

# General considerations on the spectrum of the transition matrix $P$

We assume in this paragraph that  $E$  is finite,  $\#E = n$ . Note that any ordering of  $E$  allows to express the transition kernel  $P$  of  $X$  as a  $n \times n$  stochastic matrix.

## Lemma (3.a)

- (i) *If  $\lambda$  is an eigenvalue of  $P$  then  $|\lambda| \leq 1$ .*
- (ii) *If  $P$  is irreducible then  $\ker(P - Id) = \text{Vect} \left\{ \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \right\}$*
- (iii) *If  $P$  is irreducible and aperiodic then  $-1$  is not an eigenvalue of  $P$ .*

# General considerations on the spectrum of the transition matrix $P$

Proof of Lemma (3.a) (i) : Let  $f : E \rightarrow \mathbb{R}$ , we have

$$|Pf(x)| = \left| \sum_{y \in E} P(x, y) f(y) \right| \leq \|f\|_{\infty} \sum_{y \in E} P(x, y) = \|f\|_{\infty},$$

thus  $\|Pf\|_{\infty} \leq \|f\|_{\infty}$ . If  $\lambda$  is an eigenvalue of  $P$  associated with eigenvalue  $f$  we have  $\|Pf\|_{\infty} = |\lambda| \|f\|_{\infty}$ , and thus  $|\lambda| \leq 1$ .

# General considerations on the spectrum of the transition matrix $P$

Proof of Lemma (3.a) (ii) : An eigenfunction  $f$  associated with eigenvalue 1 is simply a function  $f$  that is harmonic on the whole of  $E$ . By the maximum principle for harmonic functions Theorem (2.8) we conclude that  $f$  must be constant on  $E$ .

Note that this result also implies unicity of invariant distribution : it is indeed the case that

$$\dim(\ker(P - Id)) = 1 \Rightarrow \dim(\ker(P^T - Id)) = 1.$$

# General considerations on the spectrum of the transition matrix $P$

Proof of Lemma (3.a) (iii) : By exercise I.11.2 since  $P$  is irreducible, aperiodic and  $E$  is finite there must exist  $r \in \mathbb{N}^*$  such that for any  $k \geq r$ ,  $P^k(x, y) > 0$  for any  $x, y \in E$ . Now assume  $f$  is an eigenfunction associated with eigenvalue  $-1$ , it must exist  $x \in E$  such that  $f(x) \neq 0$ . Without loss of generality (even if it means taking  $-f$  instead of  $f$ ) we may assume  $f(x) > 0$ . Then  $P^{2r}f(x) = \sum_{y \in E} P^{2r}(x, y)f(y)$  implies, since  $P^{2r}$  is stochastic, that  $f$  has to be positive on the whole of  $E$ . But then  $P^{2r+1}f(x) = -f(x)$  brings a contradiction.

Note : We could also have used Perron-Frobenius theorem to prove the three assertions of the Lemma.

## Theorem (3.b)

Assume  $P$  is irreducible, reversible with respect to its unique invariant probability  $\pi$ .

- (i) The prehilbertian space  $(\mathbb{R}^E, \langle \cdot, \cdot \rangle_\pi)$  possesses an orthonormal basis of real-valued eigenfunctions  $(f_j, 1 \leq j \leq n)$  associated with real eigenvalues  $1 = \lambda_1 > \lambda_2 \geq \dots \geq \lambda_n \geq -1$ .
- (ii) For any  $t \in \mathbb{N}$ ,  $(x, y) \in E^2$ ,

$$\frac{P^t(x, y)}{\pi(y)} = \sum_{j=1}^n f_j(x) f_j(y) \lambda_j^t = 1 + \sum_{j=2}^n f_j(x) f_j(y) \lambda_j^t.$$

# Spectral decomposition for reversible chain

Proof of Theorem (3.b) (i) : Since  $\pi(x) > 0, x \in E$  it is straightforward that  $\langle f, g \rangle_\pi := \sum_{x \in E} \pi(x) f(x) g(x)$  defines a scalar product on  $\mathbb{R}^E$ . Now if  $X$  is reversible with respect to  $\pi$ ,

$$A(x, y) := \sqrt{\frac{\pi(x)}{\pi(y)}} P(x, y), (x, y) \in E^2$$

defines a symmetric operator on  $\mathbb{R}^E$  (in other words, any ordering of  $E$  makes  $A$  a  $n \times n$  symmetric matrix). By well-known linear algebra results for symmetric matrices, eigenvalues of  $A$  are real and there exists  $\{\phi_j, j = 1, \dots, n\}$  an orthonormal basis (for the usual scalar product) of real-valued eigenfunctions associated with these eigenvalues sorted in decreasing order. Now setting

$f_j(x) := \frac{\phi_j(x)}{\sqrt{\pi(x)}}, x \in E$ , we find

$$\langle f_i, f_j \rangle_\pi = \sum_{x \in E} \pi(x) f_i(x) f_j(x) = \sum_{x \in E} \phi_i(x) \phi_j(x) = \delta_{ij},$$

so  $\{f_j, 1 \leq j \leq n\}$  is orthonormal for  $\langle \cdot, \cdot \rangle_\pi$ .

# Spectral decomposition for reversible chain

It remains to check that

$$\begin{aligned} Pf_j(x) &= \sum_{y \in E} P(x, y) f_j(y) \\ &= \sum_{y \in E} \sqrt{\frac{\pi(y)}{\pi(x)}} A(x, y) \frac{\phi_j(y)}{\sqrt{\pi(y)}} \\ &= \sqrt{\frac{1}{\pi(x)}} A \phi_j(x) \\ &= \sqrt{\frac{1}{\pi(x)}} \lambda_j \phi_j(x) = \lambda_j f_j(x), \end{aligned}$$

as we wished. Now by Lemma (3.a) it must be that  $\lambda_1 = 1 > \lambda_2 \geq \dots \geq \lambda_n \geq -1$ . Note in addition that if  $X$  is aperiodic, we can moreover deduce that  $\lambda_n > -1$ .

