INFORMATION FLOW IN ONE-DIMENSIONAL MARKOV SYSTEMS¹

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ABSTRACT. The information flow in discrete Markov systems provides a method for determining that such a system has a unique invariant measure. Estimates are obtained for the information flow and conditions under which there is a unique invariant measure for a one-dimensional Markov system are obtained.

1. Introduction. Markov chains on the infinite product of discrete spaces have been introduced by O. N. Stavskaya and I. I. Pyatetskii-Shapiro [4] to model certain parts of the central nervous system. One of the main problems in the study of such systems is the determination of the invariant probability measures. The concept of information flow in such a system has been introduced by the author in [2] and its relationship with the uniqueness of the invariant measure has been demonstrated.

2. Terminology. Let A be a countable set, S a finite set and $\Gamma = S^A$. Γ will serve as the state space for the class of Markov chains to be discussed. Let $\mathcal{G}$ be the σ -algebra of subsets of Γ generated by the coordinate functions and for $B \subset A$, let $\mathcal{G}_B$ be the σ -algebra generated by the coordinate functions in B . A mapping $P: \Gamma \otimes \mathcal{G} \rightarrow [0, 1]$ is a *probability transition kernel* if for each $\gamma \in \Gamma$, $P(\gamma, \cdot)$ is a probability measure on $\mathcal{G}$ and for every $G \in \mathcal{G}$, $P(\cdot, G)$ is a $\mathcal{G}$ -measurable function.

For each $\alpha \in A$, let $N(\alpha)$ be a finite subset of A whose elements are called the *nearest neighbours* of α . The kernel $P(\cdot, \cdot)$ is said to be *synchronous* if for every finite subset $B \subset A$ and $x_\alpha \in S$, $\alpha \in B$,

$$(2.1) \quad P(y, \{\gamma: \gamma(\alpha) = x_\alpha, \alpha \in B\}) = \prod_{\alpha \in B} P(y, \{\gamma: \gamma(\alpha) = x_\alpha\}),$$

and *local* if for each fixed α and $x_\alpha \in S$, $P(\cdot, \{\gamma: \gamma(\alpha) = x_\alpha\})$ is measurable with respect to $\mathcal{G}_{N(\alpha)}$ and hence

$$(2.2) \quad P(y, \{\gamma: \gamma(\alpha) = x_\alpha\}) = q_\alpha(\pi_{N(\alpha)y}; x_\alpha)$$

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where $q_\alpha(\cdot; \cdot)$ is a probability transition function from $S^{N(\alpha)}$ to S and $\pi_{N(\alpha)}$ is the projection from Γ to $S^{N(\alpha)}$.

Let $\Omega \equiv \Gamma^{Z^+}$ where $Z^+ \equiv \{1, 2, 3, \dots\}$, let $\mathcal{F}$ denote the product σ -algebra of subsets of Ω and for $n=1, 2, 3, \dots$, let $X_n(\omega)$ denote the n th coordinate of ω . Given an initial measure m on Γ and the kernel $P(\cdot, \cdot)$ we can construct a measure P_m on $(\Omega, \mathcal{F})$ such that $\{X_n\}$ forms a Markov chain with transition probabilities given by $P(\cdot, \cdot)$.

Consider finite subalgebras $\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3$ and $\mathcal{F}_4$ of $\mathcal{F}$ and let $\mathcal{A}(\mathcal{F}_i)$ denote the set of atoms of $\mathcal{F}_i$. The *entropy* of $\mathcal{F}_i$ is defined by

$$(2.3) \quad I(\mathcal{F}_i) \equiv - \sum_{A \in \mathcal{A}(\mathcal{F}_i)} P_m(A) \log(P_m(A))$$

where all logarithms are taken to base two. The *conditional entropy* in $\mathcal{F}_1$ given $\mathcal{F}_2$ is defined by

$$(2.4) \quad I(\mathcal{F}_1 | \mathcal{F}_2) \equiv - \sum_{B \in \mathcal{A}(\mathcal{F}_2)} \sum_{A \in \mathcal{A}(\mathcal{F}_1)} P_m(A \cap B) \log(P_m(A | B)).$$

