

Useful facts from probability law of large numbers (LLN)

Markov's inequality: $\begin{array}{l} \text{r.v.} \\ X \geq 0 \\ E(X) < \infty \end{array}$ then $P(X \geq a) \leq \frac{E(X)}{a}$

Proof $E(X) \geq P(X < a) \cdot 0 + P(X \geq a) \cdot a \quad \square$

Corollary (let $f: \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ be monotonically increasing). Then $\forall t \in \mathbb{R}$

$$P(X \geq a) = P(f(X) \geq f(a)) \leq \frac{E(f(X))}{f(a)} \quad \square$$

Bernstein's inequality X_i bounded r.v.s $s_n = X_1 + \dots + X_n$

$$\text{then } P(|s_n - nE(X_i)| \geq \epsilon n) \leq c^n$$

Hoeffding-Hoeffding estimates $\forall t \in \mathbb{R}$ (X_i) exp. dist.

$$\text{then } P(s_n \geq (1+t)nE(X_i)) \leq \left(\frac{1+t}{e^t}\right)^n$$

Binomial dist: $X_i = \begin{cases} 1 & \text{w/prob } p \\ 0 & \text{w/prob } 1-p=q \end{cases}$ $E(X_i) = p$ $E(X_i^k) = p$

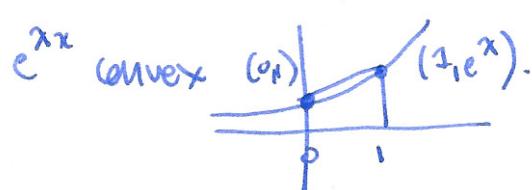
$$E(e^{tX_i}) = E\left(\sum_{k=0}^{\infty} \frac{t^k}{k!} X_i^k\right) = \sum_{k=0}^{\infty} \frac{t^k}{k!} E(X_i^k)$$

$$X_i \text{ binomial}: E(e^{tX_i}) = \frac{1+t}{1+p} + \frac{t^2}{2!} p + \frac{t^3}{3!} p + \dots = q + pe^t. \\ = pe^t + q.$$

Set $s_n = X_1 + \dots + X_n$ X_i indep. binom.

$$E(e^{ts_n}) = E(e^{t(X_1 + \dots + X_n)}) = \prod_i E(e^{tX_i}) = (pe^t + q)^n$$

More generally X_i bounded, takes values in $[0, 1]$.



$$y - \frac{1}{e^t} = (e^t - 1)x \\ y = (e^t - 1)x + 1$$

$$e^{tx} \leq e^t (e^t - 1)x + 1$$

$$\begin{aligned} E(e^{tX_i}) &\leq E((e^t - 1)X_i + 1) \\ &\leq (e^t - 1)E(X_i) + 1 \\ &\leq e^t E(X_i) + 1 - E(X_i) \end{aligned}$$

$$\mathbb{E}(e^{\lambda S_n}) \leq (pe^\lambda + q)^n \quad \text{for} \quad S_n = X_1 + \dots + X_n \quad x_i \stackrel{\text{i.i.d. dist}}{\sim} \text{take values in } \{0,1\}$$

Recall Markov: $P(X \geq m) \leq \frac{\mathbb{E}(e^{\lambda X})}{e^{\lambda m}}$ $\therefore \mathbb{E}(X_i) = p$.

$$\therefore P(S_n \geq m) \leq \frac{\mathbb{E}(e^{\lambda S_n})}{e^{\lambda m}} \leq \frac{(pe^\lambda + q)^m}{e^{\lambda m}} \quad \text{set } m = (p+t)n$$

$$P(S_n \geq (p+t)n) \leq \frac{(pe^\lambda + q)^n}{e^{\lambda(n(p+t))}}$$

\Rightarrow Bernstein estimate: $P(|S_n - pn| \geq \epsilon n) \leq \left(\frac{pe^\lambda + q}{e^{\lambda(p+t)}} \right)^n \quad \square$

2. Linear progress w/exp decay

Markov's inequality : $X \geq 0$ r.v. then $\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}(X)}{a}$

Proof $\mathbb{E}(X) \geq \mathbb{P}(X \leq a) \cdot 0 + \mathbb{P}(X \geq a) \cdot a \quad \square$

