

## Asymptotic Sufficiency of Maximum Likelihood Estimator in a Truncated Location Family

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### Introduction

Let  $f(x)$  be a probability density function on real line which vanishes on  $(-\infty, 0]$  and twice continuously differentiable in  $(0, \infty)$ . We consider the case that for  $\alpha \geq 2$ ,  $f(x) \sim Ax^{\alpha-1}$  as  $x \rightarrow +0$  and  $f'(x) \sim Bx^{\alpha-2}$  as  $x \rightarrow +0$  ( $0 < A, B < \infty$ ). Let  $X_1, \dots, X_n$  be an independent identically distributed random sample of size  $n$  ( $n=1, 2, \dots$ ) according to a distribution  $P_\theta$  with density  $f(x-\theta)$ , and let  $\{\hat{\theta}_n\} = \{\hat{\theta}_n(X_1, \dots, X_n)\}$  be the maximum likelihood estimator (or MLE) of  $\theta$ . In this paper we prove that under some assumptions (See Section 1.),  $\{\hat{\theta}_n\}$  is asymptotically sufficient statistic for  $\{P_\theta: \theta \in \Theta\}$  in the sense of LeCam [5]. Our theory of asymptotic sufficiency of MLE is based on the asymptotic properties of MLE and likelihood function, which have been studied in non-regular cases by Akahira [1], Takeuchi [6], Takeuchi and Akahira [7] and Woodroffe [9]. Asymptotic sufficiency of MLE has been discussed under the regular conditions by Kaufman [4] and LeCam [5]. In Akahira [2], asymptotic sufficiency has been discussed in a non-regular case when the density function, with a location parameter, has a compact support on  $R^1$  and positive values at the end points.

In Section 1 notations and assumptions are stated, and in Section 2 we state some known results concerning order of consistency of MLE and  $\min(X_1, \dots, X_n)$  (cf. [1], [6], [7], [9]). In Section 3 we will show that MLE is asymptotically sufficient for  $\{P_\theta: \theta \in \Theta\}$  in our non-regular case.

### §1. Notations and assumptions.

Let  $X$  be a sample space whose generic point is denoted by  $x$ ,  $\mathcal{B}$  a  $\sigma$ -field of subset of  $X$  and  $\{P_\theta: \theta \in \Theta\}$  a set of probability measures on

$\mathcal{B}$ , where  $\theta$  is called a parameter space. In this paper it will be assumed that  $X = \theta = R^1$ . For each  $n = 1, 2, \dots$ , let  $(X^n, \mathcal{B}^n)$  be the cartesian product of  $n$  copies of  $(X, \mathcal{B})$  and  $P_{n\theta}$  corresponding product measure of  $P_\theta$ . The point of  $X^n$  will be denoted by  $\tilde{x}_n = (x_1, \dots, x_n)$  and the corresponding random sample by  $\tilde{X}_n = (X_1, \dots, X_n)$ . We suppose that  $P_\theta (\theta \in \Theta)$  is absolutely continuous with respect to the Lebesgue measure  $\mu$  on  $R^1$ . Then we denote the density  $dP_\theta/d\mu$  by  $f(x, \theta)$ .

We suppose that  $\theta$  is a location parameter (i.e.,  $f(x, \theta) = f(x - \theta)$ ) and consider following assumptions (I), (II), (III), (IV) and (V).

$$(I) \quad \begin{aligned} f(x) &> 0 \text{ if } x > 0 \\ f(x) &= 0 \text{ if } x \leq 0 \end{aligned}$$

$$(II) \quad f(x) \text{ is twice continuously differentiable in } (0, \infty), \text{ and for } \alpha \geq 2$$

$$\lim_{x \rightarrow +0} x^{1-\alpha} f(x) = A \quad 0 < A < \infty,$$

$$\lim_{x \rightarrow +0} x^{2-\alpha} f'(x) = B \quad 0 < B < \infty,$$

and

$$\lim_{x \rightarrow +\infty} f(x) = 0$$

and  $f''(x)$  is a bounded function.

Let  $g(x) = \log f(x)$  ( $0 < x < \infty$ ).

$$(III) \quad \int_0^\infty |g(x)| f(x) dx < \infty,$$

$$(IV) \quad \text{for every } \delta > 0, \int_\delta^\infty g'(x)^2 f(x) dx < \infty,$$

$$(V) \quad \text{for every } a > 0, \text{ there exists a } \delta \text{ (} 0 < \delta < a \text{) for which}$$

$$\int_a^\infty \sup_{|t| \leq \delta} |g''(x-t)| f(x) dx < \infty.$$

These assumptions are much the same as Woodroffe's conditions in [9] except for the assumption (III), but the assumption (II) is slightly different from his condition. The assumption (III) will be needed to prove the consistency of MLE (cf. Wald [8]).

## §2. Order of consistency of MLE and minimum statistic.

Under the assumption (II), if  $X_1, \dots, X_n$  is an independent identically distributed random sample from the population with density  $f(x - \theta)$ , then maximum likelihood estimators exist in the interval  $(-\infty, M_n)$ , where  $M_n = \min(X_1, \dots, X_n)$ . We denote it by  $\{\hat{\theta}_n\} = \{\hat{\theta}_n(X_1, \dots, X_n)\}$ .

We have the following lemma by the similar method as in Akahira [1], Takeuchi and Akahira [7] and Cramér [3].

