

I-PROJECTION AND CONDITIONAL LIMIT THEOREMS FOR DISCRETE PARAMETER MARKOV PROCESSES

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Let (X, \mathcal{B}) be a compact metric space with \mathcal{B} the σ -field of Borel sets. Suppose this is the state space of a discrete parameter Markov process. Let C be a closed convex set of probability measures on X . Known results on the asymptotic behavior of the probability that the empirical distributions \hat{P}_n belong to C and new results on the Markov process distribution of $\omega_0, \dots, \omega_{n-1}$ under the condition $\hat{P}_n \in C$ are obtained simultaneously through a large deviations estimate. In particular, the Markov process distribution under the condition $\hat{P}_n \in C$ is shown to have an asymptotic quasi-Markov property, generalizing a concept of Csiszár.

1. Introduction. Suppose X_1, X_2, \dots is a sequence of independent random variables taking values in an arbitrary measure space (S, \mathcal{B}) with common distribution P_X . The empirical distribution of a sample $s = (s_1, \dots, s_n) \in S^n$ is the discrete probability measure defined by

$$\hat{P}_n(s, B) = \frac{1}{n} \sum_{i=1}^n \chi_B(s_i).$$

If P_X^n is the n th Cartesian power of P_X , the probability that the empirical distribution \hat{P}_n of (X_1, \dots, X_n) belongs to a set C of probability measure on (S, \mathcal{B}) is given by

$$P\{\hat{P}_n \in C\} = P_X^n(A_n), \quad A_n = \{s: \hat{P}_n(s, \cdot) \in C\}.$$

This last probability is well defined if $A_n \in \mathcal{B}^n$. Csiszár (1984) defines a set C of probability measures as having the Sanov property if

$$(1.1) \quad \lim_{n \rightarrow \infty} \frac{1}{n} \log P\{\hat{P}_n \in C\} = -h(C, P_X),$$

where $h(C, P_X) = \inf_{Q \in C} h(Q, P_X)$ and

$$(1.2) \quad h(Q, P_X) = \begin{cases} \int \log(dQ/dP_X) dQ, & \text{if } Q \ll P_X, \\ +\infty, & \text{otherwise.} \end{cases}$$

In the event $A_n \notin \mathcal{B}^n$, the Sanov property is interpreted to mean that the limit relation holds for both the upper and lower probabilities $\bar{P}\{\hat{P}_n \in C\}$ and

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$\underline{P}\{\hat{P}_n \in C\}$. Here

$$\overline{P}\{\hat{P}_n \in C\} = P_X^n(\overline{A_n}), \quad \underline{P}\{\hat{P}_n \in C\} = P_X^n(\underline{A_n}),$$

where $\overline{A_n} \supset A_n$ and $\underline{A_n} \subset A_n$ respectively are sets in \mathcal{B}^n having minimum, respectively maximum, P_X^n measure among all such sets. The limit relation (1.1) is often referred to as Sanov's theorem due to the importance of Sanov (1957).

An alternative definition to (1.2) is

$$(1.3) \quad h(Q, P_X) = \sup_{\mathcal{P}} h_{\mathcal{P}}(Q, P_X), \quad h_{\mathcal{P}}(Q, P_X) = \sum_{i=1}^k Q(B_i) \log \frac{Q(B_i)}{P_X(B_i)},$$

where $\mathcal{P} = (B_1, \dots, B_k)$ ranges over all finite measurable partitions. Here the conventions $0 \log 0 = 0 \log 0 / 0 = 0$ and $a \log a / 0 = +\infty$ if $a > 0$ apply. A proof of the equivalence of (1.2) and (1.3) is given in Pinsker (1964), Theorem 2.4.2.

A set of probability measure Π on (S, \mathcal{B}) is completely convex if for every probability space $(\Omega, \mathcal{A}, \mu)$ and \mathcal{A} -measurable mapping $\omega \rightarrow \nu(\omega, \cdot) \in \Pi$, the probability measure $\mu\nu$ defined by

$$\mu\nu(B) = \int_{\Omega} \nu(\cdot, B) d\mu, \quad B \in \mathcal{B},$$

also belongs to Π . A convex set of probability measures Π is almost completely convex if there exist completely convex subsets $\Pi_1 \subset \Pi_2 \subset \dots$ of Π such that $\bigcup_{k=1}^{\infty} \Pi_k \supset \Pi \cap \Lambda_f$, Λ_f the set of probability measures on (S, \mathcal{B}) whose support is a finite subset of S . Csiszár (1984) shows that the Sanov property for an almost completely convex set C of probability measures implies that the X_1, \dots, X_n are asymptotically quasi-independent under the condition $\hat{P}_n \in C$. To describe this result, a probability measure P^* is called the *I-projection* of P_X on C if $h(P^*, P_X) = h(C, P_X)$. A probability measure P^* is called the *generalized I-projection* if any sequence of $P_n \in C$ with $h(P_n, P_X) \rightarrow h(C, P_X)$ converges to P^* in variation. For C a convex set of probability measures, the generalized *I-projection* exists [Csiszár (1975), Theorem 2.1 and Remark]. If $X^n = (X_1, \dots, X_n)$ and $P_{X^n | \hat{P}_n \in C}$ denotes the conditional P_X^n distribution of X^n under the condition $\hat{P}_n \in C$, a completely convex set, the asymptotic quasi-independence shown by Csiszár (1984), Theorem 1, is

$$(1.4) \quad \lim_{n \rightarrow \infty} \frac{1}{n} h(P_{X^n | \hat{P}_n \in C}, (P^*)^n) = 0,$$

where P^* is the generalized *I-projection* of P_X on C .

Here an analogous result is formulated for a discrete parameter Markov process with state space a compact metric space X with its σ -field of Borel sets. We assume the Markov process has stationary transition probability function $\pi(dy|x)$. In addition, we assume for $\lambda(dx)$ a probability measure on X

that:

1. $\pi(dy|x) = \pi(y|x)\lambda(dy)$. Then $\pi(y|x)$ may be chosen jointly measurable in x and y .
2. There exist constants a and A such that $0 < a \leq \pi(y|x) \leq A < \infty$ for all $x \in X$ and almost all λ (measure) $y \in X$.
3. For any continuous function $f(y)$

$$\int_X \pi(dy|x) f(y)$$

is a continuous function of x . Under assumptions 1 and 2, the same will hold for any $f(y) \in L^1(\lambda)$.

Let (Ω_x, \mathcal{B}) denote the measure space of all sequences $(\omega_0, \omega_1, \omega_2, \dots)$ with $\omega_0 = x \in X, \omega_j \in X$ and \mathcal{B} the Borel sets of Ω_x . Then $(\Omega_x, \mathcal{B}) = \prod_{i=0}^\infty (X_i, \mathcal{B}_i)$, where $X_i = X$ and \mathcal{B}_i the Borel sets on $X, i = 1, 2, \dots$, and $X_0 = x, \mathcal{B}_0 = \{x\}$. The transition function $\pi(dy|x)$ induces a probability measure on Ω_x ; call it P_x . Impose the weak topology on the space $\mathcal{M}(X)$ of probability measures on X . Let $\hat{P}_n(\omega, \cdot)$ be the empirical distribution of $(\omega_0, \dots, \omega_{n-1}), \omega \in \Omega_x$. Then for each $n, \hat{P}_n(\omega, \cdot): \Omega_x \rightarrow \mathcal{M}(X)$ is a continuous map on $(\omega_0, \dots, \omega_{n-1})$, so for any measurable $S \in \mathcal{M}(X), \{\omega: \hat{P}_n(\omega, \cdot) \in S\}$ is measurable.

Donsker and Varadhan (1975, 1976) described the asymptotic probabilities that $\hat{P}_n(\omega, \cdot)$ lies in closed and open sets of $\mathcal{M}(X)$.

For any open set $G \subset \mathcal{M}(X)$,

$$(1.5) \quad \liminf_{n \rightarrow \infty} \frac{1}{n} \log P_x\{\hat{P}_n(\omega, \cdot) \in G\} \geq - \inf_{\mu \in G} I(\mu),$$

uniformly for $x \in X$ [Donsker and Varadhan (1976), Corollary 3.4]. Here

$$(1.6) \quad I(\mu) = - \inf_{u \in \mathcal{U}_1} \int_X \log\left(\frac{\pi u}{u}\right)(x) \mu(dx),$$

where \mathcal{U}_1 is the set of continuous positive functions on X and

$$\pi u(x) = \int_X u(y) \pi(dy|x).$$

Also for any closed set $C \in \mathcal{M}(X)$,

$$(1.7) \quad \limsup_{n \rightarrow \infty} \frac{1}{n} \log \sup_{x \in X} P_x\{\hat{P}_n(\omega, \cdot) \in C\} \leq - \inf_{\mu \in C} I(\mu)$$

[Donsker and Varadhan (1976), Theorem 4.4].

We first define an I -projection appropriate to this context. In the literature, an I -projection is a minimizing element of a divergence or a measure of entropy [Csiszár (1975), (1984) and Csiszár, Cover and Choi (1987)]. Under assumption 3 on $\pi(dy|x), I(\mu)$ defined by (1.6) is a lower semicontinuous function of μ so that if C is a closed set in $\mathcal{M}(X)$,

$$(1.8) \quad I(C) = \inf_{\mu \in C} I(\mu) = I(\mu^*)$$

for some $\mu^* \in C$. Let Λ_0 be the set of probability measures on $X \times X$ whose marginals are equal. A theorem of Donsker and Varadhan (1976), which is precisely stated as part of Theorem 2.2, is that there is some element P^* of Λ_0 with marginals equal to μ^* which is naturally associated with $I(\mu^*)$. We define such a P^* to be an I -projection of π onto C . We establish the uniqueness of P^* in Theorem 2.3 under the additional assumptions that C is convex, C^0 is nonempty and $I(C^0) < \infty$.

The I -projection thus defined stands in clear relation to that of Csiszár, Cover and Choi (1987) in their study of second-order empirical distributions of a finite-state Markov chain. Theorem 2.9 of this paper, which identifies P^* for a convex set of C of interest, is a partial generalization of one of their examples (cf. Theorem 4 and the remarks following it). It is related to earlier results for finite-state Markov chains obtained by Justesen and Hoholdt (1984) and Spitzer (1972).

Let $\Omega = \prod_{i=-\infty}^{\infty} X_i$, $X_i = X$ for all i , and let \mathcal{B} be the σ -field of Borel sets of Ω . As before, $(\Omega, \mathcal{B}) = \prod_{i=-\infty}^{\infty} (X_i, \mathcal{B}_i)$, where for each i , \mathcal{B}_i is the σ -field of Borel sets on X . Ω is a compact space with metric

$$\rho(\omega, \omega') = \sum_{i=-\infty}^{\infty} \frac{1}{2^{|i|}} \frac{d(\omega_i, \omega'_i)}{1 + d(\omega_i, \omega'_i)},$$

where $d(\cdot, \cdot)$ is the metric on X .

Now for $\omega \in \Omega$, define ω_n by

$$\begin{aligned} \omega_n(i) &= \omega(i), & 0 \leq i \leq n-1, \\ \omega_n(i+n) &= \omega_n(i) & \text{for all } i, -\infty < i < \infty. \end{aligned}$$

Let $(\theta_i \omega_n)(j) = \omega_n(i+j)$, $0 \leq i \leq n-1$, and for a Borel set A in Ω define

$$R_{n,\omega}(A) = \frac{1}{n} \sum_{i=0}^{n-1} \chi_A(\theta_i \omega_n).$$

$R_{n,\omega}$ is the n th-order empirical distribution of ω_n . For each $\omega \in \Omega$ and $n > 0$, $R_{n,\omega}(\cdot)$ is a stationary process. Impose the weak topology on the set $M_S(\Omega)$ of stationary processes on (Ω, \mathcal{B}) . For each n , $R_{n,\omega}(\cdot): \Omega \rightarrow M_S(\Omega)$ is a continuous map of $(\omega_0, \dots, \omega_{n-1})$. Let C be a closed convex set with nonempty interior satisfying $I(C^0) < \infty$. Let P^* be the I -projection of π onto C . Then P^* defines a stationary Markov process on (Ω, \mathcal{B}) which we again denote by P^* .

We now add the assumption that $I(C) = I(C^0)$ so that we have the Markov process analog of the Sanov property. Lemma 3.1 proves that in terms of the metric for the weak topology on $M_S(\Omega)$, $R_{n,\omega}$ converges to P^* in conditional P_x -probability given $\hat{P}_n(\omega, \cdot) \in C$, uniformly for $x \in X$. Also for each A a Borel set in \mathcal{B} and each $n > 0$, $R_{n,\omega}(A): \Omega \rightarrow \mathbb{R}$ is a measurable function of $\omega_0, \dots, \omega_{n-1}$. Then it is possible to define stationary processes

$$R_{n,x}^C(\cdot) = E^{P_x}\{R_{n,\omega}(\cdot) | \hat{P}_n(\omega, \cdot) \in C\}.$$

Theorem 3.2 shows that the processes $R_{n,x}^C$ converge weakly to P^* .

Let $u(x)$ be a probability density function with respect to $\lambda(dx)$. Let P_u be the Markov process on $\prod_{i=0}^\infty(X_i, \mathcal{B}_i)$, $X_i = X$, \mathcal{B}_i the σ -field of Borel sets of X , with initial distribution $u(x)\lambda(dx)$ and probability transition function $\pi(dy|x)$. The results of Section 3 imply that the measures

$$(1.9) \quad R_{n,u}^C(\cdot) = E^{P_u}\{R_{n,\omega}(\cdot)|\hat{P}_n(\omega, \cdot) \in C\}$$

converge weakly to P^* (cf. the remarks prior to Corollary 5.2). Suppose that each $(\omega_0, \omega_1, \omega_2, \dots)$ is a sequence of independent, identically distributed random variables with the common distribution $\lambda(dx)$, that is, $\pi(y|x) = 1$. Let \mathcal{F}_m^n denote the sub- σ -field of \mathcal{B} generated by ω_i , $n \leq i \leq m$. Suppose $B \in \mathcal{F}_{n-1}^0$. Setting $u(x) = 1$,

$$E^{P_1}\{R_{n,\omega}(B)|\hat{P}_n(\omega, \cdot) \in C\} = P^{\wedge n}\{B|\hat{P}_n(\omega, \cdot) \in C\},$$

where λ^n is the n th Cartesian power of $\lambda(dx)$ (cf. Lemma 4.3). Csiszár, Cover and Choi (1987), Theorem 1, show that for sequences of independent, identically distributed random variables on a finite set X , the joint distribution of $\omega_0, \omega_1, \dots, \omega_m$ under the condition $\hat{P}_n \in C$ converges to $(P^*)^m$ as $n \rightarrow \infty$, P^* the I -projection of λ on C . Thus the weak convergence established here in Section 3 is a generalization of this result to discrete parameter Markov processes on a compact state space.

