generated by these measures and an arbitrary adapted rule  $\ell$ , then  $X$  is transient.*

The following result will be used in the proof of Theorem 1.2 but is also of independent interest, since it gives a sufficient condition on the covariance matrices of the measures used in order to generate a transient random walk  $X$  for an arbitrary adapted rule  $\ell$ .

For a matrix  $A$  we write  $A^T$  for its transpose,  $\lambda_{\max}(A)$  for its maximum eigenvalue and  $\text{tr}(A)$  for its trace.

**Theorem 1.3.** *Let  $\mu_1, \dots, \mu_k$  be mean 0 measures in  $\mathbb{R}^d$ ,  $d \geq 3$ , with  $2 + \beta$  moments, for some  $\beta > 0$ . Suppose that there exists a matrix  $A$  such that for all  $i$  we have*

$$\text{tr}(AM_i A^T) > 2\lambda_{\max}(AM_i A^T), \tag{1.1}$$

where  $M_i$  is the covariance matrix of the measure  $\mu_i$ . If  $X$  is a random walk generated by these measures and an arbitrary adapted rule  $\ell$ , then  $X$  is transient.

We will refer to (1.1) as the *trace condition*.

It turns out that the local central limit theorem implies the following lower bound on the number of measures needed to generate a transient walk.

**Proposition 1.4.** *Let  $\mu_1, \dots, \mu_k$  be mean 0 measures in  $d \geq 2k + 1$  with  $2 + \beta$  moments, for some  $\beta > 0$ . Then the random walk  $X$  generated by these measures and an arbitrary adapted rule  $\ell$  is transient.*

We will prove Proposition 1.4 in the beginning of Section 2 and then Theorems 1.3 and 1.2 in Sections 2.1 and 2.2 respectively. Then in Proposition 2.6 in Section 2.3 we discuss the case when the covariance matrices are jointly diagonalizable. We present a conjectured sufficient condition for transience at the end of the paper.

## 1.2 Recurrence

We now define a random walk in  $d$  dimensions, which is generated by  $d$  measures that are fully supported in  $\mathbb{R}^d$  and we will prove that it is recurrent.

Let  $e_0, \dots, e_{d-1}$  be the coordinate vectors in  $\mathbb{Z}^d$ . We consider a random walk  $(X_n, n = 0, 1, 2, \dots)$  on  $\mathbb{Z}^d, d \geq 3$ , defined in the following way. Fix a parameter  $\gamma > 0$ , and for  $x = (x_0, \dots, x_{d-1}) \in \mathbb{Z}^d$  define  $\varrho(x) = \min\{k : |x_k| = \max_{j=0, \dots, d-1} |x_j|\}$ . Then

$$X_{n+1} = X_n + \xi_{n+1},$$

where  $\xi_{n+1} = \pm e_{\varrho(X_n)}$  with probabilities  $\frac{\gamma}{2(\gamma+d-1)}$  and  $\xi_{n+1} = \pm e_k$  for  $k \neq \varrho(X_n)$  with probabilities  $\frac{1}{2(\gamma+d-1)}$ . In words, we choose the maximal (in absolute value) coordinate of  $X_n$  with weight  $\gamma$  and all the other coordinates with weight 1, and then add 1 or  $-1$  to the chosen coordinate with equal probabilities.

**Theorem 1.5.** *For each  $d \geq 3$  there exists large enough  $\gamma_d$  such that the random walk  $X$  is recurrent for all  $\gamma \geq \gamma_d$ .*

We will prove Theorem 1.5 in Section 3. The proof of this result relies on the explicit construction of a suitable Lyapunov function, but it is rather involved, so in Section 3 we also give simpler examples of a finite number of  $d$ -dimensional measures and adapted rules that generate a recurrent walk in  $d$  dimensions.

## 2 Proofs of transience

In this section we give the proofs of the results on transience. We first prove Proposition 1.4, since its proof is short and elementary.

**Proof of Proposition 1.4.** In order to prove this proposition, let us first give an equivalent definition of the random walk that we are considering.

For each  $j = 1, \dots, k$ , let  $\zeta_1^j, \zeta_2^j, \dots$  be i.i.d. with law  $\mu_j$ . For an adapted rule  $\ell$  we define for all  $j \in \{1, \dots, k\}$

$$r(j, i) = \sum_{m=1}^i \mathbf{1}(\ell(m) = j)$$

and then writing  $\hat{r}_i = r(\ell(i), i) + 1$  we let

$$X_{i+1} = X_i + \zeta_{\hat{r}_i}^{\ell(i)}.$$

It is easy to see by induction that the process  $X$  has the same law as the process of Definition 1.1. Let  $R > 0$  and for every  $n$  we define the event

$$A_n = \left\{ \exists i_1, \dots, i_k \geq 0 : i_1 + \dots + i_k = n \text{ and } \sum_{j=1}^k \sum_{\ell=1}^{i_j} \zeta_i^j \in \mathcal{B}(0, R) \right\}.$$

We now fix a choice of  $i_1, \dots, i_k$  such that  $i_1 + \dots + i_k = n$ . Then by [5, Corollary/Theorem 6.2] we get for a positive constant  $c$

$$\mathbb{P} \left( \sum_{j=1}^k \sum_{\ell=1}^{i_j} \zeta_i^j \in \mathcal{B}(0, R) \right) \leq \frac{cR^d}{n^{d/2}},$$

since there must exist some  $i_j$  which is at least  $n/k$ . It is easy to see that the total number of  $k$ -tuples  $(i_1, \dots, i_k)$  with  $i_j \geq 0$  for all  $j$  and  $\sum_j i_j = n$  is equal to  $\binom{n-1}{k-1}$ . Since  $\binom{n+k-1}{k-1} \leq c_1 n^{k-1}$ , for a positive constant  $c_1$ , we deduce that

$$\mathbb{P}(A_n) \leq c'R^d \frac{n^{k-1}}{n^{d/2}} = \frac{c'R^d}{n^{d/2-k+1}},$$

which is summable if  $d \geq 2k + 1$ . Hence, from Borel-Cantelli we obtain that a.s. only finitely many of the events  $A_n$  happen.

Now notice that for every  $n$  we have

$$\{X_n \in \mathcal{B}(0, R)\} \subseteq A_n,$$

and hence we deduce that a.s. for all sufficiently large  $n$ , the random walk at time  $n$  will stay outside of the ball  $\mathcal{B}(0, R)$ . Since this is true for any  $R > 0$ , we get that if  $d \geq 2k + 1$  the random walk is transient.  $\square$

## 2.1 Trace condition and transience

In this section we give the proof of Theorem 1.3. First we state and prove some preliminary results.

The following lemma is a standard result, but we state and prove it here for the sake of completeness.

**Lemma 2.1.** *Let  $(S_t)$  be a random walk generated by  $k$  zero mean measures and an arbitrary adapted rule  $\ell$ . Let  $\mathcal{F}_t = \sigma(S_0, \dots, S_t)$  be its natural filtration. Let  $\alpha, r_0 > 0$  and define  $\varphi(x) = \|x\|^{-\alpha} \wedge r_0^{-\alpha}$ . If the process  $(\varphi(S_t))$  is a super-martingale, then  $S$  is transient, in the sense that a.s.*

$$\|S_t\| \rightarrow \infty \text{ as } t \rightarrow \infty.$$

**Proof.** We first show that a.s.

$$\limsup_{t \rightarrow \infty} \|S_t\| = \infty. \tag{2.1}$$

Indeed, there exist  $u \in \mathbb{S}^{d-1}$ ,  $\varepsilon > 0$  and  $h > 0$  such that for all  $j \in \{1, \dots, k\}$

$$\mathbb{P}(\langle Z_j, u \rangle > \varepsilon) \geq h,$$

where  $Z_j \sim \mu_j$ . This implies that for all  $m, n \in \mathbb{N}$  we have

$$\mathbb{P}(\langle S_{n+m} - S_n, u \rangle > \varepsilon m \mid \mathcal{F}_n) \geq h^m.$$

Hence this shows that a.s.  $\limsup_t |\langle S_t, u \rangle| \geq \varepsilon m/2$  for all  $m$ , and so (2.1) holds. Clearly, this implies that a.s.

$$\liminf_{t \rightarrow \infty} \varphi(S_t) = 0. \quad (2.2)$$

Since  $(\varphi(S_t))_t$  is a positive super-martingale, the a.s. super-martingale convergence theorem gives that  $\lim_{t \rightarrow \infty} \varphi(S_t)$  exists a.s. and thus from (2.2) we deduce that a.s.  $\lim_{t \rightarrow \infty} \varphi(S_t) = 0$ , which means that a.s.  $\|S_t\| \rightarrow \infty$  as  $t \rightarrow \infty$ .  $\square$

The following lemma shows that if the covariance matrices of the measures used to generate the walk  $X$  satisfy the trace condition (1.1), then there is a function  $\varphi$  such that  $\varphi(X)$  is a super-martingale.

