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Journal of Applied Probability, Vol. 29, No. 4. (Dec., 1992), pp. 850-860.

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COEFFICIENTS OF ERGODICITY FOR STOCHASTICALLY MONOTONE MARKOV CHAINS

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Abstract

In this paper we show that to each distance d defined on the finite state space S of a strongly ergodic Markov chain there corresponds a coefficient ρ_d of ergodicity based on the Wasserstein metric. For a class of stochastically monotone transition matrices P , the infimum over all such coefficients is given by the spectral radius of $P - R$, where $R = \lim_k P^k$ and is attained. This result has a probabilistic interpretation of a control of the speed of convergence of $(P^k)_{k-1}^x$ by the metric d and is linked to the second eigenvalue of P .

ERGODIC COEFFICIENTS; WASSERSTEIN METRIC; BIRTH AND DEATH MATRIX

AMS 1991 SUBJECT CLASSIFICATION: PRIMARY 60J10

1. The main results

Let $S = \{1, 2, \dots, N\}$ be the finite state space of a Markov chain with transition matrix $P = (p_{ij})$. We recall that P is called strongly ergodic, if there is a matrix R with identical rows such that

$$(1) \quad R = \lim_{k \rightarrow \infty} P^k$$

(see [4], [5]). It is an important problem to assign a numerical value to the speed of convergence in (1). A tool for doing so is given by the following concept.

1.1. *Definition.* A coefficient of ergodicity is a scalar function ρ defined on the set of stochastic matrices satisfying

- (i) $0 \leq \rho(P)$,
- (ii) $\rho(P) = 0$ if and only if P has identical rows,
- (iii) for all stochastic matrices P_1, P_2 , $\rho(P_1 P_2) \leq \rho(P_1) \rho(P_2)$.

1.2. *Example.* Typical examples of coefficients of ergodicity are Dobrushin's coefficient [2]:

Received 14 December 1990; revision received 10 October 1991.

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$$\rho_0(P) := \frac{1}{2} \sup_{i,j} \sum_k |p_{ik} - p_{jk}| = 1 - \inf_{i,j} \sum_k \min(p_{ik}, p_{jk}),$$

and Birkhoff's coefficient [10]:

$$\rho_B(P) := \sup_{\substack{x,y > 0 \\ x \neq \lambda y}} \frac{d_B(x'P, y'P)}{d_B(x', y')},$$

where

$$d_B(x', y') = \max_{i,j} \ln \left[\frac{x_i y_j}{x_j y_i} \right] \quad x_i, y_i \neq 0.$$

It is known that $\rho_B \geq \rho_0$ ([10], p. 110) and that P is strongly ergodic if and only if there is a $M > 0$ such that $\rho_0(P^M) < 1$ (see [5]). There are however examples of strongly ergodic matrices with $\rho_0(P) = \rho_B(P) = 1$, for example the 'birth and death' matrices considered below.

In the present paper we study the coefficients of ergodicity induced by a metric d on S via the Wasserstein distance, which extends d to $\mathcal{P}(S)$, the set of all probability measures on S (for reference see [3]).

1.3. *Definition.* For $\mu, \nu \in \mathcal{P}(S)$, the Wasserstein distance between μ and ν is defined as

$$(2) \quad d^W(\mu, \nu) = \inf \{ \mathbb{E}(d(X, Y)) : X \text{ and } Y \text{ are } S\text{-valued random variables with distributions } \mu \text{ and } \nu \text{ respectively} \}.$$

By identifying the points i of S with the corresponding Dirac measures δ_i one readily observes that the Wasserstein distance d^W on $\mathcal{P}(S)$ indeed extends the original metric d on S .

Let us now introduce the central concept of this paper.

1.4. *Definition.* Let P be a stochastic matrix on the finite state space S . For a metric d on S define

$$(3) \quad \rho_d(P) = \sup_{i,j \in S} \frac{d^W(\delta_i P, \delta_j P)}{d(i, j)}.$$

We call $\rho_d(P)$ the d -coefficient of P , because it is easily verified that ρ_d satisfies the requirements of Definition 1.1. Indeed, in order to establish 1.1 (iii) it suffices to observe that

$$(4) \quad \rho_d(P) = \sup_{\mu, \nu \in \mathcal{P}(S)} \frac{d^W(\mu P, \nu P)}{d^W(\mu, \nu)}.$$

Note in passing that, in general, $\rho_d(P)$ may be greater than 1. However, there always is a metric which gives $\rho_d(P) \leq 1$, as shown by the subsequent example.

