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## THE BERRY-ESSEEN BOUND FOR MAXIMUM LIKELIHOOD ESTIMATES OF TRANSLATION PARAMETER OF TRUNCATED DISTRIBUTION

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**1. Introduction.** Let  $X_1, \dots, X_n$  be independent random variables with common density  $f(x-\theta)$ ,  $-\infty < x, \theta < \infty$ , where  $\theta$  is an unknown translation parameter. We shall consider here the case that  $f(x)$  is a uniformly continuous density which vanishes on the interval  $(-\infty, 0)$  and is positive on the interval  $(0, \infty)$  and particularly

$$f(x) \sim \alpha x \quad \text{as } x \rightarrow +0$$

with  $0 < \alpha < \infty$ . Let  $\hat{\theta}_n = \hat{\theta}_n(X_1, \dots, X_n)$  be a m.l.e. (maximum likelihood estimate) of  $\theta$  for the sample size  $n$ . Woodrooffe [1] showed that  $(\frac{1}{2}\alpha n \log n)^{1/2} \times (\hat{\theta}_n - \theta)$  has an asymptotic standard normal distribution. The purpose of the present paper is to estimate the speed of convergence of  $a_n(\hat{\theta}_n - \theta)$  to the standard normal distribution. Here  $2a_n^2 = \alpha n(\log n + \log \log n)$ . Similar results for minimum contrast estimates in the regular case were given by Michel and Pfanzagl [2] and Pfanzagl [3]. More precisely, Pfanzagl [3] showed that for every compact  $K$  there exists a constant  $c_K$  such that for all  $\theta \in K$ ,  $n \geq 1$  and  $t \in R$

$$\left| P_\theta \left\{ \frac{n^{1/2}(\theta_n^* - \theta)}{\beta(\theta)} < t \right\} - \frac{1}{\sqrt{2\pi}} \int_{-\infty}^t \exp\left(-\frac{r^2}{2}\right) dr \right| \leq c_K n^{-1/2},$$

where  $\theta_n^*$  denotes a minimum contrast estimate for the sample size  $n$ .

**2. Conditions and the main result.** We shall impose the following regularity conditions on  $f(x)$ . These conditions are stronger than those made by Woodrooffe [1].

### CONDITIONS

- (i)  $f(x)$  is a uniformly continuous density which vanishes on  $(-\infty, 0)$  and is positive on  $(0, \infty)$ .
- (ii)  $f(x)$  is continuously differentiable on  $(0, \infty)$  with derivative  $f'(x)$  and  $f'(x)$  is absolutely continuous on every compact subinterval of  $(0, \infty)$  with de-

rivative  $f''(x)$ .

(iii) For some  $\alpha$  and  $r$ ,  $0 < \alpha, r < \infty$

$$f'(x) = \alpha + O(x^r) \text{ and } f''(x) = O(x^{r-1}) \quad \text{as } x \rightarrow +0.$$

Let  $g(x) = \log f(x)$  for  $x > 0$ . Then  $g(x)$  will be continuously differentiable on  $(0, \infty)$  with derivative  $g' = f'/f$  and  $g'(x)$  will be absolutely continuous on every compact subinterval of  $(0, \infty)$  with derivative  $g'' = (ff'' - f'^2)/f^2$ .

(iv) For every  $t \geq 0$

$$\int_0^\infty \{g(x+t)\}^2 f(x) dx < \infty.$$

(v) For every  $a > 0$ , there is a  $\delta > 0$ , for which

$$\int_a^\infty \sup_{|u| \leq \delta} |g'(x+u)|^3 f(x) dx < \infty.$$

(vi) For every  $a > 0$ , there is a  $\delta > 0$ , for which

$$\int_a^\infty \sup_{|u| \leq \delta} \{g''(x+u)\}^2 f(x) dx < \infty.$$

REMARK. Under conditions (i) and (ii), condition (iii) is equivalent to the following condition (iii)'.