We introduce the new definition *asymptotically quasi-Markov* as follows. A sequence of measures P_n on (X_0, \dots, X_{n-1}) , $n = 1, 2, \dots$, is said to be asymptotically quasi-Markov if there exists a stationary transition probability function $Q(dy|x)$ such that

$$(1.10) \quad \lim_{n \rightarrow \infty} \frac{1}{n} h(P_n, \overline{Q}_n) = 0,$$

where \overline{Q}_n is the probability measure on (X_0, \dots, X_{n-1}) defined by the transition probability function $Q(dy|x)$ with initial distribution given by the first marginal of P_n . In Lemma 4.4 a large deviations estimate is proved which establishes the asymptotic quasi-Markov property for certain sequences of measures. Suppose that the probability density function $u(x)$ is bounded from above. Then Theorem 4.5 establishes that the measures $R_{n,u}^C$ defined by (1.9) on $\prod_{i=0}^n(X_i, \mathcal{B}_i)$ give a sequence which is asymptotically quasi-Markov with respect to the transition probability function of P^* which is uniquely defined a.e. λ . When the sequence of measures P_n in the definition comes from the restriction of stationary processes R_n on Ω to $\prod_{i=0}^{n-1}(X_i, \mathcal{B}_i)$, as is the case with the measures $R_{n,u}^C$, the asymptotic quasi-Markov property with respect to the transition probability function $P^*(dy|x)$ is a stronger property than the weak convergence of R_n to P^* . The sense of this is made precise in Corollary 5.2.

Under the additional assumption that $u(x)$ is bounded away from 0, Corollary 5.3 shows that the conditional P_u distribution of X_0, \dots, X_{n-1} under the condition $\hat{P}_n(\omega, \cdot) \in C$ is asymptotically quasi-Markov with respect to the probability transition function $P^*(dy|x)$. This is a generalization of Csiszár's limit (1.4) for independent, identically distributed random variables

to Markov processes on a compact metric space. These conditional measures do not enjoy the same properties as the measures $R_{n,u}^C$ described above, so the implications of the asymptotic quasi-Markov property are less significant. However, one consequence is as follows. Let

$$(1.11) \quad P_n(\cdot) = P_u\{(\cdot)|\hat{P}_n(\omega, \cdot) \in C\}.$$

Let \overline{Q}_n be the Markov process with transition probability function $P^*(dy|x)$ and initial distribution given by the first marginal of P_n . Then if $B_n \in \mathcal{F}_{n-1}^0$,

$$\lim_{n \rightarrow \infty} P_n(B_n) = 0$$

if

$$\overline{Q}_n(B_n) \leq \exp(-\alpha n), \quad n = 1, 2, \dots,$$

for some $\alpha > 0$. This follows from (1.10) since (1.3) implies that

$$P_n(B_n) \log \frac{P_n(B_n)}{\overline{Q}_n(B_n)} + (1 - P_n(B_n)) \log \frac{1 - P_n(B_n)}{1 - \overline{Q}_n(B_n)} \leq h(P_n, \overline{Q}_n).$$

2. I-Projection of π onto C . Let C be a closed set of $\mathcal{M}(X)$. Let M_C be the subset of Λ_0 whose marginals are equal to an element of C . For $Q \in \Lambda_0$, define

$$h^1(Q|\pi) = h(Q, \overline{P}),$$

where \overline{P} is the measure $q(dx)\pi(dy|x)$, $q(dx)$ the marginal of Q . An I -projection P^* of π onto C is defined as an element of M_C for which

$$\inf_{Q \in M_C} h^1(Q|\pi) = h^1(P^*|\pi).$$

Donsker and Varadhan (1975), Lemma 2.1, show that for P and Q probability measures on a Polish space X with σ -field given by the Borel sets, then $h(Q, P)$ defined by (1.2) can alternatively be defined as

$$(2.1) \quad h(Q, P) = \sup_{\mu \in \mathcal{Q}_1} \left[\int_X \log u(x) Q(dx) - \log \int_X u(x) P(dx) \right],$$

where \mathcal{Q}_1 is the set of continuous functions on X for which there exist constants c_1 and c_2 such that $0 < c_1 \leq u(x) \leq c_2 < \infty$. In particular, for fixed P , $h(Q, P)$ is a lower semicontinuous function of Q in the weak topology on $\mathcal{M}(X)$ and for fixed Q , $h(Q, P)$ is a lower semicontinuous function of P .

LEMMA 2.1. *Under assumption 3 on $\pi(dy|x)$, $h^1(Q|\pi)$ is a lower semicontinuous, convex function of Q .*

PROOF. Let $q(dx)$ denote the marginal of Q . Then from (2.1),

$$h^1(Q|\pi) = \sup_{u \in \mathcal{Q}_1} \left[\int \int_{X \times X} \log u(x, y) Q(dx, dy) - \log \int \int_{X \times X} u(x, y) q(dx) \pi(dy|x) \right],$$

where \mathcal{U}_1 is the set of continuous functions $u(x, y) > 0$ on $X \times X$. For each $u \in \mathcal{U}_1$,

$$\int \int_{X \times X} \log u(x, y) Q(dx, dy) - \log \int \int_{X \times X} u(x, y) q(dx) \pi(dy|x)$$

is a continuous, convex function of Q . The lemma follows. \square

For C a closed set, M_C is a compact set of probability distributions on $X \times X$, and the existence of an I -projection of π onto M_C follows from Lemma 2.1. To relate an I -projection as defined above to $I(C)$ defined by (1.8) requires a result of Donsker and Varadhan (1976), Theorem 2.1. This and a further result of theirs that will be required [Donsker and Varadhan (1976), Lemma 2.5] are stated as the following theorem.

THEOREM 2.2. *Let (X, \mathcal{B}) be a Polish space with \mathcal{B} the σ -field of Borel sets. Let M_μ be the set of probability measures on $X \times X$ having both marginals μ . If $\pi(dy|x)$ is the transition probability function of a discrete parameter Markov process with (X, \mathcal{B}) as state space, then*

$$I(\mu) = \inf_{P \in M_\mu} h^1(P|\pi).$$

Suppose that $\pi(dy|x)$ satisfies assumption 3, so that there is a $P \in M_\mu$ for which the infimum is actually achieved. If there exists a reference measure λ on X such that $\pi(dy|x) = \pi(y|x)\lambda(dy)$, if $I(\mu) < \infty$ and $\pi(y|x) > 0$ a.e. $\mu \times \mu$, then there are measurable functions $a(x)$ and $b(y)$ such that

$$P(dx, dy) = \frac{a(x)}{b(y)} \pi(y|x) u(dx) \lambda(dy),$$

where $0 \leq a(x) < \infty$ a.e. μ and $0 < b(y)$ a.e. λ .

Now

$$\begin{aligned} \inf_{Q \in M_C} h^1(Q|\pi) &= \inf_{\mu \in C} \inf_{Q \in M_\mu} h^1(Q|\pi) \\ &= \inf_{\mu \in C} I(\mu) \\ &= I(C). \end{aligned}$$

For C a closed set, an I -projection P^* of π onto C is an element of M_C satisfying

$$I(C) = h^1(P^*|\pi).$$

The marginals of P^* minimize $I(\mu)$ for $\mu \in C$.

In this section we establish the following theorem.

THEOREM 2.3. *Let C be a closed convex set with nonempty interior C^0 . Suppose that $I(C^0) < \infty$. Then an I -projection of π onto C is unique. It is a measure P^* having probability density $P^*(x, y)$ with respect to $\lambda \times \lambda$ which is*

positive a.e. $\lambda \times \lambda$. Further, for any $Q \in M_C$,

$$h^1(Q|\pi) \geq h^1(Q|P^*(\cdot|\cdot)) + h^1(P^*|\pi).$$

For the proof of Theorem 2.3, we establish the following lemmas.

LEMMA 2.4. Let $Q \in M_C$. If $h^1(Q|\pi) < \infty$, then $Q(dx, dy) \ll \lambda \times \lambda$ and

$$h^1(Q|\pi) = \int \int_{X \times X} Q(x, y) \log \frac{Q(x, y)}{q(x)\pi(y|x)} \lambda(dx)\lambda(dy),$$

where $Q(x, y)$ is the density Q with respect to $\lambda \times \lambda$ and $q(x)$ is the density of q with respect to λ .

PROOF. Since $h^1(Q|\pi) < \infty$, it follows that $Q(dx, dy) \ll q(dx)\pi(y|x)\lambda(dy)$. Further from Theorem 2.2, $I(q) < \infty$. It can be shown [cf. the proof of Lemma 4.1 in Donsker and Varadhan (1975)] that $I(q) < \infty$ implies that $q \ll \lambda$. Then $Q(dx, dy) \ll \lambda \times \lambda$ and the rest of the lemma follows from (1.2). \square

LEMMA 2.5. Let C be a measurable set in $\mathcal{M}(X)$ such that C^0 is nonempty and $I(C^0) < \infty$. Then there is a measure Q in M_C with a positive density with respect to $\lambda \times \lambda$ satisfying $h^1(Q|\pi) < \infty$.

PROOF. Let $\mu \in C^0$ satisfy $I(\mu) < \infty$. Then $\mu \ll \lambda$. Let

$$\mu_n = (1 - 1/n)\mu + (1/n)\lambda.$$

Then $d\mu_n/d\lambda \geq 1/n$ λ -a.e. The sequence μ_n converges in variation to μ so for sufficiently large n , $\mu_n \in C^0$. Let $\bar{\mu}$ be such a μ_n and suppose $d\bar{\mu}/d\lambda = m(x) \geq \eta$. Let

$$m_n(x) = \frac{m(x) \wedge n}{\int_X [m(x) \wedge n] \lambda(dx)},$$

where n is chosen greater than or equal to η and so large that $\int_X [m(x) \wedge n] \lambda(dx) \geq 1/2$. Let $\bar{\mu}_n(dx) = m_n(x)\lambda(dx)$. Then $\bar{\mu}_n$ converges in variation to $\bar{\mu}$ so for sufficiently large n , $\bar{\mu}_n \in C^0$. By construction, $\eta \leq m_n(x) \leq 2n$. Let $\nu(dx)$ be such an element $\bar{\mu}_n$ and let $d\nu/d\lambda = u(x)$. Define $Q(dx, dy) = u(x)u(y)\lambda(dx)\lambda(dy)$. By the bounds on $u(x)$ and $\pi(y|x)$, it follows that

$$h^1(Q|\pi) = \int \int_{X \times X} u(x)u(y) \log \frac{u(y)}{\pi(y|x)} \lambda(dx)\lambda(dy) < \infty. \quad \square$$

LEMMA 2.6. Let C be a closed convex set with nonempty interior C^0 satisfying $I(C^0) < \infty$. Suppose $P^* \in M_C$ is such that

$$I(C) = h^1(P^*|\pi).$$

Then P^* has a density $P^*(x, y)$ with respect to $\lambda \times \lambda$ which is positive a.e. $\lambda \times \lambda$ and for any $Q \in M_C$,

$$h^1(Q|\pi) \geq h^1(Q|P^*(\cdot|\cdot)) + h^1(P^*|\pi).$$

PROOF. Suppose $P \in M_C$ satisfies $h^1(P|\pi) < \infty$. Consider $h^1(\varepsilon P + (1 - \varepsilon)P^*|\pi)$, $0 \leq \varepsilon \leq 1$. By the convexity of $h^1(Q|\pi)$ as a function of Q , this is a convex function of ε . Since $h^1(P^*|\pi) \leq h^1(\varepsilon P + (1 - \varepsilon)P^*|\pi)$, $h^1(\varepsilon P + (1 - \varepsilon)P^*|\pi)$ is a nondecreasing function of ε . Then

$$(2.2) \quad \lim_{\varepsilon \rightarrow 0} \frac{d}{d\varepsilon} h^1(\varepsilon P + (1 - \varepsilon)P^*|\pi) \geq 0,$$

provided the derivatives exist.

For $Q \in M_C$, let q denote its marginal. Then $I(q) \leq h^1(Q|\pi)$ so that if $h^1(Q|\pi)$ is finite, so is $I(q)$. It is an easy consequence of the bounds on $\pi(\cdot|\cdot)$ and (1.6) that

$$h(q, \lambda) - \log A \leq I(q) \leq h(q, \lambda) - \log a$$

[Donsker and Varadhan (1975), Lemma 2.8] so that if $I(q) < \infty$, $h(q, \lambda) < \infty$.

Writing $P_\varepsilon(x, y) = \varepsilon P(x, y) + (1 - \varepsilon)P^*(x, y)$ and using the same notation for the marginals,

$$(2.3) \quad \begin{aligned} h^1(\varepsilon P + (1 - \varepsilon)P^*|\pi) &= \iint_{X \times X} P_\varepsilon(x, y) \log \frac{P_\varepsilon(x, y)}{p_\varepsilon(x)\pi(y|x)} \lambda(dx)\lambda(dy) \\ &= \iint_{X \times X} P_\varepsilon(x, y) \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} \lambda(dx)\lambda(dy) \\ &\quad - \int_X p_\varepsilon(x) \log p_\varepsilon(x) \lambda(dx). \end{aligned}$$

Further, for $0 \leq \varepsilon \leq 1$,

$$(2.4)(i) \quad \iint_{X \times X} P_\varepsilon(x, y) \left| \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} \right| \lambda(dx)\lambda(dy) < \infty,$$

$$(2.4)(ii) \quad \int_X p_\varepsilon(x) |\log p_\varepsilon(x)| \lambda(dx) < \infty.$$

For each integral in (2.3) a derivative exists for $0 < \varepsilon < 1$. Consider the first integral. Here

$$\begin{aligned} \frac{d}{d\varepsilon} P_\varepsilon(x, y) \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} &= (P(x, y) - P^*(x, y)) \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} \\ &\quad + P(x, y) - P^*(x, y). \end{aligned}$$

Using the bounds

$$(2.5)(i) \quad \begin{aligned} \log^+ \frac{P_\varepsilon(x, y)}{\pi(y|x)} &= \log^+ \left[\varepsilon \frac{P(x, y)}{\pi(y|x)} + (1 - \varepsilon) \frac{P^*(x, y)}{\pi(y|x)} \right] \\ &\leq \log^+ \left[\frac{P(x, y)}{\pi(y|x)} + \frac{P^*(x, y)}{\pi(y|x)} \right] \\ &\leq \log 2 + \log^+ \left[\frac{P_{1/2}(x, y)}{\pi(y|x)} \right] \end{aligned}$$

and

$$\begin{aligned}
 \log^- \frac{P_\varepsilon(x, y)}{\pi(y|x)} &= \log^- \left[\varepsilon \frac{P(x, y)}{\pi(y|x)} + (1 - \varepsilon) \frac{P^*(x, y)}{\pi(y|x)} \right] \\
 (2.5)(ii) \quad &\leq \log^- \left[\min(\varepsilon, 1 - \varepsilon) \left(\frac{P(x, y)}{\pi(y|x)} + \frac{P^*(x, y)}{\pi(y|x)} \right) \right] \\
 &\leq \log^- (2 \min(\varepsilon, 1 - \varepsilon)) + \log^- \left[\frac{P_{1/2}(x, y)}{\pi(y|x)} \right]
 \end{aligned}$$

combined with (2.4)(i) shows by dominated convergence that the derivative can be taken inside the integral sign and is $L^1(\lambda \times \lambda)$. Thus

$$\begin{aligned}
 \frac{d}{d\varepsilon} \int \int_{X \times X} P_\varepsilon(x, y) \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} \lambda(dx) \lambda(dy) \\
 = \int \int_{X \times X} (P(x, y) - P^*(x, y)) \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} \lambda(dx) \lambda(dy).
 \end{aligned}$$