1.5. *Example.* Let d_0 be the discrete metric on S , $d_0(i, j) = \delta_{i,j}$. As is easily seen, the corresponding Wasserstein extension is $d_0(\mu, \nu) = (1/2) \|\mu - \nu\|_1$ and hence

$$\rho_{d_0}(P) = (1/2) \sup_{i,j} \sum_k |p_{ik} - p_{jk}| = \rho_0(P) \leq 1.$$

Thus Dobrushin’s coefficient defined in 1.2 appears as a special case of Definition 1.4.

We obtain the following characterisation of strong ergodicity (the proof is given in 3.4 below).

1.6. *Theorem.* The stochastic matrix $P = (p_{ij})$ on the finite state space S is strongly ergodic iff there is a metric d on S such that $\rho_d(P) < 1$.

The central question treated in this paper is to investigate the infimum $\kappa(P)$ of $\rho_d(P)$ for a strongly ergodic transition matrix P , when d runs through the metrics on S . We show (Proposition 3.1) that a lower bound for $\kappa(P)$ is given by the absolute value $|\lambda_2|$ of the second eigenvalue of P .

In general $\kappa(P)$ is bigger than $|\lambda_2|$, as will be shown in Example 3.2. However, for an important subclass of stochastic matrices $\kappa(P)$ is attained by some $\rho_d(P)$ and equals the second largest eigenvalue of P . In order to describe this subclass, some definitions are needed.

1.7. *Definition.* A metric d on S is called *one-dimensional* if d is inherited from the euclidean distance of \mathbb{R} via an order-preserving injection of S into \mathbb{R} ; in other words if for every $1 \leq i < j \leq N$,

$$d(i, j) = \sum_{k=i}^{j-1} d(k, k + 1).$$

A row vector $v = (v_i)_{i=1}^N$ satisfying

$$v_{i+1} - v_i = d(i, i + 1), \quad 1 \leq i < N$$

will be called a *primitive* of the one-dimensional metric d .

The Wasserstein metric pertaining to a one-dimensional distance may easily be computed according to 1.8 (or 1.11).

1.8. *Lemma.* Let d be a one-dimensional metric on S and $\mu = (\mu_1, \dots, \mu_N)$, $\nu = (\nu_1, \dots, \nu_N) \in \mathcal{P}(S)$. Let $F = (F_1, \dots, F_N)$, $G = (G_1, \dots, G_N)$ be the distribution functions of μ and ν respectively,

$$F_i = \sum_{j=1}^i \mu_j, \quad G_i = \sum_{j=1}^i \nu_j,$$

and $v = (v_i)_{i=1}^N$ a primitive of d . Then

$$(5) \quad d^W(\mu, \nu) = \sum_{i=1}^{N-1} |F_i - G_i| (v_{i+1} - v_i).$$

This lemma is just a special case of the following well-known result, a proof of which may be found in [11].

1.9. *Lemma.* Let μ, ν be two probability measures with finite expectations on \mathbb{R} endowed with the euclidean metric d_1 . Then

$$(6) \quad d_1^W(\mu, \nu) = \int_{-\infty}^{+\infty} |F(u) - G(u)| du$$

where F (or G) is the distribution function of μ (or ν).

1.10. *Definition.* On the set $\mathcal{P}(S)$ we define a partial order by saying $\mu \geq \nu$ if the distribution function of ν dominates that of μ , i.e.

$$\mu \geq \nu \Leftrightarrow \sum_{j=i}^N \mu_j \geq \sum_{j=i}^N \nu_j, \quad \text{for } 1 \leq i \leq N.$$

A stochastic matrix P on S is called *stochastically monotone* [1] if $\mu \geq \nu \Rightarrow \mu P \geq \nu P$.