(iii)' For some  $\alpha$  and  $r$ ,  $0 < \alpha, r < \infty$

$$f(x) = \alpha x + O(x^{1+r}), \quad g'(x) = x^{-1} + O(x^{r-1}) \text{ and } g''(x) = -x^{-2} + O(x^{r-2})$$

as  $x \rightarrow +0$ .

EXAMPLES ([1]). Let

$$f(x) = r \left[ \Gamma \left( \frac{2}{r} \right) \right]^{-1} x \exp(-x^r), \quad x > 0, \quad \text{for some } r > 0,$$

$$\text{or } f(x) = \frac{1}{d(1+d)} \frac{x}{(1+x)^{2+d}}, \quad x > 0, \quad \text{for some } d > 0,$$

then conditions (i)–(vi) are all satisfied.

Let  $M_n = \min(X_1, \dots, X_n)$  and  $G_n(t) = \sum_{i=1}^n g(X_i - t)$  for  $t < M_n$ . Condition (i) insures that m.l.e.'s exist in the interval  $(-\infty, M_n)$ . Let  $\hat{\theta}_n$ ,  $n \geq 1$ , be a sequence of m.l.e.'s. If conditions (i) and (ii) are satisfied, then

$$-\infty < \hat{\theta}_n < M_n \text{ and } G'_n(\hat{\theta}_n) = 0$$

with probability 1.

**Theorem.** Suppose that conditions (i)–(vi) are all satisfied. Let  $\hat{\theta}_n$ ,  $n \geq 1$ , denote a sequence of m.l.e.'s for  $\prod_{i=1}^n f(X_i - \theta)$  and let  $2a_n^2 = \alpha n(\log n + \log \log n)$ . Then there exists a constant  $c_1$  such that for all  $\theta \in R$ ,  $n \geq 1$  and  $t \leq 0$

$$(2.1) \quad |P_\theta\{a_n(\hat{\theta}_n - \theta) \leq t\} - \Phi(t)| \leq c_1(\log n)^{-1}.$$

Also, for every  $s$ ,  $0 < s < 1$ , there exists a constant  $c_2$  such that for all  $\theta \in R$ ,  $n \geq 1$  and  $t > 0$

$$(2.2) \quad |P_\theta\{a_n(\hat{\theta}_n - \theta) \leq t\} - \Phi(t)| \leq c_2(\log n)^{s-1}.$$

Here

$$\Phi(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^t \exp\left(-\frac{x^2}{2}\right) dx.$$

REMARK. (1) The assertion of (2.2) holds with  $(\log n)^{-1}$  instead of  $(\log n)^{s-1}$  provided  $t$  is restricted to a finite interval  $(0, M]$ .

(2) We used  $\{\frac{1}{2}\alpha n(\log n + \log \log n)\}^{1/2}$  as the convergence order of m.l.e. to the true parameter  $\theta$ . However our result is true for any  $a_n$ ,  $n \geq 1$ , satisfying that  $\alpha n a_n^{-2} \log a_n = 1 + O((\log n)^{-1})$ . Obviously, this condition includes the case that  $a_n = \{\frac{1}{2}\alpha n(\log n + \log \log n)\}^{1/2}$  but excludes the case that  $a_n = (\frac{1}{2}\alpha n \log n)^{1/2}$ .

**3. Some lemmas.** Since  $\theta$  is a translation parameter, it will suffice to prove our result in the special case that  $\theta = 0$ . Hereafter, suppose that  $\theta = 0$ . The following Lemma 1 refines the result of Woodrooffe [1].

**Lemma 1.** *Let conditions (i)–(iii) and (vi) be satisfied. Then, for sufficiently small  $\varepsilon > 0$ , there exists  $c \geq 0$  such that*

$$(3.1) \quad P\left\{\sup_{-\varepsilon \leq t < x_n} \frac{1}{n} G_n''(t) \geq -1\right\} \leq cn^{-1}$$

for all  $n \geq 1$ .