**Lemma 2.2.** *Let  $\varphi(x) = \|x\|^{-\alpha} \wedge 1$ , for  $x \in \mathbb{R}^d$ . Let  $\mu_1, \dots, \mu_k$  be zero mean measures in  $\mathbb{R}^d$  with  $2 + \beta$  moments, for some  $\beta > 0$ , and with covariance matrices  $M_1, \dots, M_k$  satisfying for all  $i = 1, \dots, k$*

$$\text{tr}(M_i) > 2\lambda_{\max}(M_i).$$

*There exists  $\alpha > 0$  small enough and a constant  $r_0$  so that if  $\|x\| \geq r_0$ , then for all  $i = 1, \dots, k$  if  $Z_i \sim \mu_i$*

$$\mathbb{E}[\varphi(x + Z_i) - \varphi(x)] \leq 0. \quad (2.3)$$

**Proof.** It suffices to prove (2.3) for a fixed  $i$ . Since the covariance matrix  $M_i$  is positive definite, there is an orthogonal matrix  $U$  such that  $UM_iU^T$  is diagonal with non-negative eigenvalues. The matrix  $UM_iU^T$  is the covariance matrix of the random variable  $UZ_i$ .

Since  $U$  is orthogonal, we get that for all  $x$

$$\varphi(U(x + Z_i)) = \varphi(x + Z_i) \quad \text{and} \quad \varphi(Ux) = \varphi(x). \quad (2.4)$$

In order to prove the lemma, we will apply Taylor expansion up to second order terms to the function  $\varphi$  around  $Ux$  evaluated at  $UZ_i$ . We will drop the dependence on  $i$  from  $UZ_i$  and write simply  $Z$  and  $x$  instead of  $UZ$  and  $Ux$  in view of (2.4) to lighten the notation.

So, let  $Z$  have covariance matrix  $M$  which is in diagonal form and with diagonal elements  $\lambda_1, \dots, \lambda_d$ . Let  $\tilde{Z} = Z\mathbf{1}(\|Z\| \leq \|x\|/2)$ . Note that if a.s.  $\|Z\| \leq B$  for a positive constant  $B$ , then  $\tilde{Z} = Z$  if  $\|x\| \geq 2B$ . The calculations below are a bit simpler in this case, since  $\tilde{Z}$  would have mean 0 and the same covariance matrix as  $Z$ .

If  $\|x\| \geq 2$ , then  $\|x + \tilde{Z}\| \geq 1$  and so  $\varphi(x + \tilde{Z}) = \|x + \tilde{Z}\|^{-\alpha}$ . In what follows we abbreviate

$$\varphi'_i(x) = \frac{\partial \varphi(x)}{\partial x_i}, \quad \varphi''_{ij}(x) = \frac{\partial^2 \varphi(x)}{\partial x_i \partial x_j}, \quad \varphi'''_{ijk}(x) = \frac{\partial^3 \varphi(x)}{\partial x_i \partial x_j \partial x_k}.$$

Applying Taylor expansion to  $\varphi$  up to second order terms gives for some  $\eta \in (0, 1)$

$$\begin{aligned} \varphi(x + \tilde{Z}) &= \varphi(x) + \langle \nabla \varphi(x), \tilde{Z} \rangle + \frac{1}{2} \sum_{i,j=1}^d \varphi''_{ij}(x) \tilde{Z}_i \tilde{Z}_j + \frac{1}{3!} \sum_{i,j,k=1}^d \varphi'''_{ijk}(x + \eta \tilde{Z}) \tilde{Z}_i \tilde{Z}_j \tilde{Z}_k \\ &= \varphi(x) + \langle \nabla \varphi(x), \tilde{Z} \rangle + \frac{1}{2} \sum_{i,j=1}^d \varphi''_{ij}(x) Z_i Z_j + \frac{1}{3!} \sum_{i,j,k=1}^d \varphi'''_{ijk}(x + \eta \tilde{Z}) \tilde{Z}_i \tilde{Z}_j \tilde{Z}_k \\ &\quad - \sum_{i,j=1}^d \varphi''_{ij}(x) Z_i Z_j \mathbf{1} \left( \|Z\| \geq \frac{\|x\|}{2} \right). \end{aligned}$$

**Claim 2.3.** *There exist positive constants  $C, C_1$  such that for all  $i, j$*

$$\left| \mathbb{E} \left[ \langle \nabla \varphi(x), \tilde{Z} \rangle \right] \right| \leq \frac{C}{\|x\|^{\alpha+\beta+2}} \quad \text{and} \quad \mathbb{E}[Z_i Z_j \mathbf{1}(\|Z\| \geq \|x\|/2)] \leq \frac{C_1}{\|x\|^\beta}.$$

**Proof.** By Hölder's inequality we have

$$\mathbb{E}[\|Z\| \mathbf{1}(\|Z\| \geq \|x\|/2)] \leq \frac{2^{\beta+1} \mathbb{E}[\|Z\|^{\beta+2}]}{\|x\|^{\beta+1}} \leq \frac{K}{\|x\|^{\beta+1}}.$$

Since  $\mathbb{E}[Z] = 0$ , we have  $\mathbb{E}[\tilde{Z}] = \mathbb{E}[\tilde{Z} - Z]$ , and hence

$$\left\| \mathbb{E}[\tilde{Z}] \right\| = \left\| \mathbb{E}[Z \mathbf{1}(\|Z\| \geq \|x\|/2)] \right\| \leq \mathbb{E}[\|Z\| \mathbf{1}(\|Z\| \geq \|x\|/2)] \leq \frac{K}{\|x\|^{\beta+1}}.$$

For the first term of the Taylor expansion we have for a positive constant  $C$

$$\left| \mathbb{E} \left[ \langle \nabla \varphi(x), \tilde{Z} \rangle \right] \right| = \sum_{i=1}^d \frac{\alpha |x_i|}{\|x\|^{\alpha+2}} \left| \mathbb{E}[\tilde{Z}_i] \right| \leq \sum_{i=1}^d \frac{\alpha |x_i|}{\|x\|^{\alpha+2}} \left\| \mathbb{E}[\tilde{Z}] \right\| \leq \frac{\alpha d K \|x\|}{\|x\|^{\alpha+\beta+3}} = \frac{C}{\|x\|^{\alpha+\beta+2}}.$$

For all  $i, j$  we have by Hölder's inequality again

$$\mathbb{E}[Z_i Z_j \mathbf{1}(\|Z\| \geq \|x\|/2)] \leq \mathbb{E}[\|Z\|^2 \mathbf{1}(\|Z\| \geq \|x\|/2)] \leq \frac{C_1}{\|x\|^\beta},$$

thus proving the claim. □

We continue proving Lemma 2.2. For the second order terms we write

$$\mathbb{E}[\tilde{Z}_i \tilde{Z}_j] = \mathbb{E}[Z_i Z_j \mathbf{1}(\|Z\| \leq \|x\|/2)] = \mathbb{E}[Z_i Z_j] - \mathbb{E}[Z_i Z_j \mathbf{1}(\|Z\| \geq \|x\|/2)],$$

and hence since for  $i \neq j$  we have  $\mathbb{E}[Z_i Z_j] = 0$ , by Claim 2.3 we get

$$\left| \mathbb{E}[\tilde{Z}_i \tilde{Z}_j] \right| \leq \frac{C_1}{\|x\|^\beta} \quad \text{and} \quad \left| \sum_{i=1}^d \varphi''_{ii}(x) \mathbb{E}[Z_i^2 \mathbf{1}(\|Z\| \geq \|x\|/2)] \right| \leq \frac{C_2}{\|x\|^{\alpha+\beta+2}}.$$

Since for all  $i$  we have  $\mathbb{E}[Z_i^2] = \lambda_i$ , we obtain

$$\sum_{i=1}^d \varphi''_{ii}(x) \mathbb{E}[Z_i^2] = \sum_{i=1}^d \lambda_i \frac{-\alpha \|x\|^2 + \alpha(\alpha+2)x_i^2}{\|x\|^{\alpha+4}} = \sum_{i=1}^d \frac{\alpha x_i^2 (\lambda_i(\alpha+2) - \sum_{j=1}^d \lambda_j)}{\|x\|^{\alpha+4}}. \quad (2.5)$$

The rest of the second order terms can be bounded as follows:

$$\left| \sum_{i \neq j} \varphi''_{ij}(x) \mathbb{E}[\tilde{Z}_i \tilde{Z}_j] \right| = \sum_{i \neq j} \frac{\alpha(\alpha+2) |x_i| |x_j|}{\|x\|^{\alpha+4}} \left| \mathbb{E}[\tilde{Z}_i \tilde{Z}_j] \right| \leq \sum_{i \neq j} \frac{\alpha(\alpha+2) |x_i| |x_j|}{\|x\|^{\alpha+4}} \frac{C_1}{\|x\|^\beta} \leq \frac{C_3}{\|x\|^{\alpha+\beta+2}}.$$