Arguing similarly with the second integral in (2.3) shows that

$$\begin{aligned}
 \frac{d}{d\varepsilon} h^1(\varepsilon P + (1 - \varepsilon) P^* | \pi) \\
 (2.6) \quad = \int \int_{X \times X} (P(x, y) - P^*(x, y)) \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} \lambda(dx) \lambda(dy) \\
 - \int_X (p(x) - p^*(x)) \log p_\varepsilon(x) \lambda(dx).
 \end{aligned}$$

Now using the bound (2.5)(i) and the bound

$$\begin{aligned}
 \log^- \frac{P_\varepsilon(x, y)}{\pi(y|x)} &\leq \log^- \left[(1 - \varepsilon) \frac{P^*(x, y)}{\pi(y|x)} \right] \\
 &\leq \log^- (1 - \varepsilon) + \log^- \left(\frac{P^*(x, y)}{\pi(y|x)} \right)
 \end{aligned}$$

shows by dominated convergence that

$$\begin{aligned}
 \lim_{\varepsilon \rightarrow 0} \int \int_{X \times X} P^*(x, y) \log \frac{P_\varepsilon(x, y)}{\pi(y|x)} \lambda(dx) \lambda(dy) \\
 = \int \int_{X \times X} P^*(x, y) \log \frac{P^*(x, y)}{\pi(y|x)} \lambda(dx) \lambda(dy).
 \end{aligned}$$

Similarly,

$$\lim_{\varepsilon \rightarrow 0} \int_X p^*(x) \log p_\varepsilon(x) \lambda(dx) = \int_X p^*(x) \log p^*(x) \lambda(dx).$$

It follows from (2.6) and (2.2) that

$$\begin{aligned} & \lim_{\varepsilon \rightarrow 0} \int \int_{X \times X} P(x, y) \log \frac{P_\varepsilon(x, y)}{p_\varepsilon(x) \pi(y|x)} \lambda(dx) \lambda(dy) \\ & \geq \int \int_{X \times X} P^*(x, y) \log \frac{P^*(x, y)}{p^*(x) \pi(y|x)} \lambda(dx) \lambda(dy). \end{aligned}$$

Rewriting the integral on the left-hand side as

$$\begin{aligned} & \int_{X \times X} P(x, y) \log \frac{P(x, y)}{p(x) \pi(y|x)} \lambda(dx) \lambda(dy) \\ & - \int \int_{X \times X} P(x, y) \log \frac{P(x, y)}{p(x) P_\varepsilon(y|x)} \lambda(dx) \lambda(dy) \end{aligned}$$

shows that

$$\begin{aligned} (2.7) \quad & \lim_{\varepsilon \rightarrow 0} \int_{X \times X} P(x, y) \log \frac{P(x, y)}{p(x) P_\varepsilon(y|x)} \lambda(dx) \lambda(dy) \\ & \leq h^1(P|\pi) - h^1(P^*|\pi). \end{aligned}$$

We can write the integral on the left-hand side of (2.7) as

$$\int_X p(x) \lambda(dx) h(P(dy|x), P_\varepsilon(dy|x)),$$

where $P_\varepsilon(dy|x) = P_\varepsilon(y|x) \lambda(dy)$. Clearly $h(P(dy|x), P_\varepsilon(dy|x))$ is defined for $p(dx)$ a.e. x .

By Fatou's lemma,

$$\begin{aligned} (2.8) \quad & \int_X p(x) \lambda(dx) \liminf_{\varepsilon \rightarrow 0} (h(P(dy|x), P_\varepsilon(dy|x))) \\ & \leq \lim_{\varepsilon \rightarrow 0} \int \int_{X \times X} P(x, y) \log \frac{P(x, y)}{p(x) P_\varepsilon(y|x)} \lambda(dx) \lambda(dy). \end{aligned}$$

Now on the set of $p(dx)$ measure 1 where $P_\varepsilon(dy|x)$ is defined, we see that as $\varepsilon \rightarrow 0$, $P_\varepsilon(dy|x)$ converges in variation to $P^*(dy|x)$ when $p^*(x) > 0$ and $P_\varepsilon(dy|x)$ is $P(dy|x)$ when $p^*(x) = 0$. By the lower semicontinuity of $h(Q, P)$ as a function of P for fixed Q , it follows that

$$\begin{aligned} (2.9) \quad & h\left(P(dy|x), \lim_{\varepsilon \rightarrow 0} P_\varepsilon(dy|x)\right) \\ & = \begin{cases} h(P(dy|x), P^*(dy|x)), & p^*(x) > 0, \\ h(P(dy|x), P(dy|x)) = 0, & p^*(x) = 0, \end{cases} \\ & \leq \liminf_{\varepsilon \rightarrow 0} (h(P(dy|x), P_\varepsilon(dy|x))). \end{aligned}$$

Let E be the set in X , where $p^*(x) > 0$. In view of (2.7) and (2.8) it follows that $P(dy|x) \ll P^*(dy|x)$ for $p(dx)$ a.e. x in E . Since by Lemma 2.5 there is a

Q in M_C with a positive density with respect to $\lambda \times \lambda$ satisfying $h^1(Q|\pi) < \infty$, it follows that $P^*(y|x) > 0$ for $\lambda \times \lambda$ a.e. (x, y) in $E \times X$. Then $\int_E P^*(x)P^*(y|x)\lambda(dx) = p^*(y)$ for λ -a.e. y so that $p^*(y) > 0$ for λ -a.e. y . It follows that $E = X/N$ where N is a $\lambda(dx)$ null set. This establishes the positivity of $P^*(x, y)$ a.e. $\lambda \times \lambda$.

To conclude the proof of Lemma 2.6, it follows from (2.7), (2.8) and (2.9) that

$$h^1(P|P^*(\cdot|\cdot)) \leq h^1(P|\pi) - h^1(P^*|\pi)$$

or

$$(2.10) \quad h^1(P|\pi) \geq h^1(P|P^*(\cdot|\cdot)) + h^1(P^*|\pi)$$

for $P \in M_C$ satisfying $h^1(P|\pi) < \infty$. For the general case, $P^*(dy|x)$ is only defined λ -a.e. x . Extend it arbitrarily to make it a transition probability satisfying $P^*(dy|x) = P^*(y|x)\lambda(dy)$. Then $h^1(P|P^*(\cdot|\cdot)) < \infty$ for $P \in M_C$ implies the marginal p of P satisfies $p \ll \lambda$ so $h^1(P|P^*(\cdot|\cdot))$ is well defined. Since (2.10) is obviously true if $h^1(P|\pi) = \infty$, the lemma is established. \square

COROLLARY 2.7. *Let C and P^* be as in Lemma 2.4. Then an I -projection P^* of π onto C is unique.*

PROOF. Suppose that P_1^* and P_2^* both satisfy

$$I(C) = h^1(P_1^*|\pi) = h^1(P_2^*|\pi).$$

It follows from (2.10) that

$$h^1(P_2^*|\pi) \geq h^1(P_2^*|P_1^*(\cdot|\cdot)) + h^1(P_1^*|\pi).$$

Then $h^1(P_2^*|P_1^*(\cdot|\cdot)) = 0$ or $h^1(P_1^*|\pi)$ would be strictly less than $h^1(P_2^*|\pi)$. Since

$$h^1(P_2^*|P_1^*(\cdot|\cdot)) = \int_X p_2^*(dx) \int P_2^*(dy|x) \log \frac{P_2^*(y|x)}{P_1^*(y|x)},$$

it follows, using the fact that $p_2^*(x) > 0$ a.e. $\lambda(dx)$ that

$$(2.11) \quad P_2^*(dy|x) = P_1^*(dy|x), \quad \lambda \text{ a.e. } x.$$

Extend $P_1^*(dy|x)$ arbitrarily to make it a transition probability satisfying $P_1^*(dy|x) = P_1^*(y|x)\lambda(dy)$. Let I^* be the I -function with transition probability $P_1^*(dy|x)$. Then from Theorem 2.2,

$$I^*(p_2^*) \leq h^1(P_1^*|P_1^*(\cdot|\cdot)) = 0,$$

so that $p_2^*(dx)$ is an invariant measure for the transition probability $P_1^*(dy|x)$ [Donsker and Varadhan (1975), Lemma 4.1]. P_1^* defines a stationary Markov process on (Ω, \mathcal{B}) with transition probability function $P_1^*(dy|x)$ and invariant measure $p_1^*(dx)$. Using the positivity of $P_1^*(y|x)$ $\lambda \times \lambda$ -a.e., the P_1^* process is ergodic. Then the ergodic theorem and the positivity of $p_1^*(x)$ a.e. λ ensure that the transition probability function $P^*(dy|x)$ has a unique invariant

measure [Harris (1956), Theorem 1]. Then $p_1^*(dx) = p_2^*(dx)$ which in view of (2.11) implies $P_1^* = P_2^*$. \square

COROLLARY 2.8. *Let P^* be the I-projection of π onto C as above. Then $P^*(dy|x)$ can be chosen to have the following property: There is a function $b(y)$, $0 < b(y) < \infty$ λ -a.e. y such that if $h(y) \in L^1(1/b(y)\lambda(dy))$, then*

$$(2.12) \quad \int_X P^*(dy|x)h(y)$$

is a continuous function of x .

PROOF. It follows from Theorem 2.2 and Lemma 2.6 that there are measurable functions $a(x)$ and $b(y)$ such that

$$P(x, y) = p(x) \frac{a(x)}{b(y)} \pi(y|x) \quad \text{a.e. } \lambda \times \lambda,$$

where $0 < a(x) < \infty$ a.e. $\lambda(dx)$ and $0 < b(y) < \infty$ a.e. $\lambda(dy)$. Then

$$a(x)p(x) \int_X \frac{\pi(y|x)}{b(y)} \lambda(dy) = p(x) \quad \text{a.e. } \lambda(dx).$$

Since $p(x) > 0$ a.e. $\lambda(dx)$,

$$\int \frac{\pi(y|x)}{b(y)} \lambda(dy) = \frac{1}{a(x)} \quad \text{a.e. } \lambda(dx).$$

By altering $a(x)$ on a set of measure 0, it is possible to assume that this equation holds for all x . Since $a \leq \pi(y|x)$ for all x and λ -a.e. y and since $P(x, y) \in L^1(\lambda \times \lambda)$, it follows from Fubini's theorem that $1/b(y) \in L^1(\lambda(dy))$. It then follows from assumption 3 on $\pi(y|x)$ that $a(x)$ is continuous. Now define

$$P^*(y|x) = \frac{a(x)}{b(y)} \pi(y|x).$$

Then if $h(y) \in L^1(1/b(y)\lambda(dy))$,

$$\int_X P^*(dy|x)h(y) = a(x) \int_X \pi(y|x)h(y) \frac{1}{b(y)} \lambda(dy).$$

Again using assumption 3 on $\pi(y|x)$, this is a continuous function of x . \square

Consider a somewhat stronger continuity assumption on $\pi(dy|x)$ than assumption 3:

4. $\pi(y|x)$ as a map from $x \rightarrow L_1(\lambda)$ is continuous.

Under assumption 4, Theorem 2.9 sharpens the results of Corollary 2.8 in a case of interest. It is a partial generalization of an example of Csiszár, Cover and Choi (1987), as explained in Section 1.

THEOREM 2.9. *Let $C = \{\mu \in \mathcal{M}(X) : \int_X f_i d\mu \geq \gamma_i, i = 1, \dots, n\}$ for continuous, real-valued functions f_1, f_2, \dots, f_n on X . Suppose there is some $\mu \in C$ satisfying*

$$(2.13) \quad \begin{aligned} (a) \quad & \int_X f_i d\mu > \gamma_i \quad i = 1, \dots, n, \\ (b) \quad & I(\mu) < \infty. \end{aligned}$$

Assume the transition probability density $\pi(y|x)$ satisfies assumption 4.

Let \mathbb{R}_n^+ denote $\{\zeta \in \mathbb{R}^n, \zeta_i \geq 0, i = 1, \dots, n\}$. Let T_ζ be the mapping of the set of continuous functions on $X, C(X)$, onto itself given by

$$T_\zeta g(x) = e^{\sum_{i=1}^n \zeta_i f_i(x)} \int_X g(y) \pi(y|x) \lambda(dy).$$

Let V_ζ be the unique positive eigenvector for T_ζ and let $\psi_\zeta \in L^1(\lambda)$ be the unique almost everywhere positive eigenvector for T_ζ^ , the adjoint of T_ζ , corresponding to the same positive eigenvalue ρ_ζ , which is greatest in modulus of all the eigenvalues of T_ζ . Assume V_ζ and ψ_ζ have been normalized so that*

$$(2.14) \quad \int_X V_\zeta(x) \psi_\zeta(x) \lambda(dx) = 1.$$

Then

$$(2.15) \quad I(C) = \max_{\zeta \in \mathbb{R}_n^+} \left(\sum_{i=1}^n \zeta_i \gamma_i - \log \rho_\zeta \right)$$

and

$$P^*(x, y) = (V_\zeta(y) \pi(y|x) e^{\sum_{i=1}^n \zeta_i f_i(x)} \psi_\zeta(x)) / \rho_\zeta$$

for ζ attaining the maximum in (2.15). Further $I(C) = I(C^0)$, so the analog of the Sanov property holds.

Given that $\pi(y|x)$ is a transition probability density, assumption 4 is a necessary and sufficient condition for T_ζ to be a compact operator [Edwards (1965), Proposition 9.5.17]. The lower bound (assumption 2) on $\pi(y|x)$ and the continuity of $f_i, i = 1, \dots, n$, ensure that T_ζ is a strongly positive operator, so a theorem of Krein and Rutman (1948), Theorem 6.3, proves the existence of V_ζ, ψ_ζ and ρ_ζ as in the statement of the theorem.

The set C described in the theorem is weakly closed and convex. Any measure μ satisfying (2.13)(a) is an element of the interior C^0 . In particular, the hypotheses of Theorem 2.3 are satisfied, so an I -projection of π onto C exists and is unique. To see $I(C^0) = I(C)$, suppose μ satisfies (2.13)(a) and (b) and let ν_1 be any element of C . Then $\nu_\alpha = (1 - \alpha)\mu + \alpha\nu_1 \in C^0$ and by convexity,

$$\begin{aligned} \limsup_{\alpha \rightarrow 1} I(\nu_\alpha) &\leq \limsup_{\alpha \rightarrow 1} [(1 - \alpha)I(\mu) + \alpha I(\nu_1)] \\ &= I(\nu_1). \end{aligned}$$

The remainder of the theorem is proved in a sequence of four lemmas.

LEMMA 2.10. *Let P^* be the unique I-projection of π onto C . Then*

$$(2.16) \quad I(C) = h^1(P^*|\pi) = \inf_{Q \in M_C} h(Q, p^*(dx)\pi(dy|x)),$$

where p^* is the marginal distribution of P^* .