Proof. Let  $a > 0$  be so small that  $g''(x) \leq -\frac{1}{2}x^{-2}$  for  $0 < x \leq 2a$ . There is a sufficiently small number  $0 < \varepsilon < a$  such that

$$\int_0^a (x + \varepsilon)^{-2} f(x) dx > 2 \int_a^\infty \sup_{|t| \leq \varepsilon} |g''(x + t)| f(x) dx + 5$$

because the left-hand integral diverges to  $\infty$  as  $\varepsilon \rightarrow 0$ . Then the event  $M_n \leq \varepsilon$  implies that

$$\sup_{-\varepsilon \leq t < x_n} \frac{1}{n} G_n''(t) \leq -\frac{1}{2n} \sum_u^v (X_u + \varepsilon)^{-2} + \frac{1}{n} \sum_u^\infty \sup_{|t| \leq \varepsilon} |g''(X_u + t)|$$

where  $\sum_u^v$  denotes summation over  $i \leq n$  for which  $u \leq X_i < v$ . Hence the relations  $M_n \leq \varepsilon$  and  $\sup_{-\varepsilon \leq t < x_n} \frac{1}{n} G_n''(t) \geq -1$  imply

$$\left| \frac{1}{n} \sum_{i=0}^n (X_i + \varepsilon)^{-2} - \int_0^\infty (x + \varepsilon)^{-2} f(x) dx \right| \geq 1$$

or

$$\left| \frac{1}{n} \sum_{i=0}^n \sup_{|t| \leq \varepsilon} |g''(X_i + t)| - \int_{-\varepsilon}^\infty \sup_{|t| \leq \varepsilon} |g''(x + t)| f(x) dx \right| \geq 1.$$

Hence we have

$$\begin{aligned} & P \left\{ \sup_{-2 \leq t \leq 2} \frac{1}{n} G''(t) \geq -1 \right\} \\ & \leq P \{ M_n > \varepsilon \} + P \left\{ \left| \frac{1}{n} \sum_{i=0}^n (X_i + \varepsilon)^{-2} - \int_0^\infty (x + \varepsilon)^{-2} f(x) dx \right| \geq 1 \right\} \\ & \quad + P \left\{ \left| \frac{1}{n} \sum_{i=0}^n \sup_{|t| \leq \varepsilon} |g''(X_i + t)| - \int_{-\varepsilon}^\infty \sup_{|t| \leq \varepsilon} |g''(x + t)| f(x) dx \right| \geq 1 \right\}. \end{aligned}$$

Since  $P \{ M_n > \varepsilon \} = o(n^{-1})$ , Lemma 1 follows from condition (vi) and Chebychev's inequality.

Woodroffe [1] mentioned that condition (i) and

$$\int_0^\infty -g(x)f(x) dx < \infty,$$

which is a weaker condition than (iv), imply all assumptions of Wald [4]. Thus we can make use of his results.

**Lemma 2.** *Let  $\hat{\theta}_n$ ,  $n \geq 1$ , be a sequence of m.l.e.'s. Suppose that conditions (i)–(iii) and (iv) hold. Then for every  $\varepsilon > 0$  there exists  $c \geq 0$  such that*

$$P \{ |\hat{\theta}_n| \geq \varepsilon \} \leq cn^{-1}$$

for all  $n \geq 1$ .

Proof. Let  $M$  be a positive number chosen such that

$$E \{ \log \sup_{t < -M} f(X - t) \} < E \{ \log f(X) \}.$$

For every  $t \in [-M, -\varepsilon]$  there exists an open neighborhood  $U_t$  of  $t$  such that

$$E \{ \log \sup_{u \in U_t} f(X - u) \} < E \{ \log f(X) \}.$$

The existence of such a positive number  $M$  and that of such a  $U_t$  follow from Wald [4]. As  $\{U_t : t \in [-M, -\varepsilon]\}$  covers the compact set  $[-M, -\varepsilon]$ , there exists a finite subcover of this set  $[-M, -\varepsilon]$  determined by  $t_j \in [-M, -\varepsilon]$ ,  $j = 1, \dots, m$ . For notational convenience, let  $U_0 = (-\infty, -M)$  and  $U_j = U_{t_j}$ ,  $j = 1, \dots, m$ . If  $|\hat{\theta}_n| \geq \varepsilon$  and  $M_n < \varepsilon$ , then  $-\infty < \hat{\theta}_n \leq -\varepsilon$  and therefore  $\hat{\theta}_n \in U_j$  for some  $j \in \{0, 1, \dots, m\}$ , that is to say,