1.11. *Remark.* If μ, ν are measures on S with $\mu \geq \nu$ and d is a one-dimensional metric on S then Lemma 1.8 reduces to a particularly easy formula, namely

$$(7) \quad d^W(\mu, \nu) = \langle \mu - \nu, v \rangle$$

where v is a primitive of d and $\langle \cdot, \cdot \rangle$ is the inner product in \mathbb{R}^N . Indeed, we may argue by ‘partial integration’:

$$\begin{aligned} d^W(\mu, \nu) &= \sum_{i=1}^{N-1} (G_i - F_i)(v_{i+1} - v_i) \\ &= \sum_{i=1}^{N-1} \left(\sum_{j=1}^i (\nu_j - \mu_j) \right) (v_{i+1} - v_i) \\ &= \sum_{j=1}^{N-1} \left((\nu_j - \mu_j) \sum_{i=j}^{N-1} (v_{i+1} - v_i) \right) \\ &= \sum_{j=1}^N (\mu_j - \nu_j)(v_j - v_N) \\ &= \langle \mu - \nu, v \rangle. \end{aligned}$$

1.12. *Definition.* A stochastic matrix P on the state space S is called *lumpable* [7] if there is a non-trivial partition of the state space $S = \cup_{k=1}^K A_k$ such that

$$i \mapsto \sum_{j \in A_k} p_{ij} \text{ is constant within each partition set.}$$

We say that P is *lumpable into intervals* if there is a partition as above such that all A_k are intervals of S .

The notions of lumpability and lumpability into intervals do not coincide, as may be seen by considering

$$P = \begin{pmatrix} 2/3 & 1/3 & 0 \\ 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \end{pmatrix}.$$

Taking the partition $\{1, 3\}, \{2\}$ one observes that P is lumpable; it is just as easy to verify that P is not lumpable into intervals.

Now we can formulate the central result of this paper.

1.13. *Main theorem.* Let P be a strongly ergodic stochastically monotone matrix on the finite state space $S = \{1, \dots, N\}$ which is not lumpable into intervals.

Then there is a simple eigenvalue $\lambda_2 \in]0, 1[$, which satisfies $\lambda_2 \geq |\lambda_i|$ for all eigenvalues λ_i of P except for the simple eigenvalue $\lambda_1 = 1$. The corresponding right eigenvector $v = (v_i)_{i=1}^N$ is strictly increasing.

Defining the one-dimensional metric d on S by $d(i, j) = |v_i - v_j|$ we have $\rho_d(P) = \lambda_2$ and this metric is unique in the following sense: for every one-dimensional metric d_1 on S such that $\rho_{d_1}(P) \leq \lambda_2$, d_1 coincides with d up to a scalar factor.

The proof of this theorem is given in Section 4. Whereas Theorem 1.13 discusses the role of the *right* eigenvector v associated with λ_2 , the following theorem investigates the role of the *left* eigenvector (the proof is given in 4.2 below).

1.14. *Theorem.* Let $v = (v_1, \dots, v_N)$ be the left eigenvector pertaining to λ_2 , normalized by $\langle v, v \rangle = \sum_{i=1}^N v_i v_i = 1$. If λ_2 is the only eigenvalue of P of absolute value equal to λ_2 , then, for every $i, j \in S$, $\lim_{n \rightarrow \infty} (\delta_i - \delta_j)P^n / \lambda_2^n = d(i, j)v$ where the convergence takes place with respect to the norm $\| \cdot \|_1$.

2. Birth and death matrices as basic examples

Let P be a stochastic matrix describing a general birth and death process on $S = \{1, \dots, N\}$, i.e.

$$P = \begin{bmatrix} r_1 & p_1 & & & & \\ q_2 & r_2 & p_2 & & & \mathbf{0} \\ & \dots & \dots & \dots & & \\ \mathbf{0} & & q_{N-1} & r_{N-1} & p_{N-1} & \\ & & & q_N & r_N & \end{bmatrix}$$

such that, letting $q_2 = p_N = 0$, for every $1 \leq i \leq N$ we have $q_i + r_i + p_i = 1$. Note that P is stochastically monotone iff for $1 \leq i \leq N - 1$, $q_i + r_i \geq q_{i+1}$. We claim that P is not lumpable into intervals iff for every $2 \leq i \leq N - 1$, q_i and p_i are different from 0. Indeed suppose that $q_i = 0$ for some $2 \leq i \leq N - 1$ (the case of $p_i = 0$ is similar): then the partition of S into $\{1\}, \{2\}, \dots, \{i - 1\}, \{i, i + 1, \dots, N\}$ satisfies the requirements of Definition 1.12. The proof of the reverse implication is left to the reader.

