

3/1/10

Thm 4.9

Suppose that P is irreducible and aperiodic then $\exists \alpha \in (0,1)$ and $C > 0$ such that

$$\|P^t(x, \cdot) - \pi\|_{TV} \leq C \alpha^t$$

Proof

$\exists r > 0$ such that $P^r(x,y) > 0,$

$\forall x,y.$

Choose δ such that

$$P'(x, y) \geq \delta \pi(y), \quad \forall x, y$$

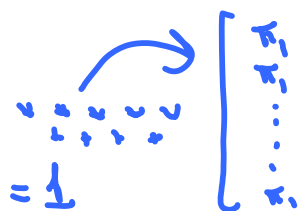
Let $\Pi = \begin{bmatrix} \pi \\ \pi \\ \vdots \\ \pi \end{bmatrix}$ and write

$$P' = (1 - \theta)\Pi + \theta Q \quad \text{define } Q$$

Q is stochastic i.e. $Q \underline{1} = \underline{1}$

$$\theta Q \underline{1} = P' \underline{1} - (1 - \theta) \Pi \underline{1} = \theta \underline{1}$$

$$M \Pi = \Pi \text{ if } M \text{ is stochastic}$$



A diagram illustrating the multiplication of a row vector of ones by a column vector of probabilities. On the left, a row vector of five ones is shown with an arrow pointing to a column vector of five probabilities, $\begin{bmatrix} \pi_1 \\ \pi_2 \\ \vdots \\ \pi_n \end{bmatrix}$. The result of the multiplication is indicated as 1.

and

$$\Pi M = \Pi \text{ if } \pi M = \pi$$

Claim $P^{rk} = (1 - \theta^k) \Pi + \theta^k Q^k$

Proof Induction on k .

$k=1$, by definition of Q

$$\begin{aligned}
p^{r(k+1)} &= ((1 - \theta^k) \mathbb{I} + \theta^k Q^k) p^r && \text{inductive assumption} \\
&= (1 - \theta^k) \underbrace{\mathbb{I} p^r}_{\mathbb{I}} + \theta^k Q^k p^r \\
&= (1 - \theta^k) \mathbb{I} + \theta^k Q^k p^r \\
&= (1 - \theta^k) \mathbb{I} + \theta^k Q^k ((1 - \theta) \mathbb{I} + \theta Q) \\
&= \mathbb{I} - \theta^k \mathbb{I} + \theta^k (1 - \theta) \mathbb{I} + \theta^{k+1} Q^{k+1} \\
&\quad \quad \quad Q^k \text{ is stochastic} \\
&= \mathbb{I} (1 - \theta^{k+1}) + \theta^{k+1} Q^{k+1}
\end{aligned}$$

□

$$\begin{aligned}
P^{rk+j} - \Pi &= ((1 - \theta^k) \Pi + \theta^k Q^k) P^j - \Pi \\
&= (1 - \theta^k) \Pi + \theta^k Q^k P^j - \Pi \\
&= \theta^k (Q^k P^j - \Pi)
\end{aligned}$$

Stochastic

Fix row x_0

$$\|P^{rk+j}(x_0, \cdot) - \pi\|_{TV} \leq \theta^k$$

A, B stoch
 $\Downarrow$
 AB stoch.
 $AB1 = A1 = 1$



4.4

$$d(t) = \max_{x \in \Omega} \|P^t(x, \cdot) - \pi\|_{TV}$$

$$\bar{d}(t) = \max_{x, y} \|P^t(x, \cdot) - P^t(y, \cdot)\|_{TV}$$

Lemma 4.1)

$$d(t) \leq \bar{d}(t) \leq 2 d(t)$$

Proof

$$\begin{aligned} \bar{d}(t) &\leq \max_{x, y} \left[\|P^t(x, \cdot) - \pi\|_{TV} + \|\pi - P^t(y, \cdot)\|_{TV} \right] \\ &\leq 2 d(t) \end{aligned}$$

$$\pi(A) = \sum_{x \in A} \left[\sum_{y \in \Omega} \pi(y) P^t(y, x) \right]$$

$$= \sum_{y \in \Omega} \pi(y) P^t(y, A)$$

So

$$\|P^t(x, \cdot) - \pi\|_{TV} = \max_A |P^t(x, A) - \pi(A)|$$

$$= \max_A \left| \sum_{y \in \Omega} \pi(y) (P^t(x, A) - P^t(y, A)) \right|$$

$$\leq \max_A \sum_{y \in \Omega} \pi(y) |P^t(x, A) - P^t(y, A)|$$

$$\leq \max_A \sum_{y \in \Omega} \pi(y) |P^t(x, A) - P^t(y, A)|$$

$$\leq \sum_{y \in \Omega} \pi(y) \max_A |P^t(x, A) - P^t(y, A)|$$

$$= \sum_{y \in \Omega} \pi(y) \|P^t(x, \cdot) - P^t(y, \cdot)\|_{TV}$$

$$\leq \max_y \|P^t(x, \cdot) - P^t(y, \cdot)\|_{TV}$$

$$\leq \bar{d}(t)$$

$$\Rightarrow d(t) \leq \bar{d}(t).$$

Claim

$$(i) \quad d(t) = \sup_{\mu \in \mathcal{P}} \|\mu P^t - \pi\|_{TV}$$

($\mathcal{P}$: distributions on Ω)