LEMMA 2.1. *Suppose that the assumptions (I), (II), (IV) and (V) are satisfied with  $\alpha > 2$ . Then  $I < \infty$  and  $I = -\int_0^\infty g''(x)f(x)dx$ , where  $I = \int_0^\infty g'(x)^2 f(x)dx$  denotes Fisher information number.*

The first part in the following theorem is obtained in [1], [6], [7], [8] and [9], and the second part is obtained in [1], [3], [6], [7] and [8].

THEOREM 2.1. *Suppose that the assumptions (I)~(V) are satisfied.*

(i) *If  $\alpha = 2$ , then for any compact subset  $K$  of  $\Theta$ ,  $\sqrt{c_1 n \log n} (\hat{\theta}_n - \theta)$  converges in law to the standard normal distribution  $N(0, 1)$  as  $n \rightarrow \infty$  uniformly in  $\theta \in K$ , where  $c_1 = B^2/2A$ .*

(ii) *If  $\alpha > 2$ , then for any compact subset  $K$  of  $\Theta$ ,  $\sqrt{nI} (\hat{\theta}_n - \theta)$  converges in law to the standard normal distribution  $N(0, 1)$  as  $n \rightarrow \infty$  uniformly in  $\theta \in K$ .*

The following definition is due to Akahira [1] or Takeuchi [6].

DEFINITION 2.1. For an increasing sequence of positive numbers  $\{c_n\}$  ( $c_n$  tending to infinity) an estimator  $\{T_n\}$  ( $n = 1, 2, \dots$ ) is called *consistent with order  $\{c_n\}$* , if for every  $\varepsilon > 0$  and every  $\theta' \in \Theta$ , there exist a sufficiently small number  $\delta$  and a sufficiently large number  $L$  such that

$$\overline{\lim}_{n \rightarrow \infty} \sup_{\theta: |\theta - \theta'| < \delta} P_{n\theta}(\{c_n | T_n - \theta| \geq L\}) < \varepsilon.$$

By Definition 2.1 and Theorem 2.1 we can state that if  $\alpha = 2$  then MLE is consistent with order  $\{(n \log n)^{1/2}\}$ , and if  $\alpha > 2$  then MLE is consistent with order  $\{n^{1/2}\}$ .

Next we state a result concerning  $M_n$ .

THEOREM 2.2 (Woodroffe [9]). *Suppose that the assumptions (I), (II) are satisfied. If  $\alpha \geq 2$ , then  $M_n$  is consistent with order  $\{n^{1/\alpha}\}$ .*

More precisely, it will be obtained that if  $\alpha \geq 2$ , then for all  $t > 0$ ,  $P_{n\theta}(n^{1/\alpha}(M_n - \theta) > t) \rightarrow \exp(-At^\alpha/\alpha)$  as  $n \rightarrow \infty$  uniformly in  $\theta \in \Theta$ . However we will not require the exact limit distribution for  $M_n$  in the sequel.

### §3. Asymptotic sufficiency of MLE.

In the beginning we state some lemmas.

LEMMA 3.1 (Woodroffe [9]). *Suppose that the assumptions (I) and (II) are satisfied with  $\alpha = 2$ . Let  $0 < \delta < \infty$  and define  $Z_i = X_i^{-1}$  if  $0 < X_i < \delta$*

and  $Z_i = 0$  if  $X_i \geq \delta$   $i = 1, 2, \dots, n$ . Then

$$(c_2 n \log n)^{-1} \sum_{i=1}^n Z_i^2 \longrightarrow 1 \text{ in probability as } n \longrightarrow \infty,$$

where  $c_2 = A/2$ .

We define

$$p_n(\tilde{x}_n, \theta) = \prod_{i=1}^n f(x_i - \theta)$$

$$\lambda_n(\tilde{x}_n, \theta) = \log p_n(\tilde{x}_n, \theta) \text{ if } M_n > \theta$$

$$G_n''(t) = [\partial^2 \lambda_n(\tilde{x}_n, \theta) / \partial \theta^2]_{\theta=t}.$$

Next we state a result concerning likelihood function. The following lemma is a slight modification of Lemma 3.4 in [9] and it will be shown by similar method.

LEMMA 3.2. Suppose that the assumptions (I), (II) and (V) are satisfied.

(i) If  $\alpha = 2$ , then for positive  $\beta_n$  satisfying  $\beta_n^{-1} = o(n^{-1/2})$ ,

$$\sup_{|t| \leq 1} |(c_1 n \log n)^{-1} G_n''(\theta + t\beta_n^{-1}) + 1| \longrightarrow 0$$

in  $P_{n\theta}$ -probability as  $n \rightarrow \infty$  uniformly in  $\theta \in \Theta$ .

(ii) If  $\alpha > 2$ , then for positive  $\beta_n$  satisfying  $\beta_n^{-1} = o(n^{-1/\alpha})$ ,

$$\sup_{|t| \leq 1} |n^{-1} G_n''(\theta + t\beta_n^{-1}) + I| \longrightarrow 0$$

in  $P_{n\theta}$ -probability as  $n \rightarrow \infty$  uniformly in  $\theta \in \Theta$ .

PROOF. Since  $\theta$  is a location parameter, we can restrict our attention to the case  $\theta = 0$ .