The *mutual information* in the algebras $\mathcal{F}_1$ and $\mathcal{F}_2$ is defined by

$$(2.5) \quad \begin{aligned} I(\mathcal{F}_1 \wedge \mathcal{F}_2) &\equiv I(\mathcal{F}_1) - I(\mathcal{F}_1 | \mathcal{F}_2) \\ &= \sum_{B \in \mathcal{A}(\mathcal{F}_2)} \sum_{A \in \mathcal{A}(\mathcal{F}_1)} P_m(A \cap B) \log[P_m(A \cap B) / P_m(A)P_m(B)] \end{aligned}$$

and the *mutual information* in $\mathcal{F}_1, \mathcal{F}_2$ and $\mathcal{F}_3$ is defined by

$$(2.6) \quad I(\mathcal{F}_1 \wedge \mathcal{F}_2 \wedge \mathcal{F}_3) \equiv I(\mathcal{F}_1 \wedge \mathcal{F}_2) - I(\mathcal{F}_1 \wedge \mathcal{F}_2 | \mathcal{F}_3).$$

Note that $I(\mathcal{F}_1 \wedge \mathcal{F}_2) = I(\mathcal{F}_2 \wedge \mathcal{F}_1)$ and $I(\mathcal{F}_i \wedge \mathcal{F}_j \wedge \mathcal{F}_k)$ is symmetric in i, j, k (refer to N. Abramson [1]).

We also define *conditional mutual information* as follows:

$$(2.7) \quad \begin{aligned} I(\mathcal{F}_1 \wedge \mathcal{F}_2 | \mathcal{F}_3) &\equiv I(\mathcal{F}_1 | \mathcal{F}_3) - I(\mathcal{F}_1 | \mathcal{F}_2 \vee \mathcal{F}_3) \\ &= \sum_{C \in \mathcal{A}(\mathcal{F}_3)} P_m(C) \sum_{B \in \mathcal{A}(\mathcal{F}_2)} \sum_{A \in \mathcal{A}(\mathcal{F}_1)} P_m(A \cap B | C) \\ &\quad \cdot \log[P_m(A \cap B | C) / P_m(A | C)P_m(B | C)] \end{aligned}$$

$$(2.8) \quad \begin{aligned} I(\mathcal{F}_1 \wedge \mathcal{F}_2 \wedge \mathcal{F}_3 | \mathcal{F}_4) &\equiv I(\mathcal{F}_1 \wedge \mathcal{F}_2 | \mathcal{F}_4) - I(\mathcal{F}_1 \wedge \mathcal{F}_2 | \mathcal{F}_3 \vee \mathcal{F}_4) \end{aligned}$$

where $\mathcal{F}_2 \vee \mathcal{F}_3$ denotes the smallest algebra containing both $\mathcal{F}_2$ and $\mathcal{F}_3$. Note that $I(\mathcal{F}_1 \wedge \mathcal{F}_2) \geq 0$ and $I(\mathcal{F}_1 \wedge \mathcal{F}_2 | \mathcal{F}_3) \geq 0$ but that

$$I(\mathcal{F}_1 \wedge \mathcal{F}_2 \wedge \mathcal{F}_3) \quad \text{and} \quad I(\mathcal{F}_1 \wedge \mathcal{F}_2 \wedge \mathcal{F}_3 | \mathcal{F}_4)$$

can either be positive or negative.

Now let $\Omega' \equiv \{0, 1\} \otimes \Omega$, let $X_0(\omega')$ denote the first coordinate of ω' and let $\mathcal{F}_0 \equiv \sigma(X_0)$. Given a probability $(p, 1-p)$ on $\{0, 1\}$ and two measures m_0 and m_1 on $(\Gamma, \mathcal{G})$ we can construct a measure P on $(\Omega', \mathcal{F}_0 \otimes \mathcal{F})$ such that $\{X_n\}$ is a Markov chain with

$$P(X_0 = 0) = p$$

and

$$P(X_1 \in G \mid X_0 = 0) = m_0(G), \quad P(X_1 \in G \mid X_0 = 1) = m_1(G).$$

and such that $X_1, X_2, X_3, \dots$ is a time homogeneous Markov chain with transition probabilities given by the kernel $P(\cdot, \cdot)$.

Given $J \subset A$, let $\mathcal{F}_J^n \equiv \sigma\{X_{n,\alpha} : \alpha \in J\}$ where for $\omega \in \Omega'$, $n \geq 1$, $\alpha \in A$, $X_{n,\alpha}$ is defined to be the α -coordinate of $X_n(\omega) \in S^A$. For fixed α , consider $\mathcal{F}_{N(\alpha)}^1$ as the input and $\mathcal{F}_{\{\alpha\}}^2$ as the output of a communications channel. The *transmission coefficient* of the channel is defined to be

$$(2.9) \quad \rho(\alpha) \equiv \text{Sup } I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha\}}^2) / I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha)}^1)$$

where the supremum is taken over all choices of p , m_0 and m_1 . Because of the Markov property $I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha\}}^2 \mid \mathcal{F}_{N(\alpha)}^1) = 0$ and therefore

$$\begin{aligned} I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha\}}^2) &= I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha)}^1 \wedge \mathcal{F}_{\{\alpha\}}^2) \\ &= I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha)}^1) - I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha)}^1 \mid \mathcal{F}_{\{\alpha\}}^2). \end{aligned}$$

