

THE CENTRAL LIMIT THEOREM FOR MARKOV CHAINS WITH THE SIMULTANEOUS TOTAL VARIATION CONVERGENCE OF THE CHAIN

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1. Introduction.

Let $(X)_{n \geq 0}$ be an aperiodic positive recurrent Harris chain on a general measurable state space $(E, \mathcal{E})$ with n -step transition probabilities $P^n(x, A)$, $x \in E$, $A \in \mathcal{E}$, and with invariant probability measure π . Let f be a real-valued π -integrable function with $\pi(f) = \int f d\pi = 0$. Write $S_n = \sum_{i=0}^n f(X_i)$.

Orey's convergence theorem ([4, Ch. I, Theorem 7.1]) states that

$$(1) \quad P^n(x, \cdot) \rightarrow \pi(\cdot)$$

in total variation norm, as $n \rightarrow \infty$, for all $x \in E$. Cogburn ([1, Cor. 4.2]) has shown that under suitable conditions

$$(2) \quad S_n / \sqrt{n} \rightarrow N(0, \sigma^2)$$

in distribution, as $n \rightarrow \infty$, for certain $0 \leq \sigma^2 < \infty$.

The main aim of this paper is to combine these results to obtain a simultaneous version of these two convergence results. Moreover, we shall give, by using the splitting technique introduced in [2], an elementary proof for the asymptotic normality of S_n .

2. The main result.

We assume that the σ -field $\mathcal{E}$ is countably generated (see Remark 2). We shall denote by P_μ the probability measure on the sample space $(E^\infty, \mathcal{E}^\infty)$ of the chain corresponding to the initial distribution μ . If $\mu = \varepsilon_x$ is the probability measure assigning unit mass to the point x , we write $P_\mu = P_x$. The corresponding expectation is denoted by E_μ (E_x). We shall write $\|\cdot\|$ for the total variation of a signed measure on $(E, \mathcal{E})$ and Φ for the standard normal distribution function.

THEOREM. *Assume that (2) holds for some $\sigma > 0$. Then for every real number t*

$$(3) \quad \|P_\mu\{S_n/\sigma\sqrt{n} \leq t; X_n \in \cdot\} - \Phi(t)\pi(\cdot)\| \rightarrow 0, \quad \text{as } n \rightarrow \infty.$$

PROOF. Associate to every positive integer n a positive integer $\tilde{n} \leq n$ such that

$$n - \tilde{n} \rightarrow \infty, \quad \tilde{n}/n \rightarrow 1$$

and

$$(4) \quad (S_n - S_{\tilde{n}})/\sigma\sqrt{n} \rightarrow 0 \text{ in } P_\mu\text{-probability, as } n \rightarrow \infty.$$

This is possible due to the convergence in distribution of $S_n - S_{n-k}$ for any fixed k . Define

$$\Phi_n(t, A) = P_\mu\{S_n/\sigma\sqrt{n} \leq t; X_n \in A\},$$

$$\tilde{\Phi}_n(t, A) = P_\mu\{S_{\tilde{n}}/\sigma\sqrt{n} \leq t; X_n \in A\},$$

$$A_{M,\varepsilon} = \{x \in E \mid \|P^n(x, \cdot) - \pi(\cdot)\| < \varepsilon \quad \forall m \geq M\}.$$

Then for $n - \tilde{n} \geq M$

$$\begin{aligned} & |\tilde{\Phi}_n(t, A) - \Phi(t)\pi(A)| \\ &= |E_\mu[(P_{X_{\tilde{n}}}(X_{n-\tilde{n}} \in A) - \pi(A)); S_{\tilde{n}}/\sigma\sqrt{n} \leq t] \\ &\quad + \pi(A)(P_\mu\{S_{\tilde{n}}/\sigma\sqrt{n} \leq t\} - \Phi(t))| \\ &\leq \varepsilon + P_\mu\{X_{\tilde{n}} \in A_{M,\varepsilon}^c\} + |P_\mu\{S_{\tilde{n}}/\sigma\sqrt{n} \leq t\} - \Phi(t)|. \end{aligned}$$