(Corollary) Let $\phi: \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ be a monotonically increasing function. Then

$$\mathbb{P}(|X| \geq a) = \mathbb{P}(\phi(|X|) \geq \phi(a)) \leq \frac{\mathbb{E}(\phi(|X|))}{\phi(a)} \quad \square$$

Chebyshev-Hoeffding bound Z_i sequence of id. dist. ind. exp. r.v.s. Then $\forall t \geq 0$

$$\mathbb{P}(Z_1 + \dots + Z_n \geq (1+t)n\mathbb{E}(Z_i)) \leq \left(\frac{1+t}{e^t}\right)^n.$$

Proof Let Z_i have pdf $f(x) = \begin{cases} \alpha e^{-\alpha x} & x \geq 0 \\ 0 & x < 0 \end{cases}$ $\mathbb{E}(Z_i) = \frac{1}{\alpha}$. $S_n = Z_1 + \dots + Z_n$

moment generating function $\mathbb{E}(e^{\lambda Z_i}) = \mathbb{E}(1 + \lambda Z_i + \frac{\lambda^2}{2} Z_i^2 + \dots) = 1 + \lambda \mathbb{E}(Z_i) + \frac{\lambda^2}{2} \mathbb{E}(Z_i)^2 + \dots$

$$\mathbb{E}(e^{\lambda Z_i}) = \int_0^\infty \alpha e^{-\alpha x} \cdot e^{\lambda x} dx = \frac{\alpha}{-\alpha + \lambda} \left[e^{(-\alpha + \lambda)x} \right]_0^\infty = \frac{\alpha}{\alpha - \lambda} \quad (0 < \lambda < \alpha)$$

$$\mathbb{E}(e^{\lambda S_n}) = \mathbb{E}(e^{\lambda(Z_1 + \dots + Z_n)}) = \mathbb{E}(e^{\lambda Z_1} \cdot e^{\lambda Z_2} \cdots e^{\lambda Z_n}) = \mathbb{E}(e^{\lambda Z_1}) \cdots \mathbb{E}(e^{\lambda Z_n}) = \left(\frac{\alpha}{\alpha - \lambda}\right)^n.$$

Markov's inequality: $\mathbb{P}(S_n \geq s) \leq \frac{\mathbb{E}(e^{\lambda S_n})}{e^{\lambda s}} = \frac{1}{e^{\lambda s} \left(\frac{\alpha}{\alpha - \lambda}\right)^n} \quad \textcircled{d}$

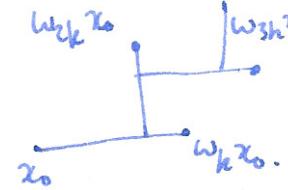
fact: \textcircled{d} minimized by $\lambda = \alpha - \frac{n}{s}$.

so $\mathbb{P}(S_n \geq s) \leq \left(\frac{\alpha s}{n}\right)^n e^{-\alpha s + n\alpha}$, where $s = (1+t)n\mathbb{E}(Z_i) = (1+t)n\frac{1}{\alpha}$.

then $\mathbb{P}(S_n \geq (1+t)n\mathbb{E}(Z_i)) \leq \left(\frac{1+t}{e^t}\right)^n \quad \square$.

Theorem $(r, \mu) \subset X$, μ non-elementary bounded support in X . Then $\exists l, K_C$ s.t.

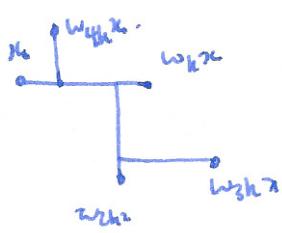
$$\mathbb{P}(d_X(x_0, w_n x_0) \leq l n) \leq K_C^n$$



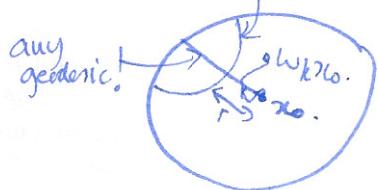
Proof take 2-steps at a time.