Since $I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha)}^1 \mid \mathcal{F}_{\{\alpha\}}^2) \geq 0$,

$$I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha\}}^2) \leq I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha)}^1)$$

and hence $\rho(\alpha) \leq 1$. We call the system *strictly stochastic* if $\rho(\alpha) < 1$. It has been shown in [1] that the transmission coefficient for the binary symmetric channel is strictly less than one and it is reasonable to conjecture that $\rho < 1$ for a large class of channels. The concept of transmission coefficient was first considered by A. Renyi in some of his unpublished work.

3. Information flow in Markov systems. Consider a local synchronous Markov system with $\rho(\alpha) \leq \rho < 1$ for all $\alpha \in A$. Let $J = \{\alpha_0, \dots, \alpha_m\}$ be a finite subset of A . Then

$$\begin{aligned} I(\mathcal{F}_J^{n+1} \wedge \mathcal{F}_0) &= I(\mathcal{F}_{\{\alpha_0\}}^{n+1} \wedge \mathcal{F}_0) + I(\mathcal{F}_{\{\alpha_1\}}^{n+1} \wedge \mathcal{F}_0 \mid \mathcal{F}_{\{\alpha_0\}}^{n+1}) \\ &\quad + \dots + I(\mathcal{F}_{\{\alpha_m\}}^{n+1} \wedge \mathcal{F}_0 \mid \mathcal{F}_{\{\alpha_0, \dots, \alpha_{m-1}\}}^{n+1}). \end{aligned}$$

LEMMA 3.1. Let $B_1 = \{\alpha_1, \dots, \alpha_r\}$ and $B_2 = \{\beta_1, \dots, \beta_k\}$ be finite (possibly empty) subsets of A , $\alpha_0 \in A$, $\alpha_0 \notin B_1$ and $n \geq 1$. Then

$$(3.1) \quad I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0\}}^{n+1} \mid \mathcal{F}_{B_1}^{n+1} \vee \mathcal{F}_{B_2}^n) \leq \rho I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha_0)}^n \mid \mathcal{F}_{B_1}^{n+1} \vee \mathcal{F}_{B_2}^n)$$

where we adopt the convention that

$$\begin{aligned} I(\mathcal{F}_0 \wedge \mathcal{F}_B^m \mid \mathcal{F}_{B_1}^{n+1} \vee \mathcal{F}_{B_2}^n) &= I(\mathcal{F}_0 \wedge \mathcal{F}_B^m \mid \mathcal{F}_{B_1}^{n+1}) \quad \text{if } B_2 = \emptyset \\ &= I(\mathcal{F}_0 \wedge \mathcal{F}_B^m) \quad \text{if } B_1 = B_2 = \emptyset. \end{aligned}$$

PROOF. Given $x_{\alpha_0} \in S$, $x_\alpha \in S$, $\alpha \in B_1$, $y_\beta \in S$, $\beta \in B_2 \cup N(\alpha_0)$ and $j \in \{0, 1\}$, it can be verified by a straightforward calculation involving Equations (2.1) and (2.2) that

$$\begin{aligned} (3.2) \quad & P(X_{n+1, \alpha_0} = x_{\alpha_0} \mid X_0 = j; X_{n+1, \alpha} = x_\alpha, \\ & \alpha \in B_1; X_{n, \beta} = y_\beta, \beta \in B_2 \cup N(\alpha_0)) \\ & = q_{\alpha_0}(y_\beta, \beta \in N(\alpha_0); x_{\alpha_0}). \end{aligned}$$

This implies that conditioned on $\mathcal{F}_{N(\alpha_0)}^n$, $\mathcal{F}_{\{\alpha_0\}}^{n+1}$ is independent of

$$\mathcal{F}_{B_1}^{n+1} \vee \mathcal{F}_{B_2 - N(\alpha_0)}^n \vee \mathcal{F}_0.$$

