

On the Rate of Convergence in the Central Limit Theorem for Markov-Chains

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1. Introduction

All results concerning the accuracy of the normal approximation for sums of not necessarily independent random variables assume Doeblin's condition or the condition of φ -mixing (see e.g. [1, 3, 5, 7, 9]). Both assumptions mean in some sense that the random variables are "asymptotically independent", and they are rarely fulfilled for Markov-chains.

Using Doeblin's condition or the condition of φ -mixing the rate of convergence to the normal distribution obtained in some of the papers cited above is of order $n^{-1/2}$. The authors do not know of any results on the accuracy of the normal approximation holding without such conditions. In this paper we prove under weak moment conditions that for Markov-chains the normal approximation is of order $n^{-\alpha}$ for each $\alpha < 1/4$.

2. Notations

Let $\mathbb{N}_0 := \mathbb{N} \cup \{0\}$, where \mathbb{N} is the set of natural numbers.

Let (Ω, \mathcal{A}, P) be a probability space and $X_n, n \in \mathbb{N}_0$, be a positive recurrent irreducible Markov-chain on (Ω, \mathcal{A}, P) with countable state space I . For each $v \in \mathbb{N}, i \in I$, denote by $\tau_v^{(i)}$ the time of the v -th entrance into the state i , by $r_v^{(i)} = \tau_{v+1}^{(i)} - \tau_v^{(i)}$ the v -th return time of the state i and by $I_n^{(i)}$ the number of entrances into the state i up to time n .

If $\varphi: I \rightarrow \mathbb{R}$ define

$$\varphi_v^{(i)}(\omega) = \sum_{k=\tau_v^{(i)}(\omega)}^{\tau_{v+1}^{(i)}(\omega)-1} \varphi(X_k(\omega)), \omega \in \Omega.$$

It is well known that the functions $\varphi_v^{(i)}, v \in \mathbb{N}$, are independent and identically distributed.

For $\varphi \equiv 1$ we have $\varphi_v^{(i)} = r_v^{(i)}$. For $\varphi = 1_{(i)}$ we have $\varphi_v^{(i)} \equiv 1$. Let $\pi_i = \frac{1}{\mu_i}$, where μ_i is the mean recurrence time of the state i . Since $X_n, n \in \mathbb{N}_0$, is positive recurrent we have $\pi_i > 0$.

If $|\varphi|_v^{(i)}$ is P -integrable then $\sum_{j \in I} \pi_j \varphi(j)$ is absolutely convergent and

$$P[\varphi_v^{(i)}] = \frac{1}{\pi_i} S(\varphi)$$

where $S(\varphi) = \sum_{j \in I} \pi_j \varphi(j)$.

$L_r(P)$ is the space of all \mathcal{A} -measurable functions $f: \Omega \rightarrow \mathbb{R}$ with $P[|f|^r] < \infty$, $r \geq 1$.

Φ denotes the distribution function of the normal distribution with mean 0 and variance 1.

If $a_n, b_n \in \mathbb{R}$, $n \in \mathbb{N}$, we write

$$a_n = O(b_n) \text{ iff } \sup_{n \in \mathbb{N}} \left| \frac{a_n}{b_n} \right| < \infty.$$

3. The Results

The following Theorem is an essential tool for the proof of our main Theorem 3. It seems to the authors that Theorem 1 is of some interest of its own. It shows that for the number $I_n^{(i)}$ of entrances into the state i up to time n the approximation by the normal distribution is of order $n^{-1/2}$. So it sharpens the result of our Theorem 3

for a special case, namely for $\varphi = 1_{(i)}$. In this case we have $I_n^{(i)}(\omega) = \sum_{v=0}^n \varphi(X_v(\omega))$ and $\text{var}(\pi_i r_v^{(i)}) = \text{var}(\varphi_v^{(i)} - S(\varphi) r_v^{(i)})$.