PROOF. Equation (2.16) means that P^* is the I-projection onto M_C of the two-dimensional measure $p^*(dx)\pi(dy|x)$ as defined by Csiszár (1975). To establish (2.16), suppose $Q \in M_C$ satisfies $h(Q, p^*(dx)\pi(dy|x)) < \infty$. Equation (2.1) implies the one-dimensional divergence $h(q, p^*) < \infty$ for the marginal q of Q . From (1.2) there follows

$$h(Q, p^*(dx)\pi(dy|x)) = h^1(Q|\pi) + h(q, p^*).$$

From (2.10),

$$h(Q|\pi) \geq h^1(Q|P^*(\cdot|\cdot)) + h^1(P^*|\pi).$$

Adding $h(q, p^*)$ to both sides and using $h(Q, P^*) = h^1(Q|P^*(\cdot|\cdot)) + h(q, p^*)$ shows

$$\begin{aligned} h(Q, p^*(dx)\pi(dy|x)) &\geq h(Q, P^*) + h^1(P^*|\pi) \\ &\geq h(Q, P^*) + \inf_{Q \in M_C} h(Q, p^*(dx)\pi(dy|x)). \end{aligned}$$

This last equation determines P^* as the unique I-projection of $p^*(dx)\pi(dy|x)$ onto M_C [Csiszár (1975), Theorem 2.2]. \square

LEMMA 2.11. *Let $f_i(x), i = 1, 2, \dots, n$, be real-valued measurable functions on a measure space $(X, \mathcal{B}, \lambda)$. Then the convex cone $K = \sum_{i=1}^n \alpha_i f_i(x), \alpha_i \geq 0$, is closed in the topology of pointwise sequential convergence on the space of real-valued measurable functions.*

PROOF. First suppose that the functions $f_i(x), i = 1, 2, \dots, n$, are linearly independent λ -a.e. Suppose there exists a sequence $\sum_{i=1}^n \alpha_{m_i} f_i(x)$ converging pointwise λ -a.e. to a real-valued function $g(x)$. Let c_{m_i} be the sequence

$$\begin{aligned} (\alpha_{1_i} - \alpha_{2_i}, \alpha_{1_i} - \alpha_{3_i}, \alpha_{1_i} - \alpha_{4_i}, \dots, \alpha_{2_i} - \alpha_{3_i}, \alpha_{2_i} - \alpha_{4_i}, \dots, \\ \alpha_{n_i} - \alpha_{n+1_i}, \alpha_{n_i} - \alpha_{n+2_i}, \dots). \end{aligned}$$

Then $\lim_{m \rightarrow \infty} \sum_{i=1}^n c_{m_i} f_i(x) = 0$. Let

$$(2.17) \quad c'_{m_i} = c_{m_i} / \max(|c_{m_1}|, |c_{m_2}|, \dots, |c_{m_n}|, 1).$$

Then $\lim_{m \rightarrow \infty} \sum_{i=1}^n c'_{m_i} f_i(x) = 0$ and $|c'_{m_i}| \leq 1$ for $i = 1, \dots, n$. However, any subsequential limit of the vector-valued sequence $\{c'_m\}$ is 0 from the linear independence of the functions $f_i(x), i = 1, \dots, n, \lambda$ -a.e. It follows that the sequence $\{c'_m\}$ converges to 0. From the definition (2.17), it follows that the sequence $\{c_m\}$ converges to 0. But then $\{\alpha_{m_i}\}$ is Cauchy for each $i = 1, \dots, n$, which concludes the proof in this case.

For the general case, suppose that k is the dimension of the real linear subspace spanned by $\{f_i\}_{i=1}^n$. Then any element h of the convex cone K can be

written as a nonnegative linear combination of some subcollection of k linearly independent functions of $\{f_1, f_2, \dots, f_n\}$. This follows exactly as in the proof of Carathéodory's theorem [Rockafellar (1970), Theorem 17.1]. Thus K is a finite union of sets each of which is closed in the topology of pointwise sequential convergence. \square

LEMMA 2.12. *Let V_ζ, ψ_ζ and ρ_ζ be defined as in the statement of Theorem 2.9. Then the I -projection P^* of π onto C has density*

$$P^*(x, y) = (V_\zeta(y)\pi(y|x)e^{\sum_{i=1}^{\zeta} f_i(x)}\psi_\zeta(x))/\rho_\zeta$$

with respect to $\lambda \times \lambda$ for some $\zeta \in \mathbb{R}_n^+$.

PROOF. Lemma 2.10 shows that P^* is the I -projection on $p^*(dx)\pi(dy|x)$ onto M_C . Let $\{g_k\}_{k=1}^\infty$ be a countable dense collection of continuous functions on X . Then M_C can be described as the set of all measures on $X \times X$:

$$\left\{ P: \int \int_{X \times X} f dP \geq 0, f \in \mathcal{F} \right\},$$

where \mathcal{F} is the convex cone generated by nonnegative finite linear combinations of

$$\{h_j(x, y)\} = \{f_i(x) - \gamma_i\}_{i=1}^n \cup \{\pm(g_k(x) - g_k(y))\}_{k=1}^\infty.$$

It now follows from Csiszár (1984), Lemma 3.4, that $\log(P^*(y|x)/\pi(y|x)) - I(C)$ belongs to the $L^1(P^*)$ -closure of \mathcal{F} . Since $P^* \sim \lambda \times \lambda$, there exist functions

$$\sum_{i=1}^n \alpha_{m_i}(f_i(x) - \gamma_i) + \sum_{k=1}^{M_m} \beta_{m_k}(g_k(x) - g_k(y)),$$

$\alpha_{m_i} \geq 0$ and $\beta_{m_k} \in \mathbb{R}$ which converge in $\lambda \times \lambda$ measure to $\log P^*(y|x)/\pi(y|x) - I(C)$. It follows from Donsker and Varadhan (1975), Lemma 2.3, that there is a subsequence (\bar{m}) and a sequence of constants $(a_{\bar{m}})$ so that

$$(2.18)(i) \quad \lim_{\bar{m} \rightarrow \infty} \left(\sum_{i=1}^n \alpha_{\bar{m}_i}(f_i(x) - \gamma_i) + \sum_{k=1}^{M_{\bar{m}}} \beta_{\bar{m}_k} g_k(x) - a_{\bar{m}} \right) = f(x)$$

exists for λ -a.e. x and

$$(2.18)(ii) \quad \lim_{\bar{m} \rightarrow \infty} \left(- \sum_{k=1}^{M_{\bar{m}}} \beta_{\bar{m}_k} g_k(y) + a_{\bar{m}} \right) = g(y)$$

exists for λ -a.e. y and $\log(P^*(y|x)/\pi(y|x)) - I(C) = f(x) + g(y)$ for $\lambda \times \lambda$ -a.e. (x, y) . Comparing (2.18)(i) and (2.18)(ii), it follows that for λ -a.e. x ,

$$\lim_{\bar{m} \rightarrow \infty} \sum_{i=1}^n \alpha_{\bar{m}_i}(f_i(x) - \gamma_i) = f(x) + g(x).$$

In view of Lemma 2.11, there exist constants $\zeta_i, i = 1, \dots, n, \zeta_i \geq 0$ such that

$$\sum_{i=1}^n \zeta_i (f_i(x) - \gamma_i) = f(x) + g(x), \quad \lambda\text{-a.e.}$$

Thus the conditional density satisfies

$$P^*(y|x) = e^{I(C)} e^{\sum_{i=1}^n \zeta_i (f_i(x) - \gamma_i)} e^{-g(x)} e^{g(y)} \pi(y|x), \quad \lambda \times \lambda\text{-a.e.}$$

Since $P^*(y|x)$ is a transition probability density function, there follows

$$\begin{aligned} e^{\sum_{i=1}^n \zeta_i f_i(x)} \int_X e^{g(y)} \pi(y|x) \lambda(dy) \\ = e^{-I(C)} e^{\sum_{i=1}^n \zeta_i \gamma_i} e^{g(x)}, \quad \lambda\text{-a.e.} \end{aligned}$$

Redefine $g(x)$ on a set of measure 0 so that the equation is valid for all x . Using assumption 3 on $\pi(y|x)$, $g(x)$ is continuous. Then $e^{g(x)}$ is the unique positive eigenvector for T_ζ^* with positive eigenvalue

$$(2.19) \quad \rho_\zeta = \exp\left(\sum_{i=1}^n \zeta_i \gamma_i - I(C)\right).$$

By definition of $P^* \in M_C$, the I -projection P^* has identical marginals. Letting $p^*(x)$ be the density of the marginal with respect to λ , there follows

$$\begin{aligned} \int p^*(x) e^{-g(x)} e^{\sum_{i=1}^n \zeta_i f_i(x)} \pi(y|x) \lambda(dx) \\ = e^{-I(C)} e^{\sum_{i=1}^n \zeta_i \gamma_i} p^*(y) e^{-g(y)}. \end{aligned}$$

Then $p^*(y) e^{-g(y)} \in L^1(\lambda)$ is the unique positive eigenvector for T_ζ^* corresponding to the same eigenvalue. Since the product $V_\zeta(x) \psi_\zeta(x) = p^*(x)$, (2.14) holds. The conclusion of the lemma follows. \square

LEMMA 2.13. Under the assumption of Theorem 2.9,

$$I(C) = \max_{\zeta \in \mathbb{R}_n^+} \left(\sum_{i=1}^n \zeta_i \gamma_i - \log \rho_\zeta \right),$$

where ρ_ζ is the (positive) eigenvalue of greatest modulus for the operator T_ζ .

PROOF. For any vector $\zeta \in \mathbb{R}_n^+$, let

$$P_\zeta(x, y) = (V_\zeta(y) \pi(y|x) e^{\sum_{i=1}^n \zeta_i f_i(x)} \psi_\zeta(x)) / \rho_\zeta,$$

where V_ζ, ψ_ζ and ρ_ζ are as defined in Theorem 2.9. From Lemma 2.12, the I -projection P^* of π onto C has $\lambda \times \lambda$ density $P^*(x, y) = P_{\zeta^*}(x, y)$ for some $\zeta^* \in \mathbb{R}_n^+$. It follows from (2.19) that

$$(2.20) \quad I(C) = \sum_{i=1}^n \zeta_i^* \gamma_i - \log \rho_{\zeta^*}.$$

Let $\Lambda = \{P' \in \Lambda_0, P' \sim \lambda \times \lambda\}$. Arguing exactly as in the proof of Corollary 2.7, (2.10) for all $Q \in M_C$ uniquely determines P^* among the set of $P' \in \Lambda$.

Thus if $P' \in \Lambda$, $P' \neq P^*$, there exists some $Q \in M_C$, $h^1(Q|\pi) < \infty$ such that

$$h^1(Q|\pi) < h^1(Q|P'(\cdot|\cdot)) + I(C).$$

From Lemma 2.4 it follows that

$$I(C) > \int \int_{X \times X} Q(x, y) \log \frac{P'(y|x)}{\pi(y|x)} \lambda(dx) \lambda(dy).$$

Let \tilde{M}_C denote the set of $Q \in M_C$ satisfying $h^1(Q|\pi) < \infty$. The argument above and (2.10) imply that for any $P' \in \Lambda$,

$$I(C) \geq \inf_{Q \in \tilde{M}_C} \int \int_{X \times X} Q(x, y) \log \frac{P'(y|x)}{\pi(y|x)} \lambda(dx) \lambda(dy),$$

with strict inequality if $P' \neq P^*$. Applying this to $P' \in \Lambda$ with density P_ζ , observing that the marginal of P_ζ is

$$p_\zeta(dx) = \psi_\zeta(x) V_\zeta(x) \lambda(dx),$$

one obtains

$$\begin{aligned} I(C) &\geq \inf_{Q \in \tilde{M}_C} \int \int_{X \times X} Q(x, y) \log \frac{V_\zeta(y) e^{\sum_{i=1}^n \zeta_i f_i(x)}}{V_\zeta(x) \rho_\zeta} \\ (2.21) \quad &= \inf_{Q \in \tilde{M}_C} \left(\int \int_{X \times X} Q(x, y) \sum_{i=1}^n \zeta_i f_i(x) - \log \rho_\zeta \right) \\ &\geq \left(\sum_{i=1}^n \zeta_i \gamma_i - \log \rho_\zeta \right) \quad \text{for } \zeta \in \mathbb{R}_n^+, \end{aligned}$$

where the inequality is strict if $\zeta \neq \zeta^*$. The conclusion of the lemma follows from (2.20) and (2.21). \square

3. Convergence of $R_{n,\omega}$ in conditional probability. Let (Ω, \mathcal{B}) be as in Section 1. Let $h_{\mathcal{F}_m^n}(\cdot, \cdot)$ denote the entropy when the supremum in (2.1) is taken over positive functions $u(x) \in C(\Omega)$, the continuous functions on Ω , which depend only on the coordinates ω_i , $n \leq i \leq m$.

Let P be a measure on \mathcal{F}_∞^s with $s \leq t$. Suppose $P\{\omega: \omega(t) = \bar{\omega}(t)\} = 1$. Define a measure $\delta_{\bar{\omega}} \otimes_t P$ on Ω by

$$\begin{aligned} (\delta_{\bar{\omega}} \otimes_t P)\{\omega(t_1) \in A_1, \omega(t_2) \in A_2, \dots, \omega(t_n) \in A_n\} \\ = \chi_{A_1}(\bar{\omega}(t_1)) \chi_{A_2}(\bar{\omega}(t_2)) \cdots \chi_{A_k}(\bar{\omega}(t_k)) \\ \times P\{\omega(t_{k+1}) \in A_{k+1}, \dots, \omega(t_n) \in A_n\}, \end{aligned}$$

where $t_1 < t_2 < \cdots < t_k \leq t \leq t_{k+1} < \cdots < t_n$. Suppose $\pi(dy|x)$ is a transition probability function giving rise to a Markov process P_x on Ω_x . For $\omega \in \Omega$, let $P_\omega = \delta_\omega \otimes_0 P_{\omega(0)}$ and define a measure \hat{Q} on Ω by

$$(3.1) \quad \hat{Q} = \int_\Omega P_\omega Q(d\omega).$$

For $Q \in M_S(\Omega)$ define the entropy of Q with respect to π by

$$H(Q|\pi) = h_{\mathcal{F}_1^\infty}(Q, \hat{Q}).$$

By (2.1),

$$(3.2) \quad H(Q|\pi) = \sup_{u \in \mathcal{U}} \left[\int_{\Omega} \log u(\omega) Q(d\omega) - \log \int_{\Omega} u(\omega) \hat{Q}(d\omega) \right],$$

where \mathcal{U} is the set of positive continuous functions which only depend on ω_i , $i \leq 1$. By (3.1),

$$\int_{\Omega} u(\omega) \hat{Q}(d\omega) = \int_{\Omega} E^{P^\omega}(u) Q(d\omega).$$

Under assumption 3 on the probability transition function $\pi(dy|x)$, $\omega \rightarrow E^{P^\omega}(u)$ is a continuous function for $u \in \mathcal{U}$. Then the expression in brackets in (3.2) is a continuous function of Q . It follows that $H(Q|\pi)$ is lower semicontinuous.

These definitions are required for the proof of the following lemma.

LEMMA 3.1. *Let C be a closed convex set in $\mathcal{M}(X)$ satisfying $I(C) = I(C^0) < \infty$. Let P^* be the I-projection of π onto C considered as a stationary process on (Ω, \mathcal{B}) . Then in terms of the metric for the weak topology on $M_S(\Omega)$, $R_{n,\omega}$ converges to P^* in conditional P_x -probability given $\hat{P}_n(\omega, \cdot) \in C$, uniformly for $x \in X$.*

PROOF. It follows from (1.5), (1.7) and the assumption that $I(C) = I(C^0) < \infty$ that

$$(3.3) \quad \lim_{n \rightarrow \infty} \frac{1}{n} \log P_x \{ \hat{P}_n(\omega, \cdot) \in C \} = -I(C),$$

uniformly for $x \in X$. Let Π_C be the set of $Q \in M_S(\Omega)$ with marginals in C . Then $\hat{P}_n(\omega, \cdot) \in C$ is equivalent to $R_{n,\omega} \in \Pi_C$.