In view of (2.7) it suffices to show that

$$\begin{aligned} (3.3) \quad & I(\mathcal{F}_{\{\alpha_0\}}^{n+1} \wedge \mathcal{F}_0 \mid X_{n+1, \alpha} = x_\alpha, \alpha \in B_1; X_{n, \beta} = y_\beta, \beta \in B_2) \\ & \leq \rho(\alpha_0) I(\mathcal{F}_{N(\alpha_0)}^n \wedge \mathcal{F}_0 \mid X_{n+1, \alpha} = x_\alpha, \alpha \in B_1; X_{n, \beta} = y_\beta, \beta \in B_2). \end{aligned}$$

But (3.2) demonstrates that even conditioned on the event

$$\{X_{n+1, \alpha} = x_\alpha, \alpha \in B_1; X_{n, \beta} = y_\beta, \beta \in B_2\},$$

the channel from $\mathcal{F}_{N(\alpha_0)}^n$ to $\mathcal{F}_{\{\alpha_0\}}^{n+1}$ is defined by $q_{\alpha_0}(\cdot; \cdot)$ and hence is identical to the channel from $\mathcal{F}_{N(\alpha_0)}^1$ to $\mathcal{F}_{\{\alpha_0\}}^2$. If we then consider the definition (2.9) of $\rho(\alpha_0)$ with the roles of m_0 and m_1 in that definition being played by

$$P(X_n \in \cdot \mid X_{n+1, \alpha} = x_\alpha, \alpha \in B_1; X_{n, \beta} = y_\beta, \beta \in B_2; X_0 = j), \quad j = 0, 1,$$

then (3.3) follows and the proof is complete.

For future use we now derive some basic inequalities.

$$\begin{aligned} (3.4) \quad & I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha_r)}^n \mid \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1}) \\ & = I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha_r)}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha_r)}^n \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1}) \\ & = I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha_r)}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1}) \\ & \quad + I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1} \mid \mathcal{F}_{N(\alpha_r)}^n). \end{aligned}$$

But

$$I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1} \mid \mathcal{F}_{N(\alpha_r)}^n \vee \mathcal{F}_{(N(\alpha_0) \cup \dots \cup N(\alpha_{r-1}))}^n) = 0$$

and therefore

$$\begin{aligned}
 (3.5) \quad & I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1} \mid \mathcal{F}_{N(\alpha_r)}^n) \\
 &= I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1} \wedge \mathcal{F}_{(N(\alpha_0) \cup \dots \cup N(\alpha_{r-1}))}^n \mid \mathcal{F}_{N(\alpha_r)}^n) \\
 &\leq I(\mathcal{F}_0 \wedge \mathcal{F}_{(N(\alpha_0) \cup \dots \cup N(\alpha_{r-1}))}^n \mid \mathcal{F}_{N(\alpha_r)}^n).
 \end{aligned}$$

Therefore from (3.4) and (3.5),

$$\begin{aligned}
 (3.6) \quad & I(\mathcal{F}_0 \wedge \mathcal{F}_{N(\alpha_r)}^n \mid \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1}) \\
 &\leq I(\mathcal{F}_0 \wedge \mathcal{F}_{(N(\alpha_0) \cup \dots \cup N(\alpha_r))}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_{r-1}\}}^{n+1}).
 \end{aligned}$$

In the remainder of this section we restrict our attention to the case in which $A = \mathbb{Z}^1$, the set of integers. For simplicity we assume that the local transition probabilities are the same at each site and we restrict our attention to measures m_0 and m_1 which are invariant under the spatial shift on A . Under this assumption but without assuming that m_0 and m_1 are invariant under reflections we have the following result.

LEMMA 3.2. *If m_0 and m_1 are invariant under the spatial shift on $\mathbb{Z}^1$, then*

$$I(\mathcal{F}_{\{\alpha_m, \dots, \alpha_{m+r}\}}^n \wedge \mathcal{F}_0 \mid \mathcal{F}_{\{\alpha_0, \dots, \alpha_{m-1}\}}^n) = I(\mathcal{F}_{\{\alpha_{-r}, \dots, \alpha_0\}}^n \wedge \mathcal{F}_0 \mid \mathcal{F}_{\{\alpha_1, \dots, \alpha_m\}}^n).$$

PROOF.