$$n^{-1} \sum_{i=1}^n \log \sup_{t \in U_j} f(X_i - t) \geq n^{-1} \sum_{i=1}^n \log f(X_i)$$

for some  $j \in \{0, 1, \dots, m\}$ . Write

$$b_j = E \{ \log f(X) \} - E \{ \log \sup_{t \in U_j} f(X - t) \} > 0, \quad j = 0, 1, \dots, m$$

and let  $2b = \min \{b_j; j = 0, 1, \dots, m\} > 0$ . Then

$$|n^{-1} \sum_{i=1}^n \log \sup_{t \in U_j} f(X_i - t) - E \{ \log \sup_{t \in U_j} f(X - t) \}| < b, \quad j = 0, 1, \dots, m$$

and

$$|n^{-1} \sum_{i=1}^n \log f(X_i) - E \{ \log f(X) \}| < b$$

imply

$$n^{-1} \sum_{i=1}^n \log \sup_{t \in U_j} f(X_i - t) < n^{-1} \sum_{i=1}^n \log f(X_i), \quad j = 0, 1, \dots, m.$$

Hence we have

$$\begin{aligned} P \{ |\hat{\theta}_n| \geq \varepsilon \} &\leq P \{ |\hat{\theta}_n| \geq \varepsilon, M_n < \varepsilon \} + P \{ M_n \geq \varepsilon \} \\ &\leq \sum_{j=0}^m P \{ |n^{-1} \sum_{i=1}^n \log \sup_{t \in U_j} f(X_i - t) - E \{ \log \sup_{t \in U_j} f(X - t) \}| \geq b \} \\ &\quad + P \{ |n^{-1} \sum_{i=1}^n \log f(X_i) - E \{ \log f(X) \}| \geq b \} + P \{ M_n \geq \varepsilon \}. \end{aligned}$$

Now, by conditions (i)–(iii) and (iv), the assertion follows from Chebyshev's inequality.

For  $i = 1, \dots, n$  and  $0 \leq t \leq (\log n)^{1/2}$ , let

$$Z_{ni} = Z_{ni}(X_i, t) = Y_{ni} - E \{ Y_{ni} \},$$

where

$$\begin{aligned} Y_{ni} &= Y_{ni}(X_i, t) = g'(X_i + a_n^{-1}t), & \text{if } X_i > a_n^{-1}, \\ &= 0 & \text{if } X_i \leq a_n^{-1}. \end{aligned}$$

Here  $E$  denotes expectation. Moreover, let  $b_n(t) = E \{ Z_{n1}(X_1, t) \}^2$ .

**Lemma 3.** *Let conditions (i)–(iii), (v) and (vi) be satisfied. Then there exists a constant  $c$  such that for all  $x \in R$ ,  $n \geq 1$  and  $0 \leq t \leq (\log n)^{1/2}$*

$$|P \{ (nb_n(t))^{-1/2} \sum_{i=1}^n Z_{ni}(X_i, t) < x \} - \Phi(x)| \leq c(\log n)^{-1}.$$

**Proof.** We shall first show that

$$(3.2) \quad E \{ Y_{n1} \} = -t\alpha a_n^{-1} \log a_n(1+t)^{-1} + O(a_n^{-1}(1+t)),$$

$$(3.3) \quad E \{ Y_{n1}^2 \} = \alpha \log a_n(1+t)^{-1} + O(1),$$

$$(3.4) \quad E\{|Y_{n1}|^3\} = O(a_n(1+t)^{-1}).$$

By condition (iii)', choose  $a > 0$  and  $c_0 \geq 0$  such that

$$(3.5) \quad |f(x) - \alpha x| \leq c_0 x^{1+r}, \quad |g'(x) - x^{-1}| \leq c_0 x^{r-1} \text{ and } |g''(x) + x^{-2}| \leq c_0 x^{r-2}$$