At first we prove the part (i). From the assumption (II), we have  $g''(x) \sim -B^2/(A^2 x^2)$  as  $x \rightarrow +0$ . For arbitrarily given  $0 < \varepsilon < 1$ , let  $a > 0$  be so small that  $|(A^2 x^2 g''(x))/B^2 + 1| \leq \varepsilon$  for  $0 < x \leq 2a$ . For  $0 < c < d \leq \infty$ , let  $\sum_c^d$  denote the summation over all  $i = 1, 2, \dots, n$  for which  $c < X_i < d$ . If  $M_n \geq \beta_n^{-1}/\varepsilon$ , which holds with probability approaching to one, then for  $t$  and  $\beta_n$  satisfying  $|t| \leq 1$  and  $\beta_n^{-1} < a$  respectively,

$$\begin{aligned} (3.1) \quad & (c_1 n \log n)^{-1} G_n''(t\beta_n^{-1}) \\ &= (c_1 n \log n)^{-1} \left( \sum_0^a g''(X_i - t\beta_n^{-1}) + \sum_a^\infty g''(X_i - t\beta_n^{-1}) \right) \\ &\leq -\frac{B^2(1-\varepsilon)}{A^2} (c_1 n \log n)^{-1} \sum_0^a (X_i - t\beta_n^{-1})^{-2} \end{aligned}$$

$$\begin{aligned}
 & + (c_1 n \log n)^{-1} \sum_a^\infty \sup_{|t| \leq \beta_n^{-1}} |g''(X_i - t)| \\
 & \leq -(1-\varepsilon)(1+\varepsilon)^{-2} (c_2 n \log n)^{-1} \sum_0^a X_i^{-2} + o_p(1) \\
 & \longrightarrow -(1-\varepsilon)(1+\varepsilon)^{-2} \text{ in } P_{n_0}\text{-probability as } n \longrightarrow \infty .
 \end{aligned}$$

We have used Lemma 3.1 and assumption (V) in the final steps in (3.1). Similarly we obtain

$$(3.2) \quad \lim_{n \rightarrow \infty} (c_1 n \log n)^{-1} G_n''(t\beta_n^{-1}) \geq -(1+\varepsilon)(1-\varepsilon)^{-2}$$

in  $P_{n_0}$ -probability. Since  $\varepsilon > 0$  is arbitrary, from (3.1) and (3.2), we have completed the proof of part (i).

Next we prove the part (ii). For arbitrarily given  $0 < \varepsilon < 1$ , probability of the event  $M_n \geq \beta_n^{-1}/\varepsilon$  approaches to one as  $n \rightarrow \infty$ . From the assumption (II), if  $2 < \alpha < 3$  then  $g''(x) \sim -B^2/A^2 x^2$  as  $x \rightarrow +0$  and if  $\alpha \geq 3$  then  $x^{\alpha-1} g''(x) = O(1)$  as  $x \rightarrow +0$ . Therefore, we divide the proof into two cases. At first we prove the lemma in the case  $2 < \alpha < 3$ . Let  $a$  so small that

$$\left| \frac{A^2 x^2}{B^2} g''(x) + 1 \right| \leq \varepsilon \quad \text{for } 0 < x \leq 2a .$$

If  $M_n \geq \beta_n^{-1}/\varepsilon$ , then for  $t$  and  $\beta_n$  satisfying  $|t| \leq 1$  and  $\beta_n^{-1} < a$  respectively and for a suitable  $\delta > 0$  and  $b > a$  we have

$$\begin{aligned}
 & n^{-1} G_n''(t\beta_n^{-1}) \\
 & = n^{-1} \left( \sum_0^a g''(X_i - t\beta_n^{-1}) + \sum_a^\infty g''(X_i - t\beta_n^{-1}) \right) \\
 & \leq -\frac{B^2(1-\varepsilon)}{nA^2} \sum_0^a (X_i - t\beta_n^{-1})^{-2} + \frac{1}{n} \sum_a^\infty \sup_{|t| \leq \beta_n^{-1}} g''(X_i - t) \\
 & \leq -\frac{B^2(1-\varepsilon)(1+\varepsilon)^{-2}}{nA^2} \sum_0^a X_i^{-2} + \frac{1}{n} \sum_a^\infty \sup_{|t| \leq \beta_n^{-1}} g''(X_i - t) \\
 & \leq \frac{(1-\varepsilon)(1+\varepsilon)^{-3}}{n} \sum_0^a g''(X_i) + \frac{1}{n} \sum_a^b \sup_{|t| \leq \delta} g''(X_i - t) \\
 & \quad + \frac{1}{n} \sum_b^\infty \sup_{|t| \leq \delta} g''(X_i - t) \\
 & = (1-\varepsilon)(1+\varepsilon)^{-3} J_{1n}(a) + J_{2n}(a, b, \delta) + J_{3n}(b, \delta) ,
 \end{aligned}$$

where

$$J_{1n}(a) = \frac{1}{n} \sum_0^a g''(X_i) ,$$

$$J_{2n}(a, b, \delta) = \frac{1}{n} \sum_a^b \sup_{|t| \leq \delta} g''(X_t - t),$$

$$J_{3n}(b, \delta) = \frac{1}{n} \sum_b^\infty \sup_{|t| \leq \delta} g''(X_t - t).$$