For the remainder in the Taylor expansion we have

$$\max_{i,j,k} \left| \varphi'''_{ijk}(x + \eta \tilde{Z}) \right| \leq \frac{C}{\|x + \eta \tilde{Z}\|^{\alpha+3}} \leq \frac{C_4}{\|x\|^{\alpha+3}},$$

since  $\|\tilde{Z}\| \leq \|x\|/2$ . We want to control  $\mathbb{E}[\varphi(x+Z) - \varphi(x)]$ . We write

$$\mathbb{E}[\varphi(x+Z) - \varphi(x)] = \mathbb{E}[\varphi(x+Z) - \varphi(x+\tilde{Z})] + \mathbb{E}[\varphi(x+\tilde{Z}) - \varphi(x)] \quad (2.6)$$

and by Markov's inequality since  $\mathbb{E}[\|Z\|^{2+\beta}] < \infty$

$$\mathbb{E}\left[\left|\varphi(x+Z) - \varphi(x+\tilde{Z})\right|\right] \leq \mathbb{P}(\|Z\| \geq \|x\|/2) \leq \frac{C_5}{\|x\|^{\beta+2}}.$$

Since  $\beta > 0$ , if we take  $0 < \alpha < \beta$ , then we obtain that there exists a constant  $r_0 > 1$  so that for  $\|x\| > r_0$

$$\begin{aligned} \left|\mathbb{E}\left[\langle \nabla \varphi(x), \tilde{Z} \rangle\right]\right| + \frac{1}{2} \left| \sum_{i,j=1}^d \varphi''_{ij}(x) \mathbb{E}\left[Z_i Z_j \mathbf{1}\left(\|Z\| \geq \frac{\|x\|}{2}\right)\right] \right| + \frac{1}{3!} \sum_{i,j,k=1}^d \left| \mathbb{E}\left[\varphi'''_{ijk}(x + \eta \tilde{Z}) \tilde{Z}_i \tilde{Z}_j \tilde{Z}_k\right] \right| \\ + \left| \mathbb{E}\left[\varphi(x+\tilde{Z}) - \varphi(x+Z)\right] \right| \leq \left| \frac{1}{2} \sum_{i,j=1}^d \varphi''_{ij}(x) \mathbb{E}[Z_i Z_j] \right|. \end{aligned} \quad (2.7)$$

The assumption on the trace of the matrix  $M$  gives that for  $\alpha$  small enough (smaller than  $\beta$ )  $\sum_{j=1}^d \lambda_j > \lambda_i(\alpha + 2)$  for all  $i$ , and hence using (2.5) we get for  $\|x\| \geq r_0$

$$\sum_{i=1}^d \varphi''_{ii}(x) \mathbb{E}[Z_i^2] < 0.$$

This and the inequality (2.7) finishes the proof.  $\square$

We now have all the required ingredients to give the proof of Theorem 1.3.

**Proof of Theorem 1.3.** Let  $r_0 > 1$  be the constant of Lemma 2.2. Let  $\tilde{\varphi}(x) = \|x\|^{-\alpha} \wedge r_0^{-\alpha}$ , for  $\alpha > 0$  as in Lemma 2.2. Notice that when  $\|x\| \geq r_0$ , then  $\tilde{\varphi}(x) = \varphi(x) = \|x\|^{-\alpha}$ . We will first show that if  $Y_t = AX_t$ , then

$$\mathbb{E}[\tilde{\varphi}(Y_{t+1}) \mid \mathcal{F}_t] \leq \tilde{\varphi}(Y_t). \quad (2.8)$$

Since  $r_0 > 1$ , we have  $\tilde{\varphi}(x) \leq \varphi(x)$  for all  $x$ . So we get

$$\begin{aligned} \mathbb{E}[\tilde{\varphi}(Y_{t+1}) - \tilde{\varphi}(Y_t) \mid \mathcal{F}_t] &= \mathbb{E}[(\tilde{\varphi}(Y_{t+1}) - \tilde{\varphi}(Y_t)) \mathbf{1}(\|Y_t\| \geq r_0) \mid \mathcal{F}_t] \\ &\quad + \mathbb{E}[(\tilde{\varphi}(Y_{t+1}) - \tilde{\varphi}(Y_t)) \mathbf{1}(\|Y_t\| < r_0) \mid \mathcal{F}_t] \\ &\leq \mathbb{E}[(\varphi(Y_{t+1}) - \varphi(Y_t)) \mathbf{1}(\|Y_t\| \geq r_0) \mid \mathcal{F}_t], \end{aligned}$$

since  $\tilde{\varphi}(Y_t) = r_0^{-\alpha}$  if  $\|Y_t\| < r_0$  and  $\tilde{\varphi}(x) \leq r_0^{-\alpha}$  for all  $x$ . Since the covariance matrices of the measures used to generate the walk  $Y$  satisfy the trace condition (1.1), Lemma 2.2 gives that

$$\mathbb{E}[(\varphi(Y_{t+1}) - \varphi(Y_t)) \mathbf{1}(\|Y_t\| \geq r_0) \mid \mathcal{F}_t] \leq 0$$

and this completes the proof of (2.8). Therefore by Lemma 2.1 we get that a.s.  $\|AX_t\| = \|Y_t\| \rightarrow \infty$  as  $t \rightarrow \infty$ . Since for all  $t$  we have  $\|AX_t\| \leq \|A\| \|S_t\|$  and  $\|A\| > 0$ , we deduce that a.s.

$$\|X_t\| \rightarrow \infty \text{ as } t \rightarrow \infty,$$

which concludes the proof of the theorem.  $\square$

## 2.2 Two measures in 3 dimensions

In this section we give the proof of Theorem 1.5.

**Proposition 2.4.** *Let  $M_1, M_2$  be  $3 \times 3$  invertible positive definite matrices. Then there exists a  $3 \times 3$  matrix  $A$  such that*

$$\operatorname{tr}(AM_iA^T) > 2\lambda_{\max}(AM_iA^T) \quad \forall i = 1, 2.$$

**Proof.** We prove Proposition 2.4 by constructing the matrix  $A$  of Theorem 1.3 directly.

Let  $\mu_1, \mu_2$  have covariance matrices  $M_1$  and  $M_2$  respectively and  $\xi_i \sim \mu_i$  for  $i = 1, 2$ . Since  $M_1$  is positive definite, there exists an orthogonal matrix  $U$  such that  $UM_1U^T$  is diagonal, i.e.

$$UM_1U^T = \begin{pmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{pmatrix},$$

where  $a, b, c > 0$  are the eigenvalues of  $M_1$ . If we now multiply the vector  $U\xi_1$  by the matrix  $D$  given by

$$D = \begin{pmatrix} \frac{1}{\sqrt{a}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{b}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{c}} \end{pmatrix},$$

then  $\operatorname{Cov}(DU\xi_1) = I$ , where  $I$  stands for the  $3 \times 3$  identity matrix.

So far we have applied the matrix  $DU$  to the vector  $\xi_1$  and we have to apply the same transformation to the vector  $\xi_2$ . The vector  $DU\xi_2$  will have covariance matrix  $\widetilde{M}_2$ . Since it is positive definite, it can be diagonalised, so there exists an orthogonal matrix  $V$  such that

$$V\widetilde{M}_2V^T = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix},$$

where  $\lambda_1 \geq \lambda_2 \geq \lambda_3 > 0$  are the eigenvalues in decreasing order. Applying the same transformation to  $DU\xi_1$  is not going to change its identity covariance matrix, since  $V$  is orthogonal.

The condition we want to satisfy is

$$\lambda_1 + \lambda_2 + \lambda_3 > 2\lambda_i,$$

for all  $i = 1, 2, 3$ . Since the eigenvalues are in decreasing order, it is clear that this inequality is always satisfied for  $i = 2, 3$ . Suppose that  $\lambda_2 + \lambda_3 \leq \lambda_1$ . Multiplying  $DU\xi_2$  by the matrix

$$B = \begin{pmatrix} \frac{\sqrt{\lambda_2}}{\sqrt{\lambda_1}} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

will give us a random vector with covariance matrix

$$\begin{pmatrix} \lambda_2 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix},$$

which clearly satisfies the trace condition (1.1). Multiplying  $VDU\xi_1$  by the same matrix will give us a vector with covariance matrix

$$\begin{pmatrix} \frac{\lambda_2}{\lambda_1} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

which satisfies the trace condition (1.1), since  $\lambda_2 \leq \lambda_1$ .  $\square$

**Proof of Theorem 1.2.** By projection to the first three coordinates, it is clear that it suffices to prove the theorem in 3 dimensions.

In  $d = 3$ , the statement of the theorem follows from Theorem 1.3 and Proposition 2.4.  $\square$

**Remark 2.5.** It can be seen from the proof of Proposition 2.4 that if the measures  $\mu_1$  and  $\mu_2$  are supported on any 3 dimensional subspaces of  $\mathbb{R}^d$ , then a walk  $X$  generated by these measures and an arbitrary adapted rule is transient.

### 2.3 The diagonal case

In this section we consider a particular case when for some basis of  $\mathbb{R}^d$  the covariance matrices are in diagonal form and invertible. In this setting we prove that a random walk generated by  $d - 1$  measures and an arbitrary rule  $\ell$  is transient.

