

Strong Uniform Consistency of the Product Limit Estimator under Variable Censoring

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1. Introduction

Let X_1, \dots, X_N, \dots be an i.i.d. sequence of random variables, with continuous distribution function $F(x)$, and let Y_1, \dots, Y_N be another sequence of independent random variables with right continuous distribution functions $G_1(x), \dots, G_N(x), \dots$. We suppose that $\{X_i\}$ and $\{Y_i\}$ are mutually independent.

Let

$$Z_i = \min\{X_i, Y_i\} \quad \text{and} \quad \delta_i = [X_i \leq Y_i] \quad i = 1, 2, \dots$$

($[A]$ denotes the indicator of the event A).

As it is well known, for this problem the $F_N^*(x)$ product limit estimator of Kaplan Meier [6] is maximum likelihood estimator. For i.i.d. Y_i -s it was recently proved [3], that if $F(x)$ is continuous and $G(T_F) < 1$ where $T_F = \{\sup x; F(x) < 1\}$ then

$$P \left(\sup_{-\infty < x < +\infty} |F_N^*(x) - F(x)| = O \left(\sqrt{\frac{\log \log N}{N}} \right) \right) = 1. \quad (1.1)$$

The case of variable censoring (i.e. Y_i 's have different distributions) was discussed in [2].

Let $P(Z_i < x) = H_i(x)$, $\bar{F}(x) = 1 - F(x)$ and define $\bar{G}_i(x)$, $\bar{H}_i(x) (= \bar{F}(x) \bar{G}_i(x))$ similarly. Denote

$$M_N(t) = \sum_{k=1}^N [Z_k > t], \quad m_N(t) = E(M_N(t)) = \bar{F}(t) \sum_{k=1}^N \bar{G}_k(t),$$

$$\bar{G}(N, t) = \sum_{k=1}^N \bar{G}_k(t).$$

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Recently Gill [5] proved that $\sup_{-\infty < u \leq t} |F_N^*(u) - F(u)| \xrightarrow{P} 0$ if $M_N(t) \xrightarrow{P} +\infty$ and $F(t^-) < 1$ (where \xrightarrow{P} denotes stochastic convergence).

We shall prove the following

Theorem 1. *Suppose that F is continuous and*

$$\frac{\log N}{\bar{G}(N, T_F)} \rightarrow 0. \tag{1.2}$$

Then

$$P \left(\sup_{-\infty < u < +\infty} |F_N^*(u) - F(u)| = O \left(\sqrt{\frac{\log N}{\bar{G}(N, T_F)}} \right) \right) = 1. \tag{1.3}$$

Remark. To get a better insight into the meaning of the theorem, denote by $G_{(N)}(t) = \frac{1}{N} \sum_{i=1}^N G_i(t)$ the average of the censoring distributions. Then condition (1.2) implies that $T_F < T_{G_{(N)}}$ for all but finitely many N (in particular $T_F < \infty$). Theorem 1 can also be stated as

$$\overline{\lim}_{N \rightarrow \infty} \sqrt{1 - G_{(N)}(T_F)} \sqrt{\frac{N}{\log N}} \sup_{-\infty < u < +\infty} |F_N^*(u) - F(u)| \leq K \quad \text{a.s.}$$

Consequently if $\overline{\lim}_{N \rightarrow \infty} G_{(N)}(T_F) < 1$ then the rate is $O(\sqrt{\log N/N})$, if not, then the $\sqrt{1 - G_{(N)}(T_F)}$ factor worsen this rate.

Corollary 1. *Suppose that $F(t)$ is continuous in $(-\infty, t]$, and $\log N/\bar{G}(N, t) \rightarrow 0$, then*

$$P \left(\sup_{-\infty < u \leq t} |F_N^*(u) - F(u)| = O \left(\sqrt{\frac{\log N}{\bar{G}(N, t)}} \right) \right) = 1.$$

Corollary 2. *If $F(t)$ is continuous and $\underline{\lim}(\bar{G}(N, T_F)/N^\alpha) = a > 0$, for any $0 < \alpha \leq 1$, then*

$$P \left(\sup_{-\infty < u < \infty} |F_N^*(u) - F(u)| = O \left(\sqrt{\frac{\log N}{N^\alpha}} \right) \right) = 1.$$

Our technic is similar to the paper [3]. Theorem 1 gives a much stronger result under less restrictive conditions than the above mentioned theorem in [2]. It is important to emphasize that in course of proving Theorem 1 we need some theorems on strong uniform behaviour of empirical distributions of non-identically distributed random variables, which seems to be new.

