

# ① LECTURE 19: Last remarks on Markov chains

① Ergodicity:  $V_x(n) := \sum_{i=0}^{n-1} \mathbb{1}\{Y_i = x\}$  = "time spent @ x".

If  $\mu$  stationary prob. measure, expect  $\frac{V_x(n)}{n} \rightarrow \mu(x) = \frac{1}{\underbrace{E_x T_x}_{=: t_x}}$ .

Thm: If  $(Y_n)$  irreducible + recurrent,  $\forall x, y$ ,

$$P_x \left[ \frac{V_y(n)}{n} \rightarrow \frac{1}{t_y} \right] = 1. \quad (\text{even if } t_y = \infty!)$$

If further positive recurrent, i.e.  $t_y < \infty \forall y$ , then  $\forall f: S \rightarrow \mathbb{R}$  bdd,

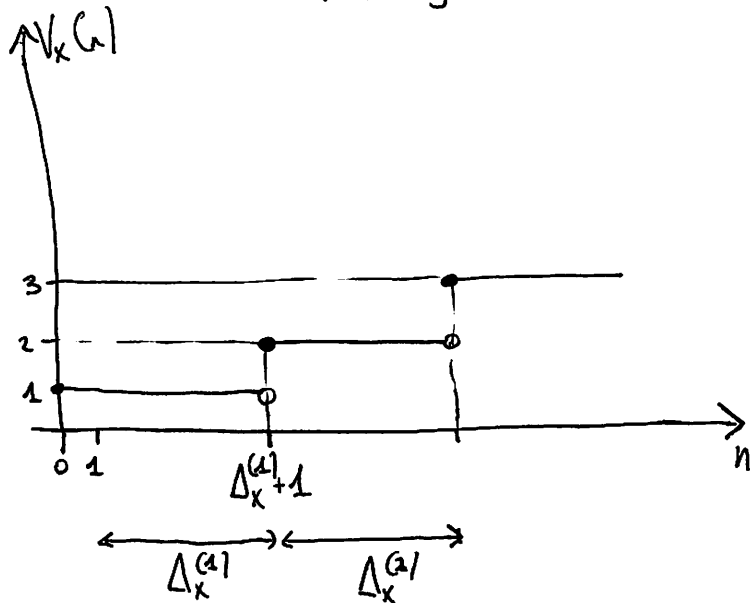
$$P_x \left[ \frac{1}{n} \sum_{i=0}^{n-1} f(Y_i) \rightarrow \underbrace{E f(y)}_{y \sim \mu} \right] = 1 \quad (\text{for } \mu \text{ unique stationary prob.})$$

(pos. rec. case.)

PF: Exc: WLOG,  $x = y$  (initial  $x \rightarrow y$  part insubstantial.)

$T_x^{(k)}$  := time of  $k^{\text{th}}$  visit to  $x$ ,  $T_x^{(0)} = 0$ ,  $\Delta_x^{(k)} = T_x^{(k)} - T_x^{(k-1)} \geq 0$

Strong Markov property  $\Rightarrow \Delta_x^{(k)}$  iid,  $E \Delta_x^{(k)} = t_x$ .



$$1 + \Delta_x^{(1)} + \dots + \Delta_x^{(V_x(n)-1)} \leq n$$

$$\leq \Delta_x^{(1)} + \dots + \Delta_x^{(V_x(n))}$$

$$\downarrow$$

$$\left| \frac{n}{V_x(n)} - \frac{\Delta_x^{(1)} + \dots + \Delta_x^{(V_x(n))}}{V_x(n)} \right|$$

$$\leq \frac{1 + \Delta_x^{(V_x(n))}}{V_x(n)}$$

Recurrence  $\Rightarrow V_x(n) \rightarrow \infty$  a.s.  $\Rightarrow$  this  $\rightarrow 0$  a.s.

② SLLN  $\Rightarrow \frac{\Delta_x^{(n)} + \dots + \Delta_x^{(V_x(n))}}{V_x(n)} \xrightarrow{\text{a.s.}} t_x \Rightarrow \frac{n}{V_x(n)} \xrightarrow{\text{a.s.}} t_x$   
 $\Rightarrow \frac{V_x(n)}{n} \xrightarrow{\text{a.s.}} \frac{1}{t_x} = \mu(x)$

For odd functions  $f: S \rightarrow \mathbb{R}$ , wlog  $|f(y)| \leq 1$

$$\begin{aligned} \left| \frac{1}{n} \sum_{i=0}^{n-1} f(Y_i) - \sum_y \mu(y) f(y) \right| &= \left| \sum_y \left( \frac{V_y(n)}{n} - \mu(y) \right) f(y) \right| \\ &= \sum_y V_y(n) f(y) \leq \sum_y \left| \frac{V_y(n)}{n} - \mu(y) \right| \\ &\leq \sum_{y \in A} \left| \frac{V_y(n)}{n} - \mu(y) \right| + \sum_{y \notin A} \frac{V_y(n)}{n} + \mu(A^c) \\ &\leq 2 \sum_{y \in A} \left| \frac{V_y(n)}{n} - \mu(y) \right| + 2\mu(A^c). \end{aligned}$$

Choose large finite  $A \rightarrow$  a.s.  $\limsup \leq \epsilon, \forall \epsilon > 0$ .