As a special case, consider the matrix

$$P_a = \begin{bmatrix} a & 1-a & 0 & & \\ a & 0 & 1-a & & \mathbf{0} \\ & \dots & \dots & \dots & \\ \mathbf{0} & & & a & 0 & 1-a \\ & & & & a & 1-a \end{bmatrix}$$

for $0 < a < 1$. Clearly P_a is strongly ergodic and the stationary distribution is given by $((1-a)/a)^n$ (up to the normalizing factor $\sum_{n=1}^N ((1-a)/a)^n$). If $N \geq 4$ then $\rho_0(P) = 1$ and in fact $\rho_0(P^k) = 1$ for $k \leq N - 3$. Hence Dobrushin's coefficient of ergodicity gives non-trivial information only for high powers of P .

On the other hand consider, for $a \neq 1/2$, the metric

$$(8) \quad d(i, j) = \left| \left(\frac{a}{1-a} \right)^{i/2} - \left(\frac{a}{1-a} \right)^{j/2} \right|.$$

An easy direct computation gives

$$(9) \quad d^W(\delta_i P_a, \delta_j P_a) \leq 2\sqrt{a(1-a)}d(i, j)$$

hence

$$(10) \quad \rho_d(P_a) \leq 2\sqrt{a(1-a)}$$

which — at least in the case $a \neq 1/2$ — gives non-trivial information about P_a itself and not only about some high power of P_a . Considering $i, j \in S$, (9) tells us that by applying P_a the Wasserstein distance of the probability measures $\delta_i P_a$ and $\delta_j P_a$ is smaller than the original distance by a factor of at least $\rho_d(P_a)$.

Note that equality holds in (9) iff neither i nor j equals 1 or N . In particular, equality holds in (10) for $N \geq 4$.

The question arises whether this metric is 'optimal'. For the application of the Main Theorem 1.13 we have to find the eigenvalues of P_a , which are $\lambda_1 = 1$ and for $2 \leq j \leq N$,

$$(11) \quad \lambda_j = 2\sqrt{a(1-a)} \cos \left(\frac{(j-1)\pi}{N} \right)$$

(see [6], Chapter 4.4). By considering the corresponding right eigenvectors one finds that the 'optimal' metric is not (8), but

$$D(i, j) = \sum_{k=i}^{j-1} \left(\frac{a}{1-a} \right)^{k/2} \sin \left(\frac{k\pi}{N} \right).$$

For this metric

$$\rho_D(P_a) = \lambda_2 = 2\sqrt{a(1-a)} \cos \left(\frac{\pi}{N} \right) < 1$$

for all $0 < a < 1$.

3. Proof of Theorem 1.6

The proof requires some preliminary results.

3.1. *Proposition.* Let P be a stochastic matrix on the finite state space $S = \{1, \dots, N\}$ and d a metric on S . Then $\rho_d(P) \geq |\lambda_2|$ where $\{\lambda_1, \lambda_2, \dots, \lambda_N\}$ are the eigenvalues of P ordered such that $1 = \lambda_1 \geq |\lambda_2| \geq \dots \geq |\lambda_N|$.

Proof. Denote by H the subspace of $l^1(S)$ orthogonal to the constant function $(1, \dots, 1)$ on S . Note that H is invariant under P by left multiplication and that the restriction of P to H has the eigenvalues $\{\lambda_1, \lambda_2, \dots, \lambda_N\}$.

We first show the proposition for the case of the discrete metric $d = d_0$ considered in Example 1.5. In this case $d_0(\mu, \nu) = \|\mu - \nu\|_1$ and one easily observes that $\rho_{d_0}(P)$ is just the norm of the restriction of P to H with respect to the norm $\|\cdot\|$ on H . The assertion of the proposition thus reduces to the well-known fact that the operator of norm of $P|_H$ is greater than or equal to the spectral radius $|\lambda_2|$ of $P|_H$. In fact this argument shows that, for $n \in \mathbb{N}$, $\rho_{d_0}(P^n) \geq |\lambda_2|^n$.

