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# Weak Convergence of a Random Walk in a Random Environment

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Abstract. Let  $\pi_i(x)$ , i = 1, ..., d,  $x \in Z^d$ , satisfy  $\pi_i(x) \ge \alpha > 0$ , and  $\pi_1(x) + ... + \pi_d(x) = 1$ . Define a Markov chain on  $Z^d$  by specifying that a particle at x takes a jump of + 1 in the *i*<sup>th</sup> direction with probability  $\frac{1}{2}\pi_i(x)$  and a jump of -1 in the *i*<sup>th</sup> direction with probability  $\frac{1}{2}\pi_i(x)$  are chosen from a stationary, ergodic distribution, then for almost all  $\pi$  the corresponding chain converges weakly to a Brownian motion.

## 1. Introduction

Let  $Z^d$  be the integer lattice and let  $e_i$ , i = 1, ..., d, denote the unit vector whose  $i^{\text{th}}$  component is equal to 1. Let

$$S = \{ (p_1, \dots, p_d) \in \mathbb{R}^d : p_i \ge 0, p_1 + \dots + p_d = 1 \},\$$

and suppose we have a function  $\pi: \mathbb{Z}^d \to S$ . Then a Markov chain  $X_{\pi}(j)$  on  $\mathbb{Z}^d$  is generated with transition probability

$$P\{X_{\pi}(j+1) = x \pm e_i | X_{\pi}(j) = x\} = \frac{1}{2}\pi_i(x), \tag{1.1}$$

and generator

$$L_{\pi}g(x) = \sum_{i=1}^{d} \frac{1}{2}\pi_i(x) \{g(x+e_i) + g(x-e_i)\}.$$

If the function  $\pi$  is chosen from some probability distribution on S, this gives an example of a random walk in a random environment.

For any  $\pi$ , we can consider the limiting distribution of the process  $X_{\pi}$  satisfying  $X_{\pi}(0) = 0$  and (1.1). Let  $\alpha > 0$  and set

$$S^{\alpha} = \{(p_1, \ldots, p_d) \in S : p_i \geq \alpha\},\$$

and let  $C^{\alpha}$  be the set of functions  $\pi: \mathbb{Z}^d \to S^{\alpha}$ . The main result of this paper is:

**Theorem 1.** Let  $\mu$  be a stationary ergodic measure on  $C^{\alpha}$ . Then there exists  $b \in S^{\alpha}$  such

that for  $\mu$ —almost all  $\pi \in C^{\alpha}$ , the processes

$$X_{\pi}^{(n)}(t) = \frac{1}{\sqrt{n}} X_{\pi}([nt])$$

converge in distribution to a Brownian motion with covariance  $(b_i \delta_{ii})$ 

A special case of this theorem occurs when the  $\pi(x)$  are independent, identically distributed random variables taking values in  $S^{\alpha}$ .

A similar theorem for diffusion processes with random coefficients was proved by Papanicolaou and Varadhan [3], and a considerable portion of this paper is only a restating of their proof in the context of discrete random walk. The crucial new step is Lemma 4, which replaces Lemma 3.1 of their paper. This is a discrete version of an *a priori* estimate for solutions of uniformly elliptic equations. The ideas of Krylov [2] are used in the proof of Lemma 4; properties of concave functions are used to estimate solutions to a discrete Monge–Ampere equation.

#### 2. An Ergodic Theorem on the Space of Environments

Fix an environment  $\pi \in C^{\alpha}$ , and assume  $X_{\pi}(0) = 0$ . Let  $Z_j = (Z_j^1, \ldots, Z_j^d) = X_{\pi}(j) - X_{\pi}(j-1)$ , and let  $\mathcal{F}_j = \sigma\{Z_1, \ldots, Z_j\}$ . Let  $Y_j = \pi(X_{\pi}(j))$ . Then  $Y_j$  is measurable with respect to  $\mathcal{F}_j$ , and

$$P\{Z_{j} = e_{i} | \mathcal{T}_{j-1}\} = P\{Z_{j} = -e_{i} | \mathcal{T}_{j-1}\} = \frac{1}{2}Y_{j}^{i}.$$