**Proposition 2.6.** *Let  $d \geq 4$  and  $\mu_1, \dots, \mu_{d-1}$  be mean 0 probability measures in  $\mathbb{R}^d$  with  $2 + \beta$  moments, for some  $\beta > 0$ . Let  $M_1, \dots, M_{d-1}$  be their covariance matrices and suppose that  $M_i M_j = M_j M_i$  for all  $i, j$ . Then there exists a  $d \times d$  matrix  $A$  such that*

$$\text{tr}(AM_i A^T) > 2\lambda_{\max}(AM_i A^T) \quad \forall i \leq d - 1.$$

*Therefore, a random walk  $X$  generated by the measures  $(\mu_i)_{i=1}^{d-1}$  and an arbitrary adapted rule  $\ell$  is transient.*

Before giving the proof of Proposition 2.6 we prove the following:

**Claim 2.7.** *Let  $M_1, \dots, M_k$  be  $d \times d$  invertible diagonal matrices with positive entries on the diagonal. For  $A \neq 0$  we define*

$$\Psi(A) = \max_{1 \leq j \leq k} \frac{\|AM_j A^T\|}{\text{tr}(AM_j A^T)}. \quad (2.9)$$

*Then the minimum of  $\Psi(A)$  exists among all diagonal matrices  $A$  and the minimizing matrix  $\tilde{A}$  is invertible.*

**Proof.** Since  $M_j$  is an invertible positive definite matrix, we can write  $M_j = B_j B_j^T = B_j^2$ , where  $B_j = B_j^T$  is an invertible matrix.

Since scaling  $A$  does not change the ratio in (2.9), we may assume that  $\|A\| = 1$  and restrict attention to such matrices. It is easy to see that the set  $S = \{A \text{ diagonal} : \|A\| = 1\}$  is compact and the function  $f_j(A) = \|AM_j A^T\|$  is continuous on  $S$ .

Let  $g_j(A) = \text{tr}(AM_j A^T) = \text{tr}(AB_j B_j^T A^T) = \|AB_j\|^2$ , where  $\|C\|^2 = \sum_{i,j=1}^d c_{i,j}^2$  and we used  $\text{tr}(CC^T) = \|C\|^2$ .

Since  $B_j$  is invertible, we have  $AB_j \neq 0$  for  $A \neq 0$ , so  $g_j$  does not vanish on  $S$ . Thus as  $g_j$  is continuous on  $S$ , we conclude that

$$A \mapsto \max_{1 \leq j \leq k} \frac{f_j(A)}{g_j(A)}$$

is continuous on  $S$  and hence has a minimum.

Let  $\tilde{A}$  be the minimizing matrix with diagonal elements  $\lambda_1, \dots, \lambda_d \geq 0$ . We will show that  $\tilde{A}$  is invertible. Suppose the contrary and assume without loss of generality that  $\lambda_d = 0$ .

We prove that if we replace  $\lambda_d = 0$  by a small  $\varepsilon > 0$ , then we get a matrix  $\tilde{A}_\varepsilon$  with  $\Psi(\tilde{A}_\varepsilon) < \Psi(\tilde{A})$ . Let the diagonal elements of  $M_i$  be  $(a_j^i)_{j=1}^d$ , which are all strictly positive. Then for the matrix  $M_i$  we will have for  $s$  such that  $\|M_i\| = a_s^i$

$$\frac{\lambda_{\max}(\tilde{A}M_i\tilde{A})}{\text{tr}(\tilde{A}M_i\tilde{A})} = \frac{\lambda_s a_s^i}{\sum_j \lambda_j a_j^i}.$$

If  $\tilde{A}_\varepsilon$  has the same elements as  $\tilde{A}$  except for the  $(d, d)$  element which is replaced by  $\varepsilon > 0$  such that  $\varepsilon < \frac{\lambda_i a_j^i}{a_i^i}$  for all  $i = 1, \dots, d-1$  and all  $j = 1, \dots, d-1$ , then

$$\text{tr}(\tilde{A}_\varepsilon M_i \tilde{A}_\varepsilon) = \text{tr}(\tilde{A} M_i \tilde{A}) + \varepsilon a_d^i,$$

while  $\lambda_{\max}(\tilde{A}_\varepsilon M_i \tilde{A}_\varepsilon) = \lambda_{\max}(\tilde{A} M_i \tilde{A})$ .

Replacing each 0 element of  $\tilde{A}$  by a sufficiently small number gives a matrix with smaller value of  $\Psi$ , which contradicts the choice of  $\tilde{A}$ . Hence this shows that  $\tilde{A}$  is invertible.  $\square$

**Proof of Proposition 2.6.** Since  $M_i M_j = M_j M_i$  for all  $i, j$ , it follows (see for instance [7, Theorem 2.5.5]) that there is one orthogonal matrix that diagonalizes all the matrices  $M_i$ . So from now on we suppose that the  $M_i$ 's are diagonal.

Recall the definition of  $\Psi$  from (2.9). Let  $\tilde{A}$  be the  $d \times d$  invertible matrix that minimizes  $\Psi$  among all diagonal matrices (recall Claim 2.7).

Write  $\tilde{M}_i = \tilde{A} M_i \tilde{A}^T$  and

$$J = \left\{ j \leq d-1 : \frac{\|\tilde{M}_j\|}{\text{tr}(\tilde{M}_j)} = \Psi(\tilde{A}) \right\}.$$

Since  $\tilde{A}$  and  $M_i$  are diagonal invertible matrices, it follows that  $\tilde{M}_i$  is also a diagonal invertible matrix. For each  $j \leq d-1$  we can find  $v_j \in \mathbb{R}^d$  such that  $\|v_j\| = 1$  and  $\tilde{M}_j v_j = \|\tilde{M}_j\| v_j$ . Note that since  $\tilde{M}_j$  is diagonal, it follows that  $v_j$  can be chosen to be one of the standard basis vectors of  $\mathbb{R}^d$ . Let  $w \in \mathbb{R}^d$  have  $\|w\| = 1$  and  $w \perp \{v_1, \dots, v_{d-1}\}$ . Then  $w$  will also be one of the standard basis vectors of  $\mathbb{R}^d$ .

Next, we separate two cases.

Case 1: For some  $j \in J$  there is  $u_j \perp v_j$  with  $\|u_j\| = 1$  and  $\tilde{M}_j u_j = \|\tilde{M}_j\| u_j$ . In this case,

$$\text{tr}(\tilde{M}_j) > \langle \tilde{M}_j v_j, v_j \rangle + \langle \tilde{M}_j u_j, u_j \rangle = 2\|\tilde{M}_j\|, \quad (2.10)$$

where the strict inequality follows from the fact that  $\tilde{M}_j$  is invertible. Hence in the case where  $\|\tilde{M}_j\|$  has multiplicity at least 2, we are done.

Case 2: For each  $j \in J$  the leading eigenvalue  $\|\widetilde{M}_j\|$  of  $\widetilde{M}_j$  has multiplicity one. We will show that this case leads to a contradiction; that is we can find another matrix with smaller value of  $\Psi$  contradicting the choice of  $\widetilde{A}$  as the minimizer.

Let  $A_\varepsilon$  be the  $d \times d$  matrix such that  $A_\varepsilon w = (1 + \varepsilon)w$  and  $A_\varepsilon z = z$  for all  $z \perp w$ . Note that  $A_\varepsilon$  will also be diagonal, since  $w$  is one of the standard basis vectors of  $\mathbb{R}^d$ .

Let us denote by  $\gamma_j$  the second largest eigenvalue of  $\widetilde{M}_j$ . Then the assumption of case 2 implies that for each  $j \in J$  we have  $\gamma_j < \|\widetilde{M}_j\|$  and  $\|\widetilde{M}_j y\| \leq \gamma_j \|y\|$  for all  $y \perp v_j$ .

Choose  $\varepsilon > 0$  such that  $(1 + \varepsilon)^2 \|\widetilde{M}_i\| < \text{tr}(\widetilde{M}_i) \Psi(\widetilde{A})$  for all  $i \notin J$  and  $(1 + \varepsilon)^2 \gamma_j < \|\widetilde{M}_j\|$  for all  $j \in J$ .

Note that since  $A_\varepsilon$  is diagonal,  $A_\varepsilon^T = A_\varepsilon$  and  $\widetilde{A} A_\varepsilon$  is diagonal satisfying

$$\Psi(A_\varepsilon \widetilde{A}) = \max_{1 \leq i \leq d-1} \frac{\|A_\varepsilon \widetilde{M}_i A_\varepsilon\|}{\text{tr}(A_\varepsilon \widetilde{M}_i A_\varepsilon)}.$$

By completing  $\{w, v_j\}$  to an orthonormal basis  $\{b_m\}_{m=1}^d$  of  $\mathbb{R}^d$  we see that for all  $i \leq d-1$

$$\text{tr}(A_\varepsilon \widetilde{M}_i A_\varepsilon) > \text{tr}(\widetilde{M}_i), \quad (2.11)$$

since  $\text{tr}(M) = \sum_{m=1}^d \langle M b_m, b_m \rangle$  for any matrix  $M$  and any orthonormal basis. The strict inequality follows again from the fact that the matrix  $A_\varepsilon \widetilde{M}_i A_\varepsilon$  is invertible. Also

$$\|A_\varepsilon \widetilde{M}_i A_\varepsilon\| \leq \|A_\varepsilon\|^2 \|\widetilde{M}_i\| = (1 + \varepsilon)^2 \|\widetilde{M}_i\|$$

and for  $j \in J$  we have for all  $y \perp v_j$

$$\|A_\varepsilon \widetilde{M}_j A_\varepsilon y\| \leq (1 + \varepsilon) \|M_j(A_\varepsilon y)\| \leq (1 + \varepsilon) \gamma_j \|A_\varepsilon y\| \leq (1 + \varepsilon)^2 \gamma_j \|y\|,$$

since  $A_\varepsilon y \perp v_j$ .