By Lemma 2.1 and assumption (V),

$$(3.3) \quad J_{1n}(a) \longrightarrow J_1(a) \quad \text{in } P_{n_0}\text{-probability as } n \longrightarrow \infty,$$

$$(3.4) \quad J_{2n}(a, b, \delta) \longrightarrow J_2(a, b, \delta) \quad \text{in } P_{n_0}\text{-probability as } n \longrightarrow \infty,$$

$$(3.5) \quad J_{3n}(b, \delta) \longrightarrow J_3(b, \delta) \quad \text{in } P_{n_0}\text{-probability as } n \longrightarrow \infty,$$

where

$$J_1(a) = \int_0^a g''(x)f(x)dx,$$

$$J_2(a, b, \delta) = \int_a^b \sup_{|t| \leq \delta} g''(x-t)f(x)dx,$$

$$J_3(b, \delta) = \int_b^\infty \sup_{|t| \leq \delta} g''(x-t)f(x)dx.$$

From Lemma 2.1, assumption (V) and the continuousness of  $g''(x)$ , we obtain that for sufficiently small  $a$ , sufficiently large  $b$  and suitable  $\delta$ ,

$$(3.6) \quad J_1(a) < \varepsilon,$$

$$(3.7) \quad J_2(a, b, \delta) < \int_a^b g''(x)f(x)dx + \varepsilon < -I + 2\varepsilon,$$

$$(3.8) \quad J_3(b, \delta) < \varepsilon.$$

By (3.3)~(3.8), we have

$$(3.9) \quad \begin{aligned} & (1-\varepsilon)(1+\varepsilon)^{-3}J_{1n}(a) + J_{2n}(a, b, \delta) + J_{3n}(b, \delta) \\ & \longrightarrow (1-\varepsilon)(1+\varepsilon)^{-3}J_1(a) + J_2(a, b, \delta) + J_3(b, \delta) \\ & \quad (\text{in } P_{n_0}\text{-probability as } n \longrightarrow \infty) \\ & \leq \varepsilon(1-\varepsilon)(1+\varepsilon)^{-3} + 3\varepsilon - I. \end{aligned}$$

Similarly we obtain

$$(3.10) \quad \varliminf_{n \rightarrow 0} n^{-1}G_n''(t\beta_n^{-1}) \geq -\varepsilon(1+\varepsilon)(1-\varepsilon)^{-3} - 3\varepsilon - I \quad \text{in } P_{n_0}\text{-probability}.$$

Since  $\varepsilon > 0$  is arbitrary, from (3.9) and (3.10) we have completed the proof in the case  $2 < \alpha < 3$ .

Next we prove the lemma in the case  $3 \leq \alpha$ . For some constant

$M > 0$ , let  $a$  be so small that

$$|x^{\alpha-1}g''(x)| \leq M \text{ for } 0 < x \leq 2a .$$

If  $M_n \geq \beta_n^{-1}/\epsilon$ , then for  $t$  and  $\beta_n$  satisfying  $|t| \leq 1$  and  $\beta_n^{-1} < a$  respectively and for a suitable  $\delta > 0$  and  $b > a$  we have

$$\begin{aligned} & \frac{1}{n}G''(t\beta_n^{-1}) \\ & \leq \frac{M}{n} \sum_0^a (X_i - t\beta_n^{-1})^{1-\alpha} + \frac{1}{n} \sum_a^\infty g''(X_i - t\beta_n^{-1}) \\ & \leq \frac{M(1+\epsilon)^{1-\alpha}}{n} \sum_0^a X_i^{1-\alpha} + \frac{1}{n} \sum_a^b \sup_{|t| \leq \delta} g''(X_i - t) \\ & \quad + \frac{1}{n} \sum_b^\infty \sup_{|t| \leq \delta} g''(X_i - t) \\ & = M(1+\epsilon)^{1-\alpha} J'_{1n}(a) + J'_{2n}(a, b, \delta) + J'_{3n}(b, \delta) , \end{aligned}$$

where

$$\begin{aligned} J'_{1n}(a) &= \frac{1}{n} \sum_0^a X_i^{1-\alpha} , \\ J'_{2n}(a, b, \delta) &= \frac{1}{n} \sum_a^b \sup_{|t| \leq \delta} g''(X_i - t) , \\ J'_{3n}(b, \delta) &= \frac{1}{n} \sum_b^\infty \sup_{|t| \leq \delta} g''(X_i - t) . \end{aligned}$$

By the assumptions (II) and (V),

(3.11)  $J'_{1n}(a) \longrightarrow M'a$  in  $P_{n_0}$ -probability as  $n \rightarrow \infty$ , where  $M' > 0$  is some constant,

(3.12)  $J'_{2n}(a, b, \delta) \longrightarrow J'_2(a, b, \delta)$  in  $P_{n_0}$ -probability as  $n \rightarrow \infty$ ,

(3.13)  $J'_{3n}(b, \delta) \longrightarrow J'_3(b, \delta)$  in  $P_{n_0}$ -probability as  $n \rightarrow \infty$ ,

where

$$\begin{aligned} J'_2(a, b, \delta) &= \int_a^b \sup_{|t| \leq \delta} g''(x-t)f(x)dx , \\ J'_3(b, \delta) &= \int_b^\infty \sup_{|t| \leq \delta} g''(x-t)f(x)dx . \end{aligned}$$