# Spectral decomposition for reversible chain

Proof of Theorem (3.b) (ii) : Writing the decomposition of  $\mathbb{1}_{\{y\}}$  along the orthonormal basis  $(f_j, 1 \leq j \leq n)$ , we have

$$\mathbb{1}_{\{y\}}(\cdot) = \sum_{j=1}^n \langle f, f_j \rangle_{\pi} f_j(\cdot) = \sum_{j=1}^n f_j(y) \pi(y) f_j(\cdot).$$

Now

$$\begin{aligned} P^t(x, y) = P^t \mathbb{1}_{\{y\}}(x) &= \sum_{j=1}^n f_j(y) \pi(y) P^t f_j(x) \\ &= \sum_{j=1}^n \lambda_j^t f_j(y) \pi(y) f_j(x) \end{aligned}$$

Now by Lemma (3.a)  $f_1(x) = 1$  for any  $x \in E$ , so the first term in the sum above is  $\pi(y)$ , yielding the desired result.



# Bounding $t_{\text{mix}}(\varepsilon)$ using spectral decomposition

## Theorem

Assume that the chain  $X$  is irreducible, reversible, aperiodic.

We define  $|\lambda^*| = \max\{|\lambda_i|, i \geq 2\}$ , and the (absolute) spectral gap  $\gamma^* := 1 - |\lambda^*|$ , which is  $> 0$  in this setting by Lemma 4.a.

We also define the relaxation time  $t_{\text{relax}} = \frac{1}{\gamma^*}$ . and let

$$\pi_{\min} = \min_{x \in E} \pi(x).$$

Then

$$|\lambda^*|^t \leq 2d(t) \leq \frac{|\lambda^*|^t}{\pi_{\min}},$$

and

$$(t_{\text{relax}} - 1) \log \left( \frac{1}{2\varepsilon} \right) \leq t_{\text{mix}}(\varepsilon) \leq \log \left( \frac{1}{2\varepsilon\pi_{\min}} \right) t_{\text{relax}}.$$

# Proof of upper bound for $t_{\text{mix}}(\varepsilon)$ using spectral decomposition

We start by observing that

$$\begin{aligned}\|P^t(x, \cdot) - \pi\|_{TV} &= \frac{1}{2} \sum_{y \in E} \pi(y) \left| \frac{P^t(x, y)}{\pi(y)} - 1 \right| \\ &\leq \frac{1}{2} \max_{y \in E} \left| \frac{P^t(x, y)}{\pi(y)} - 1 \right|.\end{aligned}$$

By spectral decomposition, then Cauchy-Schwarz we have

$$\begin{aligned}\left| \frac{P^t(x, y)}{\pi(y)} - 1 \right| &= \left| \sum_{j=2}^n \lambda_j^t f_j(x) f_j(y) \right| \\ &\leq \max_{j \geq 2} |\lambda_j|^t \left( \sum_{j=2}^n f_j^2(x) \right)^{1/2} \left( \sum_{j=2}^n f_j^2(y) \right)^{1/2}\end{aligned}$$

# Proof of upper bound for $t_{\text{mix}}(\varepsilon)$ using spectral decomposition

It remains to bound above  $\left(\sum_{j=2}^n f_j^2(x)\right)^{1/2}$ . For that, use orthonormality of the basis  $\{f_j\}_{1 \leq j \leq n}$  to get

$$\begin{aligned}\pi(x) &= \langle \mathbf{1}_x, \mathbf{1}_x \rangle_\pi \\ &= \left\langle \sum_{j=1}^n \pi(x) f_j(x) f_j, \sum_{j=1}^n \pi(x) f_j(x) f_j \right\rangle_\pi \\ &= \sum_{j=1}^n \pi^2(x) f_j^2(x),\end{aligned}$$

so that  $\left(\sum_{j=2}^n f_j^2(x)\right)^{1/2} \leq \frac{1}{\sqrt{\pi(x)}}$ . In the end, we have proven that  $d(t) \leq \frac{|\lambda^*|^t}{\pi_{\min}}$ , as required. The upper bound for  $t_{\text{mix}}(\varepsilon)$  then follows from its definition and the fact that  $\max_{j \geq 2} |\lambda_j|^t \leq \exp(-\gamma^* t)$ .

# Proof of lower bound for $t_{\text{mix}}(\varepsilon)$ using spectral decomposition

The starting point is that if  $f : E \rightarrow \mathbb{R}$ , then

$$|P^t(x, \cdot)f - \pi f| = \sum_{y \in E} |P^t(x, y) - \pi(y)||f(y)| \leq 2\|f\|_\infty d(t).$$

Now a good choice is to take  $f = f_2$  or  $f = f_n$  the eigenfunction associated to the eigenvalue  $\lambda$  such that  $|\lambda| = \max_{j \geq 2} |\lambda_j|$  (the one realizing the spectral gap). In that case, not only  $P^t f = \lambda^t f$ , but moreover  $\pi f = 0$  because  $f$  is orthogonal to the first (constant) eigenvector. Choosing  $x$  such that  $|f(x)| = \|f\|_\infty$ , we get, as required,

$$|\lambda|^t = (1 - \gamma^*)^t \leq 2d(t).$$

The lower bound for  $t_{\text{mix}}(\varepsilon)$  then follows from its definition and elementary considerations, using in particular that  $\log(|\lambda|^{-1}) \geq |\lambda|^{-1} - 1$ .