Theorem 1. *Let $X_n, n \geq 0$, be a positive recurrent, irreducible Markov-chain and let the state $i \in I$ be fixed. Assume that*

- (a) $\tau_1^{(i)} \in L_1(P)$, $r_v^{(i)} \in L_3(P)$,
- (b) $\sigma_i^2 = \text{var}(\pi_i \cdot r_v^{(i)}) > 0$.

Then

$$\sup_{t \in \mathbb{R}} \left| P \left\{ \omega: \frac{I_n^{(i)}(\omega) - n \pi_i}{\sigma_i \sqrt{n \pi_i}} < t \right\} - \Phi(t) \right| = O(n^{-1/2}).$$

Proof. Since $1 - \Phi(t) \leq \frac{1}{t} e^{-\frac{t^2}{2}}$ for $t > 0$ we have $\Phi(-n^{1/4}) = 1 - \Phi(n^{1/4}) = O(n^{-1/2})$.

Hence it suffices to prove

$$\sup_{|t| \leq n^{1/4}} \left| P \left\{ \omega: \frac{I_n^{(i)}(\omega) - n \pi_i}{\sigma_i \sqrt{n \pi_i}} < t \right\} - \Phi(t) \right| = O(n^{-1/2}).$$

This is equivalent to

$$\sup_{|t| \leq n^{1/4}} \left| P \left\{ \omega: \frac{I_n^{(i)}(\omega) - n \pi_i}{\sigma_i \sqrt{n \pi_i}} \geq t \right\} - \Phi(-t) \right| = O(n^{-1/2}). \quad (1)$$

Let $k_n(t) = \langle t \sigma_i \sqrt{n \pi_i} + n \pi_i \rangle$, where $\langle x \rangle = \min \{k \in \mathbb{N} : x \leq k\}$. Then there exist $n_0 \in \mathbb{N}$ and $c_1, c_2 > 0$, $c_1 < c_2$ such that

$$n \geq n_0, \quad |t| \leq n^{1/4} \quad \text{imply} \quad k_n(t) \geq 2, \quad c_1 \leq \frac{k_n(t) - 1}{n} \leq c_2. \quad (2)$$

We have for $n \geq n_0$

$$\begin{aligned} P \left\{ \omega : \frac{I_n^{(i)}(\omega) - n \pi_i}{\sigma_i \sqrt{n \pi_i}} \geq t \right\} &= P \{ \omega : I_n^{(i)}(\omega) \geq k_n(t) \} \\ &= P \{ \omega : \tau_1^{(i)}(\omega) + r_1^{(i)}(\omega) + \dots + r_{k_n(t)-1}^{(i)}(\omega) \leq n \} \\ &= P \left\{ \omega : \frac{\tau_1^{(i)}(\omega) + r_1^{(i)}(\omega) + \dots + r_{k_n(t)-1}^{(i)}(\omega) - (k_n(t) - 1) \mu_i}{\sigma_i \mu_i \sqrt{k_n(t) - 1}} \leq a_n(t) \right\} \end{aligned}$$

where

$$a_n(t) = \frac{1}{\sigma_i \mu_i \sqrt{k_n(t) - 1}} (n - (k_n(t) - 1) \mu_i) \quad \text{and} \quad \mu_i = \frac{1}{\pi_i}.$$

Since $(\tau_1^{(i)}, r_1^{(i)}, r_2^{(i)}, \dots)$ is a sequence of independent functions and $r_v^{(i)} \in L_3(P)$, $v \in \mathbb{N}$, are identically distributed with mean μ_i and variance $(\mu_i \sigma_i)^2$ and since $\tau_1^{(i)}$ is integrable a little modification of the Theorem of Berry-Esseen yields together with (2) that for $n \geq n_0$

$$\begin{aligned} \sup_{|t| \leq n^{1/4}} \left| P \left\{ \omega : \frac{\tau_1^{(i)}(\omega) + r_1^{(i)}(\omega) + \dots + r_{k_n(t)-1}^{(i)}(\omega) - (k_n(t) - 1) \mu_i}{\mu_i \sigma_i \sqrt{k_n(t) - 1}} \leq a_n(t) \right\} \right. \\ \left. - \Phi(a_n(t)) \right| = O(n^{-1/2}). \end{aligned}$$