Rk: Previously to estimate  $\mathbb{E} f(x)$  with MCMC, would run  $x \sim \mu$   
 $Y_n^{(1)}, \dots, Y_n^{(k)} \stackrel{\text{iid}}{\sim} \mu_n \approx \mu$ , form estimate  $\frac{1}{k} \sum_{i=1}^k f(Y_n^{(i)})$ .  
 Ergodicity  $\Rightarrow$  enough to take  $\frac{1}{n} \sum_{i=1}^n f(Y_i)$  - "one" chain.

② Convergence estimates:  $S$  finite  $\leftarrow |S| = N$ , irreducible, recurrent,  
 $\mu$  stationary prob. measure,  $P_{ij} := p(i, j)$ ,  $P \in \mathbb{R}^{N \times N}$ ,  $\mu_i := \mu(i)$   
 $\mu \in \mathbb{R}^N$ .

Def: Reversible if  $\mu_i P_{ij} = \mu_j P_{ji} \forall i, j \in [N]$ .  
 $\mu_i P_{ij} P_{jk} P_{kl} = \mu_j P_{ji} P_{kj} P_{lk} P_{kl} = \mu_l P_{lk} P_{kj} P_{ji}$   $\rightarrow$  equal prob. to see forward vs. reverse sequence @ stationarity.

③  $\mu \rightsquigarrow (D_\mu)_{ii} = \mu_i$  diagonal mx.

Reversibility  $\iff D_\mu P = P^T D_\mu \iff D_\mu P$  symmetric.

$\implies D_\mu^{1/2} P D_\mu^{-1/2} =: M$  also symmetric.

$(\sqrt{\mu})_i := \sqrt{\mu_i} \implies M \sqrt{\mu} = D_\mu^{1/2} P \mathbf{1} = D_\mu^{1/2} \mathbf{1} = \sqrt{\mu}$ .  
 $\implies \sqrt{\mu}$  eigvec with  $\lambda = 1$ .

Proof:  $\|M\| \leq 1$ .

pf:  $\|M\| = \max_{f \in \mathbb{R}^N, f \neq 0} \frac{|f^T M f|}{\|f\|^2} = \max_{f \neq 0} \frac{|f^T D_\mu^{1/2} P D_\mu^{-1/2} f|}{(f^T f)}$   
 $(\text{let } f := D_\mu^{1/2} g) = \max_{g \neq 0} \frac{|g^T D_\mu P g|}{(g^T D_\mu g)} = \max_{g \neq 0} \frac{|\mathbb{E}_\mu g(Y_0) g(Y_1)|}{\mathbb{E}_\mu g(Y_0)^2} \stackrel{\text{Cauchy-Schwarz}}{\leq} 1$

So, if  $\lambda_1 \geq \dots \geq \lambda_N$  sorted eigvals,  $\lambda_1 = 1$ .

Suppose  $|\lambda_2|, |\lambda_N| < 1 \implies M^k = D_\mu^{1/2} P^k D_\mu^{-1/2} \approx \sqrt{\mu} \sqrt{\mu}^T$   
 $\implies P^k \approx \mathbf{1} \mu^T$  : same as convergence! Rk:  $\|\sqrt{\mu}\| = 1$

Concretely,

$$\begin{aligned} \max(|\lambda_2|, |\lambda_N|)^k &\geq \|M^k - \sqrt{\mu} \sqrt{\mu}^T\| = \|D_\mu^{1/2} (P^k - \mathbf{1} \mu^T) D_\mu^{-1/2}\| \\ &\geq \sqrt{\frac{\min \mu_i}{\max \mu_i}} \|P^k - \mathbf{1} \mu^T\| \end{aligned}$$

$$\text{Thm: } \frac{\max_{x \in S} |\mathbb{E}_x f(Y_k) - \mathbb{E}_{y \sim \mu} f(y)|}{\sqrt{\text{Var}_{y \sim \mu} f(y)}} \leq \sqrt{\frac{\max \mu_i}{\min \mu_i}} \cdot (\max(|\lambda_2|, |\lambda_N|))^k$$

④ Ex:  $G$   $d$ -regular graph (all degrees =  $d$ ),  $p$  given by SRW.

$$A = \text{adjacency mx} \rightarrow P = \frac{1}{d} A.$$

$$N \text{ vertices} \rightarrow \mu_i \equiv \frac{1}{N} \rightarrow M = P, M\mathbf{1} = \mathbf{1}.$$

If  $|\lambda_2(P)|, |\lambda_N(P)| \leq (1-\varepsilon)$   $\Rightarrow$  exponentially fast mixing!  
"  $\frac{1}{d} \lambda_2(A)$  "  $\frac{1}{d} \lambda_N(A)$

Prop:  $\lambda_2(A) = d \iff G$  disconnected  $\rightarrow$  MC reducible  
 $\lambda_N(A) = -d \iff G$  bipartite  $\rightarrow$  MC periodic

Otherwise, exp. fast convergence.

Rk: Expanders = graphs w/  $|\lambda_2|, |\lambda_N| \leq 1-\varepsilon$  for  $\varepsilon, d$  const  
as  $N \rightarrow \infty$ . Many CS applications!