2. Definitions, notations

In what follows we list some more notations.

$$\beta_i(t) = [Z_i \leq t, \delta_i = 1] \quad i = 1, 2, \dots, \quad (2.1)$$

$$B_N(t) = \sum_{i=1}^N \beta_i(t), \quad b_N(t) = E(B_N(t)) = \sum_{i=1}^N \int_{-\infty}^t \bar{G}_i(u^-) dF(u), \quad (2.2)$$

$$\tau_N(\omega) = \max_{j \leq N} \{Z_j(\omega)\}. \quad (2.3)$$

The definition of the product limit estimator $F_N^*(t)$ (in case of continuous F), and its' modification $F_N^0(t)$ are the following

$$\bar{F}_N^*(t) = \begin{cases} \prod_{j=1}^N \left(\frac{M_N(Z_j)}{M_N(Z_j) + 1} \right)^{\beta_j(t)} & \text{if } t \leq \tau_N(\omega) \\ 0 & \text{if } t > \tau_N(\omega), \end{cases}$$

$$\bar{F}_N^0(t) = \begin{cases} \prod_{j=1}^N \left(\frac{M_N(Z_j) + 1}{M_N(Z_j) + 2} \right)^{\beta_j(t)} & \text{if } t \leq \tau_N(\omega) \\ 0 & \text{if } t > \tau_N(\omega). \end{cases}$$

3. Uniform Properties of Empirical Distribution of Nonidentically Distributed Random Variables

Our basic tool is the following exponential bound (see Petrov [7] p. 52).

Lemma 3.1. Let ξ_1, \dots, ξ_N be a sequence of independent random variables. $S_N = \sum_{i=1}^N \xi_i$. Suppose that there exist $\lambda_1, \lambda_2, \dots, \lambda_N$ and U positive real numbers such that

$$E(e^{u\xi_k}) \leq e^{(1/2)\lambda_k u^2} \quad k = 1, 2, \dots, N \text{ for } 0 \leq u \leq U. \quad (3.1)$$

Let $A = \sum_{k=1}^N \lambda_k$. Then

$$P(S_N > x) \leq \exp \left\{ -\frac{x^2}{2A} \right\} \quad \text{if } 0 \leq x \leq AU, \quad (3.2)$$

$$P(S_N > x) \leq \exp \left\{ -\frac{Ux}{2} \right\} \quad \text{if } x \geq AU, \quad (3.3)$$

$$P(|S_N| > x) \leq 2 \exp \left\{ -\frac{x^2}{2A} \right\} \quad \text{if } 0 \leq x \leq AU, \quad (3.4)$$

$$P(|S_N| > x) \leq 2 \exp \left\{ -\frac{Ux}{2} \right\} \quad \text{if } x > AU. \quad (3.5)$$

Remark 3.2. Let $\{\alpha_i\}_{i=1}^{\infty}$ be a sequence of independent Bernoulli variables $P(\alpha_i = 1) = a_i$, $P(\alpha_i = 0) = 1 - a_i$. Let $A_N = \sum_{i=1}^N a_i$. Denote $\xi_i = \alpha_i - a_i$, $E(\xi_i) = 0$, $i = 1, 2, \dots$

$$E(e^{u\xi_i}) \leq E(1 + u\xi_i + u^2\xi_i^2) = 1 + u^2 E(\xi_i^2) \leq \exp(u^2 E(\xi_i^2)) \quad (3.6)$$

if only

$$|u\xi_i| = |u(\alpha_i - a_i)| \leq \frac{1}{2}.$$

As $|\alpha_i - a_i| \leq 1$ and $E(\xi_i^2) = a_i(1 - a_i) \leq a_i$, $E(e^{u\xi_i}) \leq \exp\{u^2 a_i\}$ if $0 \leq u \leq \frac{1}{2}$. Using the notations of Lemma 3.1 we got

$$U = \frac{1}{2}, \quad \lambda_i \geq 2a_i \quad i = 1, 2, \dots \quad \Lambda \geq 2A_N. \quad (3.7)$$