Therefore it suffices to prove

$$\sup_{|t| \leq n^{1/4}} |\Phi(a_n(t)) - \Phi(-t)| = O(n^{-1/2}). \quad (3)$$

Since $\pi_i \mu_i = 1$ we have for $n \geq n_0$ that

$$(k_n(t) - 1) \mu_i = n + t \sigma_i \sqrt{n \pi_i} + r_n(t)$$

with $|r_n(t)| \leq \mu_i$. Hence

$$\begin{aligned} a_n(t) &= -\frac{t \sqrt{n}}{\sqrt{(k_n(t) - 1) \mu_i}} + O(n^{-1/2}) \\ &= -\frac{t}{\sqrt{1 + b_n(t)}} + O(n^{-1/2}) \end{aligned} \quad (4)$$

with $b_n(t) = \frac{1}{\sqrt{n}} (t \sigma_i \sqrt{\pi_i} + r_n'(t))$ where $|r_n'(t)| \leq \mu_i / \sqrt{n}$. There exists $n_1 \in \mathbb{N}$ such that

$$n \geq n_1, \quad |t| \leq n^{1/4} \quad \text{implies} \quad \frac{1}{2} \leq 1 + b_n(t) \leq \frac{3}{2}. \quad (5)$$

To prove (3) it suffices to show according to (4) that

$$\sup_{|t| \leq n^{1/4}} \left| \Phi \left(\frac{t}{\sqrt{1 + b_n(t)}} \right) - \Phi(t) \right| = O(n^{-1/2}). \quad (6)$$

Using (5) we have for all $n \geq n_1$, $|t| \leq n^{1/4}$ that

$$\begin{aligned} \left| \Phi \left(\frac{t}{\sqrt{1+b_n(t)}} \right) - \Phi(t) \right| &\leq |t| \left| \frac{1}{\sqrt{1+b_n(t)}} - 1 \right| \cdot \max \left(e^{-\frac{t^2}{2}}, e^{-\frac{1}{2} \frac{t^2}{1+b_n(t)}} \right) \\ &\leq |t| \left| \frac{1}{\sqrt{1+b_n(t)}} - 1 \right| \cdot e^{-\frac{1}{3}t^2}. \end{aligned}$$

Since $\left| \frac{1}{\sqrt{1+b_n(t)}} - 1 \right| \leq 2|b_n(t)|$ we obtain for $n \geq n_1$ and $|t| \leq n^{1/4}$ that

$$\left| \Phi \left(\frac{t}{\sqrt{1+b_n(t)}} \right) - \Phi(t) \right| \leq 2|t||b_n(t)| \cdot e^{-\frac{1}{3}t^2} \leq \frac{1}{\sqrt{n}} 2|t| e^{-\frac{1}{3}t^2} (|t| \sigma_i \sqrt{\mu_i} + \mu_i)$$

which proves (6).

Remark 2. Under the assumptions of Theorem 1 we have

$$P\{\omega: |l_n^{(i)}(\omega) - n\pi_i| > d(n \cdot \log n)^{1/2}\} = O(n^{-1/2})$$

where $d = \sigma_i \sqrt{\pi_i}$.

Proof. According to Theorem 1 we have

$$\begin{aligned} P\{\omega: |l_n^{(i)}(\omega) - n\pi_i| > d(n \cdot \log n)^{1/2}\} &= P\left\{ \omega: \left| \frac{l_n^{(i)}(\omega) - n\pi_i}{\sigma_i \sqrt{n\pi_i}} \right| > (\log n)^{1/2} \right\} \\ &= 2(1 - \Phi((\log n)^{1/2})) + O(n^{-1/2}) \\ &= O(n^{-1/2}). \end{aligned}$$

Theorem 3. Let X_n , $n \geq 0$, be a positive recurrent, irreducible Markov chain, starting at $X_0 \equiv i$.