$$\begin{aligned}
 & I(\mathcal{F}_{\{\alpha_{-r}, \dots, \alpha_{m+r}\}}^n \wedge \mathcal{F}_0) \\
 &= I(\mathcal{F}_{\{\alpha_{-r}, \dots, \alpha_{m-1}\}}^n \wedge \mathcal{F}_0) + (\mathcal{F}_{\{\alpha_m, \dots, \alpha_{m+r}\}}^n \wedge \mathcal{F}_0 \mid \mathcal{F}_{\{\alpha_{-r}, \dots, \alpha_{m-1}\}}^n)
 \end{aligned}$$

and

$$\begin{aligned}
 & I(\mathcal{F}_{\{\alpha_{-r}, \dots, \alpha_{m+r}\}}^n \wedge \mathcal{F}_0) \\
 &= I(\mathcal{F}_{\{\alpha_1, \dots, \alpha_{m+r}\}}^n \wedge \mathcal{F}_0) + I(\mathcal{F}_{\{\alpha_{-r}, \dots, \alpha_0\}}^n \wedge \mathcal{F}_0 \mid \mathcal{F}_{\{\alpha_1, \dots, \alpha_{m+r}\}}^n).
 \end{aligned}$$

Hence the result follows since by spatial invariance

$$I(\mathcal{F}_{\{\alpha_{-r}, \dots, \alpha_{m-1}\}}^n \wedge \mathcal{F}_0) = I(\mathcal{F}_{\{\alpha_1, \dots, \alpha_{m+r}\}}^n \wedge \mathcal{F}_0).$$

We now assume that for each α_r , $N(\alpha_r) = \{\alpha_{r-s}, \dots, \alpha_{r-1}, \alpha_r, \alpha_{r+1}, \dots, \alpha_{r+s}\}$. For $k=0, 1, 2, \dots$, let

$$F_n(k) \equiv I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_k\}}^n).$$

A measure m is a *stationary probability* for the Markov system if, for $G \in \mathcal{G}$, $m(G) = \int P(\gamma, G) m(d\gamma)$.

We now calculate the amount of information about the initial state which is contained in a finite subsystem at the n th epoch.

PROPOSITION 3.1. *Let m_0 and m_1 be two distinct spatially invariant probability measures. Then*

$$F_{n+1}(k) \leq \rho F_n(k+2s) + \rho(1-\rho)F_n(k+2s-1) + \cdots + \rho(1-\rho)^k F_n(2s).$$

PROOF. By Lemma 3.1 we have

$$F_{n+1}(0) \leq \rho I(\mathcal{F}_{N(0)}^n \wedge \mathcal{F}_0) = \rho F_n(2s)$$

since $N(0) = \{-s, \dots, 0, \dots, s\}$ and we have assumed spatial invariance. Similarly, for $k \geq 1$, Lemma 3.1 and (3.6) imply that

$$\begin{aligned} F_{n+1}(k) - F_{n+1}(k-1) &= I(\mathcal{F}_0 \wedge \mathcal{F}_{\{k\}}^{n+1} \mid \mathcal{F}_{\{0, \dots, k-1\}}^{n+1}) \\ &\leq \rho [I(\mathcal{F}_0 \wedge \mathcal{F}_{(N(0) \cup \dots \cup N(k))}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0, \dots, k-1\}}^{n+1})]. \end{aligned}$$

Hence since $N(0) \cup \dots \cup N(k) = \{-s, \dots, 0, \dots, s+k\}$,

$$(3.7) \quad F_{n+1}(k) - F_{n+1}(k-1) = \rho [F_n(k+2s) - F_{n+1}(k-1)].$$

But Equation (3.7) can be rewritten as

$$(3.8) \quad F_{n+1}(k) \leq \rho F_n(k+2s) + (1-\rho)F_{n+1}(k-1).$$

Then, by induction

$$F_{n+1}(k) \leq \rho F_n(k+2s) + \rho(1-\rho)F_n(k+2s-1) + \cdots + \rho(1-\rho)^k F_n(2s).$$

Using the ideas of Proposition 3.1 we now obtain a stronger inequality for the information flow.

PROPOSITION 3.2.

$$(3.9) \quad F_{n+1}(k) \leq \rho H_n(k) + \rho(1-\rho)H_n(k-1) + \cdots + \rho(1-\rho)^k H_n(0)$$

where

$$\begin{aligned} (3.10) \quad H_n(k) &= (1-\rho)^{k+1} F_n(2s) \\ &\quad + \{\rho(1-\rho)^k F_n(2s) + \rho(1-\rho)^{k-1} F_n(2s+1) + \cdots + \rho F_n(2s+k)\}. \end{aligned}$$