In what follows we prove some uniform properties of $M_N(u)$. (Though we use the same $M_N(u)$ notation here as in the rest of the paper for the empirical of $Z_i = \min(X_i, Y_i)$, in these 2 theorems we do not suppose anything about the minimum structure of Z_i $\{Z_i\}$ are independent but non-identically distributed.)

Theorem 2. (i) If $\frac{2}{\sqrt{m_N(t)}} < \varepsilon < \sqrt{m_N(t)}$, and $m_N(t) \geq 1$ then

$$P\left(\sup_{-\infty < u \leq t} \left| \frac{M_N(u) - m_N(u)}{\sqrt{m_N(u)}} \right| > \varepsilon\right) \leq 4N \exp\{-2^{-7} \varepsilon^2\}. \quad (3.8)$$

(ii) If $\frac{\log N}{m_N(t)} \rightarrow 0$, then

$$P\left(\sup_{-\infty < u \leq t} \left| \frac{M_N(u) - m_N(u)}{\sqrt{m_N(u)}} \right| = O(\sqrt{\log N})\right) = 1. \quad (3.9)$$

Proof. For fixed N and t let $-\infty = u_0 < u_1 < \dots < u_{k(N)} = t$ be a partition of $(-\infty, t]$ such that

$$\delta_N(i) = m_N(u_{i-1}) - m_N(u_i^-) \leq 1 \quad i = 1, 2, \dots, k(N), \text{ and } k(N) \leq N - 1 \quad (3.10)$$

$(m_N(u) \text{ is right continuous, hence } m_N(u) = m_N(u^+)).$

Since $m_N(u)$ is monotone decreasing and $m_N(-\infty) = N$, such partition always exists.

$$\begin{aligned} P\left(\sup_{-\infty < u \leq t} \left| \frac{M_N(u) - m_N(u)}{\sqrt{m_N(u)}} \right| > \varepsilon\right) &\leq \sum_{i=1}^{k(N)} P\left(\sup_{u_{i-1} \leq u < u_i} \left| \frac{M_N(u) - m_N(u)}{\sqrt{m_N(u)}} \right| > \varepsilon\right) \\ &\leq \sum_{i=1}^{k(N)} P\left(\frac{\sup_{u_{i-1} \leq u < u_i} |M_N(u) - m_N(u)|}{\sqrt{m_N(u_i^-)}} > \varepsilon\right) + P\left(\frac{|M_N(t) - m_N(t)|}{\sqrt{m_N(t)}} > \varepsilon\right) \\ &\leq \sum_{i=1}^{k(N)} \left\{ P\left(|M_N(u_{i-1}) - m_N(u_{i-1})| > \frac{\varepsilon\sqrt{m_N(u_i^-)} - \delta_N(i)}{2}\right) \right. \\ &\quad \left. + P\left(|M_N(u_i^-) - m_N(u_i^-)| > \frac{\varepsilon\sqrt{m_N(u_i^-)} - \delta_N(i)}{2}\right) \right\} + P\left(\frac{|M_N(t) - m_N(t)|}{\sqrt{m_N(t)}} > \varepsilon\right). \end{aligned} \quad (3.11)$$

In the last line of (3.11) we used the monotonicity of $M_N(u)$ and $m_N(u)$.

