

Convergence of some time inhomogeneous Markov chains via spectral techniques

Jessica Zuniga
with Laurent Saloff-Coste

- Mironov (2002)
(Not so) random shuffles of RC4.
 - total variation upper bound of $O(n \log n)$ for cyclic-to-random shuffle
 - lower bound of $O(n)$ for cyclic-to-random shuffle
- Mossel, Peres, Sinclair (2004)
Shuffling by semi-random transpositions.
 - total variation upper bound of $O(n \log n)$ for any semi-random transposition shuffle
 - lower bound of $O(n \log n)$ for cyclic-to-random shuffle
- This paper was developed independently and by similar arguments as improved upper bound for semi-random transpositions [2006]

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Basic notation

V a finite set equipped with $(K_n)_{n \geq 1}$ s.t.

$$K_n(x, y) \geq 0 \text{ and } \sum_y K_n(x, y) = 1.$$

The associated Markov chain: $X = (X_n)_{n \geq 0}$

$$\begin{aligned} &P(X_n = x | X_{n-1} = y, X_{n-2} = x_{n-2}, \dots, X_0 = x_0) \\ &= P(X_n = x | X_{n-1} = y) \\ &= K_n(x, y) \end{aligned}$$

Let μ_0 be the distribution of X_0 . The distribution μ_n of X_n is

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where $K_{n+1} = K_n$ and for $m \geq n$

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Major assumption: There exists a measure π that is invariant for the sequence $(K_n)_1^\infty$, i.e.

$$\pi K_n = \pi.$$

Large class of examples: random walks on groups.

Let $G \neq \{1\}$ finite group equipped with a probability measure μ . The Markov kernel

$$K(x, y) = \mu(x^{-1}y)$$

has $\pi = \mu$ as an invariant measure.

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Let $V = G$ a finite group equipped with a probability measure p . The Markov kernel

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Any sequence of probability measures $(\mu_n)_1^\infty$ on G converges to π if and only if μ_n converges to π in total variation norm.

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$$K_{n,m}(x, y) = p_{n+1} * \cdots * p_m(x^{-1}y)$$

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Definition: Let $\mathcal{Q} = \{Q_1, \dots, Q_n\}$ have invariant measure π . (\mathcal{Q}, π) is ergodic if for any $(K_i)_1^\infty$ with invariant measure π and $K_i \in \mathcal{Q}$ for infinitely many i then

$$\lim_{n \rightarrow \infty} K_{0,n}(x, z) - K_{0,n}(y, z) = 0$$

for all $x, y, z \in V$.

Remark:

- Let $\mathcal{Q} = \{Q\}$. (\mathcal{Q}, π) is ergodic is stronger than

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Spectral analysis

(K, π) is a linear map on $\ell^2(V, \pi)$.

Let $u, v \in \ell^2(V, \pi)$.

$$\langle Ku, v \rangle = \sum_{x \in V} \langle Kx, v(x) \rangle$$

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- K^* has associated Markov kernel

$$K^*(x, y) = \pi(y)K(y, x)/\pi(x).$$

$$\langle Ku, v \rangle = \sum_{x \in V} \sum_{y \in V} K(x, y)u(y)v(x)\pi(x)$$

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Distances on $\ell^2(V, \pi)$:

$$d_{TV}(\mu, \pi) = \sup_{A \in \mathcal{V}} |\mu(A) - \pi(A)|$$

$$d_2(\mu, \pi)^2 = \sum_y \left| \frac{\mu(y)}{\pi(y)} - 1 \right|^2 \pi(y)$$

Distance between $\ell^2(V, \pi)$ and $\ell^2(V, \pi')$

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Eigenvalues of K :

$$1 = \beta_0(K) \geq \beta_1(K) \geq \cdots \geq \beta_{|V|-1}(K) \geq -1.$$

Singular values of K on $\ell^2(V, \pi)$:

$$1 = \sigma_0(K) \geq \sigma_1(K) \geq \cdots \geq \sigma_{|V|-1}(K) \geq 0$$

where

$$\sigma_i(K) = \sqrt{\beta_i(KK^*)} = \sqrt{\beta_i(K^*K)}.$$

Theorem: *Cauchy (K, π)* Let $\{e_i\}_{i=1}^{|V|}$ be a basis of $\mathcal{P}(V, \pi)$ with $\langle e_i, e_j \rangle = \delta_{ij}(K^*)$ (assume $\beta_i = 1$). Then

$$\langle Ke_i, Ke_j \rangle = \beta_{i-1} \delta_{ij} + \beta_{i+1} \delta_{ij+1}.$$

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Theorem: Consider (K, π) . Let $(\psi_i)_{i=0}^{|V|-1}$ be a basis of $\ell^2(V, \pi)$ such that $KK^*\psi_i = \sigma_i(K)^2\psi_i$ (assume $\psi_0 = 1$.) Then

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Main technical result

Theorem Let $(K_j)_{j=1}^{\infty}$ be a sequence in V with positive invariant measure π . For $j \geq 1$ and $0 \leq i \leq |V| - 1$ let $\sigma_i(K_j)$ be the singular values of K_j on $\ell^2(V, \pi)$ then

$$d_2(K_{0,n}(x, \cdot), \pi) \leq (\pi(x)^{-1} - 1)^{1/2} \prod_{j=1}^n \sigma_1(K_j)$$

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Main idea of proof:

For all $k = 1, \dots, |V| - 1$

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- Let $\mathcal{Q} = \{Q\}$ have invariant measure π .