for  $0 < x \leq 2a$ . Next choose  $\delta > 0$  such that conditions (v) and (vi) hold. Then we may establish (3.2) as follows. Since

$$g'(x + a_n^{-1}t) = g'(x) + \int_0^{a_n^{-1}t} g''(x+u) du$$

we have

$$\begin{aligned} E\{Y_{n1}\} &= \int_{a_n^{-1}}^{\infty} g'(x)f(x)dx + \int_{a_n^{-1}}^{\infty} \left\{ \int_0^{a_n^{-1}t} g''(x+u) du \right\} f(x)dx \\ &= I_1 + I_2, \quad \text{say.} \end{aligned}$$

It is easily seen that

$$I_1 = - \int_0^{a_n^{-1}} g'(x) f(x) dx,$$

so that  $I_1 = O(a_n^{-1})$  by (3.5). Next we put

$$\begin{aligned} I_2 &= \int_{a_n^{-1}}^a \left\{ \int_0^{a_n^{-1}t} g''(x+u) du \right\} f(x) dx + \int_a^{\infty} \left\{ \int_0^{a_n^{-1}t} g''(x+u) du \right\} f(x) dx \\ &= I_{21} + I_{22}, \quad \text{say.} \end{aligned}$$

By condition (vi), we have  $I_{22} = O(a_n^{-1}t)$ . Moreover let

$$I_{21} = I_{211} + I_{212} + I_{213},$$

where

$$\begin{aligned} I_{211} &= - \int_{a_n^{-1}}^a \left\{ \int_0^{a_n^{-1}t} (x+u)^{-2} du \right\} \alpha x dx, \\ I_{212} &= - \int_{a_n^{-1}}^a \left\{ \int_0^{a_n^{-1}t} (x+u)^{-2} du \right\} (f(x) - \alpha x) dx, \\ I_{213} &= \int_{a_n^{-1}}^a \left\{ \int_0^{a_n^{-1}t} [g''(x+u) + (x+u)^{-2}] du \right\} f(x) dx. \end{aligned}$$

By easy computation, (3.5) implies that

$$I_{211} = -t\alpha a_n^{-1} \log a_n(1+t)^{-1} + O(a_n^{-1}t),$$

$$I_{212} = O(a_n^{-1}t)$$

and

$$I_{213} = O(a_n^{-1}t),$$

so that (3.2) is established.

To establish (3.3), let

$$\begin{aligned} E\{Y_{n1}^2\} &= \int_{a_n^{-1}}^a \{g'(x+a_n^{-1}t)\}^2 f(x) dx + \int_a^\infty \{g'(x+a_n^{-1}t)\}^2 f(x) dx \\ &= J_1 + J_2, \quad \text{say.} \end{aligned}$$

Condition (v) implies that  $J_2=O(1)$ . Divide  $J_1$  into  $J_{11}$ ,  $J_{12}$ ,  $J_{13}$  and  $J_{14}$  as follows:

$$\begin{aligned} J_{11} &= \int_{a_n^{-1}}^a (x+a_n^{-1}t)^{-2} \alpha x dx, \\ J_{12} &= \int_{a_n^{-1}}^a (x+a_n^{-1}t)^{-2} (f(x)-\alpha x) dx, \\ J_{13} &= \int_{a_n^{-1}}^a 2(x+a_n^{-1}t)^{-1} \{g'(x+a_n^{-1}t)-(x+a_n^{-1}t)^{-1}\} f(x) dx, \\ J_{14} &= \int_{a_n^{-1}}^a \{g'(x+a_n^{-1}t)-(x+a_n^{-1}t)^{-1}\}^2 f(x) dx. \end{aligned}$$

Then, by (3.5), we have

$$J_{11} = \alpha \log a_n (1+t)^{-1} + O(1),$$

$$J_{12} = O(1),$$

$$J_{13} = O(1)$$

and

$$J_{14} = O(1),$$

so that (3.3) is established.

