#### Week 8

# Large Deviations for Random Walks

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## Nash Inequality (continued)

**Theorem 8.0.1.** Let  $(\Gamma, \mu)$  be a weighted graph, and let  $\alpha \geq 1$ . TFAE.

- (a) (Nash Inequality)  $(\Gamma, \mu)$  satisfies  $(N_{\alpha})$
- (b) (On Diagonal Bounds) There exists  $C_H > 0$  such that for every  $x \in V$  and  $n \geq 0$

$$p_n(x,x) \le \frac{C_H}{(n \lor 1)^{\alpha/2}}$$

(c) (Off Diagonal Bounds) There exists  $C'_H > 0$  such that for every  $x, y \in V$  and  $n \ge 0$ 

$$p_n(x,y) \le \frac{C_H'}{(n \lor 1)^{\alpha/2}}$$

*Proof.* We provide only a sketch of the proof. From Worksheet 2,  $(a) \Longrightarrow (b)$  holds, and  $(c) \Longrightarrow (b)$  is trivial. First, we show  $(b) \Longrightarrow (c)$ . So assume (b). Let  $m \ge 0$ . If n is even, with n = 2m, then for any  $x, y \in V$ , we have

$$p_{2m}(x,x) \le \frac{C_H}{(2m \vee 1)^{\alpha/2}}$$
 and  $p_{2m}(y,y) \le \frac{C_H}{(2m \vee 1)^{\alpha/2}}$ 

As an exercise, show that  $p_{2m}(x,y) \leq \sqrt{p_{2m}(x,x)p_{2m}(y,y)}$ , and using this, we get  $(b) \implies (c)$  with  $C'_H = C_H$ . If n = 2m + 1, then, since  $p_{2m+1}(x,y) \leq \sqrt{p_{2m}(x,x)p_{2m+2}(y,y)}$  (by a similar exercise), we get

$$p_{2m+1}(x,y) \le \sqrt{\frac{C_H^2}{(2m\vee 1)^{\alpha/2}(2m+2\vee 1)^{\alpha/2}}} \le \frac{C'}{(2m+1\vee 1)^{\alpha/2}}$$

for some C'>0. To show the last inequality above, use the fact that there exists  $C_{\alpha}>0$  such that  $(2m)^{\alpha/2}(2m+2)^{\alpha/2} \leq C_{\alpha}(2m+1)^{\alpha/2}$  (details left as exercises). Thus  $(b) \Longrightarrow (c)$ . Now, we show  $(c) \Longrightarrow (a)$ . Assuming (c), observe that (by taking supremum over  $x \in V$ )

$$|P_n f(x)| \le \sum_{y \in V} p_n(x, y) |f(y)| \mu_y \implies ||P_n f||_{\infty} \le \frac{C_H}{(n \vee 1)^{\alpha/2}} ||f||_1$$

and 
$$\|P_n f\|_2^2 = \langle P_n f, P_n f \rangle = \langle P_{2n} f, f \rangle \le \|P_{2n} f\|_{\infty} \|f\|_1 \le \frac{C_H}{(2n \vee 1)^{\alpha/2}} \|f\|_1^2$$
 (8.1)

Now, we make use of the following inequality - (verify!)

$$\mathcal{E}(f, f) \ge \frac{1}{2n} [\|f\|_2^2 - \|P_n f\|_2^2]$$

Using this, and (8.1), we get

$$\mathcal{E}(f, f) \ge \frac{1}{2n} \left[ \|f\|_2^2 - \frac{C_H}{(2n \vee 1^{\alpha/2})} \|f\|_1^2 \right]$$

WLOG, assume  $||f||_1 = 1$ , and choose smallest possible k such that

$$\frac{C_H}{(2n \vee 1)^{\alpha/2}} \le \frac{\|f\|_2^2}{2}$$
 so that  $\mathcal{E}(f, f) \ge \frac{1}{4k} \|f\|_2^2$ 

Since  $k \geq 1$ , we have  $k^{-\alpha/2} \leq C^2 \|f\|_2^2$  for some C > 0, and hence  $k^{-\alpha/2} \leq C \|f\|_2$ . Therefore,

$$\mathcal{E}(f, f) \ge \frac{C_2 \|f\|_2^2}{\|f\|_2^{\frac{4}{\alpha}}} = C_2 \|f\|_2^{2-4/\alpha} \implies (N_\alpha)$$

8.1 Carne-Varopoulos Bound

We begin with a few lemmas and some results involving Chebyshev polynomials.