PROOF. From Lemma 3.1 and (3.4) we have for $k \geq 1$,

$$\begin{aligned} (3.11) \quad F_{n+1}(k) - F_{n+1}(k-1) &= I(\mathcal{F}_{\{k\}}^{n+1} \wedge \mathcal{F}_0 \mid \mathcal{F}_{\{0, \dots, k-1\}}^{n+1}) \\ &\leq \rho [I(\mathcal{F}_0 \wedge \mathcal{F}_{N(k)}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0, \dots, k-1\}}^{n+1}) + I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0, \dots, k-1\}}^{n+1} \mid \mathcal{F}_{N(k)}^n)] \end{aligned}$$

For $r=0, 1, 2, \dots$, let

$$G_{n+1}(r) \equiv I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0, \dots, r\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n).$$

Then

$$(3.12) \quad F_{n+1}(k) \leq (1 - \rho)F_{n+1}(k - 1) + \rho[F_n(2s) + G_{n+1}(k - 1)].$$

By Lemma 3.2

$$G_{n+1}(0) = I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0\}}^{n+1} \mid \mathcal{F}_{N(1)}^n) = I(\mathcal{F}_0 \wedge \mathcal{F}_{\{1\}}^{n+1} \mid \mathcal{F}_{N(0)}^n).$$

But by Lemma 3.1,

$$\begin{aligned} I(\mathcal{F}_0 \wedge \mathcal{F}_{\{1\}}^{n+1} \mid \mathcal{F}_{N(0)}^n) &\leq \rho I(\mathcal{F}_0 \wedge \mathcal{F}_{N(1)}^n \mid \mathcal{F}_{N(0)}^n) \\ &= \rho(F_n(2s + 1) - F_n(2s)) \end{aligned}$$

and, hence,

$$(3.13) \quad G_{n+1}(0) \leq \rho(F_n(2s + 1) - F_n(2s)).$$

For $r \geq 1$,

$$\begin{aligned} G_{n+1}(r) - G_{n+1}(r - 1) &= I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0, \dots, r\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0, \dots, r-1\}}^{n+1} \mid \mathcal{F}_{N(r)}^n) \\ &= I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0, \dots, r\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{\{1, \dots, r\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n) \\ &= I(\mathcal{F}_0 \wedge \mathcal{F}_{\{0\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n \vee \mathcal{F}_{\{1, \dots, r\}}^{n+1}). \end{aligned}$$

But Lemma 3.1 implies that

$$(3.14) \quad G_{n+1}(r) - G_{n+1}(r - 1) \leq \rho I(\mathcal{F}_0 \wedge \mathcal{F}_{N(0)}^n \mid \mathcal{F}_{N(r+1)}^n \vee \mathcal{F}_{\{1, \dots, r\}}^{n+1}).$$

But following the method of derivation of Equations (3.4) and (3.5),

$$\begin{aligned} I(\mathcal{F}_0 \wedge \mathcal{F}_{N(0)}^n \mid \mathcal{F}_{N(r+1)}^n \vee \mathcal{F}_{\{1, \dots, r\}}^{n+1}) &= I(\mathcal{F}_0 \wedge \mathcal{F}_{N(0)}^n \mid \mathcal{F}_{N(r+1)}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{N(0)}^n \wedge \mathcal{F}_{\{1, \dots, r\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n) \\ &= I(\mathcal{F}_0 \wedge \mathcal{F}_{N(0)}^n \mid \mathcal{F}_{N(r+1)}^n) \\ &\quad + I(\mathcal{F}_0 \wedge \mathcal{F}_{\{1, \dots, r\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n \vee \mathcal{F}_{N(0)}^n) - I(\mathcal{F}_0 \wedge \mathcal{F}_{\{1, \dots, r\}}^{n+1} \mid \mathcal{F}_{N(r+1)}^n) \\ &\leq I(\mathcal{F}_0 \wedge \mathcal{F}_{N(0)}^n \mid \mathcal{F}_{N(r+1)}^n) \\ &\quad + I(\mathcal{F}_0 \wedge \mathcal{F}_{(N(1) \cup \dots \cup N(r))}^n \mid \mathcal{F}_{N(r+1)}^n \vee \mathcal{F}_{N(0)}^n) - G_{n+1}(r - 1) \\ &= I(\mathcal{F}_0 \wedge \mathcal{F}_{(N(0) \cup \dots \cup N(r))}^n \mid \mathcal{F}_{N(r+1)}^n) - G_{n+1}(r - 1) \\ &= F_n(r + 2s + 1) - F_n(2s) - G_{n+1}(r - 1). \end{aligned}$$

Therefore combining the last result with (3.14), we have

$$(3.15) \quad G_{n+1}(r) \leq (1 - \rho)G_{n+1}(r - 1) + \rho(F_n(r + 2s + 1) - F_n(2s)).$$