According to the similar method treated in the case  $2 < \alpha < 3$ , we have for a sufficiently small  $a > 0$  and a sufficiently large  $b$ ,

$$(3.14) \quad M'a < \varepsilon ,$$

$$(3.15) \quad J'_2(a, b, \delta) < -I + 2\varepsilon ,$$

$$(3.16) \quad J'_3(b, \delta) < \varepsilon .$$

From (3.11)~(3.16),

$$(3.17) \quad \begin{aligned} & M(1+\varepsilon)^{1-\alpha} J'_{1n}(a) + J'_{2n}(a, b, \delta) + J'_{3n}(b, \delta) \\ & \longrightarrow MM'(1+\varepsilon)^{1-\alpha} a + J'_2(a, b, \delta) + J'_3(b, \delta) \text{ (in } P_{n_0}\text{-probability as} \\ & \quad n \longrightarrow \infty) \\ & \leq M\varepsilon(1+\varepsilon)^{1-\alpha} + 3\varepsilon - I . \end{aligned}$$

Similarly we obtain

$$(3.18) \quad \varliminf_{n \rightarrow \infty} n^{-1} G''_n(t\beta_n^{-1}) \geq -M\varepsilon(1+\varepsilon)^{1-\alpha} - 3\varepsilon - I \text{ in } P_{n_0}\text{-probability as} \\ n \longrightarrow \infty .$$

By (3.17) and (3.18), we have completed the proof in the case  $3 \leq \alpha$ , since  $\varepsilon > 0$  is arbitrary.

In the following we make use of next notations.

$$\begin{aligned} A_n^{(1)}(\delta) &= \{\tilde{x}_n : \sqrt{n \log n} |\hat{\theta}_n - \theta| < \delta\} \\ A_n^{(2)}(\delta) &= \{\tilde{x}_n : \sqrt{n} |\hat{\theta}_n - \theta| < \delta\} \\ B_n^{(1)}(\varepsilon) &= \{\tilde{x}_n : |(c_1 n \log n)^{-1} G''_n(\hat{\theta}_n) + 1| < \varepsilon\} \\ B_n^{(2)}(\varepsilon) &= \{\tilde{x}_n : |n^{-1} G''_n(\hat{\theta}_n) + I| < \varepsilon\} \\ C_n^{(1)} &= \{\tilde{x}_n : \hat{\theta}_n + (n \log n)^{-1/2} < M_n\} \\ C_n^{(2)} &= \{\tilde{x}_n : \hat{\theta}_n + n^{-1/2} < M_n\} . \end{aligned}$$

**LEMMA 3.3.** *Suppose that the assumptions (I), (II), (III), (IV) and (V) are satisfied. If  $\alpha=2$  ( $\alpha>2$ ), then for any compact subset  $K$  of  $\Theta$ ,  $P_{n\theta}(C_n^{(1)})$  ( $P_{n\theta}(C_n^{(2)})$ )  $\rightarrow 1$  as  $n \rightarrow \infty$  uniformly in  $\theta \in K$ , and there exists a positive null sequence  $\{\varepsilon_n\}$  and a positive divergent sequence  $\{\delta_n\}$  such that  $P_{n\theta}(A_n^{(1)}(\delta_n))$  ( $P_{n\theta}(A_n^{(2)}(\delta_n))$ )  $\rightarrow 1$  and  $P_{n\theta}(B_n^{(1)}(\varepsilon_n))$  ( $P_{n\theta}(B_n^{(2)}(\varepsilon_n))$ )  $\rightarrow 1$  as  $n \rightarrow \infty$  both uniformly on any compact subset of  $\Theta$  and that  $\delta_n^2 \varepsilon_n \rightarrow 0$  as  $n \rightarrow \infty$ .*

**PROOF.** Let  $K$  be any compact subset of  $\Theta$  throughout this proof. By Theorem 2.1 we obtain that for any positive divergent sequence  $\{\delta_n\}$ ,  $P_{n\theta}(A_n^{(1)}(\delta_n)) \rightarrow 1$  as  $n \rightarrow \infty$  uniformly in  $\theta \in K$  when  $\alpha=2$ , and  $P_{n\theta}(A_n^{(2)}(\delta_n)) \rightarrow 1$  as  $n \rightarrow \infty$  uniformly in  $\theta \in K$  when  $\alpha>2$ . By Theorems 2.1 and 2.2, we have



$$\begin{aligned} &P_{n\theta}(C_n^{(1)}) \\ &= P_{n\theta}(\{\tilde{x}_n: \sqrt{n \log n} (\hat{\theta}_n - \theta) + 1 < \sqrt{n \log n} (M_n - \theta)\}) \\ &\longrightarrow 1 \text{ as } n \longrightarrow \infty \text{ uniformly in } \theta \in K \text{ when } \alpha = 2, \end{aligned}$$

and

$$\begin{aligned} &P_{n\theta}(C_n^{(2)}) \\ &= P_{n\theta}(\{\tilde{x}_n: \sqrt{n} (\hat{\theta}_n - \theta) + 1 < \sqrt{n} (M_n - \theta)\}) \\ &\longrightarrow 1 \text{ as } n \longrightarrow \infty \text{ uniformly in } \theta \in K \text{ when } \alpha > 2. \end{aligned}$$

By the first part in Lemma 3.2, there exists a positive null sequence  $\{\varepsilon_n\}$  such that

$$\begin{aligned} (3.19) \quad &P_{n\theta}(\{\tilde{x}_n: \sup_{|t| \leq 1} |(c_1 n \log n)^{-1} G_n''(\theta + t(n \log \log n)^{-1/2}) + 1| > \varepsilon_n\}) \longrightarrow 0 \\ &\text{as } n \longrightarrow \infty \text{ uniformly in } \theta \in K. \end{aligned}$$