**Lemma 8.1.1.** Let  $\{S_n\}_{n\geq 0}$  denote the simple symmetric random walk on  $\mathbb{Z}$  with  $S_0=0$ . Then

(a) 
$$\mathbf{P}(S_n \ge D) \le \exp\left(-\frac{D^2}{2n}\right)$$

(b) 
$$\mathbf{E}[\lambda^{S_n}] = \sum_{r \in \mathbb{Z}} \lambda^r \mathbf{P}(S_n = r) = 2^{-n} \sum_{r=0}^n \binom{n}{r} \left(\frac{1}{\lambda}\right)^{2n-r}$$

*Proof.* (a) was given in Worksheet 2, and (b) is trivial using results from Week 1.  $\Box$ 

**Definition 8.1.1.** (Chebyshev Polynomials) For  $-1 \le t \le 1$ , define

$$H_k(t) := \frac{1}{2}(t + i\sqrt{1 - t^2})^k + \frac{1}{2}(t - i\sqrt{1 - t^2})^k$$

**Lemma 8.1.2.** For each  $k \geq 0$ , we have

(a)  $H_k$  is a real polynomial of degree k.

(b) 
$$t^n = \sum_{k \in \mathbb{Z}} \mathbf{P}(S_n = k) H_{|k|}(t)$$

*Proof.* To show (a), fix  $t \in [-1,1]$  and set  $s = \sqrt{1-t^2}$ . Observe that

$$H_k(t) = \frac{1}{2} \sum_{r=0}^{k} {k \choose r} t^{k-r} [(is)^r + (-is)^r] = \frac{1}{2} \sum_{r=0}^{k/2} {k \choose 2r} t^{k-2r} \psi(s)$$

where  $\psi$  is some real function of s.

To show (b) set  $z_1 = t + is$  and  $z_2 = t - is$  so that  $|z_1| = |z_2| = 1$  and  $z_1 = 1$ . Then,

$$H_k(t) = \frac{1}{2}(z_1^k + z_2^k) = H_{-k}(t) \implies |H_k(t) \le 1|$$

Now, observe that  $t = (z_1 + z_2)/2$ , so that

$$t^n = \sum_{k=0}^n \frac{1}{2^n} \binom{n}{k} z_1^k z_2^{n-k} = \sum_{k=0}^n \frac{1}{2^n} \binom{n}{k} z_1^{2k-n} = \frac{1}{2^n} \sum_{r \in \mathbb{Z}} \mathbf{P}(S_n = r) z_1^r$$

Repeating the same arguments above, we get

$$t^n = \frac{1}{2^n} \sum_{r \in \mathbb{Z}} \mathbf{P}(S_n = r) z_1^r = \frac{1}{2^n} \sum_{r \in \mathbb{Z}} \mathbf{P}(S_n = r) z_2^r$$

$$\implies t^n = \frac{1}{2^n} \sum_{r \in \mathbb{Z}} \mathbf{P}(S_n = r) \left( \frac{z_1^r + z_2^r}{2} \right) = \sum_{r \in \mathbb{Z}} \mathbf{P}(S_n = r) H_{|r|}(t)$$

**Theorem 8.1.1.** (Carne-Varopoulos bound) Let  $(\Gamma, \mu)$  be a weighted graph. Then, for every  $x, y \in V$  and  $n \geq 1$ 

$$p_n(x,y) \le \frac{2}{\sqrt{\mu_x \mu_y}} \exp\left(-\frac{d(x,y)^2}{2n}\right)$$

*Proof.* Proved in Worksheet 2.

# 8.2 Large Deviations for Random Walks

Let  $\{\xi_i\}_{i\geq 1}$  be IID  $\mathbb{Z}$  valued random variables such that  $\mathbf{E}[\xi_1] = \mu$  and  $\operatorname{Var}[\xi_1] < \infty$ . Define  $S_0 = 0$  and  $S_n = \sum_{i=1}^n \xi_i$ . Then, the strong law of large numbers (SLLN) and the central limit theorem (CLT) respectively state that

$$\mathbf{P}\left(\lim_{n\to\infty}\frac{S_n}{n}=\mu\right)=1 \text{ and } \frac{S_n-n\mu}{\sqrt{n}} \stackrel{d}{\longrightarrow} \mathcal{N}(0,1)$$

Thus, the CLT loosely states that  $S_n \approx n\mu + \sqrt{n}Z$ , where  $Z \sim \mathcal{N}(0,1)$ .

As an exercise, show that for every  $\epsilon > 0$ ,  $\mathbf{P}(A_n^{\epsilon}) \to 0$  as  $n \to \infty$ , where  $A_n^{\epsilon} = \{S_n \ge n(\mu + \epsilon)\}$ . What is the rate of decay of  $\mathbf{P}(A_n^{\epsilon})$  (as  $n \to \infty$ )?