Since (Ω, \mathcal{B}) is a Polish space, the weak topology on the set of probability measures on Ω is metrizable. Let $\Delta(\cdot, \cdot)$ denote this metric. Define

$$\Pi_C^\varepsilon = \{ Q \in \Pi_C : \Delta(Q, P^*) \geq \varepsilon \}.$$

Π_C and Π_C^ε are closed sets of $M_S(\Omega)$, which is compact, so both Π_C and Π_C^ε are compact. Under assumption 3 the methods of Donsker and Varadhan (1983) show that

$$(3.4) \quad \limsup_{n \rightarrow \infty} \frac{1}{n} \log \sup_{x \in X} P_x \{ R_{n,\omega} \in \Pi_C^\varepsilon \} \leq - \inf_{Q \in \Pi_C^\varepsilon} H(Q|\pi).$$

A proof of (3.4) is given in the Appendix, Theorem A.1.

$H(Q|\pi)$ is lower-semicontinuous in Q so that both $H(\Pi_C|\pi) = \inf_{Q \in \Pi_C} H(Q|\pi)$ and $H(\Pi_C^\varepsilon|\pi) = \inf_{Q \in \Pi_C^\varepsilon} H(Q|\pi)$ are achieved. Using the contraction principle of Donsker and Varadhan (1983), Theorem 6.1,

$$\begin{aligned} H(\Pi_C|\pi) &= \inf_{\mu \in C} \inf_{\{Q: q(Q)=\mu\}} H(Q|\pi) \\ &= \inf_{\mu \in C} I(\mu) = I(C), \end{aligned}$$

where $q(Q)$ denotes the marginal of Q . Thus $H(\Pi_C|\pi)$ is achieved by P^* . We will show in Lemma 3.3 that P^* is the unique minimum. Then for any $\varepsilon > 0$, $H(\Pi_C^\varepsilon|\pi) > H(\Pi_C|\pi)$. Fix ε and pick ε^1 such that $2\varepsilon^1 < H(\Pi_C^\varepsilon|\pi) - H(\Pi_C|\pi)$. It follows from (3.3) and (3.4) that $\exists N$ such that for $n \geq N$ and every $x \in X$,

$$\begin{aligned} P_x\{\Delta(R_{n,\omega}, P^*) \geq \varepsilon | \hat{P}_n(\omega, \cdot) \in C\} \\ &= \frac{P_x\{R_{n,\omega} \in \Pi_C^\varepsilon\}}{P_x\{\hat{P}_n(\omega, \cdot) \in C\}} \\ &\leq \frac{e^{-n(H(\Pi_C^\varepsilon|\pi) - \varepsilon^1)}}{e^{-n(H(\Pi_C|\pi) + \varepsilon^1)}} \\ &= e^{-n(H(\Pi_C^\varepsilon|\pi) - H(\Pi_C|\pi) - 2\varepsilon^1)}, \end{aligned}$$

so that

$$\lim_{n \rightarrow \infty} P_x\{\Delta(R_{n,\omega}, P^*) \geq \varepsilon | \hat{P}_n(\omega, \cdot) \in C\} = 0, \quad \text{uniformly in } x,$$

which establishes the theorem. \square

THEOREM 3.2. *The stationary processes defined by*

$$R_{n,x}^C(\cdot) = E^{P_x}\{R_{n,\omega}(\cdot) | \hat{P}_n(\omega, \cdot) \in C\}$$

converge weakly to P^ for all $x \in X$.*

PROOF. For any $f \in C(\Omega)$, it follows as in Theorem 3.1 that

$$(3.5) \quad \lim_{n \rightarrow \infty} P_x\left\{\left|\int f dR_{n,\omega} - \int f dP^*\right| \geq \varepsilon | P_n(\omega, \cdot) \in C\right\} = 0,$$

uniformly for $x \in X$.

Now for any $f \in L^1(R_{n,x}^C)$,

$$\int_{\Omega} f dR_{n,x}^C = E^{P_x}\left\{\int f dR_{n,\omega} | \hat{P}_n(\omega, \cdot) \in C\right\}.$$

Then for $f \in C(\Omega)$,

$$\begin{aligned} & \left| \int_{\Omega} f dR_{n,x}^C - \int_{\Omega} f dP^* \right| \\ & \leq E^{P_x} \left\{ \left| \int_{\Omega} f dR_{n,\omega} - \int_{\Omega} f dP^* \right| \mid \hat{P}_n(\omega, \cdot) \in C \right\} \\ & < 2|f|P_x \left\{ \left| \int_{\Omega} f dR_{n,\omega} - \int_{\Omega} f dP^* \right| \geq \varepsilon \mid \hat{P}_n(\omega, \cdot) \in C \right\} \\ & \quad + \varepsilon \left(P_x \left\{ \left| \int_{\Omega} f dR_{n,\omega} - \int_{\Omega} f dP^* \right| < \varepsilon \mid \hat{P}_n(\omega, \cdot) \in C \right\} \right), \end{aligned}$$

so by (3.5),

$$\lim_{n \rightarrow \infty} \left| \int_{\Omega} f dR_{n,x}^C - \int_{\Omega} f dP^* \right| \leq \varepsilon.$$

Since ε is arbitrary, the weak convergence of $R_{n,x}^C$ to P^* is established.

To complete the proof of Lemma 3.1, we establish the following lemma.

LEMMA 3.3. *Let P^* , Π_C and $H(Q|\pi)$ be as in the proof of Theorem 3.1. Then*

$$H(\Pi_C|\pi) = \inf_{Q \in \Pi_C} H(Q|\pi)$$

is attained uniquely by P^ .*

PROOF. Suppose that $Q \in \Pi_C$ achieves the above infimum, which, by assumption, is finite. Let \hat{Q} be as defined by (3.1). Then $Q \ll \hat{Q}$. Denote by \hat{Q}_1^0 the restriction of \hat{Q} to \mathcal{F}_1^0 . Let $\hat{Q}_{1,\omega}^0$ be the regular conditional probability distribution of \hat{Q} given \mathcal{F}_1^0 . Then $E^{\hat{Q}_{1,\omega}^0}[dQ/d\hat{Q}]$ is a version of $dQ_1^0/d\hat{Q}_1^0$. It follows that

$$\begin{aligned} I(C) & \leq h^1(Q_1^0|\pi) \\ & = \int E^{\hat{Q}_{1,\omega}^0} \left[\frac{dQ}{d\hat{Q}} \right] \log E^{\hat{Q}_{1,\omega}^0} \left[\frac{dQ}{d\hat{Q}} \right] d\hat{Q}_1^0(\omega) \\ & \leq \int E^{\hat{Q}_{1,\omega}^0} \left[\frac{dQ}{d\hat{Q}} \log \frac{dQ}{d\hat{Q}} \right] d\hat{Q}_1^0(\omega) \\ & = \int dQ \log \frac{dQ}{d\hat{Q}} = I(C), \end{aligned}$$

where Jensen's inequality for the measure $\hat{Q}_{1,\omega}^0$ has been used. However, in

this case, we must have equality holding in the Jensen estimate for \hat{Q}_1^0 -a.e. ω . Since $x \log x$ is strictly convex, this implies for \hat{Q} -a.e. ω ,

$$(3.6) \quad \frac{dQ}{d\hat{Q}}(\omega) = E^{\hat{Q}_1^0, \omega} \left[\frac{dQ}{d\hat{Q}} \right].$$

Let $Q_{\omega(0)}$ denote the regular conditional probability distribution of Q_1^0 given \mathcal{F}_0^0 and note that $P_{\omega(0)}$ is the regular conditional probability distribution of \hat{Q}_1^0 given \mathcal{F}_0^0 . The measures Q_1^0 and \hat{Q}_1^0 have the same marginal distribution on \mathcal{F}_0^0 , which we denote by q . Then $dQ_1^0/d\hat{Q}_1^0$ is the Radon-Nikodym derivative of $Q_{\omega(0)}$ with respect to $P_{\omega(0)}$ which exists for q -a.e. $\omega(0)$. It now follows from (3.6) that

$$\frac{dQ}{d\hat{Q}} = \frac{dQ_{\omega(0)}}{dP_{\omega(0)}} \quad \text{for } \hat{Q}\text{-a.e. } \omega.$$

This shows Q is a stationary Markov process as follows: Let $B \in \mathcal{F}_0^{-\infty}$, $A \in \mathcal{F}_1^1$:

$$\begin{aligned} Q[A \cap B] &= \int_{A \cap B} \frac{dQ}{d\hat{Q}} \hat{Q}(d\omega) \\ &= \int_B E^{P_\omega} \left[\frac{dQ}{d\hat{Q}} \chi_A \right] Q(d\omega) \\ &= \int_B E^{P_\omega} \left[\frac{dQ_{\omega(0)}}{dP_{\omega(0)}} \chi_A \right] Q(d\omega) \quad [\text{by (3.1)}] \\ &= \int_B E^{P_{\omega(0)}} \left[\frac{dQ_{\omega(0)}}{dP_{\omega(0)}} \chi_A \right] Q(d\omega) \\ &= \int_B Q_{\omega(0)}(A) Q(d\omega). \end{aligned}$$

Since $Q_{\omega(0)}(A) = E^Q[A | \mathcal{F}_0^0]$, this shows that $E^Q[A | \mathcal{F}_0^{-j}] = E^Q[A | \mathcal{F}_0^0]$ for any $A \in \mathcal{F}_1^1$, $j > 0$. It follows that Q is a stationary Markov process with transition probability function $Q(A|x) = Q_x(A)$ for $A \in \mathcal{F}_1^1$. Since $I(C) = h^1(Q_1^0 | \pi)$, it follows from Corollary 2.7 that Q is the stationary Markov process P^* . \square

4. A large deviations estimate. For $u(x)$ a probability density function with respect to λ , let

$$(4.1) \quad R_{n,u}^C(\cdot) = E^{P_u} \{ R_{n,\omega}(\cdot) | \hat{P}_n(\omega, \cdot) \in C \}$$

be defined as in (1.9). In this section we show the sequence of measures $R_{n,u}^C(\cdot)$, $n = 1, 2, \dots$, is asymptotically quasi-Markov.

We begin by establishing a fundamental lemma. Let Q be a stationary process on (Ω, \mathcal{B}) with marginal q . Let Q_1^0 be the restriction of Q to \mathcal{F}_1^0 and let $Q_{\omega(0)}$ denote the regular conditional probability distribution of Q_1^0 w.r.t.

\mathcal{F}_0^0 . Then, as before, for $A \in \mathcal{F}_1^1$, $Q(A|x) = Q_x(A)$ defines a transition probability function a.e. q . Let \tilde{Q} be the stationary Markov process with transition probability $Q(A|x)$ and invariant measure q . We say that \tilde{Q} is the stationary Markov process defined by Q . Then we have the following lemma.

LEMMA 4.1. Let \bar{P} be the Markov process on $\Pi_{i=0}^\infty(X_i, \mathcal{B}_i)$, $X_i = X$, \mathcal{B}_i the Boreal σ -field on X , $0 \leq i < \infty$, with a probability transition function $P(dy|x)$ and initial distribution $q(dx)$. Let Q, \tilde{Q} be as above. Then for any n ,

$$h_{\mathcal{F}_n^0}(Q, \bar{P}) = h_{\mathcal{F}_n^0}(Q, \tilde{Q}) + nh^1(Q_1^0|P(\cdot|\cdot)).$$

PROOF. Let \bar{P}_1^0 denote the restriction of \bar{P} to \mathcal{F}_1^0 . Then we can assume $Q \ll \tilde{Q}$ on \mathcal{F}_n^0 and $Q_1^0 \ll \bar{P}_1^0$; otherwise both sides are ∞ . To establish this, suppose $h_{\mathcal{F}_n^0}(Q, \bar{P}) < \infty$. Then $Q \ll \bar{P}$ on \mathcal{F}_n^0 ; in particular, $Q_1^0 \ll \bar{P}_1^0$. Since Q_1^0 and \bar{P}_1^0 both have marginal q on \mathcal{F}_0^0 , $dQ_1^0/d\bar{P}_1^0$ is the Radon-Nikodym derivative of $Q(dy|x)$ with respect to $P(dy|x)$, which exists for q -a.e. x . Now suppose for $M \in \mathcal{F}_n^0$, $\tilde{Q}(M) = 0$. However,

$$(4.2) \quad \tilde{Q}(M) = \int_M \frac{dQ_1^0}{d\bar{P}_1^0}(\omega_0, \omega_1) \cdots \frac{dQ_1^0}{d\bar{P}_1^0}(\omega_{n-1}, \omega_n) d\bar{P}(\omega_0, \dots, \omega_n),$$

so that $\tilde{Q}(M) = 0$ implies that \bar{P} -a.e. on \mathcal{F}_n^0 , $dQ_1^0/d\bar{P}_1^0(\omega_0, \omega_1) \cdots dQ_1^0/d\bar{P}_1^0(\omega_{n-1}, \omega_n) = 0$. Let N be the \mathcal{F}_n^0 set of \bar{P} -measure 0, where this product is positive. Let $T_i = \{(\omega_{i-1}, \omega_i): dQ_1^0/d\bar{P}_1^0(\omega_{i-1}, \omega_i) = 0\}$. Using the stationarity of Q , each T_i has Q -measure 0. Then $M \subseteq N \cup \cup_{i=1}^n T_i$ so M has Q -measure 0 and $Q \ll \tilde{Q}$.

Assuming that $Q \ll \tilde{Q}$ on \mathcal{F}_n^0 and $Q_1^0 \ll \bar{P}_1^0$, which we have seen implies $\tilde{Q} \ll \bar{P}$ on \mathcal{F}_n^0 , we have

$$\frac{dQ}{d\bar{P}} = \frac{dQ}{d\tilde{Q}} \frac{d\tilde{Q}}{d\bar{P}}$$

on \mathcal{F}_n^0 . Taking log of both sides, integrating over Q and using (4.2) gives

$$h_{\mathcal{F}_n^0}(Q, \bar{P}) = h_{\mathcal{F}_n^0}(Q, \tilde{Q}) + \int dQ(\omega_0, \dots, \omega_n) \log \frac{dQ_1^0}{d\bar{P}_1^0}(\omega_0, \omega_1) \cdots \frac{dQ_1^0}{d\bar{P}_1^0}(\omega_{n-1}, \omega_n).$$

Using the stationarity of Q , the last integral on the right is $nh^1(Q_1^0|P(\cdot|\cdot))$. □

The following lemma establishes the analog in this situation of the almost completely convex condition required by Csiszár (1984) on the convex set C described in Section 1.

LEMMA 4.2. Let $R_{n,u}^C(\cdot)$ be as defined in (4.1) and let Π_C be the set of $M_S(\Omega)$ whose marginals are in C , a weakly closed convex set. Then $R_{n,u}^C(\cdot) \in \Pi_C$.