Let $\frac{2}{\sqrt{m_N(t)}} < \varepsilon < \sqrt{m_N(t)}$. Under condition (i) on ε

$$0 \leq \frac{\varepsilon \sqrt{m_N(u_i^-)} - \delta_N(i)}{2} \leq \frac{m_N(u_i^-)}{2} \leq m_N(u_{i-1}).$$

We estimate both terms of (3.11) by Lemma 3.1. Using (3.7) and condition (i)

$$\begin{aligned} & P\left(|M_N(u_{i-1}) - m_N(u_{i-1})| > \frac{\varepsilon \sqrt{m_N(u_i^-)} - \delta_N(i)}{2}\right) \\ & + P\left(|M_N(u_i^-) - m_N(u_i^-)| > \frac{\varepsilon \sqrt{m_N(u_i^-)} - \delta_N(i)}{2}\right) \\ & \leq 4 \exp\left\{-\frac{(\varepsilon \sqrt{m_N(u_i^-)} - \delta_N(i))^2}{4 \cdot 4 \cdot m_N(u_{i-1})}\right\} \leq 4 \exp\left\{-\frac{\varepsilon^2 m_N(u_i^-)}{2^6 m_N(u_{i-1})}\right\}. \end{aligned}$$

From $m_N(t) \geq 1$ follows that $2m_N(u_i^-) \geq m_N(u_{i-1})$ hence $\frac{m_N(u_i^-)}{m_N(u_{i-1})} \geq \frac{1}{2}$. Consequently

$$\begin{aligned} P\left(\sup_{-\infty < u \leq t} \left| \frac{M_N(u) - m_N(u)}{\sqrt{m_N(u)}} \right| > \varepsilon\right) & \leq k(N) \cdot 4 \cdot \exp\{-2^{-7} \varepsilon^2\} + 2 \exp\left(-\frac{\varepsilon^2}{4}\right) \\ & \leq 4N \exp\{-2^{-7} \varepsilon^2\} \end{aligned}$$

which proves (i).

Letting $\varepsilon_N = \sqrt{2^9 \log N}$, we obtain, that if $(\log N / m_N(t)) \rightarrow 0$, then (3.9) holds by Borel-Cantelli. \square

Theorem 3. Suppose that for the point t , $m_N(t) \geq 2$. Then for an arbitrary $\lambda \geq 2$,

$$P\left(\sup_{-\infty < u \leq t} \frac{m_N(u)}{M_N(u)} > \lambda\right) \leq N \exp\left\{-2^{-4} \left(1 - \frac{1}{\lambda}\right)^2 m_N(t)\right\}. \quad (3.12)$$

Proof. For fixed N and t let $-\infty = u_0 < u_1 < \dots < u_{k(N)} = t$ be the same partition of $(-\infty, t]$ as in Theorem 2. As both $m_N(u)$ and $M_N(u)$ are monotone decreasing

$$\begin{aligned} P\left(\sup_{-\infty < u \leq t} \frac{m_N(u)}{M_N(u)} > \lambda\right) & \leq \sum_{i=1}^{k(N)} P\left(\sup_{u_{i-1} \leq u < u_i} \frac{m_N(u)}{M_N(u)} > \lambda\right) + P\left(\frac{m_N(t)}{M_N(t)} > \lambda\right) \\ & \leq \sum_{i=1}^{k(N)} P\left(\frac{m_N(u_{i-1})}{M_N(u_i^-)} > \lambda\right) + P\left(\frac{m_N(t)}{M_N(t)} > \lambda\right), \\ P\left(\frac{m_N(u_{i-1})}{M_N(u_i^-)} > \lambda\right) & = P\left(\frac{m_N(u_{i-1})}{\lambda} > M_N(u_i^-)\right) \\ & = P\left(\frac{m_N(u_{i-1})}{\lambda} - m_N(u_i^-) > M_N(u_i^-) - m_N(u_i^-)\right) \\ & = P(m_N(u_i^-) - M_N(u_i^-) > m_N(u_i^-) - \frac{m_N(u_{i-1})}{\lambda}). \end{aligned}$$

By condition $m_N(t) \geq 2$ and (3.10) we get that $2m_N(u_{i-1}) < 3m_N(u_i^-)$. Hence as $\lambda > 2$,

$$m_N(u_i^-) - \frac{m_N(u_{i-1})}{\lambda} \geq m_N(u_i^-) \left(1 - \frac{3}{2\lambda}\right) \geq \frac{m_N(u_i^-)(\lambda-1)}{2\lambda}.$$