We conclude that  $\Psi(A_\varepsilon \widetilde{A}) < \Psi(\widetilde{A})$  by considering separately in the max defining  $\Psi$  the indices  $i \notin J$  and  $i \in J$ , and applying (2.11). This contradicts the choice of  $\widetilde{A}$  as a minimizer and establishes that case 2 is impossible.  $\square$

### 3 More measures may yield a recurrent walk

In this section we prove that the random walk described in Section 1.2 is recurrent. First we give the simpler example that was mentioned in the Introduction.

Let  $\mathbb{S}^{d-1}$  be the  $d$ -dimensional unit sphere, i.e.  $\mathbb{S}^{d-1} = \{x \in \mathbb{R}^d : \|x\| = 1\}$ . Let  $C_1, \dots, C_k$  be caps that cover the surface of the sphere with the property that the angle between any two vectors from the origin to points on the same cap is strictly smaller than  $\pi/2$ . For every cap  $C_i$ , for  $i = 1, \dots, k$ , we write  $m(C_i)$  for the vector joining 0 to the center of the cap  $C_i$ . Then we choose  $v_{i,1}, \dots, v_{i,d-1}$  to be  $d-1$  orthogonal vectors on the hyperplane orthogonal to  $m(C_i)$ .

For every  $x \in \mathbb{R}^d$ , we write  $C(x)$  for the first cap in the above ordering such that the vector joining 0 and  $x$  intersects that cap.

**Theorem 3.1.** *Let  $X$  be a walk in  $\mathbb{R}^d$  that moves as follows. When at  $x$  it moves along the direction of  $m(C(x))$  either  $+1$  or  $-1$  each with probability  $1/2$  and along each of the other  $d-1$  directions, i.e. along the vectors  $v_{i(x),1}, \dots, v_{i(x),d-1}$  it moves independently as follows:  $\pm 1$  with probabilities  $\varepsilon/2$  and stays in place with the remaining probability. Then  $X$  is a recurrent walk, i.e. there is a compact set that is visited by  $X$  infinitely many times a.s.*

**Remark 3.2.** It can be shown that the ratio of the area of the unit sphere to the area of a cap as defined above with angle  $\pi/2$  is equal to  $2/I_{1/2}(\frac{d-1}{2}, \frac{1}{2})$ , where  $I$  is the regularized incomplete beta function. It is then elementary to obtain that the last quantity can be bounded below by  $2^{d/2+1} > d$ , so that in the above theorem at least  $2^{d/2+1}$  measures are needed.

**Proof of Theorem 3.1.** We define  $\varphi(x) = \log \|x\|$ , for  $x \in \mathbb{R}^d$ . Then by Taylor expansion to second order terms we obtain for some  $\eta \in (0, 1)$

$$\varphi(x + Z) = \varphi(x) + \langle \nabla \varphi(x), Z \rangle + \frac{1}{2} \sum_{i,j} \frac{\partial^2 \varphi(x)}{\partial x_i \partial x_j} Z_i Z_j + \frac{1}{3!} \sum_{i,j,k=1}^d \frac{\partial^3 \varphi(x + \eta Z)}{\partial x_i \partial x_j \partial x_k} Z_i Z_j Z_k.$$

For each  $i$  and positive constants  $C, C_1$ , since  $Z$  is bounded, we have

$$\frac{\partial \varphi}{\partial x_i} = \frac{x_i}{\|x\|^2}, \quad \frac{\partial^2 \varphi}{\partial x_i^2} = \frac{\sum_{j \neq i} x_j^2 - x_i^2}{\|x\|^4} \quad \text{and} \quad \max_{i,j,k} \left| \frac{\partial^3 \varphi(x + \eta Z)}{\partial x_i \partial x_j \partial x_k} \right| \leq \frac{C_1}{\|x + \eta Z\|^3} \leq \frac{C}{\|x\|^3}.$$

Let  $u_1, \dots, u_d$  be the vectors (basis of  $\mathbb{R}^d$ ) as defined in the theorem. We now write both  $x$  and  $Z$  in this basis, i.e. we have that  $x = \sum_{i=1}^d x_i u_i$  and  $Z = \sum_{i=1}^d Z_i u_i$ . Then for  $i \neq j$ , by independence, we get that  $\mathbb{E}[Z_i Z_j] = 0$ , while  $\mathbb{E}[Z_1^2] = 1$  and for all  $i > 1$  we have that  $\mathbb{E}[Z_i^2] = \varepsilon$ . Hence, putting all things together we obtain that

$$\sum_{i,j} \frac{\partial^2 \varphi(x)}{\partial x_i \partial x_j} \mathbb{E}[Z_i Z_j] = \frac{(1 + \varepsilon(d-3))\|x\|^2 + 2(\varepsilon - 1)x_1^2}{\|x\|^4}. \quad (3.1)$$

For the first coordinate  $x_1$  of  $x$ , when decomposed in the basis described above, we have that

$$x_1 = \|x\| \cos \theta,$$

where  $\theta$  is strictly smaller than  $\pi/4$ , so there exists  $\delta > 0$  so that  $\cos \theta \geq (1 + \delta)\sqrt{2}/2$ . Hence, we can now bound (3.1) from above by

$$\frac{x_1^2}{\|x\|^4} \left( 2(\varepsilon - 1) + \frac{1}{2(1 + \delta)^2} (1 + \varepsilon(d-3)) \right),$$

which can be made negative by choosing  $\varepsilon$  small enough. Notice that in absolute value the last expression is at least  $c\|x\|^{-2}$  for a positive constant  $c$ , and hence since  $Z$  has mean 0, it follows that for  $\|x\|$  large enough we have

$$\left| \frac{1}{3!} \sum_{i,j,k=1}^d \mathbb{E} \left[ \frac{\partial^3 \varphi(x + \eta Z)}{\partial x_i \partial x_j \partial x_k} Z_i Z_j Z_k \right] \right| \leq \frac{1}{2} \left| \sum_{i,j=1}^d \frac{\partial^2 \varphi(x)}{\partial x_i \partial x_j} \mathbb{E}[Z_i Z_j] \right|.$$

Therefore we deduce that for  $\|x\| \geq r_0$

$$\mathbb{E}[\varphi(x + Z) - \varphi(x)] \leq 0. \quad (3.2)$$

We now show that this implies recurrence. By the same argument used to show (2.1) we get that a.s.

$$\limsup_{t \rightarrow \infty} \|X_t\| = \infty.$$

Let  $T_{r_0} = \inf\{t \geq 0 : X_t \in \mathcal{B}(0, r_0)\}$ . By (3.2) we obtain that  $\varphi(X_{t \wedge T_{r_0}})$  is a positive supermartingale. Hence the a.s. martingale convergence theorem gives that  $\lim_{t \rightarrow \infty} \varphi(X_{t \wedge T_{r_0}}) = Y$  exists a.s. and is finite. If  $T_{r_0} = \infty$  with positive probability, then since  $\varphi(x) \rightarrow \infty$  as  $x \rightarrow \infty$ , then  $\lim \varphi(X_{t \wedge T_{r_0}}) = \infty$  with positive probability, which is a contradiction. Therefore,  $T_{r_0} < \infty$  a.s.  $\square$

We will now give the proof of Theorem 1.5.