Moreover, for the sequence  $\{\varepsilon_n\}$  satisfying (3.19) we can choose a positive divergent sequence  $\{\delta_n\}$  such that

$$\begin{aligned} (3.20) \quad &\delta_n^2 \varepsilon_n \longrightarrow 0 \text{ as } n \longrightarrow \infty \text{ and } \delta_n \sqrt{n \log \log n} / \sqrt{n \log n} \longrightarrow 0 \\ &\text{as } n \longrightarrow \infty. \end{aligned}$$

From (3.19) and (3.20), we can choose a positive null sequence  $\{\varepsilon_n\}$  and a positive divergent sequence  $\{\delta_n\}$  such that

$$\begin{aligned} (3.21) \quad &P_{n\theta}(\{\tilde{x}_n: \sup_{|t| \leq 1} |(c_1 n \log n)^{-1} G_n''(\theta + t\delta_n(n \log n)^{-1/2}) + 1| > \varepsilon_n\}) \longrightarrow 0 \\ &\text{as } n \longrightarrow \infty \text{ uniformly in } \theta \in K, \end{aligned}$$

$$\begin{aligned} (3.22) \quad &\delta_n^2 \varepsilon_n \longrightarrow 0 \text{ as } n \longrightarrow \infty \text{ and } \delta_n \sqrt{n \log \log n} / \sqrt{n \log n} \longrightarrow 0 \\ &\text{as } n \longrightarrow \infty. \end{aligned}$$

By (3.21), (3.22) and the result which was shown in the beginning,

$$\begin{aligned} &P_{n\theta}(B_n^{(1)}(\varepsilon_n)) \\ &= P_{n\theta}(\{\tilde{x}_n: |(c_1 n \log n)^{-1} G_n''(\hat{\theta}_n) + 1| < \varepsilon_n\}) \\ &\geq P_{n\theta}(\{\tilde{x}_n: |(c_1 n \log n)^{-1} G_n''(\hat{\theta}_n) + 1| < \varepsilon_n\} \cap A_{n\theta}^{(1)}(\delta_n)) \\ &= P_{n\theta}(\{\tilde{x}_n: |(c_1 n \log n)^{-1} G_n''(\hat{\theta}_n) + 1| < \varepsilon_n\} | A_{n\theta}^{(1)}(\delta_n)) \\ &\quad \times P_{n\theta}(A_{n\theta}^{(1)}(\delta_n)) \\ &\geq P_{n\theta}(\{\tilde{x}_n: \sup_{|t| \leq 1} |(c_1 n \log n)^{-1} G_n''(\theta + t\delta_n(n \log n)^{-1/2}) + 1| < \varepsilon_n\}) \\ &\quad \times P_{n\theta}(A_{n\theta}^{(1)}(\delta_n)) \\ &\longrightarrow 1 \text{ as } n \longrightarrow \infty \text{ uniformly in } \theta \in K. \end{aligned}$$

Next, by the second part in Lemma 3.2 there exists a positive null sequence  $\{\varepsilon_n\}$  such that

$$(3.23) \quad P_{n\theta}(\{\tilde{x}_n: \sup_{|t| \leq 1} |n^{-1}G_n''(\theta + tn^{-2/\alpha}) + I| > \varepsilon_n\}) \longrightarrow 0 \\ \text{as } n \longrightarrow \infty \text{ uniformly in } \theta \in K.$$

For the sequence  $\{\varepsilon_n\}$  satisfying (3.23), we can choose a positive divergent sequence  $\{\delta_n\}$  such that

$$(3.24) \quad \delta_n^2 \varepsilon_n \longrightarrow 0 \text{ as } n \longrightarrow \infty \text{ and } \delta_n n^{2/\alpha} / n^{1/2} \longrightarrow 0 \text{ as } n \longrightarrow \infty.$$

Thus we can choose a positive null sequence  $\{\varepsilon_n\}$  and a positive divergent sequence  $\{\delta_n\}$  such that

$$P_{n\theta}(\{\tilde{x}_n: \sup_{|t| \leq 1} |n^{-1}G_n''(\theta + t\delta_n n^{-1/2}) + I| > \varepsilon_n\}) \longrightarrow 0 \\ \text{as } n \longrightarrow \infty \text{ uniformly in } \theta \in K, \\ \delta_n^2 \varepsilon_n \longrightarrow 0 \text{ as } n \longrightarrow \infty \text{ and } \delta_n n^{2/\alpha} / n^{1/2} \longrightarrow 0 \text{ as } n \longrightarrow \infty.$$

By the similar method as that of previous argument, we have

$$P_{n\theta}(B_n^{(2)}(\varepsilon_n)) \longrightarrow 1 \text{ as } n \longrightarrow \infty \text{ uniformly in } \theta \in K.$$

Thus the proof has been completed.

The following definition is due to LeCam [5].

**DEFINITION 3.1.** A statistic  $\{T_n\} = \{T_n(\tilde{X}_n)\}$  is called *asymptotically sufficient* for  $\{P_\theta: \theta \in \Theta\}$  if there exist non-negative functions  $q_n(\tilde{x}_n, \theta)$  such that for each  $n=1, 2, \dots$ ,  $q_n(\tilde{x}_n, \theta)$  is the product of a function of  $\tilde{x}_n$  only by a function of  $T_n$  and  $\theta$  only and

$$\limsup_{n \rightarrow \infty} \sup_{\theta \in K} \int_{X^n} \left| \prod_{i=1}^n f(x_i, \theta) - q_n(\tilde{x}_n, \theta) \prod_{i=1}^n dx_i \right| = 0$$

for any compact subset  $K$  of  $\Theta$ .