Let φ be a real-valued function defined on the state space I . Assume that

- (a) $|\varphi|_v^{(i)}, r_v^{(i)} \in L_3(P)$,
- (b) $\sigma_i^2 = \text{var}(\varphi_v^{(i)} - S(\varphi)r_v^{(i)}) > 0$.

Then

$$\begin{aligned} \sup_{t \in \mathbb{R}} \left| P \left\{ \omega: \frac{1}{\sigma_i \sqrt{nn\pi_i}} \left(\sum_{v=0}^n \varphi(X_v(\omega)) - (n+1)S(\varphi) \right) < t \right\} - \Phi(t) \right| \\ = O(n^{-1/4}(\log n)^{1/4}). \end{aligned}$$

Proof. In the following we omit the upper state index i , if no ambiguity can arise.

For each $n \geq 0$ let $\rho_n(\omega)$ be the time of the first entrance of the state i after time n , i.e.

$$\rho_n(\omega) = \min \{v > n: X_v(\omega) = i\}.$$

Let $\psi_v = \varphi_v - S(\varphi)r_v$. Then $P[\psi_v] = 0$ (see e.g. [2], p. 96).

We have the following dissection formula

$$\sum_{v=0}^n \varphi \circ X_v - (n+1)S(\varphi) = Y_n + V_n + Z_n \tag{1}$$

where

$$Y_n(\omega) = \sum \{ \psi_v(\omega) : 1 \leq v \leq I_n(\omega) \}, \quad (2)$$

$$V_n(\omega) = - \sum \{ \varphi \circ X_v(\omega) : n < v < \rho_n(\omega) \}, \quad (3)$$

$$Z_n(\omega) = -S(\varphi)(\rho_n(\omega) - (n+1)). \quad (4)$$

Since $\psi_v \in L_3(P)$, $v \in \mathbb{N}$, are independent and identically distributed and $\sigma_i^2 = \text{var } \psi_v > 0$ we obtain from Lemma 5 and Remark 2 that

$$\sup_{t \in \mathbb{R}} \left| P \left\{ \omega : \frac{Y_n(\omega)}{\sigma_i \sqrt{n \pi_i}} \leq t \right\} - \Phi(t) \right| = O(n^{-1/4} (\log n)^{1/4}).$$

According to (1), (5) and Lemma 6 it suffices to prove that for each $c > 0$

$$P \left\{ \omega : \frac{|V_n(\omega)|}{\sqrt{n}} > c \cdot \frac{(\log n)^{1/4}}{n^{1/4}} \right\} = O(n^{-1/4} (\log n)^{1/4}) \quad (6)$$

and

$$P \left\{ \omega : \frac{|Z_n(\omega)|}{\sqrt{n}} > c \cdot \frac{(\log n)^{1/4}}{n^{1/4}} \right\} = O(n^{-1/4} (\log n)^{1/4}). \quad (7)$$

If we replace in (3) the function φ by the constant function $-S(\varphi)$ we see that the “new” $V_n(\omega)$ leads to $Z_n(\omega)$ of (4). Therefore it suffices to prove only (6).

According to Remark 2 there exists a constant $d > 0$ such that

$$P \{ \omega : |I_n(\omega) - n \pi_i| \geq d(n \cdot \log n)^{1/2} \} = O(n^{-1/2}). \quad (8)$$