Then  $X_{\pi}(n) = \sum_{j=1}^{n} Z_j$  is a martingale and

$$\mathscr{E}(Z_{j}^{i_{1}}Z_{j}^{i_{2}}|\mathscr{T}_{j-1}) = \begin{cases} 0 & i_{1} \neq i_{2} \\ Y_{j-1}^{i_{1}} & i_{1} = i_{2} \end{cases}$$

Let  $V_n^i = \sum_{j=0}^{n-1} Y_j^i$ . Then the invariance principle for martingales (see e.g. Theorem 4.1 of [1]) states that  $W_n(t) = (W_n^1(t), \dots, W_n^d(t))$  converges in distribution to the standard Brownian motion on  $\mathbb{R}^d$ , where

$$W_n^i(t) \equiv (V_n^i)^{-1/2} \sum_{j=1}^{[nt]} Z_j^i.$$

Now suppose there exists a  $b \in S^{\alpha}$  such that

$$\lim_{n \to \infty} \frac{1}{n} \sum_{j=0}^{n-1} \pi(X_{\pi}(j)) = b \text{ a.s.}.$$

Then by the above argument we can conclude that

$$X^{(n)}(t) = \frac{1}{\sqrt{n}} X_{\pi}([nt])$$

converges in distribution to a Brownian motion with covariance  $(b_i \delta_{ij})$ . Therefore, in order to prove Theorem 1 it is sufficient to prove:

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**Theorem 2.** Let  $\mu$  be a stationary ergodic probability measure on  $C^{\alpha}$ . Then there exists  $b \in S^{\alpha}$  such that for  $\mu$ —almost all  $\pi \in C^{\alpha}$ ,

$$\lim_{n \to \infty} \frac{1}{n} \sum_{j=0}^{n-1} \pi(X_{\pi}(j)) = b \text{ a.s..}$$
(2.1)

This is clearly an ergodic theorem and the idea of Papanicolaou and Varadhan [3] is to find a measure on  $C^{\alpha}$  so that a standard ergodic argument can be used.

We define the canonical Markov chain with state space  $C^{\alpha}$  to be the chain whose generator  $\mathscr{L}$  is given by

$$\mathscr{L}g(\pi) = \sum_{i=1}^{d} \frac{1}{2}\pi_i(0) \{g(\tau_{e_i}\pi) + g(\tau_{-e_i}\pi)\},\$$

where  $\tau_x \pi(y) = \pi(y - x)$ . In this chain, the "particle" stays fixed at the origin and allow the environment to change around it (rather than having the particle move around a fixed environment). If we define  $g_0: C^{\alpha} \to \mathbb{R}^d$  by  $g_0(\pi) = \pi(0)$ , and let  $\mathscr{L}^j \pi$ denote the (random) environment at the *j*<sup>th</sup> step of this chain, then (2.1) is equivalent to

$$\lim_{n \to \infty} \frac{1}{n} \sum_{j=0}^{n-1} g_0(\mathscr{L}^j \pi) = b \text{ a.s. } \mu.$$
 (2.2)

By standard ergodic theory we can prove (2.2), and hence (2.1), if we prove:

**Theorem 3.** Let  $\mu$  be a stationary ergodic probability measure on  $C^{\alpha}$ . Then there exists an ergodic probability measure  $\lambda$  on  $C^{\alpha}$  which is mutually absolutely continuous with  $\mu$  and which is invariant under the canonical Markov chain  $\mathcal{L}$ .

Clearly,

$$b=\int_{C^{\alpha}}g_0(\pi)\,d\lambda(\pi).$$

To prove Theorem 3 we need some lemmas. For each n > 0, let  $T_n$  denote the elements of  $Z^d$  under the equivalence relation

$$(z_1,\ldots,z_d) \sim (w_1,\ldots,w_d)$$
 if  $\frac{1}{2n}(z_i-w_i) \in \mathbb{Z}$  for each *i*.