$$(ii) \quad \bar{d}(t) = \sup_{\mu, \nu \in \mathcal{P}} \|\mu P^t - \nu P^t\|_{TV}$$

Lemma 4.2

$$\bar{d}(s+t) \leq \bar{d}(s) \bar{d}(t)$$

Proof

For $x, y \in \Omega$ and let X_s, Y_s be an optimal coupling of $P^s(x, \cdot)$, $P^s(y, \cdot)$

$$\|P^s(x, \cdot) - P^s(y, \cdot)\|_{TV} = P(X_s \neq Y_s)$$

$$\begin{aligned} P^{s+t}(x, w) &= \sum_z P^s(x, z) P^t(z, w) \\ &= \sum_z P[X_s = z] P^t(z, w) = E(P^t(X_s, w)) \end{aligned}$$

So,

$$p^{s+t}(x_s, \omega) - p^{s+t}(y_s, \omega) = \mathbb{E} \left[p^t(X_s, \omega) - p^t(Y_s, \omega) \right]$$

and

$$\| p^{s+t}(x_s, \cdot) - p^{s+t}(y_s, \cdot) \|_{TV}$$

$$= \frac{1}{2} \sum_{\omega} | \mathbb{E} (p^t(X_s, \omega) - p^t(Y_s, \omega)) |$$

$$\leq \mathbb{E} \left(\frac{1}{2} \sum_{\omega} | p^t(X_s, \omega) - p^t(Y_s, \omega) | \right)$$

$\uparrow | \mathbb{E}(X) | \leq \mathbb{E}(|X|) - \text{Jensen's Ineq.}$

$$= \mathbb{E} (\| p^t(X_s, \cdot) - p^t(Y_s, \cdot) \|_{TV})$$

$$= E (\| P^t(X_s, \cdot) - P^t(Y_s, \cdot) \|_{TV})$$

$$\leq E (\bar{d}(t) \cdot \mathbb{1}_{X_s \neq Y_s})$$

$$= \bar{d}(t) P_t(X_s \neq Y_s)$$

↖ maximum
over x, y .

$$\leq \bar{d}(t) \bar{d}(s).$$

□

Ex 4.3 $\|\mu P - \nu P\|_{TV} \leq \|\mu - \nu\|_{TV}$

$\mu = P^t(x, \cdot)$ & $\nu = \pi$

$\|P^{t+1}(x, \cdot) - \pi\|_{TV} \leq \|P^t(x, \cdot) - \pi\|_{TV}$

$d(t) \searrow$ and similarly $\bar{d}(t) \searrow$

$$|\mu P(A) - \nu P(A)| = \left| \sum_{y \in A} \sum_{x \in \Omega} \mu_x P_{x,y} - \sum_{y \in A} \sum_{x \in \Omega} \nu_x P_{x,y} \right|$$

$$= \left| \sum_{x \in \Omega} (\mu_x - \nu_x) P_{x,A} \right|$$

$$\leq \sum_{\substack{x \in \Omega \\ \mu_x \geq \nu_x}} (\mu_x - \nu_x) = \|\mu - \nu\|_{TV}.$$

C & t positive integers

$$d(ct) \leq \bar{d}(ct) \leq \bar{d}(t)^C$$

Mixing Time

$$t_{\text{mix}}(\epsilon) = \min \{ t : d(t) \leq \epsilon \}$$

$$t_{\text{mix}} = t_{\text{mix}}(1/4)$$

something
 $< \frac{1}{2}$

$$d(l t_{\text{mix}}(\epsilon)) \leq \bar{d}(l t_{\text{mix}}(\epsilon))$$

$$\leq \bar{d}(t_{\text{mix}}(\epsilon))^l$$

$$\bar{d} \leq 2d$$

$$\leq (2\epsilon)^l$$

Ergodic Theorem: P irreducible

$$f: \Omega \rightarrow \mathbb{R}$$

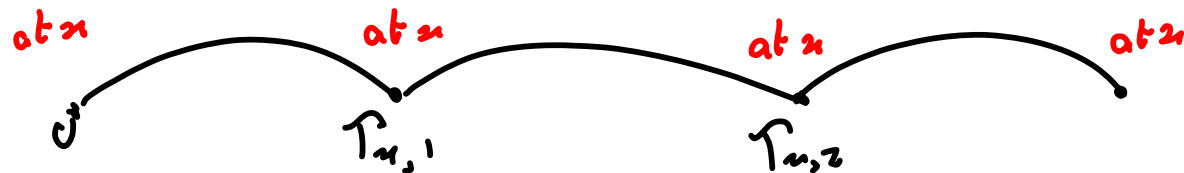
$\mu \in \mathcal{P}$, starting distribution

$$P_\mu \left\{ \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{s=0}^{t-1} f(X_s) - \sum_{\pi} \pi_{\pi} f(\pi) \right\} = 1$$