Finally, we shall establish (3.4). Let

$$\begin{aligned} E\{|Y_{n1}|^3\} &= \int_{a_n^{-1}}^a |g'(x+a_n^{-1}t)|^3 f(x) dx + \int_a^\infty |g'(x+a_n^{-1}t)|^3 f(x) dx \\ &= K_1 + K_2, \quad \text{say.} \end{aligned}$$

By condition (v), we have  $K_2=O(1)$ . Also by (3.5) we have

$$\begin{aligned} K_1 &\leq \int_{a_n^{-1}}^a \{(1+(2a)^r c_0) (x+a_n^{-1}t)^{-1}\}^3 f(x) dx \\ &= O(a_n(1+t)^{-1}). \end{aligned}$$

This implies (3.4).

From (3.2), (3.3) and (3.4), we have

$$\begin{aligned} (3.6) \quad E\{Z_{n1}^2\} &= \alpha \log a_n (1+t)^{-1} + O(1), \\ E\{|Z_{n1}|^3\} &= O(a_n(1+t)^{-1}). \end{aligned}$$

Now, the assertion of Lemma 3 follows from the Berry-Esseen theorem ([5], Theorem 12.4).

In the rest of this section, we shall study the conditional distribution of

$a_n^{-1} \sum_{i=1}^n g'(X_i - a_n^{-1}t)$  given  $M_n > a_n^{-1}t$  for  $0 < t \leq (\log n)^{1/2}$ . The conditional distribution of  $X_1, \dots, X_n$ , given  $M_n > a_n^{-1}t$ , is that of independent random variables with common density

$$\begin{aligned} f_n^*(x) &= c_n f(x), & x > a_n^{-1}t \\ &= 0 & \text{otherwise} \end{aligned}$$

where

$$c_n = \left[ \int_{a_n^{-1}t}^{\infty} f(x) dx \right]^{-1}.$$

For  $i=1, \dots, n$  and  $0 < t \leq (\log n)^{1/2}$  let

$$Z_{ni}^* = Z_{ni}^*(X_i, t) = Y_{ni}^* - E^*\{Y_{ni}^*\}$$

where

$$\begin{aligned} Y_{ni}^* &= Y_{ni}^*(X_i, t) = g'(X_i - a_n^{-1}t), & \text{if } X_i > a_n^{-1}(1+2t), \\ &= 0 & \text{if } X_i \leq a_n^{-1}(1+2t). \end{aligned}$$

Here  $E^*$  denotes conditional expectation given  $M_n > a_n^{-1}t$ . It is easily seen that  $c_n = 1 + O(n^{-1})$  for  $0 < t \leq (\log n)^{1/2}$ . Thus, in a similar way to Lemma 3, we obtain

$$\begin{aligned} E^*\{Y_{n1}^*\} &= t \alpha a_n^{-1} \log a_n(1+t)^{-1} + O(a_n^{-1}(1+t)), \\ E^*\{Z_{n1}^{*2}\} &= \alpha \log a_n(1+t)^{-1} + O(1) \end{aligned}$$

and  $E^*\{|Z_{n1}^*|^3\} = O(a_n(1+t)^{-1})$ ,

which lead to the following lemma.

**Lemma 4.** *Let conditions (i)–(iii), (v) and (vi) be satisfied. Then there exists a constant  $c$  such that for all  $x \in R$ ,  $n \geq 1$  and  $0 < t \leq (\log n)^{1/2}$*

$$|P\{(nb_n^*(t))^{-1/2} \sum_{i=1}^n Z_{ni}^*(X_i, t) < x \mid M_n > a_n^{-1}t\} - \Phi(x)| \leq c(\log n)^{-1},$$

where  $b_n^*(t) = E^*\{Z_{n1}^*(X_1, t)\}^2$ .

**4. Proof of Theorem.** As the left sides of (2.1) and (2.2) are uniformly bounded for  $\theta \in R$  and  $t \in R$ , it suffices to prove the assertion for all sufficiently large  $n$ . To simplify our notations we shall use  $n_0$  as a generic constant instead of the phrase “for all sufficiently large  $n$ ”. In the same manner we shall use  $c$  as a generic constant to denote factors occurring in the bounds.