Hence by (1), (2) and (4)

$$(5) \quad \overline{\lim}_{n \rightarrow \infty} \sup_{A \in \mathcal{G}} |\tilde{\Phi}_n(t, A) - \Phi(t)\pi(A)| \leq \varepsilon + \pi(A_{M,\varepsilon}^c),$$

which tends to 0, as first $M \uparrow \infty$ and then $\varepsilon \downarrow 0$. Thus, for every $\varepsilon > 0$,

$$\begin{aligned} & \overline{\lim}_{n \rightarrow \infty} \sup_{A \in \mathcal{G}} |\Phi_n(t, A) - \Phi(t)\pi(A)| \\ &\leq \varepsilon + \overline{\lim}_{n \rightarrow \infty} \sup_{A \in \mathcal{G}} |\Phi_n(t, A) - \tilde{\Phi}_n(t + \varepsilon, A) + \tilde{\Phi}_n(t + \varepsilon, A) - \Phi(t + \varepsilon)\pi(A)| \\ &\leq \varepsilon + \overline{\lim}_{n \rightarrow \infty} P_\mu\{|S_n - S_{\tilde{n}}|/\sigma\sqrt{n} > \varepsilon\} + 0 \\ &= \varepsilon \quad \text{by (4)}, \end{aligned}$$

which proves (3).

REMARKS. 1. Due to the continuity of the function Φ the convergence in (3) is uniform in t .

2. We have assumed that the σ -field $\mathcal{E}$ is countably generated, which assumption is needed in the proof only to guarantee the measurability of the set $A_{M,\mathcal{E}}$. This assumption can be replaced by a somewhat milder assumption “ E has a uniform subset A ”; then the possibly non-measurable functions $x \mapsto \|P^m(x, \cdot) - \pi(\cdot)\|$ are bounded above by measurable functions $g_m \leq 2$ converging to zero π -a.s., see [1, p. 511].

3. A proof for the central limit theorem for Markov chains.

In this section we shall give an elementary proof for (2) and give an expression for the parameter σ^2 .

Due to the C -set theorem (see [6, Ch. 6, Lemma 1.1]) there is a function $h: E \rightarrow [0, 1]$ with $\pi(h) > 0$, an integer $k \geq 1$ and a probability measure ν on $(E, \mathcal{E})$ such that

$$(6) \quad P^k(x, A) \geq h \otimes \nu(x, A) = h(x)\nu(A), \quad x \in E, A \in \mathcal{E}.$$

By using the splitting technique (see [2]) we can construct an increasing sequence of random times $0 < N_1 < N_2 < \dots$ for the chain $(X_{nk})_{n \geq 0}$ such that the law of the process $\{X_{N,k}, X_{N,k+1}, X_{N,k+2}, \dots\}$ is P_ν , independently of $\{X_0, X_1, \dots, X_{(N_1-1)k}\}$. Then the sums

$$Y_i = \sum_{n=N_i k}^{N_{i+1} k - 1} f(X_n), \quad i = 1, 2, \dots,$$

form a sequence of identically distributed random variables such that $\{Y_i; i \leq n\}$ and $\{Y_i; i \geq n+2\}$ are independent for all n . The mean of Y_i is

$$\begin{aligned} E_\mu Y_i &= \sum_{m=0}^{\infty} \nu(P^k - h \otimes \nu)^m \sum_{n=0}^{k-1} P^n f \\ &= k\pi(h)^{-1}\pi(f) && \text{by [2, Theorem 3]}, \\ &= 0 && \text{by assumption.} \end{aligned}$$

If the variance $\alpha^2 = E_\mu Y_i^2$ is finite, then for any integer $l \geq 2$ the sums

$$Z_m = \sum_{i=(m-1)l+1}^{ml-1} Y_i, \quad m = 1, 2, \dots,$$

are independent identically distributed variables with mean 0 and variance

$$E_\mu Z_m^2 = (l-1)E_\mu Y_1^2 + 2(l-2)E_\mu Y_1 Y_2 \stackrel{\text{def.}}{=} (l-1)\alpha^2 + 2(l-2)\alpha_{12}.$$

The central limit theorem for independent identically distributed random variables asserts that

$$\sum_{m=1}^n Z_m/\sqrt{n} \rightarrow N(0, (l-1)\alpha^2 + 2(l-2)\alpha_{12}) \text{ in distribution, as } n \rightarrow \infty.$$

