

Introduction to mixing times of random walks

Framework:

$$X_t \in \mathcal{I}_n \quad (t=0,1,\dots)$$

$$X_0 = \text{id}$$

Assumption: X_t is a Markov chain

$$\mathbb{P}(X_t = x_t \mid X_0 = x_0, X_1 = x_1, \dots, X_{t-1} = x_{t-1}) = p(x_{t-1}, x_t)$$

where $p(x,y) = \mathbb{P}(\text{go from } x \text{ to } y \text{ in 1 shuffle})$

Under mild conditions,

$$\mathbb{P}(X_t = x) \xrightarrow[t \rightarrow \infty]{} \pi(x)$$

$$\text{Usually } \pi(x) = \frac{1}{n!}$$

If μ, ν are prob. distr. on $\mathcal{I}_n$,

$$\|\mu - \nu\|_{\text{TV}} = \sup_{A \subseteq \mathcal{I}_n} \|\mu(A) - \nu(A)\| = \frac{1}{2} \sum_{x \in \mathcal{I}_n} |\mu(x) - \nu(x)|$$

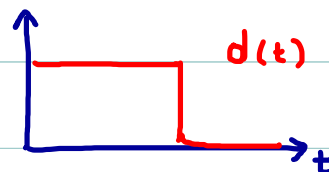
Introduce

$$d(t) = \sup_{x \in \mathcal{I}_n} \|\mathbb{P}(X_t^x) - \pi\|_{\text{TV}}$$

Observation

Diaconis - Shahshahani '81, Aldous '83

For "many" examples



Defⁿ Cutoff phenomenon occurs at some time t_{mix} as $n \rightarrow \infty$ if

$$d(t_{\text{mix}}(1-\varepsilon)) \xrightarrow{n \rightarrow \infty} 1 \quad \forall \varepsilon > 0$$

$$d(t_{\text{mix}}(1+\varepsilon)) \xrightarrow{n \rightarrow \infty} 0 \quad \forall \varepsilon > 0$$

Can always define

$$t_{\text{mix}} = \inf \{ t > 0 : d(t) \leq \frac{1}{4} \}$$

Examples

Random Transpositions

Pick two cards at random; switch them.

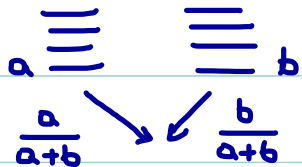
Thm (D-Sh.'81) Cutoff occurs as $n \rightarrow \infty$ for $t_{\text{mix}} = \frac{1}{2} n \log n$.

Random to top

Thm (Aldous) Cutoff at $t_{\text{mix}} = n \log n$

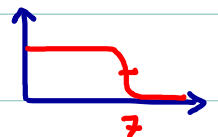
Riffle shuffle

Divide deck into 2 halves [using Binomial $(n, 1/2)$]



Thm (Aldous) Cutoff at $t_{\text{mix}} = \frac{3}{2} \log_2 n \simeq 8.55$

$n=52$ Thm (Bayer-Diaconis 1992) $t_{\text{mix}}(\frac{1}{2}) = 7$ for $n=52$



Maths techniques

- probabilistic tools
- representation theory
- analytic tools (functional ineq.)
- geometric tools

Probabilistic technique "Coupling"

Defⁿ : If μ, ν on $\mathcal{I}_n$, then a coupling is a pair (X, Y) s.t.
 $X \sim \mu$ and $Y \sim \nu$. Say coupling is successful if $X = Y$.

Prop. We have $\|\mu - \nu\|_{TV} = \inf_{(X, Y) \text{ coupling}} \mathbb{P}(X \neq Y)$

Rmk : In particular, if $\exists$ coupling (X, Y) s.t. $X = Y$ with high probability
 $\Rightarrow \|\mu - \nu\|_{TV}$ small.

Proof of $\leq$: If A is any event and (X, Y) any coupling, then

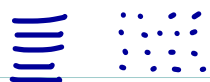
$$|\mu(A) - \nu(A)| = |\mathbb{P}(X \in A) - \mathbb{P}(Y \in A)|$$

$$= |\mathbb{P}(X \in A, X = Y) + \mathbb{P}(X \in A, X \neq Y)$$

$$- \mathbb{P}(Y \in A, X = Y) - \mathbb{P}(Y \in A, X \neq Y)| \leq \mathbb{P}(X \neq Y)$$

Example of use of coupling

Random to top : cutoff occurs at $n \log n$



X_t Y_t = imaginary deck of cards
started with $Y_0 \sim \pi$

Procedure :

At each step, pick $1 \leq i \leq n$ unif. at random

Choose card with label i , put it on top of deck.

Fact Once card with label i has been chosen, then this card is matched for both decks forever after.

Let $\tau = 1^{\text{st}}$ time all cards have been touched.