**Proof of Theorem 1.5.** By [6, Theorem 2.2.1] or analogously to the last part of the proof of Theorem 3.1, to prove recurrence it is enough to find a nonnegative function  $f$  such that  $f(x) \rightarrow \infty$  as  $x \rightarrow \infty$ , and

$$\mathbb{E}[f(X_{n+1}) - f(X_n) \mid X_n = x] \leq 0 \quad \text{for all large enough } x. \quad (3.3)$$

Before presenting the explicit construction of such a function, let us informally explain the intuition behind this construction. First of all, a straightforward computation shows that, if  $Y$  is a simple random walk in  $\mathbb{Z}^d$ , then

$$\begin{aligned} \mathbb{E}[\|Y_{n+1}\| - \|Y_n\| \mid Y_n = x] &= \frac{d-1}{2d} \frac{1}{\|x\|} + O(\|x\|^{-2}), \\ \mathbb{E}[(\|Y_{n+1}\| - \|Y_n\|)^2 \mid Y_n = x] &= \frac{1}{d} + O(\|x\|^{-1}). \end{aligned}$$

One can observe that the ratio of the drift to the second moment behaves as  $\frac{d-1}{2\|x\|}$ ; combined with the well-known fact that the SRW is recurrent for  $d = 2$  and transient for  $d \geq 3$ , this suggests that, to obtain recurrence, the constant in this ratio should not be too large (in fact, at most  $\frac{1}{2}$ ). Then, the second moment depends essentially on the dimension, and thus it is crucial to look at the drift. So, consider a (smooth in  $\mathbb{R}^d \setminus \{0\}$ ) function  $g(x) = \Theta(\|x\|)$ ; we shall try to figure out how the level sets of  $g$  should be so that the “drift outside” with respect to  $g$  “behaves well” (i.e., the drift multiplied by  $\|x\|$  is uniformly bounded above by a not-so-large constant). For that, let us look at Figure 1: level sets of  $g$  are indicated by solid lines, vectors’ sizes correspond to transition probabilities. Then, it is intuitively clear that the case of “moderate” drift corresponds to the following:

- the “preferred” direction is radial, the curvature of level lines is large, or
- the “preferred” direction is transversal and the curvature of level lines is small;

also, it is clear that “very flat” level lines always generate small drift. However, one cannot hope to make the level lines very flat everywhere, as they should go around the origin. So, the idea is to find in which places one can afford “more curved” level lines.

Observe that, for the random walk we are considering now, the preferred direction near the axes is the radial one, while in the “diagonal” regions it is in some intermediate position between transversal and radial. This indicates that the level sets of the Lyapunov function should look as depicted on Figure 2: more curved near the axes, and more flat off the axes.

We are going to use the Lyapunov function

$$f(x) = \varphi\left(\frac{x}{\|x\|}\right) \|x\|^\alpha,$$

where  $\alpha$  is a positive constant and  $\varphi : \mathbb{S}^{d-1} \mapsto \mathbb{R}$  is a positive continuous function, symmetric in the sense that for any  $(u_0, \dots, u_{d-1}) \in \mathbb{S}^{d-1}$  we have  $\varphi(u_0, \dots, u_{d-1}) = \varphi(\tau_0 u_{\sigma(0)}, \dots, \tau_{d-1} u_{\sigma(d-1)})$  for any permutation  $\sigma$  and any  $\tau \in \{-1, 1\}^d$ . By the previous discussion, to have the level sets as on Figure 2, we are aiming at constructing  $\varphi$  with values close to 1 near the “diagonals” and less than 1 near the axes.

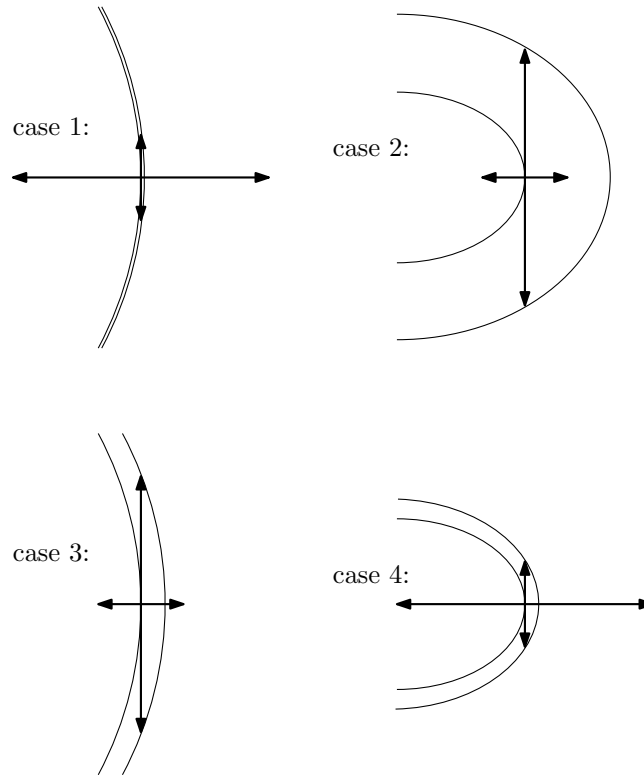


Figure 1: Looking at the level sets: how large is the drift? We have *very small* drift in case 1, *very large* drift in case 2, and *moderate* drifts in cases 3 and 4.

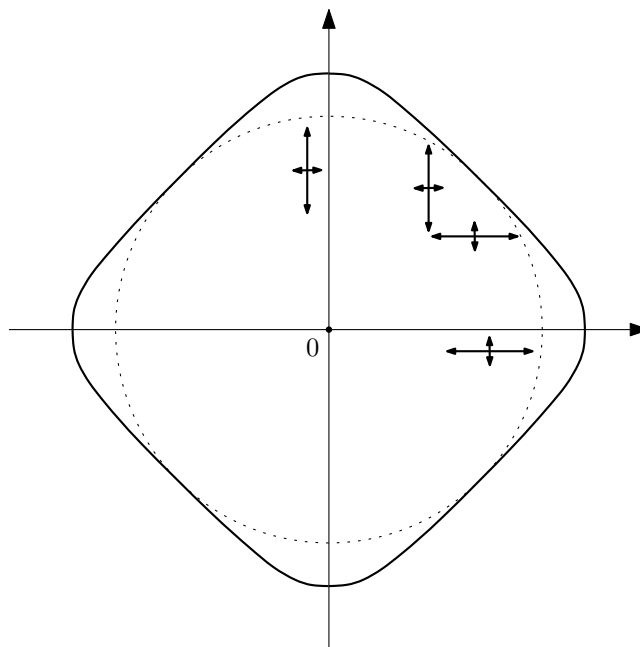


Figure 2: How the level sets of  $f$  should look like?

By symmetry, it is enough to define the function  $\varphi$  for  $u \in \mathbb{S}^{d-1}$  such that  $u_0 \geq u_1, \dots, u_{d-1} \geq 0$  (clearly, it then holds that  $u_0 > 0$ ), and, again by symmetry, it is enough to prove (3.3) for all large enough  $x \in \mathbb{Z}^d$  of the same kind. For such  $u \in \mathbb{S}^{d-1}$  abbreviate  $s_j = u_j/u_0$ ,  $j = 1, \dots, d-1$ ; observe that, if  $u = x/\|x\|$ , then  $s_j = x_j/x_0$ . We are going to look for the function (for  $u$  as above)  $\varphi(u) = 1 - \alpha\psi(s_1, \dots, s_{d-1})$ , where  $\psi$  is a function with continuous third partial derivatives on  $[0, 1]^{d-1}$  (in fact, it will become clear that the function  $\psi$  extended by means of symmetry on  $[-1, 1]^d$  has continuous third derivatives on  $[-1, 1]^d$ ; this will imply that  $o$ -s in the computations below are uniform).

Next, we proceed in the following way: we do calculations in order to figure out, which conditions the function  $\psi$  should satisfy in order to guarantee that (3.3) holds, and then try to construct a concrete example of  $\psi$  that satisfies these conditions.

First of all, a straightforward calculation shows that for any  $e \in \mathbb{Z}^d$  with  $\|e\| = 1$  we have

$$\|x + e\|^\alpha = \|x\|^\alpha \left( 1 + \alpha \frac{\langle x, e \rangle}{\|x\|^2} + \frac{\alpha}{2\|x\|^2} - \frac{1}{2}\alpha(2 - \alpha) \frac{\langle x, e \rangle^2}{\|x\|^2} \cdot \frac{1}{\|x\|^2} + o(\|x\|^{-2}) \right), \quad (3.4)$$

as  $x \rightarrow \infty$ .

In the computations below, we will use the abbreviations

$$\begin{aligned} \psi'_j &:= \frac{\partial \psi(s_1, \dots, s_{d-1})}{\partial s_j}, \quad j = 1, \dots, d-1, \\ \psi''_{ij} &:= \frac{\partial^2 \psi(s_1, \dots, s_{d-1})}{\partial s_i \partial s_j}, \quad i, j = 1, \dots, d-1. \end{aligned}$$

Let us now consider  $x \in \mathbb{Z}^d$ . From now on we will refer to the situation when  $x_0 > x_1, \dots, x_{d-1} \geq 0$  as the “non-boundary case” and  $x_0 = x_1 = \dots = x_m > x_{m+1} \geq \dots \geq x_{d-1} \geq 0$  for some  $m \geq 1$  as the “boundary case”. Observe for the boundary case the corresponding  $s$  will be of the form  $s = (1, \dots, (1)_m, s_{m+1}, \dots, s_{d-1})$ ; here and in the sequel we indicate the position of the symbol in a row by placing parentheses and putting a subscript. Also, in the situation when only one coordinate of the vector  $s$  changes, we use the notation of the form  $\psi((\tilde{s})_j)$  for  $\psi(s_1, \dots, s_{j-1}, \tilde{s}, s_{j+1}, \dots, s_{d-1})$ , possibly omitting the parentheses and the subscript when the position is clear.

First we deal with the non-boundary case.