PROOF. Consider $P_u\{\cdot | \hat{P}_n(\omega, \cdot) \in C\}$ as a measure of \mathcal{F}_{n-1}^0 . Now $\Pi_{i=0}^\infty(X_i, \mathcal{B}_i)$ is $(\Pi_{i=0}^\infty X_i, \mathcal{B})$, where \mathcal{B} is the Borel σ -field on $\Pi_{i=0}^\infty X_i$, which is in particular a separable metric space. It is standard that there are probability measures μ_j on \mathcal{F}_{n-1}^0 ,

$$\mu_j = \sum_{k=0}^{k=k_j} a_{jk} \delta_{e_{jk}},$$

whose supports are finite sets which converge weakly to $P_u\{\cdot | \hat{P}_n(\omega, \cdot) \in C\}$ [Parthasarathy (1967), Theorem (6.3)]. Let E_n be the \mathcal{F}_{n-1}^0 -measurable set of ω satisfying $\hat{P}_n(\omega, \cdot) \in C$. Without loss of generality, it may be assumed that the finite set $\{e_{jk}\}$ lies in E_n for each j and k .

Now let $f \in C(\Omega)$. Then for each $\omega \in \Omega$,

$$\int f dR_{n,\omega} = \frac{1}{n} \sum_{i=0}^{n-1} f(\theta_i \omega_n)$$

is a continuous function of $(\omega_0, \dots, \omega_{n-1})$. It follows that

$$\int \left(\int f dR_{n,\omega} \right) \mu_j = \sum_{k=0}^{k=k_j} a_{jk} \left(\int f dR_{n,e_{jk}} \right)$$

converges as $j \rightarrow \infty$ to

$$\begin{aligned} E_u \left\{ \int f dR_{n,\omega} | \hat{P}_n(\omega, \cdot) \in C \right\} \\ = \int_{\Omega} f(\omega) dR_{n,u}^C. \end{aligned}$$

Thus the measure

$$(4.3) \quad \sum_{k=0}^{k=k_j} a_{jk} R_{n,e_{jk}}$$

converges weakly as $j \rightarrow \infty$ to $R_{n,u}^C$. Since for each j and k , $e_{jk} \in E_n$, it follows that $\hat{P}_n(e_{jk}, \cdot) \in C$ or equivalently that $R_{n,e_{jk}} \in \Pi_C$. By the convexity of Π_C , each of the measures in (4.3) is in Π_C . Thus $R_{n,\omega}^C$ is a limit point of Π_C , which, being closed, implies $R_{n,u}^C \in \Pi_C$. \square

LEMMA 4.3. Let E_n be the \mathcal{F}_{n-1}^0 -measurable set $\{\omega: \hat{P}_n(\omega, \cdot) \in C\}$. The measure $R_{n,u}^C$ defined by (4.1) has a density for sets A in \mathcal{F}_{n-1}^0 with respect to λ^n given by

$$R_{n,u}^C(\omega_0, \dots, \omega_{n-1}) = \frac{1}{P_u\{E_n\}} \chi_{E_n}(\omega_0, \dots, \omega_{n-1}) \frac{1}{n} \sum_{i=0}^{n-1} \pi_i(\omega_0, \dots, \omega_{n-1}),$$

where

$$\pi_0(\omega_0, \dots, \omega_{n-1}) = u(\omega_0)\pi(\omega_1|\omega_0) \cdots \pi(\omega_{n-1}|\omega_{n-2})$$

and

$$(4.4) \quad \begin{aligned} \pi_i(\omega_0, \dots, \omega_{n-1}) &= \pi(\omega_0|\omega_{n-1})\pi(\omega_1|\omega_0) \cdots \pi(\omega_{n-i-1}|\omega_{n-i-2}) \\ &\times u(\omega_{n-i})\pi(\omega_{n-i+1}|\omega_{n-i}) \cdots \pi(\omega_{n-1}|\omega_{n-2}). \end{aligned}$$

PROOF. Observe that the map $\Omega \rightarrow \Omega$ defined by $\omega \rightarrow \omega_n$ is continuous, hence \mathcal{F}_n^0 -measurable, and the maps $\theta_i, \theta_i^{-1}: \Omega \rightarrow \Omega$ are continuous, hence measurable. Let $i > 0$ and let A be a measurable set in \mathcal{F}_{n-1}^0 . Then

$$(4.5) \quad \begin{aligned} E_u\{\chi_A(\theta_i\omega_n)\} &= \int_X \cdots \int_X \chi_A(\theta_i\omega_n)\pi_0(\omega_0, \dots, \omega_{n-1}) d\lambda^n \\ &= \int_X \cdots \int_X \chi_A(\omega_n)\pi_0(\theta_i^{-1}\omega_n) d\lambda^n \end{aligned}$$

by Fubini's theorem. It is easy to see that for $i > 0$,

$$(4.6) \quad \begin{aligned} \pi_0(\theta_i^{-1}\omega_n) &= \pi(\omega_0|\omega_{n-1})\pi(\omega_1|\omega_0) \cdots \pi(\omega_{n-i-1}|\omega_{n-i-2}) \\ &\times u(\omega_{n-i})\pi(\omega_{n-i+1}|\omega_{n-i}) \cdots \pi(\omega_{n-1}|\omega_{n-2}). \end{aligned}$$

To obtain the density of

$$R_{n,u}^C(\cdot) = E_u\{R_{n,\omega}(\cdot)|\hat{P}_n(\omega, \cdot) \in C\},$$

observe that $\omega \in E_n$ if and only if $\theta_i\omega_n \in E_n$ for any $0 \leq i \leq n - 1$. Then

$$\begin{aligned} R_{n,u}^C(\cdot) &= E_u\{R_{n,\omega}(\cdot)|\omega \in E_n\} \\ &= \frac{1}{n} \sum_{i=0}^{n-1} E_u\{\chi_{(\cdot)}(\theta_i\omega_n)|\theta_i\omega_n \in E_n\}. \end{aligned}$$

It now follows from (4.5) and (4.6) that for any set $A \in \mathcal{F}_{n-1}^0$,

$$R_{n,u}^C(\cdot) = \int \cdots \int_A \frac{1}{P_u\{E_n\}} \chi_{E_n}(\omega_0, \dots, \omega_{n-1}) \frac{1}{n} \sum_{i=0}^{n-1} \pi_i(\omega_0, \dots, \omega_{n-1}) d\lambda^n,$$

which proves the lemma. \square

Let $\bar{P}_{n,u}^*$ be the measure on \mathcal{F}_{n-1}^0 defined by the transition probability function $\bar{P}^*(dy|x)$, P^* the I -projection of π onto C and initial distribution given by the marginal of $R_{n,u}^C$. We now establish the following lemma.

LEMMA 4.4. *Let C be a closed convex set with nonempty interior C^0 satisfying $I(C^0) < \infty$. Suppose the probability density function in (4.1) is*

bounded from above. Then

$$\begin{aligned} & \frac{1}{n} \log P_u\{\hat{P}_n(\omega, \cdot) \in C\} \\ & \leq -\frac{1}{n} h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) - \frac{(n-1)}{n} I(C) + \frac{1}{n} \log\left(\frac{\sup uA}{a}\right), \end{aligned}$$

where a and A are the bounds on $\pi(y|x)$ given by assumption 3.

PROOF. Let

$$\begin{aligned} \hat{R}_{n,u}^C(\cdot) &= E_u\{R_{n,\omega}(\cdot)\} \\ &= \frac{1}{n} \sum_{i=0}^{n-1} E_u\{\chi_{(\cdot)}(\theta_i; \omega_n)\}. \end{aligned}$$

Then

$$\begin{aligned} -\log P_u\{\hat{P}_n(\omega, \cdot) \in C\} &= h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \hat{R}_{n,u}^C) \\ (4.7) \qquad \qquad \qquad &= \int_X \cdots \int_X dR_{n,u}^C \log \frac{R_{n,u}^C(\omega_0, \dots, \omega_{n-1})}{\hat{R}_{n,u}^C(\omega_0, \dots, \omega_{n-1})}, \end{aligned}$$

where $R_{n,u}^C(\omega_0, \dots, \omega_{n-1})$ and $\hat{R}_{n,u}^C(\omega_0, \dots, \omega_{n-1})$ are the densities of $R_{n,u}^C$ and $\hat{R}_{n,u}^C$, respectively, with respect to λ^n . Let $\pi^1(\omega_0, \omega_1, \dots, \omega_{n-1}) = \pi(\omega_1|\omega_0)\pi(\omega_2|\omega_1) \cdots \omega(\omega_{n-1}|\omega_{n-2})$. Let $r_{n,u}(\omega_0)$ denote the density of the marginal of $R_{n,u}^C$ with respect to λ and let $\pi_{n,u}$ be the measure on \mathcal{F}_n^0 with density $r_{n,u}(\omega_0)\pi^1(\omega_0, \dots, \omega_{n-1})$ with respect to λ^n . Now for $R_{n,u}^C$ -a.e. $(\omega_0, \dots, \omega_{n-1})$,

$$\begin{aligned} \frac{R_{n,u}^C(\omega_0, \dots, \omega_{n-1})}{\hat{R}_{n,u}^C(\omega_0, \dots, \omega_{n-1})} &= \frac{R_{n,u}^C(\omega_0, \dots, \omega_{n-1})}{\pi_{n,u}(\omega_0, \dots, \omega_{n-1})} \\ &\quad \times r_{n,u}(\omega_0) \frac{\pi^1(\omega_0, \dots, \omega_{n-1})}{\hat{R}_{n,u}^C(\omega_0, \dots, \omega_{n-1})}. \end{aligned}$$

It is possible to take the log of both sides and integrate over $R_{n,u}^C$ to obtain

$$\begin{aligned} & \int_X \cdots \int_X dR_{n,u}^C \log \frac{R_{n,u}^C}{\hat{R}_{n,u}^C} \\ (4.8) \qquad \qquad \qquad &= \int_X \cdots \int_X dR_{n,u}^C \log \frac{R_{n,u}^C}{\pi_{n,u}} \\ & \quad + \int_X \cdots \int_X dR_{n,u}^C \log r_{n,u}(\omega_0) + \int_X \cdots \int_X dR_{n,u}^C \log \frac{\pi^1}{\hat{R}_{n,u}^C}, \end{aligned}$$

provided the right-hand side is well defined. However, the first integral on the right is evidently positive as is the second, which is just $h(r_{n,u}, \lambda)$. For the

third, it follows from (4.4) and the bounds on π and u that

$$(4.9) \quad \pi_i(\omega_0, \dots, \omega_{n-1}) \leq \frac{\sup uA}{a} \pi^1(\omega_0, \dots, \omega_{n-1}),$$

so that

$$\int_X \cdots \int_X dR_{n,u}^C \log \frac{\pi^1}{\hat{R}_{n,u}^C} \geq -\log \left(\frac{\sup uA}{a} \right).$$

For (4.7), (4.8), and (4.9) it now follows that

$$(4.10) \quad -\log P_u\{\hat{P}_n(\omega, \cdot) \in C\} \geq h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \pi_{n,u}) - \log \left(\frac{\sup uA}{a} \right).$$

Applying Lemma 4.1 and letting $\tilde{R}_{n,u}^C$ denote the stationary Markov process defined by $R_{n,u}^C$, we have

$$h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \pi_{n,u}) = h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \tilde{R}_{n,u}^C) + (n-1)h^1(R_{n,u}^C | \pi).$$

Since $R_{n,u}^C \in \Pi_C$ by Lemma 4.2, $R_{n,u}^C \in M_C$ and it follows from Theorem 2.3 that

$$h^1(R_{n,u}^C | \pi) \geq h^1(R_{n,u}^C | P^*(\cdot | \cdot)) + I(C).$$

From (4.10) we have

$$(4.11) \quad \begin{aligned} -\log P_u\{\hat{P}_n(\omega, \cdot) \in C\} &\geq h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \tilde{R}_{n,u}^C) \\ &+ (n-1)h^1(R_{n,u}^C | P^*(\cdot | \cdot)) \\ &+ (n-1)I(C) - \log \left(\frac{\sup uA}{a} \right). \end{aligned}$$

Applying Lemma 4.1 again gives

$$h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \tilde{R}_{n,u}^C) = h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) + (n-1)h^1(R_{n,u}^C | P^*(\cdot | \cdot)).$$

Substituting this into (4.11) yields

$$-\log P_u\{\hat{P}_n(\omega, \cdot) \in C\} \geq h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) + (n-1)I(C) - \log \left(\frac{\sup uA}{a} \right).$$

The lemma follows. \square

THEOREM 4.5. *Suppose that in addition to the hypothesis of Lemma 4.4 we have $I(C) = I(C^0) < \infty$. Then*

$$\lim_{n \rightarrow \infty} \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) = 0,$$

so that the measures $R_{n,u}^C$ are asymptotically quasi-independent with respect to $P^*(dy|x)$, the transition probability function of the I-projection of π onto C .

PROOF. Using the uniformity of the estimate (1.5), it follows that

$$\liminf_{n \rightarrow \infty} \frac{1}{n} \log P_u \{ \hat{P}_n(\omega, \cdot) \in C^0 \} \geq -I(C^0) = -I(C).$$

It follows from Lemma 4.4 that

$$(4.12) \quad \limsup_{n \rightarrow \infty} \left(\frac{1}{n} \log P_u \{ \hat{P}_n(\omega, \cdot) \in C \} + \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) \right) \leq -I(C).$$

In particular,

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log P_u \{ \hat{P}_n(\omega, \cdot) \in C \} = -I(C).$$

It follows from (4.12) that

$$\limsup_{n \rightarrow \infty} \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) \leq 0,$$

which establishes the theorem. \square

5. Corollaries. Let C be a closed convex set with nonempty interior satisfying $I(C^0) = I(C) < \infty$, so that the measures $R_{n,u}^C$ defined by (1.9) for $u(x)$ bounded from above are asymptotically quasi-independent with respect to $P^*(dy|x)$, the probability transition function of the I -projection of π onto C . From Theorem 2.3, this function is defined for λ -a.e. x . Extend it as described in Corollary 2.8. Let \hat{Q} be the measure on Ω defined by

$$(5.1) \quad \int_{\Omega} \delta_{\omega} \otimes_0 P_{\omega(0)}^* Q(d\omega).$$

For $Q \in M_S(\Omega)$, define $h^j(Q|P^*(\cdot|\cdot)) = h_{\mathcal{F}_{-j}}(Q, \hat{Q})$.