By a standard ergodic theorem argument

$$\psi(n)/n \stackrel{\text{def.}}{=} \max \{m \mid N_{ml+1} \leq n/k\} / n \rightarrow \frac{\pi(h)}{kl}$$

almost surely, and hence in probability, as $n \rightarrow \infty$. Anscombe's theorem (e.g. [5, Ch. VIII, Theorem 7.2]) now implies that

$$(7) \quad \sum_{m=1}^{\psi(n)} Z_m/\sqrt{n} \rightarrow N\left(0, \frac{\pi(h)}{k} \left(\frac{l-1}{l} \alpha^2 + \frac{2(l-2)}{l} \alpha_{12}\right)\right)$$

in distribution, as $n \rightarrow \infty$. Similarly

$$(8) \quad \sum_{m=1}^{\psi(n)} Y_{ml}/\sqrt{n} \rightarrow N\left(0, \frac{\pi(h)}{k} \frac{\alpha^2}{l}\right) \text{ in distribution, as } n \rightarrow \infty.$$

Choosing l great enough we obtain from (7) and (8) the following proposition.

PROPOSITION. *If $\alpha^2 = E_\mu Y_i^2$ is finite, then*

$$S_n/\sqrt{n} \rightarrow N\left(0, \frac{\pi(h)}{k} (\alpha^2 + 2\alpha_{12})\right) \text{ in distribution, as } n \rightarrow \infty.$$

In order to derive a more explicit expression for the variance $\sigma^2 = (\alpha^2 + 2\alpha_{12})\pi(h)/k$, we first write

$$U_i = \sum_{n=0}^{k-1} f(X_{ik+n}), \quad i=0, 1, \dots,$$

$$m^{(2)}(x) = E_x U_0^2,$$

$$m(x, y) = E_x(U_0 \mid X_k = y),$$

$$G(x, \cdot) = \sum_{i=0}^{\infty} (P^k - h \otimes v)^i \sum_{n=0}^{k-1} P^n(x, \cdot).$$

Then

$$\begin{aligned} (9) \quad \alpha^2 + 2\alpha_{12} &= E_v \left[\sum_{i=0}^{N_1-1} U_i^2 + 2 \sum_{i=0}^{N_1-2} U_i \sum_{j=i+1}^{N_1-1} U_j \right] \\ &\quad + 2E_v \left[\sum_{i=0}^{N_1-2} U_i \sum_{j=N_1}^{N_2-1} U_j + U_{N_1-1} \sum_{j=N_1}^{N_2-1} U_j \right] \\ &= \sum_{i=0}^{\infty} v(P^k - h \otimes v)^i m^{(2)} \end{aligned}$$

$$\begin{aligned}
& + 2 \sum_{i=0}^{\infty} \iint v(P^k - h \otimes v)^i(dx) (P^k - h \otimes v)(x, dy) m(x, y) Gf(y) \\
& + 0 + 2 \sum_{i=0}^{\infty} \iint v(P^k - h \otimes v)^i(dx) h(x) v(dy) m(x, y) Gf(y) \\
& = \pi(h)^{-1} \pi(m^{(2)}) + 2\pi(h)^{-1} \iint \pi(dx) P^k(x, dy) m(x, y) Gf(y),
\end{aligned}$$

provided that (9) is finite, when U_i and U_j are replaced by $|U_i|$ and $|U_j|$, respectively. This condition is obviously sufficient for the finiteness of α^2 . Hence (9) holds with both sides finite, if $\pi(m^{(2)})$ is finite and the measure $E_\pi\{U_0; X_k \in \cdot\}$ is $|f|$ -regular (for the definition see [3, Def. 2.1]); especially if $\pi(m^{(2)})$ is finite and the function $|f|$ is special (for the definition see [6, Ch. 6. Def. 4.1]). In these cases

$$\sigma^2 = k^{-1} \pi(m^{(2)}) + 2k^{-1} \iint \pi(dx) P^k(x, dy) m(x, y) Gf(y).$$

ACKNOWLEDGMENTS. I am grateful to Esa Nummelin for valuable conversations on the subject and to Pekka Tuominen for useful comments on the paper. I would also like to thank the referee for his expert report, which led to many improvements; in particular it shortened the proof of the Theorem in Section 2.

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