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Theorem Let $\mathcal{Q} = \{Q_1, \dots, Q_k\}$ be a family of kernels on V with invariant measure π .

- (\mathcal{Q}, π) is ergodic iff $\sigma_1(Q_j) < 1$ for all $1 \leq j \leq k$.
- If (\mathcal{Q}, π) is ergodic then for any $(K_i)_1^\infty$ with invariant measure π and infinitely many $K_i \in \mathcal{Q}$ we have

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Application to time inhomogeneous random walks on finite groups

Main technical result simplifies when $V = G$, in this case $\pi = 1/|G|$.

- $(p_i)_1^\infty$ a sequence of probability measures on G .

$$P(x, y) = \pi(x^{-1}y)$$

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- $K_{n,m}(x, y) = p_{n+1} * \dots * p_m(x^{-1}y)$

- $\lim_{m \rightarrow \infty} K_{n,m}(x, y) = p_{n+1}(x^{-1}y)$

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- Set $K_{n,m}(x, y) = p_{n,m}(x^{-1}y)$

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- Set $K_{n,m}(x, y) = p_{n,m}(x^{-1}y)$
- For $0 \leq j \leq |G| - 1$ set $\sigma_j(p_i) = \sigma_j(K_i)$ where singular values are taken w.r.t π .

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- $K_{n,m}(x, y) = p_{n+1} * \cdots * p_m(x^{-1}y)$
- Set $K_{n,m}(x, y) = p_{n,m}(x^{-1}y)$
- For $0 \leq j \leq |G| - 1$ set $\sigma_j(p_i) = \sigma_j(K_i)$ where singular values are taken w.r.t π .

Theorem

Let $(p_i)_1^\infty$ be a sequence on G . Then

$$d_2(\rho_{0,n}, \pi) \leq (|G| - 1)^{1/2} \prod_1^n \sigma_1(p_j)$$

$$d_2(\rho_{0,n}, \pi) \leq \left(\sum_{i=1}^{|G|-1} \prod_{j=1}^n \sigma_i(p_j) \right)^{1/2}.$$

Example: (p_i) a sequence of generating sets of G . Let $\rho_{0,n}$ be the

$$\rho(x) = \begin{cases} 1/|S_i| & \text{if } x \in S_i \\ 0 & \text{otherwise} \end{cases}$$

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Example: $(S_j)_1^\infty$ a sequence of generating sets of G s.t. $\text{id} \in S_j$. Set

$$K_j(x, y) = \begin{cases} 1/|S_j| & \text{if } x^{-1}y \in S_j \\ 0 & \text{otherwise.} \end{cases}$$

Well known algorithm estimates give us

$$d_2(p_{0,n}, \pi) \leq \left(\sum_{i=1}^{|G|-1} \prod_{j=1}^n \sum_{x \in S_j} \sum_{y \in S_j} \mathbb{1}_{x^{-1}y=i} \right)^{1/2}$$

where $\mathbb{1}_i$ is the indicator of the set i (mapped to $\mathbb{Z}^{|G|}$ via $\mathbb{1}_i = \delta_{i, \cdot}$)

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Semi-random transpositions

Let $G = S_n$ and $\pi = 1/n!$. For $1 \leq i \leq n$ set

$$q_i(x) = \begin{cases} 1/n & \text{if } x = (i, j) \text{ for } 1 \leq j \leq n \\ 0 & \text{otherwise.} \end{cases}$$

Theorem: For $n > 1, c > 0$ and $k \geq n(\log n + c)$

$$d_2(q_1^{(k)}, \pi) \leq \sqrt{2}e^{-c}.$$

Since q_1 is reversible w.r.t. π . For any i, j , and σ , are images of each other under some inner automorphism of S_n .

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Example: how many singular values

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$p_{0,k}^r = p_1 * \dots * p_k$: distribution after k steps

Theorem: for any $r = (r_i)_1^\infty$, $\alpha \in \{1, \dots, n\}$

$$\lim_{k \rightarrow \infty} p_{0,k}^r(\alpha) = \frac{1}{n}$$

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Corollary For any $r = (r_i)_1^\infty$, $r_i \in \{1, \dots, n\}$ and $\pi \in \mathcal{P}_n$

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Proof From techniques just described

$$d_2(p_{0,k}^r, \pi)^2 \leq \sum_{m=1}^{n-1} \prod_{j=1}^k \sigma_m(q_{r_j})^2 = \sum_{m=1}^{n-1} \prod_{j=1}^k \frac{m}{n} = \sum_{m=1}^{n-1} \left(\frac{m}{n}\right)^k$$

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Remark:

Information can be lost with the inequality

$$\sum_{j=1}^k \sigma_j(K_1 \cdots K_n) \leq \sum_{j=1}^k \prod_{i=1}^n \sigma_j(K_i)^2.$$

Let $r = (r_i)_1^\infty$ be a sequence of *i.i.d.* uniform random variables taking values in $\{1, \dots, n\}$.