COROLLARY 5.1. For $h^j(\cdot|\cdot)$ defined as above,

$$\lim_{n \rightarrow \infty} h^j(R_{n,u}^C|P^*(\cdot|\cdot)) = 0.$$

PROOF. From Theorem 4.5, we have that

$$\lim_{n \rightarrow \infty} \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) = 0,$$

where $\bar{P}_{n,u}^*$ is the measure on \mathcal{F}_{n-1}^0 defined by the transition probability function $P^*(dy|x)$ and initial distribution given by the marginal of $R_{n,u}^C$. We can assume without loss of generality that for $n > 1$, $h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) < \infty$. It follows from the proof of Lemma A.4 in the Appendix [(A.5)] that

$$(5.2) \quad h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*) = \sum_{i=1}^{n-1} h^i(R_{n,u}^C|P^*(\cdot|\cdot)).$$

From their definition, $h^k(R_{n,u}^C|P^*(\cdot|\cdot)) \leq h^l(Q|P^*(\cdot|\cdot))$ if $k < l$. Then for $j \leq n - 1$,

$$\begin{aligned} \frac{n-j}{n} h^j(R_{n,u}^C|P^*(\cdot|\cdot)) &\leq \frac{1}{n} \sum_{i=1}^{n-1} h^i(R_{n,u}^C|P^*(\cdot|\cdot)) \\ &= \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(R_{n,u}^C, \bar{P}_{n,u}^*), \end{aligned}$$

so that $\lim_{n \rightarrow \infty} h^j(R_{n,u}^C|P^*(\cdot|\cdot)) = 0$. \square

Using Corollary 2.8, it follows that $h^j(Q|P^*(\cdot|\cdot))$ is a lower semicontinuous function of Q . Since $M_S(\Omega)$ is compact, it follows from Corollary 5.1 that any subsequence of $\{R_{n,u}^C\}$ contains a subsequence which converges weakly to the stationary Markov process P^* , so that $R_{n,u}^C$ converges weakly to P^* . Of course, this follows immediately from Lemma 3.1 using the uniformity of convergence for $x \in X$. However, more can be concluded from Corollary 5.1.

COROLLARY 5.2. *Let $f(\omega)$ be measurable with respect to $\mathcal{F}_j^{i_1}$ and suppose that for $|t|$ sufficiently small, $e^{tf(\omega_{i_1}, \dots, \omega_{i_j})}$ is integrable with respect to $(1/b(\omega_{i_1}) \cdots 1/b(\omega_{i_j})\lambda^j)$, where the functions $b(\cdot)$ are as in Corollary 2.8. Then $\int f(\omega) dR_{n,u}^C \rightarrow \int f(\omega) dP^*$ as $n \rightarrow \infty$.*

PROOF. The proof is similar to Csizsár (1975), Lemma 3.1. Using the stationarity of $R_{n,u}^C$, we can assume without loss of generality that $f(\omega)$ is measurable with respect to \mathcal{F}_j^1 . Using (5.2), it follows from Corollary 5.1 that

$$\lim_{n \rightarrow \infty} h_{\mathcal{F}_j^0}(R_{n,u}^C, \bar{P}_{n,u}^*) = 0.$$

Let $f_{0,j,n}$ be the Radon-Nikodym derivative of $R_{n,u}^C$ with respect to $\bar{P}_{n,u}^*$ on \mathcal{F}_j^0 . Let $Y = \prod_{i=0}^j X_i$, $X_i = X$, $i = 1, \dots, j$. The Csizsár-Kemperman-Kullback inequality is that for two probability measures P and Q on a measure space (X, \mathcal{X}) :

$$|P - Q| \leq \sqrt{2h(P, Q)}$$

[Csizsár (1967), Theorem 4.1, Kemperman (1969), Theorem 6.11, and Kullback (1967)]. It follows that

$$\lim_{n \rightarrow \infty} |R_{n,u}^C - \bar{P}_{n,u}^*|_{\mathcal{F}_j^0} = \lim_{n \rightarrow \infty} \int |f_{0,j,n} - 1| d\bar{P}_{n,u}^* = 0,$$

where $|\cdot - \cdot|_{\mathcal{F}_j^0}$ denotes the variation norm for measures on \mathcal{F}_j^0 . Let $A_K = \{\omega: f(\omega) \leq K\}$. Then

$$(5.3) \quad \lim_{n \rightarrow \infty} \left| \int_{A_K} f(\omega) dR_{n,u}^C - \int_{A_K} f(\omega) d\bar{P}_{n,u}^* \right| = 0.$$

However, for any $g(\omega)$ measurable with respect to \mathcal{F}_j^1 which is integrable

with respect to $(1/b(\omega_1) \cdots 1/b(\omega_j)\lambda^j(\omega_1, \dots, \omega_j))$, it follows from Corollary 2.8 that

$$\int_{\prod_{i=1}^j X_i} g(\omega_1, \dots, \omega_j) P^*(\omega_1|\omega_0) P^*(\omega_2|\omega_1) \cdots P^*(\omega_j|\omega_{j-1}) d\lambda^j(\omega_1, \dots, \omega_j)$$

is a continuous function of ω_0 . Since $R_{n,u}^C$ converges weakly to P^* , the marginals of $R_{n,u}^C$ converge weakly to the marginals of P^* and it follows that $\int g(\omega) d\bar{P}_{n,u}^* \rightarrow \int g(\omega) dP^*$ as $n \rightarrow \infty$. Then (5.3) implies

$$\lim_{n \rightarrow \infty} \int_{A_K} f(\omega) dR_{n,u}^C = \int_{A_K} f(\omega) dP^*.$$

To complete the proof, it suffices to show that for any $\varepsilon > 0$, there exists K such that

$$(5.4)(i) \quad \limsup_{n \rightarrow \infty} \int_{Y/A_K} |f| dR_{n,u}^C = \limsup_{n \rightarrow \infty} \int_{Y/A_K} |f| f_{0,j,n} d\bar{P}_{n,u}^* < \varepsilon$$

and

$$(5.4)(ii) \quad \int_{Y/A_K} |f| dP^* < \varepsilon.$$

To obtain this, we prove that

$$(5.5) \quad \lim_{n \rightarrow \infty} h_{\mathcal{F}_j^0}(R_{n,u}^C, \bar{P}_{n,u}^*) = \lim_{n \rightarrow \infty} \int_Y f_{0,j,n} \log f_{0,j,n} d\bar{P}_{n,u}^* = 0$$

implies that for any $A \in \mathcal{F}_j^1$,

$$(5.6) \quad \lim_{n \rightarrow \infty} \int_A f_{0,j,n} \log f_{0,j,n} d\bar{P}_{n,u}^* = 0.$$

Now

$$\int_A f_{0,j,n} \log f_{0,j,n} d\bar{P}_{n,u}^* \geq R_{n,u}^C(A) \log \frac{R_{n,u}^C(A)}{\bar{P}_{n,u}^*(A)},$$

so that

$$(5.7) \quad \liminf_{n \rightarrow \infty} \int_A f_{0,j,n} \log f_{0,j,n} d\bar{P}_{n,u}^* \geq P^*(A) \log \frac{P^*(A)}{P^*(A)} = 0.$$

Similarly,

$$(5.8) \quad \liminf_{n \rightarrow \infty} \int_{Y/A} f_{0,j,n} \log f_{0,j,n} d\bar{P}_{n,u}^* \geq 0.$$

In view of (5.5), (5.7) and (5.8), (5.6) follows.

Now pick $t > 0$ and K so that $\int_{Y/A_K} e^{t|f|} dP^* < \varepsilon t$ so that (ii) of (5.4) is satisfied. Using the inequality $ab < a \log a + e^b$, where $a = f_{0,j,n}$ and $b = t|f|$

yields

$$\int_{Y/A_K} t|f|f_{0,j,n} d\bar{P}_{n,u}^* \leq \int_{Y/A_K} f_{0,j,n} \log f_{0,j,n} d\bar{P}_{n,u}^* + \int_{Y/A_K} e^{t|f|} d\bar{P}_{n,u}^*.$$

It follows that

$$\begin{aligned} \limsup_{n \rightarrow \infty} \int_{Y/A_K} |f|f_{0,j,n} d\bar{P}_{n,u}^* &\leq \frac{1}{t} \lim_{n \rightarrow \infty} \int_{Y/A_K} e^{t|f|} d\bar{P}_{n,u}^* \\ &= \frac{1}{t} \int_{Y/A_K} e^{t|f|} dP^* \\ &< \varepsilon, \end{aligned}$$

which completes the proof. \square

Finally, we have the following corollary.

COROLLARY 5.3. *Suppose the hypotheses of Theorem 4.5 are satisfied and that additionally the probability density $u(x)$ is bounded away from 0. Then the conditional P_u -distribution of X_0, \dots, X_{n-1} under the condition $\hat{P}_n(\omega, \cdot) \in C$ is asymptotically quasi-Markov with respect to the probability transition function $P^*(dy|x)$.*

PROOF. Let E_n be the \mathcal{F}_{n-1}^0 measurable set $\{\omega: \hat{P}_n(\omega, \cdot) \in C\}$. Then the conditional P_u -distribution of X_0, \dots, X_{n-1} under the condition $\hat{P}_n(\omega, \cdot) \in C$ has the density

$$\begin{aligned} P_{n,u}(\omega_0, \dots, \omega_{n-1}) \\ = \frac{1}{P_u\{E_n\}} \chi_{E_n}(\omega_0, \dots, \omega_{n-1}) u(\omega_0) \pi(\omega_1|\omega_0) \cdots \pi(\omega_{n-1}|\omega_{n-2}). \end{aligned}$$

Let $R_{n,u}^C(\omega_0, \dots, \omega_{n-1})$ be the density of $R_{n,u}^C$ on \mathcal{F}_{n-1}^0 . Then from (4.4), we have

$$(5.9)(i) \quad P_{n,u}(\omega_0, \dots, \omega_{n-1}) \geq \frac{\inf ua}{\sup uA} R_{n,u}^C(\omega_0, \dots, \omega_{n-1}).$$

Similarly

$$(5.9)(ii) \quad P_{n,u}(\omega_0, \dots, \omega_{n-1}) \leq \frac{\sup uA}{\inf ua} R_{n,u}^C(\omega_0, \dots, \omega_{n-1}).$$

If $p_{n,u}(\omega_0)$ is the density with respect to λ of the first marginal of $P_u\{\cdot | \hat{P}_n(\omega, \cdot) \in C\}$ on \mathcal{F}_{n-1}^0 , then the same bounds must hold with respect to the density $r_{n,u}(\omega_0)$ of the marginals of $R_{n,u}^C$ with respect to λ . Let $\bar{P}_{n,u}^*$ be the probability measure on \mathcal{F}_{n-1}^0 with initial distribution $p_{n,u}(\omega_0) d\lambda(\omega_0)$ and transition probability function $P^*(dy|x)$. Theorem 2.3 insures that this has a density with respect to λ^n . Let $\bar{P}_{n,u}^*(\omega_0, \dots, \omega_{n-1})$ denote this density. Similarly, let $\bar{P}_{n,u}^*(\omega_0, \dots, \omega_{n-1})$ denote the density of $\bar{P}_{n,u}^*$ with respect to λ^n .

Then from (5.9)(i) and (ii),

$$\int P_{n,u} \log \frac{P_{n,u}}{\bar{P}_{n,u}^*} d\lambda^n \geq \left(\frac{\inf ua}{\sup uA} \right) \int R_{n,u}^C \log \frac{R_{n,u}^C}{\bar{P}_{n,u}^*} d\lambda^n + 2 \left(\frac{\inf ua}{\sup uA} \right) \log \left(\frac{\inf ua}{\sup uA} \right)$$

and

$$\int P_{n,u} \log \frac{P_{n,u}}{\bar{P}_{n,u}^*} d\lambda^n \leq \left(\frac{\sup uA}{\inf ua} \right) \int R_{n,u}^C \log \frac{R_{n,u}^C}{\bar{P}_{n,u}^*} d\lambda^n + 2 \left(\frac{\sup uA}{\inf ua} \right) \log \left(\frac{\sup uA}{\inf ua} \right).$$

It follows from Theorem 4.5 that

$$\lim_{n \rightarrow \infty} \frac{1}{n} \int P_{n,u} \log \frac{P_{n,u}}{\bar{P}_{n,u}^*} d\lambda^n = 0,$$

which establishes that the sequence of measures $P_u\{\cdot | \hat{P}_n(\omega, \cdot) \in C\}$ on \mathcal{F}_{n-1}^0 is asymptotically quasi-independent with respect to $P^*(dy|x)$. \square

APPENDIX

In this appendix, the following theorem is established.

THEOREM A.1. *Suppose that the probability transition function $\pi(dy|x)$ satisfies assumption 3 of Section 1. Then for any closed set $A \subset M_S(\Omega)$,*

$$\begin{aligned} \limsup_{n \rightarrow \infty} \frac{1}{n} \log \sup_{x \in X} P_x\{R_{n,\omega} \in A\} \\ \leq - \inf_{Q \in A} H(Q|\pi). \end{aligned}$$

The results of this section are, unless otherwise noted, direct translations of results of Donsker and Varadhan (1983) (cf. Sections 2, 3 and 4) into the language of discrete parameter processes. They are provided here for the convenience of the reader.

LEMMA A.2. *Let (X, Σ) be a Polish space and $\mathcal{F}_1 \subset \mathcal{F}_2 \subset \Sigma$ be sub- σ -fields. Let μ and λ be two measures on (X, Σ) and suppose $\mu \ll \lambda$ on the σ -field \mathcal{F}_1 . Let $\mu' = \int_X \lambda_\omega \mu(d\omega)$, where λ_ω is the conditional probability distribution of λ given \mathcal{F}_1 . Then*

$$(A.1) \quad h_{\mathcal{F}_2}(\mu, \lambda) = h_{\mathcal{F}_1}(\mu, \lambda) + h_{\mathcal{F}_2}(\mu, \mu').$$

PROOF. For $E \in \Sigma$,

$$\begin{aligned} \mu'(E) &= \int_X \lambda_\omega(E) \mu(d\omega) \\ &= \int_X \lambda_\omega(E) \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_1} \lambda(d\omega) \\ &= \int_X E^{\lambda_\omega} \left(\chi_E \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_1} \right) \lambda(d\omega) \\ &= \int_E \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_1} \lambda(d\omega), \end{aligned}$$

so that $d\mu'/d\lambda = d\mu/d\lambda|_{\mathcal{F}_1}$. In particular, $d\mu/d\lambda|_{\mathcal{F}_2}$ exists or both sides of (A.1) are equal to $+\infty$. Then for $E \in \Sigma$,

$$\begin{aligned} \mu(E) &= \int_E \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_2} \lambda(d\omega) \\ &= \int_E \left(\frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_2} / \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_1} \right) \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_1} \lambda(d\omega) \\ &= \int_E \left(\frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_2} / \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_1} \right) \mu'(d\omega). \end{aligned}$$

It follows that

$$\frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_2} = \frac{d\mu}{d\lambda} \Big|_{\mathcal{F}_1} \frac{d\mu}{d\mu'} \quad \text{a.e. } \mu'.$$

Taking the logarithm of both sides and integrating with respect to μ completes the argument. \square

Suppose that \hat{Q} is defined as in (3.1).