Hence by induction

$$\begin{aligned} (3.16) \quad G_{n+1}(r) &\leq \rho(F_n(2s + r + 1) - F_n(2s)) \\ &\quad + \dots + \rho(1 - \rho)^r(F_n(2s + 1) - F_n(2s)). \end{aligned}$$

But then, from (3.12), we have for $k \geq 1$

$$(3.17) \quad \begin{aligned} F_{n+1}(k) &\leq (1 - \rho)F_{n+1}(k - 1) \\ &+ \rho[F_n(2s) + \rho(F_n(2s + k) - F_n(2s)) \\ &+ \cdots + \rho(1 - \rho)^{k-1}(F_n(2s + 1) - F_n(2s))]. \end{aligned}$$

Hence $F_{n+1}(0) \leq \rho F_n(2s)$ and for $k \geq 1$,

$$(3.18) \quad F_{n+1}(k) \leq (1 - \rho)F_{n+1}(k - 1) + \rho H_n(k)$$

where

$$\begin{aligned} H_n(k) &= [\rho F_n(2s + k) + \cdots + \rho(1 - \rho)^{k-1}F_n(2s + 1) + \rho(1 - \rho)^k F_n(2s)] \\ &+ (1 - \rho)^{k+1}F_n(2s). \end{aligned}$$

Using induction and (3.18) it can be shown that, for $k \geq 0$,

$$F_{n+1}(k) \leq \rho H_n(k) + \rho(1 - \rho)H_n(k - 1) + \cdots + \rho(1 - \rho)^k H_n(0).$$

COROLLARY. *If $L_1(k) \equiv F_1(k)$ for each $k \geq 0$ and if $L_n(k)$ is defined recursively by $L_{n+1}(0) = \rho L_n(2s)$, and, for $k \geq 1$,*

$$(3.19) \quad \begin{aligned} L_{n+1}(k) &= (1 - \rho)L_{n+1}(k - 1) \\ &+ \rho[(1 - \rho)^{k+1}L_n(2s) \\ &+ \{\rho(1 - \rho)^k L_n(2s) + \cdots + \rho L_n(2s + k)\}] \end{aligned}$$

then for all n and k , $F_n(k) \leq L_n(k)$.

PROOF. The proof follows by induction from equation (3.17).

PROPOSITION 3.3. *Consider a one-dimensional synchronous Markov system with $N(\alpha_k) = \{\alpha_{k-s}, \cdots, \alpha_k, \cdots, \alpha_{k+s}\}$. If $\rho \leq 1/(s+1)$, then for each k*

$$F_n(k) = I(\mathcal{F}_0 \wedge \mathcal{F}_{\{\alpha_0, \dots, \alpha_k\}}^n) \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

PROOF. In view of the corollary to Proposition 3.2 it suffices to show that, for each k , $L_n(k) \rightarrow 0$ as $n \rightarrow \infty$. Since $\lim_{k \rightarrow \infty} L_1(k) \leq 1$ and the recursive equations (3.19) are linear we can assume without loss of generality that $\lim_{k \rightarrow \infty} L_1(k) = 1$ so that $L_1(\cdot)$ can be identified with the cumulative distribution function of a discrete random variable W_1 . Let $Y_1, Y_2, Y_3, \cdots$, and $Z_1, Z_2, Z_3, \cdots$, be two sequences of independent discrete random variables with distribution given by $P(Y_1 = k) = \rho(1 - \rho)^k$ for $k = 0, 1, 2, \cdots, 8$, and define the sequence of random variables $\{W_n\}$ as follows:

W_1 is defined as above; if $W_n \leq 2s$, then $W_{n+1} = Y_n$; if $W_n = k > 2s$, then $W_{n+1} = k - 2s + Y_n + Z_n$. In other words,

$$W_{n+1} = \chi_{\{W_n \leq 2s\}} Y_n + \chi_{\{W_n > 2s\}} (W_n - 2s + Y_n + Z_n),$$

where χ_G denotes the indicator function of the event G . Now it is clear that $\{W_n\}$ is a Markov chain with state space $\{0, 1, 2, \dots\}$. Let $E_n(k) \equiv P(W_n \leq k)$. Then

$$P(W_{n+1} \leq k) = P(W_n \leq 2s)P(Y_n \leq k) \\ + \sum_{l=2s+1}^{2s+k} P(2s < W_n \leq l)P(Y_n + Z_n = k + 2s - l).$$