Let us consider  $x \in \mathbb{Z}^d$  such that  $x_0 > x_1, \dots, x_{d-1} \geq 0$ . Again using (3.4) and observing that (recall  $s_j = x_j/x_0$ )  $\frac{x_j}{x_0-1} = s_j(1 + x_0^{-1} + x_0^{-2} + o(\|x\|^{-2}))$  and  $\frac{x_j}{x_0+1} = s_j(1 - x_0^{-1} + x_0^{-2} + o(\|x\|^{-2}))$ , we write

$$\begin{aligned} & \mathbb{E}[f(X_{n+1}) - f(X_n) \mid X_n = x] \\ &= -(1 - \alpha\psi(s))\|x\|^\alpha + \frac{\gamma}{2(\gamma + d - 1)} \left[ \left( 1 - \alpha\psi\left(\frac{x_1}{x_0-1}, \dots, \frac{x_{d-1}}{x_0-1}\right) \right) \|x - e_0\|^\alpha \right. \\ & \quad \left. + \left( 1 - \alpha\psi\left(\frac{x_1}{x_0+1}, \dots, \frac{x_{d-1}}{x_0+1}\right) \right) \|x + e_0\|^\alpha \right] \\ & \quad + \frac{1}{2(\gamma + d - 1)} \sum_{j=1}^{d-1} \left[ \left( 1 - \alpha\psi\left(\frac{x_j-1}{x_0}\right) \right) \|x - e_j\|^\alpha + \left( 1 - \alpha\psi\left(\frac{x_j+1}{x_0}\right) \right) \|x + e_j\|^\alpha \right] \\ &= \|x\|^\alpha \left\{ \frac{\gamma}{2(\gamma + d - 1)} \left[ \left( 1 - \alpha\psi(s) - \alpha \sum_{j=1}^{d-1} \left( \frac{s_j}{x_0} + \frac{s_j}{x_0^2} \right) \psi'_j - \frac{\alpha}{2} \sum_{i,j=1}^{d-1} \frac{s_i s_j}{x_0^2} \psi''_{ij} + o(\|x\|^{-2}) \right) \right] \right\} \end{aligned}$$

$$\begin{aligned}
& \times \left( 1 - \alpha \frac{x_0}{\|x\|^2} + \frac{\alpha}{2\|x\|^2} - \frac{1}{2}\alpha(2-\alpha) \frac{x_0^2}{\|x\|^2} \cdot \frac{1}{\|x\|^2} + o(\|x\|^{-2}) \right) \\
& + \left( 1 - \alpha\psi(s) - \alpha \sum_{j=1}^{d-1} \left( -\frac{s_j}{x_0} + \frac{s_j}{x_0^2} \right) \psi'_j - \frac{\alpha}{2} \sum_{i,j=1}^{d-1} \frac{s_i s_j}{x_0^2} \psi''_{ij} + o(\|x\|^{-2}) \right) \\
& \times \left( 1 + \alpha \frac{x_0}{\|x\|^2} + \frac{\alpha}{2\|x\|^2} - \frac{1}{2}\alpha(2-\alpha) \frac{x_0^2}{\|x\|^2} \cdot \frac{1}{\|x\|^2} + o(\|x\|^{-2}) \right) \\
& - 2(1 - \alpha\psi(s)) \Big] \\
& + \frac{1}{2(\gamma + d - 1)} \sum_{j=1}^{d-1} \left[ -2(1 - \alpha\psi(s)) + \left( 1 - \alpha\psi(s) + \alpha x_0^{-1} \psi'_j - \frac{\alpha}{2x_0^2} \psi''_{jj} \right) \right. \\
& \times \left( 1 - \alpha \frac{x_j}{\|x\|^2} + \frac{\alpha}{2\|x\|^2} - \frac{1}{2}\alpha(2-\alpha) \frac{x_j^2}{\|x\|^2} \cdot \frac{1}{\|x\|^2} + o(\|x\|^{-2}) \right) \\
& + \left( 1 - \alpha\psi(s) - \alpha x_0^{-1} \psi'_j - \frac{\alpha}{2x_0^2} \psi''_{jj} \right) \\
& \times \left. \left( 1 + \alpha \frac{x_j}{\|x\|^2} + \frac{\alpha}{2\|x\|^2} - \frac{1}{2}\alpha(2-\alpha) \frac{x_j^2}{\|x\|^2} \cdot \frac{1}{\|x\|^2} + o(\|x\|^{-2}) \right) \right] \Big\} \\
& = \alpha \|x\|^\alpha \left\{ \frac{\gamma}{\gamma + d - 1} \left[ \frac{1 - \alpha\psi(s)}{2\|x\|^2} - \frac{(2-\alpha)(1 - \alpha\psi(s))}{2\|x\|^2} \cdot \frac{x_0^2}{\|x\|^2} - \sum_{j=1}^{d-1} \left( \frac{s_j}{x_0^2} - \frac{\alpha s_j}{\|x\|^2} \right) \psi'_j \right. \right. \\
& \quad \left. \left. - \frac{1}{2} \sum_{i,j=1}^{d-1} \frac{s_i s_j}{x_0^2} \psi''_{ij} + o(\|x\|^{-2}) \right] \right. \\
& \quad + \frac{1}{\gamma + d - 1} \left[ \frac{(d-1)(1 - \alpha\psi(s))}{2\|x\|^2} + \frac{(2-\alpha)(1 - \alpha\psi(s))}{2\|x\|^2} \cdot \frac{x_0^2}{\|x\|^2} - \frac{(2-\alpha)(1 - \alpha\psi(s))}{2\|x\|^2} \right. \\
& \quad \left. \left. - \sum_{j=1}^{d-1} \frac{\alpha s_j}{\|x\|^2} \psi'_j - \frac{1}{2} \sum_{j=1}^{d-1} \frac{1}{x_0^2} \psi''_{jj} + o(\|x\|^{-2}) \right] \right\} \\
& = -\alpha \|x\|^{\alpha-2} \Phi(x, \psi) + \alpha \|x\|^{\alpha-2} (\gamma^{-1} \Phi_1(x, \psi, \gamma, \alpha) + \alpha \Phi_2(x, \psi, \gamma, \alpha)), \tag{3.5}
\end{aligned}$$

where  $\Phi_1$  and  $\Phi_2$  are uniformly bounded for large enough  $x$ , and

$$\Phi(x, \psi) = \frac{x_0^2}{\|x\|^2} - \frac{1}{2} + \frac{\|x\|^2}{x_0^2} \left( \sum_{j=1}^{d-1} s_j \psi'_j + \frac{1}{2} \sum_{i,j=1}^{d-1} s_i s_j \psi''_{ij} \right). \tag{3.6}$$

The idea is then to prove that, with a suitable choice for  $\psi$ , the quantity  $\Phi(x, \psi)$  will be uniformly positive for all large enough  $x$ , and then the second term in the right-hand side of (3.5) can be controlled by choosing large  $\gamma$  and small  $\alpha$ . This will make (3.5) negative for all large  $x$ .

Now, in order to obtain a simplified form for (3.6), we pass to the (hyper)spherical coordinates:

$$\begin{aligned}
s_1 &= r \cos \theta_1, \\
s_2 &= r \sin \theta_1 \cos \theta_2, \\
&\dots \\
s_{d-2} &= r \sin \theta_1 \dots \sin \theta_{d-3} \cos \theta_{d-2}, \\
s_{d-1} &= r \sin \theta_1 \dots \sin \theta_{d-3} \sin \theta_{d-2}.
\end{aligned}$$

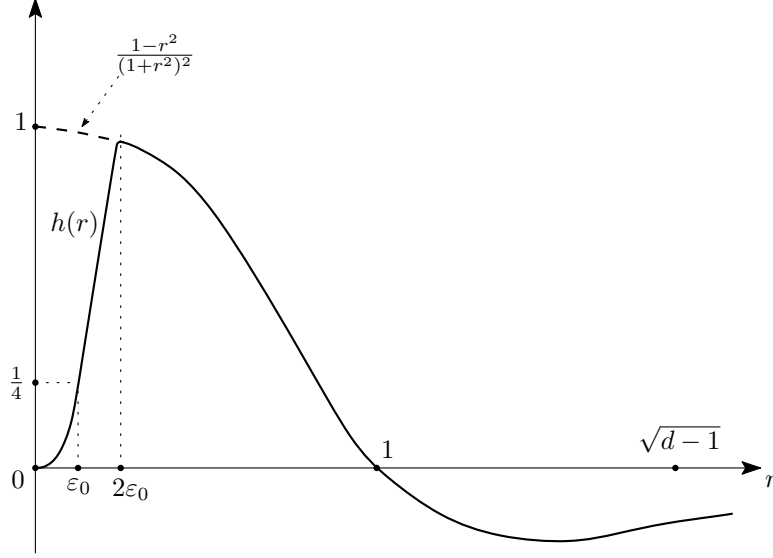


Figure 3: On the construction of  $h$

Since  $\frac{\|x\|^2}{x_0^2} = 1 + r^2$ , and (abbreviating  $\psi'_r = \frac{\partial \psi}{\partial r}$  and  $\psi''_{rr} = \frac{\partial^2 \psi}{\partial r^2}$ )

$$\psi'_r = \frac{1}{r} \sum_{j=1}^{d-1} s_j \psi'_j, \quad \psi''_{rr} = \frac{1}{r^2} \sum_{i,j=1}^{d-1} s_i s_j \psi''_{ij},$$

we have

$$\begin{aligned} \Phi(x, \psi) &= \frac{1}{1+r^2} - \frac{1}{2} + (1+r^2) \left( r \psi'_r + \frac{r^2}{2} \psi''_{rr} \right) \\ &= \frac{1+r^2}{2} \left( \frac{1-r^2}{(1+r^2)^2} + (r^2 \psi'_r)'_r \right). \end{aligned} \quad (3.7)$$