Note: $(w_n x) \rightarrow \lambda(w_n) \in \partial X \Rightarrow d_X(x_0, w_n x) \rightarrow \infty \Rightarrow \mathbb{E}(d_X(x_0, w_n x)) \rightarrow \infty.$ (2)

$$d_X(x_0, w_n x) = d_X(x_0, w_k x) + d_X(w_k x_0, w_{k+1} x) + \dots + d_X(w_{(n-1)k} x_0, w_n x).$$



$$\mathbb{P}\left(\left|d_X(x_0, w_{(n-1)k} x_0)\right|_{w_{(n-1)k} x_0} > r\right) \leq \mu_k(\text{shadow of depth } r) \leq k c^r$$



set $X_i^k = d(1, w_{ki} x_0) - d(1, w_{k(i-1)} x_0)$

$$X_i^k = Y_i^k - Z_i^k = d(1, w_{ki} x_0)_{w_{k(i-1)} x_0}.$$

$d_X(w_{(i-1)k} x_0, w_{ik} x_0)$

Bernstein estimate $\mathbb{P}\left(\left|\sum_{i=1}^n (Y_i - \mathbb{E}(Y_i))\right| \geq \epsilon n\right) \leq C^n.$

Chernoff-Hoeffding estimate $\mathbb{P}\left(\sum z_i^k \geq (1+t)n\mathbb{E}(z_i)\right) \leq \left(\frac{1+t}{e^t}\mathbb{E}\right)^n \leftarrow \text{no } k \text{ here!}$

for large k $\mathbb{E}(Y) \gg \mathbb{E}(Z).$ $\square.$

Matching: $\text{stab}_K(x) = \{g \in G \mid d_X(x, gx) \leq K\}$.

G acts X acylindrical: $\forall K \geq 0 \exists N, R$ s.t. $\forall x, y \in X, d_X(x, y) \geq R, |\text{stab}_K(x) \cap \text{stab}_K(y)| \leq N$.

G acts X, $g \in G$ is WPD if $\forall K \geq 0, \forall x \in X, \exists N$ s.t. $|\text{stab}_K(x) \cap \text{stab}_K(g^N x)| < \infty$.

Intuition from $F_2 \curvearrowright \text{Alph}(F_2)$ pick reduced word $w \in F_2$, take sample path γ . $P(w \text{ matches at } \gamma(t)) \approx 3^{-|w|}$. \rightsquigarrow gives both matching and non-matching!

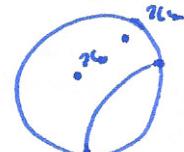
Defn $G \curvearrowright X$, we say a geodesic γ K-matches γ if \exists_{st} $g\gamma \subset N_K(\gamma)$

γ at $\gamma(t)$ if $g\gamma \subset N_K([\gamma(s(t)), \gamma(t) + l\gamma'])$

Defn $\alpha, \beta, (k, l)$ -match

Example $F_2 \curvearrowright \mathbb{H}^2$ dense image: everything matches! (not WPD, acylindrical).

some things don't match, e.g. "a" doesn't match "b" in F_2 .



Thm [MT] $(\alpha, \beta) \curvearrowright X$, $\text{supp}(\mu)$ bounded in X , g WPD

• matching: given $(k, l) \exists (B, c)$ s.t. $P(\gamma_u = [x_0, u\gamma_0] \text{ has a } (k, l)-\text{match w/ } g\gamma) \geq 1 - Bc^{\alpha}$

• non-matching: given $K \exists (B, c)$ s.t. $\forall u \in \mathbb{N}, P(\gamma_u \text{ K-matches } [x_0, u\gamma_0] \text{ at } \gamma(t_u)) \leq Bc^{\alpha}$

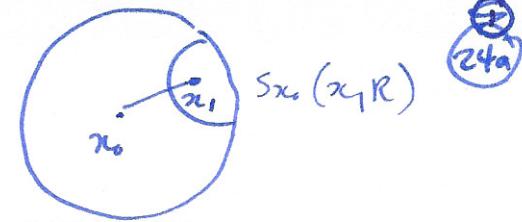


Applications: "random small cancellation conditions".