Let $K = \{v \in \mathbb{N} : |v - n \pi_i| < d(n \cdot \log n)^{1/2}\}$. Since

$$|V_n(\omega)| \leq \sum_{v=1}^{n+1} |\varphi|_v(\omega) 1_{\{\omega : I_n(\omega) = v\}}$$

we obtain, using (8), that

$$\begin{aligned} & P \left\{ \omega : \frac{|V_n(\omega)|}{\sqrt{n}} > c \frac{(\log n)^{1/4}}{n^{1/4}} \right\} \\ & \leq P \{ \omega : |I_n(\omega) - n \pi_i| \geq d(n \log n)^{1/2} \} \\ & \quad + P \{ \omega : |V_n(\omega)| > c n^{1/4} (\log n)^{1/4}; |I_n(\omega) - n \pi_i| < d(n \log n)^{1/2} \} \\ & \leq O(n^{-1/2}) + \sum_{v \in K} P \{ \omega : |\varphi|_v(\omega) > c n^{1/4} (\log n)^{1/4} \} \\ & \leq O(n^{-1/2}) + (2d(n \log n)^{1/2} + 1) e n^{-3/4} (\log n)^{-3/4} \\ & = O(n^{-1/2}) + O(n^{-1/4}) = O(n^{-1/4}) \end{aligned} \quad (*)$$

where (*) follows from the Markov-inequality with some appropriate constant $e > 0$. This proves (6) and hence the proof is finished.

Remark 4. The assertion of Theorem 3 also holds true for a general initial distribution of X_0 , if we assume additionally that

$$\tau_1^{(i)} \in L_1(P) \quad \text{and} \quad \sum_{v=0}^{\tau_1^{(i)}-1} |\varphi \circ X_v| \in L_1(P).$$

Proof. Use the notations of Theorem 3. Then we have the following dissection formula

$$\sum_{v=0}^n \varphi \circ X_v - (n+1)S(\varphi) = R_n + Y_n + V_n + Z_n$$

where $|R_n| \leq R = \sum_{v=0}^{\tau_1^{(i)}-1} |\varphi \circ X_v| \in L_1(P)$. Since by the Markov inequality

$$P \left\{ \left| \frac{R_n}{\sqrt{n}} \right| > n^{-1/4} \right\} = O(n^{-1/4})$$

the assertion follows with Lemma 6 by applying the same methods as in the proof of Theorem 3.

For the sake of completeness we cite the following results:

Lemma 5. Let $X_n, n \in \mathbb{N}$, be a sequence of independent and identically distributed random variables with $P(X_n) = 0, P(X_n^2) = 1$ and $P(|X_n|^3) < \infty$. Let $I_n: \Omega \rightarrow \mathbb{N}$ be \mathcal{A} -measurable and assume that for some constants $\alpha, d > 0$

$$P \left\{ \omega: \left| \frac{I_n(\omega)}{n} - \alpha \right| > dn^{-1/2}(\log n)^{1/2} \right\} = O(n^{-1/2}).$$

Then

$$A_n = \sup_{t \in \mathbb{R}} \left| P \left\{ \omega: \frac{\sum_{v=1}^{I_n(\omega)} X_v(\omega)}{\sqrt{n\alpha}} \leq t \right\} - \Phi(t) \right| = O(n^{-1/4}(\log n)^{1/4}).$$

Proof. See [4], Theorem 1.

A counterexample given in [4] shows that under the assumptions of Lemma 5 $A_n = O(n^{-1/4})$ does not hold true in general.

The result of Sreehari [8], applied under the assumptions of Lemma 5, leads only to $A_n = O(n^{-1/6})$.

The following Lemma is well known.

Lemma 6. Let $Y_n, Z_n: \Omega \rightarrow \mathbb{R}$ be \mathcal{A} -measurable and $\varepsilon_n > 0, n \in \mathbb{N}$, be a sequence with $\varepsilon_n \rightarrow 0$. Assume that

$$\sup_{t \in \mathbb{R}} |P(Y_n \leq t) - \Phi(t)| = O(\varepsilon_n)$$

and

$$P(|Z_n| > \varepsilon_n) = O(\varepsilon_n).$$

Then

$$\sup_{t \in \mathbb{R}} |P(Y_n + Z_n \leq t) - \Phi(t)| = O(\varepsilon_n).$$

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