Now, we define the function  $\psi$  (it will depend on  $r$  only, not on  $\theta_1, \dots, \theta_{d-2}$ ) in the following way. First, clearly, we need to define  $\psi(r)$  for  $r \in [0, \sqrt{d-1}]$ . Then, observe that

$$\int_0^{\sqrt{d-1}} \frac{1-r^2}{(1+r^2)^2} dr = \frac{\sqrt{d-1}}{d} > 0, \quad (3.8)$$

so, for a suitable (small enough)  $\varepsilon_0$  we can construct a smooth function  $h$  with the following properties (on the Cartesian plane with coordinates  $(r, y)$ , think of going from the origin along  $y = \frac{r^2}{4\varepsilon_0^2}$  until it intersects with  $y = \frac{1-r^2}{(1+r^2)^2}$  and then modify a little bit the curve around the intersection point to make it smooth, see Figure 3):

- (i)  $0 \leq h(r) \leq \frac{1-r^2}{(1+r^2)^2}$  for all  $r < 2\varepsilon_0$  and  $h(r) = \frac{1-r^2}{(1+r^2)^2}$  for  $r \geq 2\varepsilon_0$ ;
- (ii)  $h(0) = 0$  and  $h(r) \sim \frac{r^2}{4\varepsilon_0^2}$  as  $r \rightarrow 0$ ;
- (ii)  $\frac{1-r^2}{(1+r^2)^2} - h(r) > \frac{1}{2}$  for  $r \leq \varepsilon_0$ ;
- (iv)  $b := \int_0^{\sqrt{d-1}} h(r) dr > 0$  (by (3.8) it holds in fact that  $b \in (0, 1)$ );

$$(v) \int_0^r h(u) du > \frac{br^3}{3(d-1)^{3/2}} \text{ for all } r \in (0, \sqrt{d-1}].$$

Denote  $H(r) = \int_0^r h(u) du$ , so that we have  $H(\sqrt{d-1}) = b$ . Then, define for  $r \in [0, \sqrt{d-1}]$

$$\psi(r) = \int_r^{\sqrt{d-1}} \left( \frac{H(v)}{v^2} - \frac{bv}{3(d-1)^{3/2}} \right) dv. \quad (3.9)$$

For the function  $\psi$  defined in this way, we have  $r^2\psi'(r) = \frac{br^3}{3(d-1)^{3/2}} - H(r)$ , so  $h(r) + (r^2\psi'(r))' = b(d-1)^{-3/2}r^2$ . By construction, it then holds that

$$\inf_{r \in [0, \sqrt{d-1}]} \left( \frac{1-r^2}{(1+r^2)^2} + (r^2\psi'(r))' \right) \geq b(d-1)^{-3/2}\varepsilon_0^2 \wedge \frac{1}{2}, \quad (3.10)$$

and this (recall (3.6) and (3.7)) shows that, if  $\gamma$  is large enough and  $\alpha$  is small enough then the right-hand side of (3.5) is negative for all large enough  $x \in \mathbb{Z}^d$ .

To complete the proof of the theorem, it remains to deal with the boundary case.

Let  $x_0 = x_1 = \dots = x_m > x_{m+1} \geq \dots \geq x_{d-1} \geq 0$  for some  $m \geq 1$ . Using (3.4) (up to the term of order  $\|x\|^{-1}$  in the parentheses), using the fact that  $\varphi$  is invariant under permutations and observing that  $x_0$  and  $\|x\|$  are of the same order, we have

$$\begin{aligned} & \mathbb{E}[f(X_{n+1}) - f(X_n) \mid X_n = x] \\ &= -(1 - \alpha\psi(s))\|x\|^\alpha + \frac{\gamma + m}{2(\gamma + d - 1)} \left[ \left(1 - \alpha\psi\left(\left(\frac{x_0-1}{x_0}\right)_m\right)\right)\|x - e_0\|^\alpha \right. \\ & \quad \left. + \left(1 - \alpha\psi\left(\frac{x_0}{x_0+1}, \dots, \left(\frac{x_0}{x_0+1}\right)_m, \frac{x_{m+1}}{x_0+1}, \dots, \frac{x_{d-1}}{x_0+1}\right)\right)\|x + e_0\|^\alpha \right] \\ & \quad + \frac{1}{2(\gamma + d - 1)} \sum_{j=m+1}^{d-1} \left[ \left(1 - \alpha\psi\left(\frac{x_j-1}{x_0}\right)\right)\|x - e_j\|^\alpha + \left(1 - \alpha\psi\left(\frac{x_j+1}{x_0}\right)\right)\|x + e_j\|^\alpha \right] \\ &= \|x\|^\alpha \left\{ \frac{\gamma + m}{2(\gamma + d - 1)} \left[ \left(1 - \alpha\left(\psi(s) - \frac{\psi'_m}{x_0} + o(\|x\|^{-1})\right)\right) \left(1 - \alpha\frac{x_0}{\|x\|^2} + o(\|x\|^{-1})\right) \right. \right. \\ & \quad \left. \left. + \left(1 - \alpha\left(\psi(s) - \sum_{k=1}^m \frac{\psi'_k}{x_0} - \sum_{k=m+1}^{d-1} \frac{s_k\psi'_k}{x_0} + o(\|x\|^{-1})\right)\right) \left(1 + \alpha\frac{x_0}{\|x\|^2} + o(\|x\|^{-1})\right) \right. \right. \\ & \quad \left. \left. - 2(1 - \alpha\psi(s)) \right] \right. \\ & \quad \left. + \frac{1}{2(\gamma + d - 1)} \sum_{j=m+1}^{d-1} \left[ \left(1 - \alpha\left(\psi(s) - \frac{\psi'_j}{x_0} + o(\|x\|^{-1})\right)\right) \left(1 - \alpha\frac{x_j}{\|x\|^2} + o(\|x\|^{-1})\right) \right. \right. \\ & \quad \left. \left. \left(1 - \alpha\left(\psi(s) + \frac{\psi'_j}{x_0} + o(\|x\|^{-1})\right)\right) \left(1 + \alpha\frac{x_j}{\|x\|^2} + o(\|x\|^{-1})\right) - 2(1 - \alpha\psi(s)) \right] \right\} \\ &= \alpha\|x\|^\alpha \frac{\gamma + m}{2(\gamma + d - 1)} \left[ \frac{1}{x_0} \left( \sum_{k=1}^{m-1} \psi'_k + 2\psi'_m + \sum_{k=m+1}^{d-1} s_k\psi'_k \right) + o(\|x\|^{-1}) \right] \quad (3.11) \end{aligned}$$

(observe that in the above calculation all the terms of order  $\|x\|^{\alpha-1}$  that correspond to the choice of coordinates  $m+1, \dots, d-1$  of  $x$ , cancel).

Now simply note that by the property (v), we have  $\psi'(r) < 0$  for all  $r \in (0, \sqrt{d-1}]$ . Observe also that for some positive constant  $\delta_0$  it holds that  $\psi'(r) \leq -\delta_0$  for all  $r \in [1, \sqrt{d-1}]$ . Then (recall that in the boundary case  $s_1 = 1$  and  $s_j \geq 0$  for all  $j = 2, \dots, d-1$ ) we have

$$\psi'_j = \frac{s_j}{r} \psi'_r \leq 0 \text{ for all } j = 1, \dots, d-1 \quad \text{and} \quad \psi'_1(s) \leq -\frac{\delta_0}{\sqrt{d-1}}.$$

This implies that the right-hand side of (3.11) is negative for all large enough  $x \in \mathbb{Z}^d$  and thus concludes the proof of Theorem 1.5.  $\square$

## A conjecture

We end this paper with an open question:

**Conjecture 3.3.** *Let  $\mu_1, \dots, \mu_{d-1}$  be  $d$ -dimensional measures in  $\mathbb{R}^d$ ,  $d \geq 4$ , with 0 mean and  $2 + \beta$  moments, for some  $\beta > 0$ , and  $\ell$  an arbitrary adapted rule. Then the walk  $X$  generated by these measures and the rule  $\ell$  is transient.*

To answer this question, by Theorem 1.3 it suffices to prove the existence of a matrix  $A$  satisfying the trace condition (1.1). So far, we were able to prove it in the case when the  $d-1$  covariance matrices are jointly diagonalizable.

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