If $t \gg \tau$, then $X_t = Y_t$

$$d(t) \leq \mathbb{P}(\tau > t)$$

Fact 2. $\frac{\tau}{n \log n} \longrightarrow 1$ in probability

For instance,

$$\mathbb{E}(\tau) = \underbrace{\frac{n}{1}}_{\substack{\text{time to} \\ \text{collect} \\ \text{last card}}} + \underbrace{\frac{n}{2}}_{\substack{\text{time to} \\ \text{collect} \\ \text{last but one}}} + \dots + \underbrace{\frac{n}{n}}_{\substack{\text{time to} \\ \text{collect} \\ \text{first card}}} \sim n \log n$$

We deduce that

$$d((1+\varepsilon)n \log n) \longrightarrow 0$$

Lower bound

$$d((1-\varepsilon)n \log n) \longrightarrow 1 \quad ?$$

Connection to repⁿ theory

Pioneered by Diaconis-Shahshahani

Setup : finite group G_n

$p(x, y) = p(yx^{-1})$ for some probability p on G_n

Hence $X_t = X_0 g_1 g_2 \dots g_t$

where g_i are iid with distr. p .

Ex. Random transp.

$p(\tau) = \frac{2}{n^2}$ for any transposition τ

$$p(\text{id}) = n \cdot \frac{1}{n^2} = \frac{1}{n}$$

Fact : Then if $P^t(x) = \mathbb{P}(X_t = x \mid X_0 = \text{id})$, then $P^t(x) = \underline{\underline{p^{*t}(x)}}$

where $f * g(x) = \sum_{y \in G_n} f(xy^{-1}) g(y)$ convolution

E.g. $P(X_2 = x \mid X_0 = \text{id}) = \sum_y p(y) p(xy^{-1})$

Now, this suggests Fourier analysis.

Defⁿ If ρ is a representation and f is a function $G \rightarrow \mathbb{C}$

$$\hat{f}(\rho) = \sum_{s \in G} f(s) \rho(s)$$

$\hat{f}(p)$ is a matrix

p = frequency

$\hat{f}(p)$ = "amplitude" corresp. to p

Fourier inversion thm :

$$f(s) = \frac{1}{|G|} \sum_p d_p \operatorname{Tr}(p(s^{-1}) \hat{f}(p)) \quad , \text{ where } d_p = \dim p \\ \hookrightarrow \text{irred. rep}^n$$

Parseval formula:

$$\sum_{s \in G} f(s) h(s^{-1}) = \frac{1}{|G|} \sum_p d_p \operatorname{Tr}(\hat{f}(p) \hat{h}(p))$$

For us, if $g(s) = h(s^{-1})$

$$\sum_{s \in G} f(s) g(s) = \frac{1}{|G|} \sum_p d_p \operatorname{Tr}(\hat{f}(p) \hat{g}(p)^*)$$

Indeed,

$$\begin{aligned} \hat{h}(p) &= \sum_{s \in G} p(s) h(s) = \sum_{s \in G} p(s) g(s^{-1}) = \\ &= \sum_{t \in G} p(t^{-1}) g(t) = \sum_{t \in G} p(t)^* g(t) = (\hat{g}(p))^* \end{aligned}$$

Observation : If $f, g : G \rightarrow \mathbb{C}$, then $\widehat{f * g} = \hat{f} \cdot \hat{g}$

and in particular, $\widehat{p^t(x)} = \hat{p}^t(x)$.

Thm (D-Sh "upper-bound lemma")

Let μ be any prob distr on G_n . Let π be uniform distr. on G_n

$$\|\mu - \pi\|_{TV}^2 \leq \frac{1}{4} \sum_* d_p \operatorname{Tr}(\hat{\mu}(p) \hat{\mu}(p)^*)$$

where $\sum_*$ is the sum over all irreducible, non-trivial reps (ignoring the trivial Id repⁿ)

Proof $\|\mu - \pi\|_{TV}^2 = \frac{1}{4} \left(\sum_{s \in G} |\mu(s) - \pi(s)| \right)^2$

$$\leq \frac{1}{4} |G| \sum_{s \in G} |\mu(s) - \pi(s)|^2$$

Cauchy-Schwarz

Use Parseval

$$\leq \frac{1}{4} |G| \frac{1}{|G|} \sum_{\rho \text{ Irred.}} d_{\rho} \text{Tr}(\hat{f}(\rho) \hat{f}(\rho)^*)$$

where $f(s) = \mu(s) - \pi(s)$.

But $\hat{f}(\rho) = \hat{\mu}(\rho) - \hat{\pi}(\rho)$

Observe that $\hat{\pi}(\rho) = 0$ unless ρ is the trivial repⁿ.