Then  $|T_n| = (2n)^d$ . If  $\pi: T_n \to S^{\alpha}$ , we may think of  $\pi$  as a periodic environment in  $C^{\alpha}$ . Let  $C_n^{\alpha}$  denote the set of such periodic environments. For  $\pi \in C_n^{\alpha}$ , let  $R_{\pi}^n$  denote the resolvent operator

$$R_{\pi}^{n}g(x) = \sum_{j=0}^{\infty} \left(1 - \frac{1}{n^{2}}\right)^{j} L_{\pi}^{j}g(x).$$

If  $g:T_n \to \mathbb{R}$  we define the usual  $L^p$  norms (with respect to normalized counting measure on  $T_n$ ),

$$\|g\|_{p} = |(2n)^{-d} \sum_{x \in T_{n}} (g(x))^{p}|^{1/p}$$
$$\|g\|_{\infty} = \sup_{x \in T_{n}} |g(x)|$$

**Lemma 4.** There exists a constant  $c_1$  (depending only on d and  $\alpha$ ) such that for every  $\pi \in C_n^{\alpha}$ ,  $g: T_n \to R$ ,

$$\|R^ng\|_{\infty} \leq c_1 n^2 \|g\|_d.$$

The proof of this lemma is delayed until Sect. 3. The next lemma follows from our assumption that  $\mu$  is stationary (see Parthasarathy [4]).

**Lemma 5.** For each n, there exists  $\pi_n \in C_n^{\alpha}$  such that if  $\mu_n$  is the probability measure on  $C^{\alpha}$  which assigns measure  $(2n)^{-d}$  to  $\tau_x \pi_n$  for each  $x \in T_n$ , then

 $\mu_n \rightarrow \mu$  weakly.

Proof of Theorem 3. Let  $\pi_n \in C_n^{\alpha}$  be a sequence as in Lemma 5 with  $\mu_n \to \mu$ . Let  $\phi_n$  be the density, with respect to normalized counting measure on  $T_n$ , of an invariant probability measure on  $T_n$  for  $\pi_n$ , i.e.  $L_{\pi_n}\phi_n = \phi_n$  and  $\|\phi_n\|_1 = 1$ . If  $R_n = R_{\pi_n}^n$  is the resolvent corresponding to  $\pi_n$ , then  $R_n\phi_n = n^2\phi_n$ . If we consider  $R_n$  as a map from  $L^d(T_n)$  to  $L^{\infty}(T_n)$ , then Lemma 4 states that the map is bounded by  $c_1n^2$ . Therefore  $R_n^n : L^1(T_n) \to L^{d/(d-1)}(T_n)$  is also bounded by  $c_1n^2$ . Since  $R_n^*\phi_n = n^2\phi_n$ , we get

$$n^{2} \|\phi_{n}\|_{d/(d-1)} \leq c_{1}n^{2} \|\phi_{n}\|_{1} = c_{1}n^{2},$$
  
$$\|\phi_{n}\|_{d/(d-1)} \leq c_{1}.$$

Let  $\lambda_n$  be the probability measure on  $C_n^{\alpha}$ ,

$$\lambda_n(\tau_x \pi_n) = (2n)^{-d} \phi_n(x).$$

Then  $\lambda_n$  is invariant under the canonical Markov chain  $\mathscr{L}$  and

$$\left\|\frac{d\lambda_n}{d\mu_n}\right\|_{d/(d-1)} \leq c_1.$$

Since  $\mu_n \to \mu$  weakly, standard arguments give that  $\lambda_n$  has a subsequence converging to a probability measure  $\lambda$  which is invariant under  $\mathscr{L}$ . Also  $\lambda \ll \mu$  and, in fact,

$$\int_{C^{\infty}} \left| \frac{d\lambda}{d\mu} \right|^{d/(d-1)} d\mu \leq c_1^{d/(d-1)}.$$

Let  $E = \{d\lambda/d\mu = 0\}$ . Since  $\lambda$  is invariant,  $\lambda(\mathscr{L}E) = \lambda(E) = 0$ , and hence  $\mathscr{L}E \subset E$ (a.s.  $\mu$ ). Since  $\mu$  is ergodic and  $\lambda \ll \mu, \mu(E) = 0$ , and hence  $\mu \ll \lambda$ . Since  $\mu$  and  $\lambda$  are mutually absolutely continuous and  $\mu$  is ergodic,  $\lambda$  is ergodic.

*Example.* Let d = 2 and  $\mu$  be product measure with  $\mu\{\pi(x) = \alpha\} = \mu\{\pi(x) = 1 - \alpha\} = \frac{1}{2}$ , where  $0 < \alpha < \frac{1}{2}$ . Then  $\mu$  is not invariant under  $\mathcal{L}$ , if  $B = \{\pi(e_1) = \alpha\}$ , then  $\mu(B) = \frac{1}{2}$ , but  $\mu(\mathcal{L}B) = \frac{3}{8} + \frac{\alpha}{4}$ . Although it is not easy to describe  $\lambda$  in this case, symmetry considerations give that  $b = (\frac{1}{2}, \frac{1}{2})$ .