Now we pass to the general case. For an arbitrary metric d on S find $c_1, c_2 > 0$ such that, for $i, j \in S$,

$$c_1 d_0(i, j) \leq d(i, j) \leq c_2^{-1} d_0(i, j).$$

Hence for every $n \in \mathbb{N}$

$$\begin{aligned} (\rho_d(P))^n &\geq \rho_d(P^n) \\ &\geq c_1 c_2 \rho_{d_0}(P^n) \\ &\geq c_1 c_2 |\lambda_2|^n \end{aligned}$$

which by taking the n th root immediately gives the assertion.

The absolute value $|\lambda_2|$ of the second eigenvalue of a strongly ergodic transition matrix therefore is a lower bound for $\rho_d(P)$. In the next example we shall see that in general $\kappa(P) = \inf\{\rho_d(P) : d \text{ a metric on } S\}$ is strictly bigger than $|\lambda_2|$.

3.2. *Example.* Let $0 < c < 1$ and consider the strongly ergodic transition matrix

$$P = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ c & 1 - c & 0 \end{pmatrix}.$$

The eigenvalues are $\lambda_1 = 1$ and $\lambda_{2,3} = -\frac{1}{2} \pm \sqrt{\frac{1}{4} - c}$. In particular, for $c = 1/4$, $\lambda_2 = \lambda_3 = -1/2$. Note that $(\delta_2 - \delta_3)P = \delta_3 - c\delta_1 - (1 - c)\delta_2$ whence for any metric d on S

$$d^w(\delta_2 P, \delta_3 P) = cd(1, 3) + (1 - c)d(2, 3),$$

which implies that

$$\rho_d(P) \geq d^w(\delta_2 P, \delta_3 P)/d(2, 3) > 1 - c.$$

For $c = 1/4$ this gives $1 - c = 3/4$ which is strictly bigger than $|\lambda_2| = 1/2$.

3.3. *Lemma.* Let P be a transition matrix and suppose that there is a non-empty subset A of the set of all (non-ordered) pairs $\{i, j\}$, $i, j \in S$, $i \neq j$, with the following property. For every $\{i, j\} \in A$ and $k \in \text{supp}(\delta_i P)$, $l \in \text{supp}(\delta_j P)$, we have $\{k, l\} \in A$.

Then P fails to be strongly ergodic.

Proof. The assumption in fact implies that if $\mu, \nu \in \mathcal{P}(S)$ are such that for $i \in \text{supp}(\mu)$, $j \in \text{supp}(\nu)$ we have $\{i, j\} \in A$ then the same property holds true for the measures μP and νP .

Indeed, write

$$\mu = \sum a_p \delta_{i_p}, \quad \nu = \sum b_q \delta_{j_q}$$

where $a_p > 0$, $b_q > 0$ and $\sum_p a_p = \sum_q b_q = 1$. Each pair $\{i_p, j_q\}$ belongs to A , hence by hypothesis for each $k \in \text{supp}(\mu P)$ and $l \in \text{supp}(\nu P)$ the pair $\{k, l\}$ belongs to A , as $k \in \text{supp}(\delta_{i_p} P)$ and $l \in \text{supp}(\delta_{j_q} P)$ for some p and q .

Hence for $\{i, j\} \in A$ it follows inductively that for every $m \in \mathbb{N}$ the measures $\delta_i P^m$ and $\delta_j P^m$ have the property defined above. In particular they have disjoint supports and therefore

$$d_0(\delta_i P^m, \delta_j P^m) = \frac{1}{2} \|(\delta_i - \delta_j) P^m\|_1 = 1 \quad \text{for } m \in \mathbb{N},$$

whence $\rho_0(P^m) = 1$ for every $m \in \mathbb{N}$ and P fails to be strongly regular by the remark in 1.2 above.