Indeed, $\hat{\pi}(\rho) = \sum_{s \in G} \frac{1}{|G|} \rho(s) = \frac{1}{|G|} \sum_{s \in G} \rho(s) =$

$$= \frac{1}{|G|} \sum_{s \in G} \rho(st) = \frac{1}{|G|} \left(\sum_{s \in G} \rho(s) \right) \rho(t)$$

true for all t , so $\sum_{s \in G} \rho(s) = 0$

When $\rho = \text{trivial rep}^n$

$$\hat{\mu}(\rho) = \sum \mu(s) \cdot 1 = 1 \Rightarrow \hat{\mu}(\rho) - \hat{\pi}(\rho) = 0 \Rightarrow$$

$$\|\mu - \pi\|_{TV}^2 \leq \frac{1}{4} \sum_{*} d_{\rho} \text{Tr}(\hat{\mu}(\rho) \hat{\mu}(\rho)^*), \text{ as desired.}$$

Applying to RW on $\mathcal{T}_n$, $X_t = \text{id} \underbrace{g_1, \dots, g_n}_{\text{iid}}$

Cor. $d(t)^2 \leq \frac{1}{4} \sum_{\rho} d_{\rho}^2 \lambda_{\rho}^{2t}$

where $\lambda_{\rho} = \left(\frac{1}{n} + \frac{n-1}{n} r(\rho) \right)$

and $r(\rho) = \frac{\chi_{\rho}(\tau)}{d_{\rho}} = \text{character ratio}$, $\chi_{\rho}(\tau) = \chi_{\rho}$ evaluated at any transposition

Proof This is because $P(x)$ is itself a class function.

Let ρ is a repⁿ and $s \in G$,

$$\begin{aligned} \rho(s) \hat{P}(\rho) \rho(s^{-1}) &= \rho(s) \left(\sum_{t \in G} P(t) P(t) \right) \rho(s^{-1}) \\ &= \sum_{t \in G} \rho(s t s^{-1}) P(t) \\ &= \sum_{t \in G} \rho(t) P(t) = \hat{P}(\rho) \end{aligned}$$

$$\Rightarrow \rho(s) \hat{P}(\rho) = \hat{P}(\rho) \rho(s) \quad \forall s \in G$$

$$\Rightarrow \text{By Schur's lemma } \hat{P}(\rho) = \lambda I$$

$$\text{Here } \lambda d_{\rho} = \text{Tr}(\hat{P}(\rho)) = \text{Tr} \left(\sum_s \rho(s) P(s) \right) = \sum_{s \in G} P(s) \chi_{\rho}(s)$$

Consequence :

$$\frac{1}{4} \sum_{\rho} d_{\rho} \text{Tr} \left(\underbrace{\hat{P}^t}_{\lambda_{\rho}^t I} \underbrace{(\hat{P}^t)^*}_{\overline{\lambda_{\rho}^t} I} \right) = \frac{1}{4} \sum_{\rho} d_{\rho}^2 |\lambda_{\rho}|^{2t}$$

Spectral Gap

Let S finite set

$p(x, y) = \text{trans. prob. on } S$

Prop (Perron-Frobenius)

1. If λ is an $(\mathbb{C})$ eigenvalue, then $|\lambda| \leq 1$.
2. If P is irreducible, then $\lambda = 1$ is an EV of dimension 1, generated by $(1, \dots, 1)$
3. If P is aperiodic and reversible, then $\forall \lambda \text{ e.v. } \in \mathbb{R}$
4. $\exists f_j$ which is ON basis of eigenfunctions wrt $\langle, \rangle_\pi$

Reversibility: $\exists \pi(x) \geq 0 \quad \pi(x) P(x, y) = \pi(y) P(y, x)$

then π is the stat. distr. of the Markov chain.

Define $L^2(S, \pi) = \text{space of functions } S \rightarrow \mathbb{R}$

with $\langle f, g \rangle_\pi = \sum_{x \in S} f(x) g(x) \pi(x)$

We can always assume $\lambda \geq 0$ by considering $\tilde{P} = \frac{I+P}{2}$ [lazy chain]

Defⁿ. Let $1 = \lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \dots \geq \lambda_n \geq 0$

$\gamma = 1 - \lambda_2 = \text{spectral gap}$

$t_{\text{rel}} = \text{relaxation time} = \frac{1}{\gamma}$

Observation: $P^t(x, y) = \mathbb{P}(X_t = y \mid X_0 = x) = (P^t \delta_x)(y)$

where $P^t f(x) = \sum P^t(x, y) f(y)$

and $\delta_y(s) = \mathbb{1}_{\{s=y\}}$

Now $\delta_y = \sum_{j=1}^n \langle \delta_y, f_j \rangle_\pi f_j = \sum_{j=1}^n f_j(y) \pi(y) f_j$