useful facts

Exponential decay for shadows

recall $S_{x_0}(x_1, R) = \{y \in X \mid (x_0)_n \geq d_X(x_0, y) - R\}$



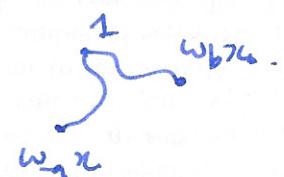
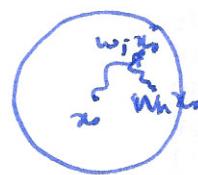
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Prop $(G, \mu) \models X$ hyp, μ non-elementary, $\text{supp}(\mu)$ bounded in X . Then there are constants K_C s.t. $\nu(S_{x_0}(x_1, R)) \leq K_C d_X(x_0, x_1) - R$ and $\mu_n(S_{x_0}(x_1, R)) \leq K_C^{d_X(x_0, x_1) - R}$

Corollary (Gauss product bounds) $(G, \mu) \models X$ hyp, as above. $\mathbb{P}\left(\left(x, w_i x_i\right)_{i \in \mathbb{Z}_0} \geq \frac{r}{k}\right)$

$\leq K_C^r$

Proof



large Gauss product

$\Rightarrow w_b x \in S_x(x, r)$. \square .

② Linear progress w/ exp decay

(finite exp moment)

Thm [Mather-Sisto] [Sunderland] $(G, \mu) \models X$, μ non-elementary, supp exp tail, i.e. $\exists \beta, \gamma$,

$\mathbb{E}(e^{\lambda d_X(x_0, x_1)}) < \infty$, then $\exists c, \delta > 0$ $\mathbb{P}(|\frac{1}{n} d_X(x_0, w_n x) - \lambda n| < \epsilon) \leq K e^{-c \epsilon}$.

Tools from probability

• Markov's inequality X r.v. $X \geq 0$ then $\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}(X)}{a}$.

Proof $\mathbb{E}(x) \geq \mathbb{P}(x < a) \cdot 0 + \mathbb{P}(x \geq a) \cdot a$. \square .

Corollary $\phi: \mathbb{R} \rightarrow \mathbb{R}$ monotonically increasing, then $\mathbb{P}(X \geq a) = \mathbb{P}(\phi(X) \geq \phi(a)) \leq \frac{\mathbb{E}(\phi(X))}{\phi(a)}$ \square

• Bernstein estimates X_i bounded r.v.s. $S_n = X_1 + \dots + X_n$ indep id. dist.

then $\mathbb{P}(|S_n - n \mathbb{E}(X_i)| \geq \epsilon n) \leq C^n$

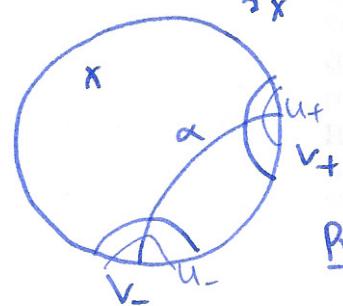
• Chernoff-Hoeffding estimates X_i finite exp moment, indep id. dist., then

$\mathbb{P}(S_n \geq (1+t)n \mathbb{E}(X_i)) \leq \left(\frac{1+t}{et}\right)^n$

• matching (sketch)

Theorem $(G, \mu) \models X$ μ non-elementary, bounded supp. in X . $\text{IP}([G_0, u_0])$ has (k, l) -match w/ α)
 $\Rightarrow 1 - B_C \sqrt{n}$.

sketch Pf (sketch): ergodicity $\Rightarrow \text{IP} \rightarrow 1$ but no rate.



$$\text{Prop}^n \quad A = \{w \in (G, \mu)^{\mathbb{Z}} \mid (\gamma_+(w), \gamma_-(w)) \in V_+ \times V_-\}.$$

$$\exists B, c \text{ s.t. } \mu^n(A \cup T^{-1}A \cup \dots \cup T^{-n}A) \geq 1 - B_C \sqrt{n}.$$

$$\begin{aligned} \text{Proof (sketch)} \text{ sufficient to show } \mu^n(G \setminus (A \cup T^{-1}A \cup \dots \cup T^{-n}A)) &\leq B_C \sqrt{n}, \\ &= \mu^n(A^c \cap T^{-1}A^c \cap \dots \cap T^{-n}A^c) \leq B_C \sqrt{n}. \end{aligned}$$

$$\text{set } A_n = A^c \cap T^{-1}A^c \cap \dots \cap T^{-n}A^c$$

$$\text{approx } \gamma^{-1}(V_+ \times V_-) \text{ by } U_k = \{w \in G^{\mathbb{Z}} \mid (w_k(w)^{x_0}, w_{k+n}(w)^{x_0}) \in V_+ \times V_-\}$$