3.4. *Proof of Theorem 1.* We proceed inductively. Consider the discrete metric d_0 and let A_0 be the set of all pairs $\{i, j\}$, $i \neq j$, $i, j \in S$. For each such pair $\{i, j\}$ we have

$$(12) \quad d_0^W(\delta_i P, \delta_j P) \leq d_0(i, j).$$

Let A_1 be the set of all pairs $\{i, j\}$ such that equality holds true in (12). By the above lemma, A_1 is a proper subset of A_0 . Define

$$d_1(i, j) = \begin{cases} 1, & \text{if } \{i, j\} \in A_1 \\ 1 - \varepsilon_1, & \text{if } \{i, j\} \notin A_1 \end{cases}$$

where $1/2 \geq \varepsilon_1 > 0$ is chosen small enough such that

$$(13) \quad d_1^W(\delta_i P, \delta_j P) \leq d_1(i, j)$$

still holds true with strict inequality for all $\{i, j\} \notin A_1$. Note that for $\{i, j\} \in A_1$ the above inequality also holds true (possibly with equality) as for those $\{i, j\}$ we have only decreased the left-hand side compared to (12). If $A_1 = \emptyset$ we stop the construction. Otherwise, suppose $A_1 \supseteq A_2 \supseteq \dots \supseteq A_n \neq \emptyset$ and d_1, \dots, d_n have been defined such that $d_n(i, j) = 1$ for $\{i, j\} \in A_n$, $d_n(i, j) < 1$ for $\{i, j\} \notin A_n$ and such that

$$(14) \quad d_n^W(\delta_i P, \delta_j P) \leq d_n(i, j)$$

for every $\{i, j\} \in A_0$ with strict inequality holding at least for $\{i, j\} \notin A_n$.

Let A_{n+1} be the set of all $\{i, j\}$ such that equality holds true in (14). By the above lemma A_{n+1} is strictly contained in A_n ; otherwise the set $A = A_n = A_{n+1}$ would satisfy the requirements of the lemma in contradiction to the strong ergodicity of P . Define

$$d_{n+1}(i, j) = \begin{cases} 1, & \text{if } \{i, j\} \in A_{n+1} \\ 1 - \varepsilon_{n+1}, & \text{if } \{i, j\} \in A_n \setminus A_{n+1} \\ d_n(i, j), & \text{otherwise} \end{cases}$$

where $1/2 \geq \varepsilon_{n+1} > 0$ is chosen small enough that

$$(15) \quad d_{n+1}^W(\delta_i P, \delta_j P) \leq d_{n+1}(i, j)$$

still holds true with strict inequality for every $\{i, j\} \notin A_{n+1}$. This completes the inductive step. After a finite number of times we arrive at the case $A_{n+1} = \emptyset$ which implies that in (15) strict inequality holds true for all pairs $\{i, j\}$. Hence d_{n+1} , which is a metric on S in view of $\varepsilon_n \leq 1/2$, verifies $\rho_{d_{n+1}}(P) < 1$.

Thus Theorem 1.6 is proved.

4. Proof of the main theorems

4.1. Proof of Theorem 1.13. Let

$$\begin{aligned} s_{ij} &= \sum_{k=1}^j p_{ik}, & j &= 1, \dots, N \\ s_{i0} &= 0, \\ t_{ij} &= s_{ij} - s_{i+1,j}, & i &= 1, \dots, N - 1. \end{aligned}$$

Let T be the $[N - 1] \times [N - 1]$ matrix

$$T = (t_{ij})_{\substack{i=1, \dots, N-1, \\ j=1, \dots, N-1}}$$

For any vector $v = (v_1, \dots, v_N)$ let v^- be the $[N - 1]$ -dimensional vector $v^- = (v_2 - v_1, \dots, v_N - v_{N-1})$. We claim that the following assertion is true: each eigenvalue $\lambda \neq 1$ of P with right eigenvector v is also an eigenvalue of T with right eigenvector v^- . Let λ be such an eigenvector. Then

$$\begin{aligned} \lambda v_i &= \sum_{j=1}^N p_{ij} v_j = \sum_{j=1}^N (s_{ij} - s_{i+1,j}) v_j \\ &= \sum_{j=1}^{N-1} s_{ij} (v_j - v_{j+1}) + v_N. \end{aligned}$$

Therefore, for $i = 1, \dots, N - 1$,

$$\lambda v_i^- = \lambda (v_{i+1} - v_i) = \sum_{j=1}^{N-1} (s_{ij} - s_{i+1,j}) (v_{j+1} - v_j) = \sum_{j=1}^{N-1} t_{ij} v_j^-.$$

Conversely let $\lambda \neq 1$ be an eigenvalue of T with corresponding right eigenvector w . We prove now λ is an eigenvalue of P and there is a right eigenvector v , such that $w = v^-$.