Now we prove the asymptotic sufficiency of MLE.

**THEOREM 3.1.** *If the assumptions (I)~(V) are satisfied, then MLE is asymptotically sufficient for  $\{P_\theta: \theta \in \Theta\}$ .*

**PROOF.** At first we prove the theorem in the case  $\alpha=2$ . Let  $\{\varepsilon_n\}$  and  $\{\delta_n\}$  be the sequences which were given in the previous lemma, and let

$$q_n(\tilde{x}_n, \theta) = p_n(\tilde{x}_n, \theta) \exp \left[ -\frac{c_1}{2} (\sqrt{n \log n} (\hat{\theta}_n - \theta))^2 \right]$$

$$\times I_{A_n^{(1)}(\delta_n) \cap B_n^{(1)}(\epsilon_n) \cap C_n^{(1)}}(\tilde{x}_n),$$

where  $I_E(\cdot)$  denotes the indicator function of a set  $E$ .

$$\begin{aligned} & \sup_{\theta \in K} \int_{X^n} |p_n(\tilde{x}_n, \theta) - q_n(\tilde{x}_n, \theta)| \prod_{i=1}^n dx_i \\ & \leq \sup_{\theta \in K} \int_{A_n^{(1)}(\delta_n) \cap B_n^{(1)}(\epsilon_n) \cap C_n^{(1)}} \left| 1 - \frac{q_n(\tilde{x}_n, \theta)}{p_n(\tilde{x}_n, \theta)} \right| p_n(\tilde{x}_n, \theta) \prod_{i=1}^n dx_i \\ & \quad + \sup_{\theta \in K} P_{n\theta}(\{A_n^{(1)}(\delta_n) \cap B_n^{(1)}(\epsilon_n) \cap C_n^{(1)}\}^c). \end{aligned}$$

By Lemma 3.3, the second term in the right-hand side converges to zero as  $n \rightarrow \infty$  for any compact subset  $K$  of  $\Theta$ . We prove that the first term converges to zero as  $n \rightarrow \infty$ . If  $\tilde{x}_n \in C_n^{(1)}$ , then  $\lambda_n(\tilde{x}_n, \theta)$  is twice continuously differentiable with respect to  $\theta$  in  $(n \log n)^{-1/2}$ -neighborhood of  $\hat{\theta}_n$ . Thus, for each  $\tilde{x}_n \in C_n^{(1)}$  we can expand  $\lambda_n(\tilde{x}_n, \theta)$  with respect to  $\theta$  around  $\hat{\theta}_n$  by Taylor's theorem. We have

$$\begin{aligned} \lambda_n(\tilde{x}_n, \theta) &= \lambda_n(\tilde{x}_n, \hat{\theta}_n) + (\theta - \hat{\theta}_n) \left[ \frac{\partial}{\partial \theta} \lambda_n(\tilde{x}_n, \theta) \right]_{\theta = \hat{\theta}_n} \\ & \quad + \frac{1}{2} (\theta - \hat{\theta}_n)^2 \left[ \frac{\partial^2}{\partial \theta^2} \lambda_n(\tilde{x}_n, \theta) \right]_{\theta = \theta_n^*}, \end{aligned}$$

where  $|\theta_n^* - \theta| < |\hat{\theta}_n - \theta|$ . Since  $\hat{\theta}_n$  is MLE for each  $n$ , the second term in the right-hand side vanishes. Therefore, from Lemma 3.3,  $\tilde{x}_n \in A_n^{(1)}(\delta_n) \cap B_n^{(1)}(\epsilon_n) \cap C_n^{(1)}$  implies that

$$\begin{aligned} & \left| 1 - \frac{q_n(\tilde{x}_n, \theta)}{p_n(\tilde{x}_n, \theta)} \right| \\ &= \left| 1 - \exp \left[ -\frac{c_1}{2} (\sqrt{n \log n} (\hat{\theta}_n - \theta))^2 \left( \frac{1}{c_1 n \log n} \left[ \frac{\partial^2}{\partial \theta^2} \lambda_n(\tilde{x}_n, \theta) \right]_{\theta = \theta_n^*} + 1 \right) \right] \right| \\ & \leq \exp \left[ \frac{c_1}{2} (\sqrt{n \log n} (\hat{\theta}_n - \theta))^2 \left| \frac{1}{c_1 n \log n} \left[ \frac{\partial^2}{\partial \theta^2} \lambda_n(\tilde{x}_n, \theta) \right]_{\theta = \theta_n^*} + 1 \right| \right] - 1 \\ & \leq \exp \left( \frac{c_1}{2} \delta_n^2 \epsilon_n \right) - 1 \\ & \longrightarrow 0 \text{ as } n \longrightarrow \infty. \end{aligned}$$

Thus we have

$$\sup_{\theta \in K} \int_{A_n^{(1)}(\delta_n) \cap B_n^{(1)}(\epsilon_n) \cap C_n^{(1)}} \left| 1 - \frac{q_n(\tilde{x}_n, \theta)}{p_n(\tilde{x}_n, \theta)} \right| p_n(\tilde{x}_n, \theta) \prod_{i=1}^n dx_i \longrightarrow 0 \text{ as } n \longrightarrow \infty.$$

The proof has been completed in the case  $\alpha=2$ .