We shall use ideas related to Woodroffe [1]. It follows from Lemma 1 and Lemma 2 that

$$(4.1) \quad P\{a_n \hat{\theta}_n \leq -t\} = P\{a_n^{-1} \sum_{i=1}^n g'(X_i + a_n^{-1}t) \geq 0\} + O(n^{-1}),$$

where  $O(n^{-1})$  is uniform in  $t \in [0, a_n \varepsilon]$ . Here  $\varepsilon > 0$  is chosen sufficiently small so that (3.1) of Lemma 1 holds. Similarly, it follows from Lemma 1 and Lemma 2 that

$$\begin{aligned} (4.2) \quad P\{a_n \hat{\theta}_n > t\} &= P\{a_n^{-1} \sum_{i=1}^n g'(X_i - a_n^{-1}t) < 0, M_n > a_n^{-1}t\} + O(n^{-1}) \\ &= P\{a_n^{-1} \sum_{i=1}^n g'(X_i - a_n^{-1}t) < 0 \mid M_n > a_n^{-1}t\} P\{M_n > a_n^{-1}t\} \\ &\quad + O(n^{-1}), \end{aligned}$$

where  $O(n^{-1})$  is uniform in  $t > 0$ .

We shall first show the validity of (2.1). By condition (iii)'

$$\begin{aligned} (4.3) \quad |P\{a_n^{-1} \sum_{i=1}^n g'(X_i + a_n^{-1}t) \geq 0\} - P\{a_n^{-1} \sum_{i=1}^n Y_{ni} \geq 0\}| &\leq \sum_{i=1}^n P\{X_i \leq a_n^{-1}\} \\ &\leq c(\log n)^{-1} \end{aligned}$$

for all  $n \geq n_0$  and  $0 \leq t \leq (\log n)^{1/2}$ . Since

$$P\{a_n^{-1} \sum_{i=1}^n Y_{ni} \geq 0\} = P\{(nb_n(t))^{-1/2} \sum_{i=1}^n Z_{ni} \geq x_n(t)\},$$

where

$$x_n(t) = -n^{1/2}(b_n(t))^{-1/2}E\{Y_{n1}\},$$

it follows from Lemma 3 that

$$(4.4) \quad |P\{a_n^{-1} \sum_{i=1}^n Y_{ni} \geq 0\} - \Phi(-x_n(t))| \leq c(\log n)^{-1}$$

for all  $n \geq 1$  and  $0 \leq t \leq (\log n)^{1/2}$ . According to (3.2) and (3.6)

$$\begin{aligned} -x_n(t) &= (na_n^{-1}E\{Y_{n1}\})(na_n^{-2}b_n(t))^{-1/2} \\ &= \{-t + 2t \log(1+t)(\log n)^{-1} + O((1+t)(\log n)^{-1})\} \\ &\quad \times \{1 - 2 \log(1+t)(\log n)^{-1} + O((\log n)^{-1})\}^{-1/2} \\ &= -t + t \log(1+t)(\log n)^{-1} + O((1+t)(\log n)^{-1}). \end{aligned}$$

Hence, for  $n \geq n_0$  and  $0 \leq t \leq (\log n)^{1/2}$

$$\begin{aligned} (4.5) \quad |\Phi(-x_n(t)) - \Phi(-t)| &\leq \frac{1}{\sqrt{2\pi}} |t - x_n(t)| \max \left\{ \exp\left(-\frac{t^2}{2}\right), \exp\left(-\frac{x_n(t)^2}{2}\right) \right\} \\ &\leq c(\log n)^{-1}. \end{aligned}$$