(Hint: 
$$\mathbf{P}(S_n \ge n(\mu + \epsilon)) \approx \mathbf{P}(\xi_i > \mu + \epsilon \ \forall \ 1 \le i \le n) = [\mathbf{P}(\xi_1 > \mu + \epsilon)]^n \approx e^{-Cn}$$
 for some  $C > 0$ )

**Theorem 8.2.1.** Let  $\{\xi_i\}_{i\geq 0}$  be IID random variables with  $\mathbf{P}(\xi_1=0)=\mathbf{P}(\xi_1=1)=1/2$ . Then, for every a>1/2,

$$\lim_{n \to \infty} \frac{1}{n} \log[\mathbf{P}(S_n \ge an)] = -I(a)$$

where

$$I(z) = \begin{cases} \log 2 + a \log a + (1 - a) \log a & \text{if } 0 \le z \le 1\\ \infty & \text{otherwise} \end{cases}$$

#### **Observations:**

- (1) Minima of I(z) is achieved at z=1/2, and the graph increases from [1/2,1]. This implies rate of exponential decay increases as  $1/2 \to a \to 1$ .
- (2) Symmetry of the function  $I(\cdot)$  around 1/2 suggests that for a < 1/2, (Requires a proof)

$$\frac{1}{n}\log[\mathbf{P}(S_n \ge an)] \to -I(a)$$

(3) The theorem implies SLLN. The idea of the proof makes use of the following inequality

$$\mathbf{P}(S_n > (1/2 + \delta)n) \le \exp\{-I(n(1/2 + \delta))\}\$$

Proof.

If, a > 1 then, since  $S_n$  can be at most n,  $\mathbf{P}(S_n > an) = 0$  so the result follows. Now, consider  $\frac{1}{2} < a \le 1$ , then

$$\mathbf{P}(S_n > an) = \sum_{an < k \le n} \mathbf{P}(S_n = k) = \sum_{an < k \le n} \binom{n}{k} \frac{1}{2^n} = \frac{1}{2^n} \sum_{an < k \le n} \binom{n}{k}$$

Let,  $Q_n(a) = \max_{an < k \le n} \binom{n}{k}$ . So, we have,

$$2^{-n} Q_n(a) \le \mathbf{P}(S_n > an) \le 2^{-n} Q_n(a) (n+1)$$
(8.2)

First equality follows from the fact that one summand in the  $\sum_{an < k \le n} \binom{n}{k}$  attains maximum and the second equality follows since, each summand of  $\sum_{0 \le k \le n} \binom{n}{k}$  is  $\le Q_n(a)$ .

#### Claim:

For,  $\frac{1}{2} < a < 1$ ,

$$\frac{1}{n}\log Q_n(a) \xrightarrow[n\to\infty]{} -a\log a - (1-a)\log(1-a)$$

Now, from (8.2),

$$-\log 2 + \frac{1}{n}\log Q_n(a) \le \frac{1}{n}\log \mathbf{P}(S_n > an) \le -\log 2 + \frac{1}{n}\log Q_n(a) + \frac{1}{n}\log(n+1)$$
 (8.3)

assuming the claim as LHS and RHS of (8.3) goes to -I(a), the result follows. We now prove the claim.

#### Proof of claim:

Since,  $a > \frac{1}{2}$ ,  $\max_{an < k \le n} \binom{n}{k} = \binom{n}{\lceil an \rceil}$ . Now, from stirling's approximation

$$\binom{n}{\lceil an \rceil} = \frac{n!}{\lceil an \rceil! (n - \lceil an \rceil)!} \sim \frac{n^n e^{-n} \sqrt{2\pi n}}{\lceil an \rceil^{\lceil an \rceil} e^{-\lceil an \rceil} \sqrt{2\pi \lceil an \rceil}} \cdot \frac{1}{(n - \lceil an \rceil)^{n - \lceil an \rceil} e^{n - \lceil an \rceil} \sqrt{2\pi (n - \lceil an \rceil)}}$$

For,  $a > \frac{1}{2}, a < 1$ ;  $\lceil an \rceil \to \infty$  and  $n - \lceil an \rceil \to \infty$  as  $n \to \infty$  (Check!) and

$$\frac{1}{n}\log Q_n(a) \sim \frac{1}{n}\left[\left(n+\frac{1}{2}\right)\log n - (\lceil an\rceil + \frac{1}{2})\log\lceil an\rceil - \left(n-\lceil an\rceil + \frac{1}{2}\right)\log(n-\lceil an\rceil) - \log(\sqrt{2\pi})\right]$$

$$= \log n + \frac{1}{2n}\log n - \frac{\lceil an\rceil}{n}\log\lceil an\rceil - \frac{1}{2n}\log\lceil an\rceil - \frac{1}{n}\log\sqrt{2\pi} - \frac{n-\lceil an\rceil}{n}\log(n-\lceil an\rceil) - \frac{1}{2}\log(n-\lceil an\rceil)$$

the second, fourth, fifth and seventh summand of the above equation tends to 0 as n tends to  $\infty$  and from the exercise (?) we have that

$$\frac{\lceil an \rceil}{n} \log \frac{\lceil an \rceil}{n} \xrightarrow[n \to \infty]{} a \log a \quad \text{and} \quad \frac{n - \lceil an \rceil}{n} \log \frac{n - \lceil an \rceil}{n} \xrightarrow[n \to \infty]{} (1 - a) \log (1 - a)$$

which proves the claim.