LEMMA A.3. *Either $h_{\mathcal{F}_n^{-\infty}}(Q, \hat{Q}) = +\infty$ for all $n > 0$ or*

$$h_{\mathcal{F}_n^{-\infty}}(Q, \hat{Q}) = nH(Q|\pi).$$

PROOF. If $H(Q|\pi) = +\infty$, then $h_{\mathcal{F}_n^{-\infty}}(Q, \hat{Q}) = +\infty$ for all $n > 0$. It may then be assumed that $H(Q|\pi) < \infty$. To argue by induction, assume $h_{\mathcal{F}_j^{-\infty}}(Q, \hat{Q}) < \infty$. Then by Lemma A.2,

$$h_{\mathcal{F}_{j+1}^{-\infty}}(Q, \hat{Q}) = h_{\mathcal{F}_j^{-\infty}}(Q, \hat{Q}) + h_{\mathcal{F}_{j+1}^{-\infty}}(Q, Q'),$$

where $Q' = \int \hat{Q}_\omega Q(d\omega)$, \hat{Q}_ω the conditional probability distribution of \hat{Q} given $\mathcal{F}_j^{-\infty}$. But $\hat{Q}_\omega = \delta_\omega \otimes_j P_{\omega(j)}$, so that, using the stationarity of Q , $h_{\mathcal{F}_{j+1}^{-\infty}}(Q, Q') = H(Q|\pi)$. \square

LEMMA A.4.

$$(A.2) \quad \lim_{n \rightarrow \infty} \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(Q, \hat{Q}) = H(Q|\pi).$$

PROOF. By Lemma A.3, either $h_{\mathcal{F}_n^{-\infty}}(Q, \hat{Q}) = +\infty$ for all n or

$$(A.3) \quad \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(Q, \hat{Q}) \leq \frac{1}{n} h_{\mathcal{F}_{n-1}^{-\infty}}(Q, \hat{Q}) = \frac{n-1}{n} H(Q|\pi).$$

Then, if for some $k > 0$, $h_{\mathcal{F}_k^0}(Q, \hat{Q}) = +\infty$, both sides of (A.2) are equal to $+\infty$. It may then be assumed that for all $k > 0$, $h_{\mathcal{F}_k^0}(Q, \hat{Q}) < \infty$. Applying Lemma A.2 gives

$$(A.4) \quad h_{\mathcal{F}_{j+1}^0}(Q, \hat{Q}) - h_{\mathcal{F}_j^0}(Q, \hat{Q}) = h_{\mathcal{F}_{j+1}^0}(Q, Q'),$$

where $Q' = \int \hat{Q}_\omega Q(d\omega)$, \hat{Q}_ω the conditional distribution of \hat{Q} given \mathcal{F}_j^0 . Here $\hat{Q}_\omega = \delta_\omega \otimes_j P_{\omega(j)}$ considered as a measure on \mathcal{F}_{j+1}^0 . Recalling the definition of $h^j(Q|\pi)$ in Section 5 and using the stationarity of Q ,

$$h_{\mathcal{F}_{j+1}^0}(Q, Q') = h_{\mathcal{F}_1^{-j}}(Q, \hat{Q}) = h^j(Q|\pi).$$

From (A.4), it follows that

$$(A.5) \quad \frac{1}{n} h_{\mathcal{F}_{n-1}^0}(Q, \hat{Q}) = \frac{1}{n} \sum_{j=1}^{n-1} h^j(Q|\pi).$$

The sequence $\{h^j(Q|\pi)\}$ is increasing. If it increases without bound, it follows from (A.5) and (A.3) that both sides of (A.2) are equal to $+\infty$. Otherwise, there is some M so that $h^j(Q|\pi) \leq M$. It follows from Moy (1961), Lemma 3, that

$$\lim_{j \rightarrow \infty} h^j(Q|\pi) = H(Q|\pi),$$

concluding the proof of the lemma. \square

LEMMA A.5. Let Λ_j denote the set of continuous functions ϕ on Ω depending only on the coordinates ω_i , $0 \leq i \leq j$, which satisfy $E^{P_x}\{e^\phi\} \leq 1$ for all $x \in X$. Assume the transition probability function $\pi(dy|x)$ satisfies assumption 3. Then

$$h_{\mathcal{F}_j^0}(Q, \hat{Q}) = \sup_{\phi \in \Lambda_j} E^Q\{\phi\}.$$

PROOF. By (2.1),

$$h_{\mathcal{F}_j^0}(Q, \hat{Q}) = \sup_{u \in \mathcal{U}'} \left[\int_{\Omega} \log u(\omega) Q(d\omega) - \log \int_{\Omega} E^{P_\omega}(u) Q(d\omega) \right],$$

where \mathcal{U}' consists of the positive, continuous functions depending only on the coordinates $\omega_i, 0 \leq i \leq j$. Writing $\log u(\omega) = \phi(\omega)$ for $u(\omega) \in \mathcal{U}'$ shows

$$h_{\mathcal{F}_j^0}(Q, \hat{Q}) \geq \sup_{\phi \in \Lambda_j} E^Q\{\phi\}.$$

Let Φ denote the set of continuous function depending on the coordinates $\omega_i, 0 \leq i \leq j$. For $\psi \in \Phi$, define

$$\bar{\psi}(x) = \log E^{P_x}\{e^\psi\}.$$

Under assumption 3 on $\pi(dy|x)$, $\bar{\psi}(x)$ is a continuous function of x . Let $\phi(\omega) = \psi(\omega) - \bar{\psi}(\omega(0))$. Then

$$\begin{aligned} E^{P_x}\{e^\phi\} &= e^{P_x\{\psi(\omega) - \bar{\psi}(\omega(0))\}} \\ &= e^{-\bar{\psi}(x)} E^{P_x}\{e^\psi\} = 1, \end{aligned}$$

so $\phi \in \Lambda_j$. Then

$$\begin{aligned} h_{\mathcal{F}_j^0}(Q, \hat{Q}) &= \sup_{\psi \in \Phi} \left[\int_{\Omega} \psi(\omega) Q(d\omega) - \log \int_{\Omega} E^{P_\omega}(e^\psi) Q(d\omega) \right] \\ &\leq \sup_{\psi \in \Phi} \left[\int_{\Omega} \psi(\omega) Q(d\omega) - \int_{\Omega} \log E^{P_\omega}(e^\psi) Q(d\omega) \right] \end{aligned}$$

by Jensen's inequality. The right-hand side

$$\begin{aligned} &= \sup_{\psi \in \Phi} \left[\int_{\Omega} (\psi(\omega) - \bar{\psi}(\omega(0))) Q(d\omega) \right] \\ &\leq \sup_{\phi \in \Lambda_j} E^Q\{\phi\}. \end{aligned} \quad \square$$

LEMMA A.6. Suppose ϕ is \mathcal{F}_{N-1}^0 measurable and $E^{P_x}\{e^\phi\} \leq 1$ for all $x \in X$. Then

$$(A.6) \quad E^{P_x} \left\{ \exp \left(\frac{1}{N} \sum_{i=0}^{n-1} \phi(\theta_i \omega) \right) \right\} \leq 1$$

for all n .

PROOF. For $j = 0, 1, \dots, N - 1$, define

$$\psi_j(\omega) = \sum_{\substack{k: k \geq 0 \\ j+kN \leq n}} \phi(\theta_{j+kN} \omega).$$

The left-hand side of (A.6) is

$$E^{P_x} \left\{ \exp \left(\frac{1}{N} \sum_{j=0}^{N-1} \psi_j(\omega) \right) \right\}.$$

Jensen's inequality implies

$$E^{P_x} \left\{ \exp \left(\frac{1}{N} \sum_{j=0}^{N-1} \psi_j(\omega) \right) \right\} \leq E^{P_x} \left\{ \frac{1}{N} \sum_{j=0}^{N-1} \exp \psi_j(\omega) \right\} \\ = \frac{1}{N} \sum_{j=0}^{N-1} E^{P_x} \{ \exp \psi_j(\omega) \}.$$

Under the hypothesis on ϕ , $E^{P_x} \{ \exp \psi_j(\omega) \} \leq 1$.

Define a measure on $M_S(\Omega)$ by

$$\Gamma_{n,x}(A) = P_x \{ \omega \in \Omega, R_{n,\omega} \in A \}. \quad \square$$

COROLLARY A.7. *Suppose that ϕ is a bounded \mathcal{F}_{N-1}^0 -measurable function satisfying $E^{P_x} \{ e^\phi \} \leq 1$ for all x . Then*

$$E^{\Gamma_{n,x}} \left\{ \exp \left(\frac{n}{N} \int_{\Omega} \phi(\omega) Q(d\omega) \right) \right\} \\ \leq \exp \left\{ 2 \sup_{\omega \in \Omega} \phi(\omega) \right\}.$$

PROOF.

$$E^{\Gamma_{n,x}} \left\{ \exp \left(\frac{n}{N} \int_{\Omega} \phi(\omega) Q(d\omega) \right) \right\} \\ = E^{P_x} \left\{ \exp \left(\frac{n}{N} \int_{\Omega} \phi(\omega') R_{n,\omega}(d\omega') \right) \right\}.$$

Now

$$\int_{\Omega} \phi(\omega') R_{n,\omega}(d\omega') = \frac{1}{n} \sum_{i=0}^{n-1} \phi(\theta_i \omega_n),$$

where ω_n is defined as in Section 1. Then

$$\left| \sum_{i=0}^{n-1} \phi(\theta_i \omega) - n \int_{\Omega} \phi(\omega') R_{n,\omega}(d\omega') \right| \leq 2(N-1) \sup_{\omega \in \Omega} |\phi(\omega)|$$

which, in view of Lemma A.6, establishes the corollary. \square

Let

$$J(A) = \limsup_{n \rightarrow \infty} \frac{1}{n} \log \sup_{x \in X} \Gamma_{n,x}(A).$$

LEMMA A.8. *Let Λ_{N-1} be as defined in the statement of Lemma A.5. For any set $A \in M_S(\Omega)$,*

$$J(A) \leq - \sup_{\substack{l: A_1, A_2, \dots, A_l \\ A \subset \cup_{j=1}^l A_j}} \inf_{1 \leq j \leq l} \sup_{N > 0} \sup_{\phi \in \Lambda_{N-1}} \inf_{Q \in A_j} \frac{1}{N} \int_{\Omega} \phi(\omega) Q(d\omega).$$

PROOF. From Corollary A.7, for any $A \in M_S(\Omega)$ and any $\phi \in \Lambda_{N-1}$,

$$\Gamma_{n,x}(A) \leq \exp\left(2 \sup_{\omega \in \Omega} \phi(\omega)\right) \exp\left(-\frac{n}{N} \inf_{Q \in A} \int_{\Omega} \phi(\omega) Q(d\omega)\right).$$

Then

$$J(A) \leq - \sup_{N > 0} \sup_{\phi \in \Lambda_{N-1}} \inf_{Q \in A} \frac{1}{N} \int_{\Omega} \phi(\omega) Q(d\omega).$$

The proof is concluded upon the observation that $J(A \cup B) \leq \max(J(A), J(B))$. \square

LEMMA A.9. Let A be a closed, thus compact set in $M_S(\Omega)$. Then

$$\begin{aligned} & \sup_{\substack{l: A_1, A_2, \dots, A_l \\ A \subset \cup_{j=1}^l A_j}} \inf_{1 \leq j \leq l} \sup_{N > 0} \sup_{\phi \in \Lambda_{N-1}} \inf_{Q \in A_j} \frac{1}{N} \int_{\Omega} \phi(\omega) Q(d\omega) \\ & \geq \inf_{Q \in A} H(Q|\pi). \end{aligned}$$

PROOF. From Lemmas A.4 and A.5, it follows that for any $\bar{Q} \in A$ and $\varepsilon > 0$, there is an $N_{\bar{Q}}$ and a $\phi_{\bar{Q}}$ such that

$$\frac{1}{N_{\bar{Q}}} \int_{\Omega} \phi_{\bar{Q}}(\omega) \bar{Q}(d\omega) \geq \inf_{Q \in A} H(Q|\pi) - \varepsilon/2.$$

Since $\phi_{\bar{Q}}$ is a continuous function on Ω , there is a neighborhood $G_{\bar{Q}}$ of \bar{Q} in $M_S(\Omega)$ such that for $Q \in G_{\bar{Q}}$,

$$\frac{1}{N_{\bar{Q}}} \int_{\Omega} \phi_{\bar{Q}}(\omega) Q(d\omega) \geq \inf_{Q \in A} H(Q|\pi) - \varepsilon.$$

The neighborhoods $G_{\bar{Q}}$ form an open cover of the compact set A . Let G_1, G_2, \dots, G_l be a finite subcover. Then

$$\inf_{1 \leq j \leq l} \sup_{N > 0} \sup_{\phi \in \Lambda_{N-1}} \inf_{Q \in G_j} \frac{1}{N} \int_{\Omega} \phi(\omega) Q(d\omega) \geq \inf_{Q \in A} H(Q|\pi) - \varepsilon.$$

The statement of the lemma follows. \square

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REFERENCES

CSISZÁR, I. (1967). Information-type measures of difference of probability distributions and indirect observations. *Studia Sci. Math. Hungar.* **2** 299-318.
 CSISZÁR, I. (1975). I -divergence geometry of probability distributions and minimization problems. *Ann. Probab.* **3** 146-158.
 CSISZÁR, I. (1984). Sanov property, generalized I -projection and a conditional limit theorem. *Ann. Probab.* **12** 768-793.

- CSISZÁR, I., COVER, T. and CHO, B. S. (1987). Conditional limit theorems under Markov conditioning. *IEEE Trans. Inform. Theory* **IT-33** 788–801.
- DONSKER, M. D. and VARADHAN, S. R. S. (1975). Asymptotic evaluation of certain Markov process expectations for large time. I. *Comm. Pure Appl. Math.* **28** 1–47.
- DONSKER, M. D. and VARADHAN, S. R. S. (1976). Asymptotic evaluation of certain Markov process expectations for large time. III. *Comm. Pure Appl. Math.* **29** 389–461.
- DONSKER, M. D. and VARADHAN, S. R. S. (1983). Asymptotic evaluation of certain Markov process expectations for large time. IV. *Comm. Pure Appl. Math.* **36** 183–212.
- EDWARDS, R. E. (1965). *Functional Analysis and Applications*. Holt, Rinehart and Winston, New York.
- HARRIS, T. E. (1956). The existence of stationary measures for certain Markov processes. *Proc. Third Berkeley Symp. Math. Statist. Probab.* **2** 113–124. Univ. California Press, Berkeley.
- JUSTESEN, J. and HOHOLDT, T. (1984). Maxentropic Markov chains. *IEEE Trans. Inform. Theory* **IT-30** 665–667.
- KEMPERMAN, J. H. B. (1969). On the optimum rate of transmitting information. *Probability and Information Theory. Lecture Notes in Math.* **89** 126–169. Springer, New York.
- KREIN, M. and RUTMAN, M. (1948). Linear operators leaving invariant a cone in a Banach space. *Uspekhi. Math. Nauk* **3** 3–95. [*Amer. Math. Soc. Trans.* (1950) **10** 199–235.]
- KULLBACK, S. (1967). A lower bound for discrimination information in terms of variation. *IEEE Trans. Inform. Theory* **IT-13** 126–127.
- MOY, S. C. (1961). Generalizations of Shannon–McMillan Theorem. *Pacific J. Math.* **11** 705–714.
- PARTHASARATHY, K. R. (1967). *Probability Measures on Metric Spaces*. Academic, San Diego.
- PINSKER, M. S. (1964). *Information and Information Stability of Random Variables and Processes*. Holden-Day, San Francisco.
- ROCKAFELLAR, R. T. (1970). *Convex Analysis*. Princeton Univ. Press.
- SANOV, I. N. (1957). On the probability of large deviations of random variables. *Mat. Sb.* **42** 11–14. [*Sel. Trans. Math. Statist. Probab.* (1961) **1** 213–244.]
- SPITZER, F. (1972). A variational characterization of finite Markov chains. *Ann. Math. Statist.* **43** 303–307.

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