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### 3. Proof of Lemma 4

It remains to prove Lemma 4. Let

$$D_n = \{(z_1, \dots, z_d) \in Z^d : |z_1| + \dots + |z_d| \le n\},$$
  
$$\partial D_n = \{z \in D_n : |z_1| + \dots + |z_d| = n\},$$
  
int  $D_n = D_n / \partial D_n.$ 

Let  $\pi \in C_n^{\alpha}$ . If  $f: D_n \to [0, \infty)$  with f(x) = 0 for  $x \in \partial D_n$ , let

$$Qf(x) = E_x \sum_{j=0}^{\tau} f(X_{\pi}(j)),$$

where  $\tau = \inf \{j: X_{\pi}(j) \in \partial D_n\}$ , and  $E_x$  denotes expectation assuming  $X_{\pi}(0) = x$ . We will prove the following:

**Lemma 6.** There exists a constant  $c_2$  (depending only on d and  $\alpha$ ) such that for every  $f:D_n \rightarrow [0, \infty)$ ,

$$\|Qf\|_{\infty} \leq c_2 n^2 \|f\|_d$$

where

$$||f||_d^d = \frac{1}{|D_n|} \sum_{x \in D_n} (f(x))^d.$$

To get Lemma 4 from Lemma 6 is routine using the fact that the expected time until hitting  $\partial D_n$  is of order  $n^2$ .

Fix n, and write  $D = D_n$ . If  $u: D \to \mathbb{R}$ , we define the second difference operators on int D by

$$\Delta_{i}u(x) = u(x + e_{i}) + u(x - e_{i}) - 2u(x).$$

We will call *u* concave on *D* if  $\Delta_i u(x) \leq 0$  for all  $x \in int D$  and all *i* (note this is weaker than the usual definition of concave). We define the discrete Monge-Ampere operator *M* on int *D* by

$$Mu=\prod_{i=1}^d \Delta_i u.$$

we will prove the following:

**Lemma 7.** Let  $f: D \to [0, \infty)$  be a function with  $f \equiv 0$  on  $\partial D$ . Then there exists a concave function  $z: D \to [0, \infty)$  such that

- (i)  $z \equiv 0$  on  $\partial D$ ,
- (ii)  $(-1)^{d} M z = f^{d}$  on int D.

Moreover, there exists a constant  $c_3$  (depending only on d) such that

(iii)  $||z||_{\infty} \leq c_3 n^2 ||f||_d$ .

Suppose that we have Lemma 7, and let us derive Lemma 6. Fix  $x \in int D$ , and let

 $X_{\pi}(j)$  be the Markov chain induced by  $\pi$  with  $X_{\pi}(0) = x$ . Then

$$E(z(X_{\pi}(1)) - z(X_{\pi}(0)) = \sum_{i=1}^{d} \frac{1}{2}\pi_{i}(x)\Delta_{i}z(x)$$
$$\leq -\frac{1}{2}\alpha |Mz(x)|^{1/d}$$
$$= -\frac{1}{2}\alpha f(x).$$

Here we have used the inequality  $(a_1b_1 + \ldots + a_db_d)^d \ge (a_1 \ldots a_d) \quad (b_1 \ldots b_d)$ . Continuing as above we may deduce

$$E[z(X_{\pi}(j \wedge \tau)) - z(X_{\pi}(0)) + \frac{1}{2}\alpha \sum_{k=0}^{(j-1) \wedge \tau} f(X_{\pi}(k))] \leq 0.$$

Letting *j* go to infinity,

$$\frac{1}{2} \alpha Q f(x) = E_{x2} \frac{1}{2} \alpha \sum_{k=0}^{\tau} f(X_{\pi}(k)) \leq z(x).$$

and Lemma 7 then gives the required bound.

To prove Lemma 7, let  $\mathcal{A}$  be the set of all concave functions u on D satisfying

(i) 
$$u \equiv 0$$
 on  $\partial D$ ,

(ii)  $(-1)^d M u \ge f^d$  on int D.