$\Rightarrow P^t(x, y) = \sum_{j=1}^n f_j(y) \pi(y) \lambda_j^t f_j(x)$

Hence $\frac{P^t(x,y)}{\pi(y)} = \sum_{j=1}^n f_j(x) f_j(y) \lambda_j^t$

Thm Assume (irred., aperiodicity, reversibility)

Let $t_{\text{mix}}(\varepsilon) = \inf \{t \geq 0 : d(t) \leq \varepsilon\}$

Then $\forall \varepsilon \in (0,1)$ $t_{\text{rel}} \log\left(\frac{1}{\varepsilon}\right) \leq t_{\text{mix}}(\varepsilon) \leq t_{\text{rel}} \log\left(\frac{1}{2\varepsilon\sqrt{\pi_{\min}}}\right)$

where

$\pi_{\min} = \min \{ \pi(x) : x \in S \}$

Proof Upper-bound:

Recall $\|P_t(x, \cdot) - \pi(\cdot)\|_{\text{TV}} = \frac{1}{2} \sum_{y \in S} |P_t(x,y) - \pi(y)|$
 $= \frac{1}{2} \sum_{y \in S} \pi(y) \left| \frac{P_t(x,y)}{\pi(y)} - 1 \right|$
 $= \frac{1}{2} \left\| \frac{P_t(x, \cdot)}{\pi(\cdot)} - 1 \right\|_1 \leq \frac{1}{2} \left\| \frac{P_t(x, \cdot)}{\pi(\cdot)} - 1 \right\|_2$
(Jensen)

$\Rightarrow 4d(t)^2 \leq \sum_{j=1}^n f_j(x)^2 \lambda_j^{2t} \leq (1-\gamma)^{2t} \sum_{j=1}^n f_j(x)^2$

Recall $\delta_x = \sum_{j=1}^n \langle \delta_x, f_j \rangle f_j = \sum_{j=1}^n f_j(x) \pi(x) f_j$

So $\langle \delta_x, \delta_x \rangle_{\pi} = \pi(x) = \sum_{j=1}^n f_j(x)^2 \pi(x)$

$\Rightarrow \frac{1}{\pi(x)} = \sum_{j=1}^n f_j(x)^2$

$\Rightarrow 4d(t)^2 \leq \frac{1}{\pi(x)} (1-\gamma)^{2t}$

$\Rightarrow d(t) \leq \frac{1}{2\sqrt{\pi_{\min}}} e^{-t\gamma}$

Hence $t_{\text{mix}}(\varepsilon) \leq t_{\text{rel}} \log\left(\frac{1}{2\varepsilon\sqrt{\pi_{\min}}}\right)$

Example: $\mathbb{Z}/n\mathbb{Z}$

$$\lambda_2 = \cos\left(\frac{2\pi}{n}\right) \Rightarrow \gamma = 1 - \cos\left(\frac{2\pi}{n}\right) \simeq \frac{2\pi^2}{n^2}$$

$$\Rightarrow \tau_{\text{rel}} = O(n^2)$$

Dirichlet form & path method

Suppose (P, π) reversible.

$$\text{Define } \mathcal{E}(f, g) = \frac{1}{2} \sum_{x, y \in S} \pi(x) P(x, y) (f(y) - f(x))(g(y) - g(x))$$

for $f, g: S \rightarrow \mathbb{R}$

$$\approx \frac{1}{2} \int \nabla f \nabla g = -\frac{1}{2} \int f \Delta g$$

$$\mathcal{E}(f, g) = \underset{\text{computation}}{\langle (I - P)f, g \rangle_\pi}$$

$$\text{Thm } \gamma = \min_{\substack{f: S \rightarrow \mathbb{R} \\ \mathbb{E}_\pi(f) = 0}} \frac{\mathcal{E}(f, f)}{\|f\|_2^2} = \min_{\substack{f: S \rightarrow \mathbb{R} \\ \mathbb{E}_\pi(f) = 0 \\ \|f\|_2 = 1}} \mathcal{E}(f, f)$$

Defⁿ: π Poincaré inequality if $\forall f: S \rightarrow \mathbb{R}$

$$\text{var}_\pi(f) \leq C \mathcal{E}(f, f) \quad (*)$$

This always holds with $C = 1/\gamma$, and this is optimal.

Any inequality such as $(*)$ gives $\tau_{\text{rel}} \leq C$.

Pointers :

- Diaconis - Saloff-Coste 1996 :

Comparison ineq.

$$\tilde{E}(f, f) \leq A E(f, f)$$

- New Y. Ollivier

Discrete notion of Ricci Curvature

$$K(x, y) \geq K_0 > 0$$

$$\Rightarrow d(t) \leq (1 - K_0)^t \text{diameter}(S).$$