Therefore

$$E_{n+1}(k) = \rho \sum_{i=0}^k (1 - \rho)^i E_n(2s) \\ + \sum_{l=2s+1}^{2s+k} (E_n(l) - E_n(2s)) \rho^2 (k + 2s - l + 1) (1 - \rho)^{k+2s-l},$$

since $P(Y_n + Z_n = r) = \rho^2(r+1)(1-\rho)^r$ for $r=0, 1, 2, \dots$. But then

$$E_{n+1}(k) - (1 - \rho)E_{n+1}(k-1) \\ = \rho E_n(2s) + \rho^2((E_n(2s+k) - E_n(2s)) \\ + \dots + (1 - \rho)^{k-1}(E_n(2s+1) - E_n(2s))).$$

Therefore $E_n(k)$ satisfies (3.19) and hence $E_n(k) = L_n(k)$ for all n and k . This means that the Markov chain $\{W_n\}$ with state space $\{0, 1, 2, \dots\}$ has no absorbing states and, as long as $W_n \in \{2s+1, 2s+2, \dots\}$, it is identical to a random walk. But according to a basic result of renewal theory (refer to W. Feller [3, Chapter 2]),

$P(W_n = k) \rightarrow 0$ as $n \rightarrow \infty$ for all k if and only if

$$E(Y_n + Z_n - 2s) = 2(1 - \rho)/\rho - 2s \geq 0.$$

Therefore $L_n(k) \rightarrow 0$ for all k as $n \rightarrow \infty$ if and only if $\rho \leq 1/(s+1)$ and the proof is complete.

Now let μ be any spatially invariant initial measure for the Markov system and let

$$\mu_n(G) \equiv \int P(X_n \in G \mid X_0 = y) \mu(dy).$$

PROPOSITION 3.4. *Under the above assumptions, the Markov system has a unique spatially invariant stationary measure if $\rho \leq 1/(s+1)$. Moreover for any finite set $B \subset A$ and any spatially invariant measure ν ,*

$$\nu_n \mid \mathcal{G}_B \rightarrow \mu_\infty \mid \mathcal{G}_B \quad \text{as } n \rightarrow \infty$$

where μ_∞ is the spatially invariant stationary measure.

PROOF. It has been shown in [2, Proposition 3.1] that at least one such stationary measure μ_∞ exists. Now let ν be another such stationary

measure. Applying Proposition 3.3 in the case $m_1 = \mu_\infty$ and $m_2 = \nu$ with the probability $(\frac{1}{2}, \frac{1}{2})$ on $\mathcal{F}_0$ it follows that, for any finite set B , $I(\mathcal{F}_0 \wedge \mathcal{F}_B^n) \rightarrow 0$ as $n \rightarrow \infty$. But since $\mu_n = \mu_\infty$ and $\nu_n = \nu$ this implies that $I(\mathcal{F}_0 \wedge \mathcal{F}_B^1) = 0$ and hence $\mathcal{F}_0$ and $\mathcal{F}_B^1$ are independent (cf. N. Abramson [1, p. 107]). But this implies that $\nu|_{\mathcal{G}_B} = \mu_\infty|_{\mathcal{G}_B}$ for every finite set B which in turn implies that $\nu = \mu_\infty$.

Finally, let ν be any spatially invariant measure. Applying Proposition (3.3) in the case $m_1 = \mu_\infty$ and $m_2 = \nu$ with the probability $(\frac{1}{2}, \frac{1}{2})$ on $\mathcal{F}_0$, it follows that, for any finite set $B \subset A$,

$$(3.20) \quad I(\mathcal{F}_0 \wedge \mathcal{F}_B^n) \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

But

$$(3.21) \quad I(\mathcal{F}_0 \wedge \mathcal{F}_B^n) = H(\tfrac{1}{2}\mu_\infty + \tfrac{1}{2}\nu_n) - \tfrac{1}{2}H(\mu_\infty) - \tfrac{1}{2}H(\nu_n)$$

where $H(\mu) = -\sum \mu_i \log \mu_i$ and on the right-hand side of (3.21) we are considering the restrictions of the measures to $\mathcal{G}_B$. But $H(\tfrac{1}{2}\mu_\infty + \tfrac{1}{2}\nu) - \tfrac{1}{2}H(\mu_\infty) - \tfrac{1}{2}H(\nu) = 0$ if and only if $\nu = \mu_\infty$, and $H(\nu)$ is continuous as a function of ν . Hence (3.20) implies that $\nu_n|_{\mathcal{G}_B} \rightarrow \mu_\infty|_{\mathcal{G}_B}$ as $n \rightarrow \infty$.

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