We first note that  $\mathscr{A}$  is non-empty: let  $h: D \to [0, \infty)$  by

$$h(x) = n(n+1) - |x|(|x|+1),$$

where  $|(x_1, ..., x_d)| = |x_1| + ... + |x_d|$ . One can check that  $(-1)^d Mh \ge 2^d$  and hence  $\beta h \in \mathscr{A}$  for  $\beta$  sufficiently large.

It is easy to check that if  $u_1, u_2 \in \mathcal{A}$ , then  $\min(u_1, u_2) \in \mathcal{A}$ ; in fact, if we let

$$z(x) = \inf_{\substack{u \in \mathscr{A}}} u(x),$$

one can verify that  $z \in \mathscr{A}$ . It remains to be shown that  $(-1)^d M z = f^d$ . Suppose  $(-1)^d M z(x) > (f(x))^d$  for some  $x \in int D$ , i.e.

$$(-1)^d \prod_{i=1}^d (z(x+e_i)+z(x-e_i)-2z(x)) > (f(x))^d.$$

Let  $\gamma < z(x)$  be such that

$$(-1)^d \prod_{i=1}^d (z(x+e_i)+z(x-e_i)-2\gamma) = (f(x))^d.$$

and set

$$v(y) = \begin{cases} z(y) & y \neq x \\ \gamma & y = x \end{cases}$$

Then again one can check that  $v \in \mathcal{A}$ , contradicting the minimality of z.

We now wish to estimate z. For  $x \in int D$ , let

$$I(x) = \{(a_1, \dots, a_d) \in \mathbb{R}^d : z(x + e_i) - z(x) \\ \leq a_i \leq z(x) - z(x - e_i)\}.$$

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Note that meas  $(I(x)) = (-1)^d Mz(x) = (f(x))^d$ . We state the next easily provable fact as a lemma:

**Lemma 8.** Let  $a \in \mathbb{R}^d$ , b > 0, and let r be the affine function  $r(x) = a \cdot x + b$ . Suppose  $r(x) \ge z(x)$  for every  $x \in D$  and  $r(x_0) = z(x_0)$  for some  $x_0 \in \text{int } D$ . Then  $a \in I(x_0)$ . Now let  $\overline{z} = ||z||_{\infty}$  and let  $\overline{x} \in \text{int } D$  with  $z(\overline{x}) = \overline{z}$ . Assume  $\overline{z} > 0$ . Let

$$A = \{a \in \mathbb{R}^d : |a| \leq \bar{z}/4n\}.$$

Fix  $a \in A$ . If  $b \ge \frac{3}{2}\overline{z}$ , then  $a \cdot x + b > \overline{z} \ge z(x)$  for every  $x \in D$ . Therefore there exists a least b (depending on a) such that  $a \cdot x + b \ge z(x)$  for all  $x \in D$ . It is easy to see that  $a \cdot x_0 + b = z(x_0)$  for some  $x_0 \in D$ , and since

$$a \cdot x_0 + b = a \cdot \bar{x} + b + a \cdot (x_0 - \bar{x}) \ge \frac{1}{2}\bar{z} > 0,$$

 $x_0 \in \text{int } D$ . By Lemma 8,  $a \in I(x_0)$ . Therefore

$$A \subset \bigcup_{x \in int D} I(x),$$
  
$$meas(A) \leq meas(\bigcup I(x)),$$
  
$$\leq \sum_{x \in D} ((f(x))^d.$$

Since meas  $(A) = (\bar{z}^d)(c_4 n)^{-d}$  for some  $c_4$ , we get

$$\bar{z} \leq c_4 n \Big[ \sum_{x \in D} (f(x))^d \Big]^{1/d}$$
$$\leq c_3 n^2 \| f \|_d.$$

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#### References

- 1. Hall, P., Heyde, C. C.: Martingale limit theory and its application. New York: Academic Press 1980
- 2. Krylov, N. V.: An inequality in the theory of stochastic integrals. Theor. Prob. Appl. 16, 438–448 (1971)
- 3. Papanicolaou, C., Varadhan, S. R. S.: Diffusions with Random coefficients. In: Essays in Honor of C. R. Rao. Amsterdam: North Holland 1982
- 4. Parthasarathy, K. R.: On the category of ergodic measure. Ill. J. Math. 5, 648-655 (1961)

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