[it depends on $E(k, j, k)$]

$$\text{set } V_k = \{w \in G^{\mathbb{Z}} \mid (w_n(w)^{x_0}, w_{n+k}(w)^{x_0}) \in U_+ \times V_- \text{ for } n=k\}.$$

$$\in V_+ \times V_- \text{ for } n \neq k$$

$$\gamma(V_k) \subseteq V_+ \times V_- \text{, so } V_k \subseteq A, \text{ so } A^c \subseteq V_k^c$$

$$\text{so } A_n \subseteq V_k^c \cap T^{-1}V_k^c \cap \dots \cap T^{-n}V_k^c = \bigcap_{i=0}^n T^{-i}V_k^c$$

pass to approx fin sets of gap size r_n .



$$A_n \subseteq \bigcap_{i=0}^{r_n} T^{-ri} V_{k+r_n}^c.$$

$$V_k \subseteq V_k \Rightarrow V_k^c = U_k^c \cup (U_k \setminus V_k).$$

$$A_n \subseteq \bigcap_{i=0}^{r_n} T^{-ri} (U_k^c \cup (U_k \setminus V_k)).$$

$$A_n \subseteq \left(\bigcap_{i=0}^{r_n} T^{-ri} U_k^c \right) \cup \left(\bigcup_{i=0}^{r_n} T^{-ri} (U_k \setminus V_k) \right).$$

↑ independent!

$$\begin{aligned} \mu^n(A_n) &\leq \mu^n(U_k^c)^{r_n} + r_n \underbrace{\mu^n(U_k \setminus V_k)}_{\text{shadow decay} \leq B_C 4^{rn}}. \\ &\rightarrow \nu(U_k^c) < 1. \end{aligned}$$

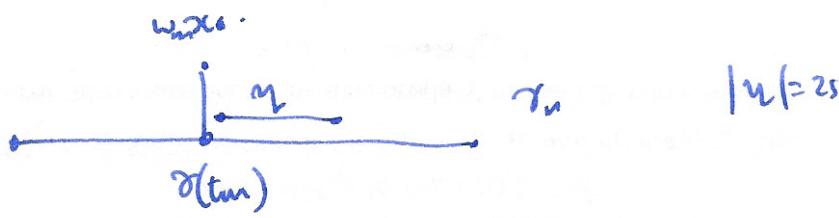


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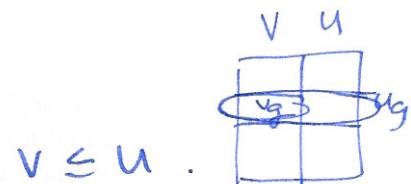
non-matching

this $(r, \mu) \in X$ μ non-elementary, bounded support in X , $\mathbb{P}([x_0, x_0 + \varepsilon] = r_n)$ $\stackrel{(K)-}{\rightarrow}$ η at $r_n(t_m)$
 $\leq Kc^m$.

Proof (sketch)



$U \subset (r, \mu)^2$ event that $g_N \subset N_K(r(t_m), r(t_m+2\varepsilon))$.
 $V \subset (r, \mu)^2$ $\exists s \forall g_N(r, \mu) \subset N_K(r(t_m), r(t_m+s))$



conditional prob $\mathbb{P}(u) \leq \mathbb{P}(u|v)$.

$U_g \subseteq u$: some specific $g_N \subset N_K(r(t_m), r(t_m+2\varepsilon))$ } $U = \bigcup_g U_g$
 V_g first half } $V = \bigcup_g V_g$

exponential decay of shadows $\Rightarrow \mathbb{P}(U_g | V_g) \leq Kc^s$

key fact for $|u| > 0$, any point of V is contained in a $\leq N(K)$ bounded number of sets V_g .
so $\mathbb{P}(u|v) \leq N(K) \cdot Kc^s$. \square .