σ_{r_i} random transposition shuffle

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$p_{0,k}^r$: random transposition shuffle

Discrete-time random walk

Time-dependent transition matrix

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Diaconis-Shahshahani:

For $c > 0$, $k \geq (n/2)(\log n + c)$

$$d_2(p_{0,k}^r, \pi) \leq \beta e^{-c}.$$

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Semi-random insertions

$c_{i,j}$: pick card in position i and insert it into position j .

$$c_{i,j} = \begin{cases} \text{id} & \text{if } i = j \\ (j, j-1, \dots, i+1, i) & \text{if } 1 \leq i < j \leq n \\ (j, j+1, \dots, i-1, i) & \text{if } 1 \leq j < i \leq n. \end{cases}$$

Random insertion measure on S_n :

$$\bar{q}(x) = \begin{cases} 1/n & \text{if } x = \text{id}, \\ 2/n^2 & \text{if } x = c_{i,j} \text{ if } |i-j| = 1 \\ 1/n^2 & \text{if } x = c_{i,j} \text{ if } |i-j| > 1 \\ 0 & \text{otherwise.} \end{cases}$$

Theorem (Diaconis and Saloff-Coleman): For all $n \geq 20$, \bar{q} and \bar{p} are ϵ -close.

Proof: \bar{q} is a \bar{p} -martingale. For all i , $\bar{q}(c_{i,j}) \leq \bar{p}(c_{i,j})$.
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Theorem (Diaconis and Saloff-Coste): For all $n \geq 28$, $c > 2$ and all $k \geq 2n(\log n + c)$

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Theorem For any $r = (r_i)_1^\infty, r_i \in \{1, \dots, n\}$

$$d_2(\tilde{p}_{0,2k}^r, \pi) \leq d_2(\tilde{q}^{(k)}, \pi).$$

For $n > 28$, $c > 2$ and $k \geq 4n(\log n + c)$

$$d_2(\tilde{p}_{0,k}^r, \pi) \leq 2e^{-(c-2)}.$$

$$d_2(\tilde{p}_{0,n}^r, \pi) \leq \sum_{i=1}^n \frac{r_i}{n} e^{-c}$$

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Proof

$$d_2(\tilde{p}_{0,2k}^r, \pi)^2 \leq \sum_{m=1}^{n-1} \prod_{i=1}^{2k} \sigma_m(\tilde{q}_i)^2$$

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$$\begin{aligned} d_2(\tilde{p}_{0,2k}^r, \pi)^2 &\leq \sum_{m=1}^{n!-1} \prod_{i=1}^{2k} \sigma_m(\tilde{q}_{r_i})^2 \\ &= \sum_{m=1}^{n!-1} \sigma_m(\tilde{q})^{2k} \\ &= \sum_{m=1}^{n!-1} \sigma_m(\tilde{q})^{2k} \end{aligned}$$

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$$d_2(\tilde{p}_{0,2k}^r, \pi) \leq d_2(\tilde{q}^{(k)}, \pi).$$

For $n > 28, c > 2$ and $k \geq 4n(\log n + c)$

$$d_2(\tilde{p}_{0,k}^r, \pi) \leq 2e^{-(c-2)}.$$

Proof

$$\begin{aligned} d_2(\tilde{p}_{0,2k}^r, \pi)^2 &\leq \sum_{m=1}^{n!-1} \prod_{i=1}^{2k} \sigma_m(\tilde{q}_{r_i})^2 \\ &= \sum_{m=1}^{n!-1} \sigma_m(\tilde{q})^{2k} \\ &= d_2(\tilde{q}^{(k)}, \pi) \end{aligned}$$

Semi-random insertions

Theorem For any $r = (r_i)_1^\infty, r_i \in \{1, \dots, n\}$

$$d_2(\tilde{p}_{0,2k}^r, \pi) \leq d_2(\tilde{q}^{(k)}, \pi).$$

For $n > 28, c > 2$ and $k \geq 4n(\log n + c)$

$$d_2(\tilde{p}_{0,k}^r, \pi) \leq 2e^{-(c-2)}.$$

Proof

$$\begin{aligned} d_2(\tilde{p}_{0,2k}^r, \pi)^2 &\leq \sum_{m=1}^{n!-1} \prod_{i=1}^{2k} \sigma_m(\tilde{q}_{r_i})^2 \\ &= \sum_{m=1}^{n!-1} \sigma_m(\tilde{q})^{2k} \\ &= d_2(\tilde{q}^{(k)}, \pi) \end{aligned}$$