Next we prove the theorem in the case  $\alpha>2$ . Let  $\{\varepsilon_n\}$  and  $\{\delta_n\}$  be the sequences which were given in Lemma 3.3, and let

$$q_n(\tilde{x}_n, \theta) = p_n(\tilde{x}_n, \theta) \exp \left[ -\frac{I}{2} (\sqrt{n}(\hat{\theta}_n - \theta))^2 \right] I_{A_{n\hat{\theta}}^{(2)}(\delta_n) \cap B_n^{(2)}(\varepsilon_n) \cap C_n^{(2)}}(\tilde{x}_n).$$

Then

$$\begin{aligned} & \sup_{\theta \in K} \int_{X^n} |p_n(\tilde{x}_n, \theta) - q_n(\tilde{x}_n, \theta)| \prod_{i=1}^n dx_i \\ & \leq \sup_{\theta \in K} \int_{A_{n\hat{\theta}}^{(2)}(\delta_n) \cap B_n^{(2)}(\varepsilon_n) \cap C_n^{(2)}} \left| 1 - \frac{q_n(\tilde{x}_n, \theta)}{p_n(\tilde{x}_n, \theta)} \right| p_n(\tilde{x}_n, \theta) \prod_{i=1}^n dx_i \\ & \quad + \sup_{\theta \in K} P_{n\theta}(\{A_{n\hat{\theta}}^{(2)}(\delta_n) \cap B_n^{(2)}(\varepsilon_n) \cap C_n^{(2)}\}^c). \end{aligned}$$

By Lemma 3.3, the second term in the right-hand side converges to zero as  $n \rightarrow \infty$ . By the similar method as that of previous argument, for each  $\tilde{x}_n \in C_n^{(2)}$  we have

$$\lambda_n(\tilde{x}_n, \theta) = \lambda_n(\tilde{x}_n, \hat{\theta}_n) + \frac{1}{2}(\hat{\theta}_n - \theta)^2 \left[ \frac{\partial^2}{\partial \theta^2} \lambda_n(\tilde{x}_n, \theta) \right]_{\theta=\theta_n^*},$$

where  $|\theta_n^* - \theta| < |\hat{\theta}_n - \theta|$ .

From Lemma 3.3,  $\tilde{x}_n \in A_{n\hat{\theta}}^{(2)}(\delta_n) \cap B_n^{(2)}(\varepsilon_n) \cap C_n^{(2)}$  implies that

$$\begin{aligned} & \left| 1 - \frac{q_n(\tilde{x}_n, \theta)}{p_n(\tilde{x}_n, \theta)} \right| \\ & = \left| 1 - \exp \left[ -\frac{1}{2} (\sqrt{n}(\hat{\theta}_n - \theta))^2 \left( \frac{1}{n} \left[ \frac{\partial^2}{\partial \theta^2} \lambda_n(\tilde{x}_n, \theta) \right]_{\theta=\theta_n^*} + I \right) \right] \right| \\ & \leq \exp \left[ \frac{1}{2} (\sqrt{n}(\hat{\theta}_n - \theta))^2 \left| \frac{1}{n} \left[ \frac{\partial^2}{\partial \theta^2} \lambda_n(\tilde{x}_n, \theta) \right]_{\theta=\theta_n^*} + I \right| \right] - 1 \\ & \leq \exp \left( \frac{1}{2} \delta_n^2 \varepsilon_n \right) - 1 \\ & \longrightarrow 0 \text{ as } n \longrightarrow \infty. \end{aligned}$$

Thus we have

$$\sup_{\theta \in K} \int_{A_{n\hat{\theta}}^{(2)}(\delta_n) \cap B_n^{(2)}(\varepsilon_n) \cap C_n^{(2)}} \left| 1 - \frac{q_n(\tilde{x}_n, \theta)}{p_n(\tilde{x}_n, \theta)} \right| p_n(\tilde{x}_n, \theta) \prod_{i=1}^n dx_i \longrightarrow 0 \text{ as } n \longrightarrow \infty.$$

The proof has been completed in the case  $\alpha>2$ .

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### References

- [1] M. AKAHIRA, Asymptotic theory for estimation of location in non-regular cases, I; Order of convergence of consistent estimators, Rep. Statist. Appl. Res. Un. Japan. Sci. Engrs., **22** (1975), 8-26.
- [2] M. AKAHIRA, A remark on asymptotic sufficiency of statistics in non-regular cases, Rep. Univ. Electro-Comm., **27-1** (1976), 125-128.
- [3] H. CRAMÉR, Mathematical Method of Statistics, Princeton University Press, Princeton, 1946.
- [4] S. KAUFMAN, Asymptotic efficiency of the maximum likelihood estimator, Ann. Inst. Statist. Math., **18** (1966), 155-178.
- [5] L. LECAM, On the asymptotic theory of estimation and testing hypotheses, Proc. Third Berkeley Symp. Stat. Prob. 1, (1956), 129-156.
- [6] K. TAKEUCHI, Asymptotic Theory in Statistical Estimation, Kyoiku-Shuppan, Tokyo, 1974 (in Japanese).
- [7] K. TAKEUCHI AND M. AKAHIRA, On the asymptotic property of statistical estimator, Sûgaku, **29** (1977), 110-123 (in Japanese).
- [8] A. WALD, Note on the consistency of the maximum likelihood estimator, Ann. Math. Statist., **20** (1949), 595-601.
- [9] M. WOODROOFE, Maximum likelihood estimation of a translation parameter of a truncated distribution, Ann. Math. Statist., **43** (1972), 113-122.

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