#### Cramer, 1930's

 $\{\xi_i\}_{i\geq 1}$  i.i.d random variables with  $\mathbf{E}[\xi_i] = \mu < \infty, \ \mathbf{E}[e^{r\xi_i}] < \infty, \ \forall \, r \in \mathbb{R}$ . For any  $a > \mu$ ,

$$\lim_{n \to \infty} \frac{1}{n} \log \mathbf{P}(S_n > an) = -I(a)$$

where,  $I(a) = \sup_{z \in \mathbb{R}} [za - \mathbf{E}[e^{z\xi}]]$ 

### Sanov, 1961 (Level 2 of LDP)

$$\mathbf{P}(S_n > an) = \mathbf{P} \circ S_n^{-1}((an, \infty)) := \mu_n((an, \infty))$$
$$-\frac{1}{n} \log \mu_n((an, \infty)) \xrightarrow[n \to \infty]{} \infty$$

# 8.3 Varadhan's LDP setup

Let,  $X_n : \Omega \to \mathbb{R}$  be a random variable of  $(\Omega, \mathcal{F}, \mathbf{P})$ . A be an event,  $\mathbf{P}_n(A) := \mathbf{P}(S_n \in A)$ , then  $\mathbf{P}(\cdot)$  is a probability on  $\mathbb{R}$ .

A sequence  $\{\mathcal{P}_n\}_{n\geq 1}$  of probability measures on  $\mathbb{R}$  (can be any metric space (X,d)) is said to satisfy large deviation principle with rate n and rate function  $I:\mathbb{R}\to [0,\infty)\cup\{\infty\}$ , if

- 1.  $I \not\equiv \infty$ , I is lower-semi continuous and has compact level sets.
- 2.  $\overline{\lim}_{n\to\infty} \frac{1}{n} \log \mathbf{P}_n(\mathcal{C}) \leq -I(\mathcal{C}) \,\forall \,\text{closed sets } \mathcal{C}$
- 3.  $\lim_{n\to\infty} \frac{1}{n} \log \mathbf{P}_n(\mathcal{O}) \ge -I(\mathcal{O}) \,\forall \,\text{open sets } \mathcal{O}$

where,  $A \subseteq \mathbb{R}$ ,  $I(A) = \inf_{y \in A} I(y)$ .

**Theorem 8.3.1.**  $\{\mathcal{P}_n\}_{n\geq 1}$  satisfied LDP with rate n then,  $I(\cdot)$  is unique.

**Theorem 8.3.2** (Varadhan's lemma). If,  $\{\mathcal{P}_n\}_{n\geq 1}$  satisfies LDP with rate n and rate function  $I(\cdot)$ , let  $F_n(x) = \mathbf{P}_n((-\infty, n])$  for some continuous and bounded above function  $F: \mathbb{R} \to \mathbb{R}$ , we have

$$\int e^{nF(x)} dF_n(x) \xrightarrow[n \to \infty]{} \sup_{x \in \mathbb{R}} [F(x) - I(x)]$$

### **Applications**

For,  $\theta \in S^1$ ,  $t \in \mathbb{R}$ ,  $u : S^1 \times \mathbb{R}_+ \to \mathbb{R}$ ,

$$\frac{\partial u}{\partial t} = \frac{1}{2} \frac{\partial^2 u}{\partial \theta^2} + V(\theta)u$$

$$u(0, \theta) = 1$$

then,

$$\frac{1}{t}\log u(t,\theta) \xrightarrow[t\to\infty]{} \lambda_1 = \sup_{f\in\cdots} \left\{ \int V(\theta)f(\theta)d\theta - \frac{1}{8} \int \frac{(f'(\theta)^2)}{f(\theta)}d\theta \right\}$$

we can represent this as follows,

$$u(t,\theta) = \mathbf{E} e^{\int_0^t V(\theta_s) ds}, \ \{\theta_s\}$$
 – brownian motion on  $S^1$ 

#### **Exercises**

1. For any  $a \in \mathbb{R}$ , show that,

$$\frac{\lceil an \rceil}{n} \xrightarrow[n \to \infty]{} a \text{ and } \frac{n - \lceil an \rceil}{n} \xrightarrow[n \to \infty]{} 1 - a$$