Proof

Suppose chain starts at x .

$$T_{x,0}^+ = 0 \text{ and } T_{x,t}^+ = \min \{ t > T_{x,t-1}^+ : X_t = x \}$$



$$Y_k = \sum_{s=\tau_{n,k-1}^+}^{\tau_{n,k}^+} f(X_s)$$

is a sequence of i.i.d. random variables

if

$$S_k = \sum_{s=0}^{k-1} f(X_s)$$

then

$$S_{\tau_{n,n}^+} = \sum_{k=1}^n Y_k$$

So, by law of large numbers

$$P_x \left\{ \lim_{n \rightarrow \infty} \frac{S_{\tau_{n,n}^+}}{n} = E_x(Y_1) \right\}$$

Now

$$\tau_{x,n}^+ = \sum_{k=1}^n \underbrace{(\tau_{x,k}^+ - \tau_{x,k-1}^+)}_{\text{i.i.d.}}$$

$$P_x \left\{ \lim_{n \rightarrow \infty} \frac{\tau_{x,n}^+}{n} = E_x(\tau_x^+) \right\}$$

$$P_x \left\{ \lim_{n \rightarrow \infty} \frac{S_{\tau_{x,n}^+}}{\tau_{x,n}^+} = \frac{E_x(Y_1)}{E_x(\tau_x^+)} \right\} = 1$$

Now

$$E_n(Y_1) = E_n \left(\sum_{s=0}^{T_n^+} f(X_s) \right)$$

$$= E_n \left(\sum_{y \in \Omega} f(y) \sum_{s=0}^{T_n^+} 1_{X_s=y} \right)$$

$$= \sum_{y \in \Omega} f(y) E_n \left(\sum_{s=0}^{T_n^+} 1_{X_s=y} \right)$$

$$\pi_y = \frac{E_n(\cdot)}{E(T_n^+)}$$

$$= \sum_{y \in \Omega} f(y) \pi(y) E(T_n^+)$$

S.

$$P_n \left\{ \lim_{n \rightarrow \infty} \frac{S_{T_{a,n}^+}}{T_{a,n}^+} = E_x(f) \right\} = 1$$

Ex 4.7 $a_n < \infty, \quad n_k \rightarrow \infty; \quad \frac{n_{k+1}}{n_k} \rightarrow 1; \quad \frac{a_1 + \dots + a_{n_k}}{n_k} \rightarrow a \Rightarrow \frac{a_1 + \dots + a_n}{n} \rightarrow a$

Let $n_k = \sum_{j \leq k} T_{x,j}^+$. $P_r \left\{ \lim_{k \rightarrow \infty} \frac{n_{k+1}}{n_k} = 1 \right\} = 1$

So $P_x \left\{ \lim_{t \rightarrow \infty} \frac{S_t}{t} = E_x(f) \right\} = 1$

We need to show that $P_r \left\{ \lim_{k \rightarrow \infty} \frac{n_{k+1}}{n_k} = 1 \right\} = 1$

This is implied by $P_r \left\{ \lim_{k \rightarrow \infty} \frac{T_{x,k}^+}{k} = 0 \right\} = 1$
 $\leftarrow n_k \geq k$

This is implied by $P_r \left\{ \lim_{k \rightarrow \infty} \frac{\tau_{x_j, k}^+}{k} = 0 \right\} = 1$

Choose $\epsilon > \delta, r$ such that $P^r(y, x) \geq \delta > 0, \forall y \neq r.$

Then

$$P_r \left\{ \frac{\tau_{x_j, k}^+}{k} \geq \epsilon \right\} \leq (1 - \delta)^{\epsilon k / r}$$

and $P_r \left\{ \lim_{k \rightarrow \infty} \frac{\tau_{x_j, k}^+}{k} \geq \epsilon \right\} \geq 0$

$$\Rightarrow P_r \left\{ \bigcap_{k=1}^{\infty} \bigcup_{j \geq k} \left\{ \frac{\tau_{x_j, k}^+}{k} \geq \epsilon \right\} \right\} \geq 0$$

$$\leq \lim_{k \rightarrow \infty} \sum_{j \geq k} (1 - \delta)^{\epsilon j / r} = 0.$$