From (4.1), (4.3), (4.4) and (4.5), there exists a constant  $c$  such that

$$(4.6) \quad |P\{a_n \hat{\theta}_n \leq -t\} - \Phi(-t)| \leq c(\log n)^{-1}$$

for all  $n \geq n_0$  and  $0 \leq t \leq (\log n)^{1/2}$ . For  $t > (\log n)^{1/2}$  we have

$$|P\{a_n\hat{\theta}_n \leq -t\} - \Phi(-t)| \leq P\{a_n\hat{\theta}_n \leq -(\log n)^{1/2}\} + \Phi(-(\log n)^{1/2}).$$

Using (4.6) and Feller ([6], p. 166, Lemma 2), we obtain

$$(4.7) \quad |P\{a_n\hat{\theta}_n \leq -t\} - \Phi(-t)| \leq c(\log n)^{-1}$$

for  $n \geq n_0$  and  $t > (\log n)^{1/2}$ . Hence (4.6) and (4.7) imply (2.1).

We next show the validity of (2.2). By condition (iii)'

$$\begin{aligned} & |P\{a_n^{-1} \sum_{i=1}^n g'(X_i - a_n^{-1}t) < 0 \mid M_n > a_n^{-1}t\} - P\{a_n^{-1} \sum_{i=1}^n Y_{ni}^* < 0 \mid M_n > a_n^{-1}t\}| \\ & \leq \sum_{i=1}^n P\{X_i \leq a_n^{-1}(1+2t) \mid M_n > a_n^{-1}t\} \\ & \leq cn a_n^{-2}(3t^2 + 4t + 1). \end{aligned}$$

Hence, for every  $s$ ,  $0 < s < 1$ , there exists a constant  $c$  such that for  $n \geq n_0$  and  $0 < t \leq (\log n)^{s/2}$

$$(4.8) \quad \begin{aligned} & |P\{a_n^{-1} \sum_{i=1}^n g'(X_i - a_n^{-1}t) < 0 \mid M_n > a_n^{-1}t\} - P\{a_n^{-1} \sum_{i=1}^n Y_{ni}^* < 0 \mid M_n > a_n^{-1}t\}| \\ & \leq c(\log n)^{s-1}. \end{aligned}$$

Applying arguments similar to those used in (4.4) and (4.5), Lemma 4 implies

$$(4.9) \quad |P\{a_n^{-1} \sum_{i=1}^n Y_{ni}^* < 0 \mid M_n > a_n^{-1}t\} - \{1 - \Phi(t)\}| \leq c(\log n)^{-1}$$

for  $n \geq n_0$  and  $0 < t \leq (\log n)^{1/2}$ . By (4.8) and (4.9) we have

$$\begin{aligned} & |P\{a_n^{-1} \sum_{i=1}^n g'(X_i - a_n^{-1}t) < 0 \mid M_n > a_n^{-1}t\} P\{M_n > a_n^{-1}t\} - \{1 - \Phi(t)\}| \\ & \leq |P\{a_n^{-1} \sum_{i=1}^n g'(X_i - a_n^{-1}t) < 0 \mid M_n > a_n^{-1}t\} - \{1 - \Phi(t)\}| P\{M_n > a_n^{-1}t\} \\ & \quad + \{1 - \Phi(t)\} P\{M_n \leq a_n^{-1}t\} \\ & \leq \{1 - \Phi(t)\} P\{M_n \leq a_n^{-1}t\} + c(\log n)^{s-1} \end{aligned}$$

for  $n \geq n_0$  and  $0 < t \leq (\log n)^{s/2}$ . Using Feller ([6], p. 166, Lemma 2), we obtain

$$\begin{aligned} \{1 - \Phi(t)\} P\{M_n \leq a_n^{-1}t\} & \leq ct \exp\left(-\frac{t^2}{2}\right) (\log n)^{-1} \\ & \leq c(\log n)^{-1} \end{aligned}$$

for  $n \geq n_0$  and  $t > 0$ . Hence, from this and (4.2) it follows that for  $n \geq n_0$  and  $0 < t \leq (\log n)^{s/2}$

$$|P\{a_n\hat{\theta}_n > t\} - \{1 - \Phi(t)\}| \leq c(\log n)^{s-1},$$

from which (2.2) is shown by a similar argument used in (4.7). Thus we complete the proof of the theorem.

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