Let v_N be the solution of

$$\lambda v_N = v_N - \sum_{j=1}^{N-1} s_{Nj} w_j$$

and define

$$v_j = v_N - \sum_{k=j}^{N-1} w_k, \quad j = 1, \dots, N-1.$$

Since

$$s_{ij} = s_{Nj} + \sum_{k=i}^{N-1} t_{kj}, \quad i = 1, \dots, N-1$$

we get

$$\begin{aligned} \sum_{j=1}^N p_{ij} v_j &= v_N - \sum_{j=1}^N (s_{ij} - s_{ij-1}) \sum_{k=j}^{N-1} w_k \\ &= v_N - \sum_{j=1}^{N-1} s_{ij} w_j = v_N - \sum_{j=1}^{N-1} \left(s_{Nj} + \sum_{k=i}^{N-1} t_{kj} \right) w_j \\ &= v_N - \sum_{j=1}^{N-1} s_{Nj} w_j - \lambda \sum_{k=i}^{N-1} w_k = \lambda v_N - \lambda \sum_{k=i}^{N-1} w_k = \lambda v_i, \end{aligned}$$

which proves the assertion above.

In order to apply the well-known Perron–Frobenius theorem on positive matrices, we have to check that T is a positive, irreducible matrix.

The fact that

$$t_{ij} = \sum_{k=1}^j p_{ik} - \sum_{k=1}^j p_{i+1,k} \geq 0$$

is a reformulation of the fact that P is stochastically monotone. Suppose that T is reducible. Then there is a set of indices $A \neq \emptyset$, $A^c \neq \emptyset$ such that

$$t_{ij} = \sum_{k=1}^j p_{ik} - \sum_{k=1}^j p_{i+1,k} = 0$$

for $i \in A, j \in A^c$. Let B be the set $B = \{i : i \in A \text{ or } i-1 \in A\}$. We may represent the set B as a finite union of disjoint intervals $B = \cup \{i : i_k \leq i \leq l_k\}$. Then $i_k \in A$, $i_k - 1 \notin A$ and $l_k \notin A$. Let the partition sets be all intervals of B and all the remaining singletons. We show that P is lumpable into these intervals.

For every k

$$\sum_{j=i_k}^{l_k} p_{ij} = \sum_{j=1}^{l_k} p_{ij} - \sum_{j=1}^{i_k-1} p_{ij}.$$

If i is the same partition as i' , then

$$\sum_{j=1}^l p_{ij} = \sum_{j=1}^l p_{i+1,j} = \dots = \sum_{j=1}^l p_{i'j}$$

for all $l \notin A$. Since $l_k \notin A$ and $i_k - 1 \notin A$, we see that $\sum_{j=i_k}^{l_k} p_{ij}$ is constant in every interval and this contradicts the assumption that P is not lumpable into intervals.

The Perron–Frobenius theorem implies that T has a positive maximal eigenvalue λ_2 , which has multiplicity 1 and a positive eigenvector w . As just proved, λ_2 is the second largest eigenvalue of P and there is a right eigenvector v of P with $w = v^-$. Consequently, v is strictly increasing.

4.2. *Proof of Theorem 1.14.* Consider the restriction of the operator $\lambda_2^{-1}P$ to the hyperplane H of $l^1(S)$ orthogonal to the constant function $(1, 1, \dots, 1)$ on S .

As in the proof of 3.1 observe that this operator has a simple eigenvalue equal to 1 and all other eigenvalues of absolute value strictly less than 1. Hence $\lambda_2^{-n}P^n|_H$ converges to the projection onto the eigenspace corresponding to the eigenvalue λ_2 of P . As v is the left and v the right eigenvector pertaining to λ_2 , normalized by $\langle v, v \rangle = 1$ we obtain

$$\begin{aligned} \lim_{n \rightarrow \infty} (S_i - S_j)P^n / \lambda_2^n &= \langle \delta_i - \delta_j, v \rangle v \\ &= d(i, j)v \end{aligned}$$

the last equality following from the definition of d .

4.3. *Remark.* It is not true in general that in the setting of the main theorem λ_2 is the only eigenvalue of P of absolute value equal to λ_2 . For the matrix P_a of the basic example we get for instance $\lambda_N = -\lambda_2$ (see (11)).

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