Consequently

$$\begin{aligned} P\left(\frac{m_N(u_{i-1})}{M_N(u_i^-)} > \lambda\right) &\leq P\left(m_N(u_i^-) - M_N(u_i^-) > \frac{m_N(u_i^-)(\lambda-1)}{2\lambda}\right) \\ &\leq \exp\left\{-\frac{m_N^2(u_i^-)(\lambda-1)^2}{4\lambda^2 \cdot 4m_N(u_i^-)}\right\} = \exp\left\{-2^{-4}\left(1 - \frac{1}{\lambda}\right)^2 m_N(u_i^-)\right\} \\ &\leq \exp\left\{-2^{-4}\left(1 - \frac{1}{\lambda}\right)^2 m_N(t)\right\} \end{aligned}$$

where we applied again Lemma 3.1 and (3.7). It is easy to see by a similar but somewhat simpler argument, that

$$P\left(\frac{m_N(t)}{M_N(t)} > \lambda\right) \leq \exp\left\{-2^{-2}\left(1 - \frac{1}{\lambda}\right)^2 m_N(t)\right\}.$$

Being $k(N) \leq N - 1$, (3.12) follows. \square

This theorem is a generalization of Lemma 1 of Wellner [10], which deals with i.i.d. r.v.-s.

4. Lemmas

Suppose throughout the rest that F is continuous.

Lemma 4.1.

$$\sup_{-\infty < u \leq t} |F_N^*(u) - F_N^0(u)| \leq \int_{-\infty}^t \frac{1}{(M_N(u) + 1)^2} dB_N(u). \quad (4.1)$$

Proof. The same as Lemma 2.2. in [3]. Let

$$R_N(u) = \int_{-\infty}^u \frac{1}{M_N(s)} dB_N(s), \quad \text{and} \quad R(u) = \int_{-\infty}^u \frac{1}{m_N(s)} db_N(s). \quad (4.2)$$

Observe that for $u < T_F$

$$R(u) = \int_{-\infty}^u \frac{1}{m_N(s)} db_N(s) = \int_{-\infty}^u \frac{\bar{G}(N, s^-)}{\bar{G}(N, s) \bar{F}(s)} dF(s) = -\log \bar{F}(u). \quad (4.3)$$

By Taylor expansion, as in [3] (formulae (2.1)–(2.3), (2.9)–(2.10)) we get that

$$\begin{aligned} |\bar{F}_N^*(u) - \bar{F}(u)| &\leq |\bar{F}_N^*(u) - \bar{F}^0(u)| + |\log \bar{F}_N^0(u) + R_N(u) \\ &\quad + \bar{F}(u)|R_N(u) - R(u)| + \frac{1}{2}\bar{F}(u) \exp|R_N(u) - R(u)| \cdot |R_N(u) - R(u)|^2. \end{aligned} \quad (4.4)$$

Observe that

$$\begin{aligned} R_N(u) - R(u) &= \int_{-\infty}^u \frac{1}{M_N(s)} dB_N(s) - \int_{-\infty}^u \frac{1}{m_N(s)} db_N(s) \\ &= \int_{-\infty}^u \left(\frac{1}{M_N(s)} - \frac{1}{m_N(s)} \right) dB_N(s) + \int_{-\infty}^u \frac{1}{m_N(s)} d(B_N(s) - b_N(s)). \end{aligned} \quad (4.5)$$

Suppose that $\frac{\log N}{\bar{G}(N, T_F)} \rightarrow 0$ (hence T_F is finite), and consider the following sequence of points: $T_1, T_2, \dots, T_N \dots$ defined by the equation

$$\bar{F}(T_N) = \sqrt{\frac{\log N}{\bar{G}(N, T_F)}}. \quad (4.6)$$

(This sequence is well-defined if $N \geq N^*$ by the above condition.)

Lemma 4.2. *If T_N is defined by (4.6) and (1.2) holds then for almost all ω there exists an $N_0(\omega)$ such that if $N > N_0(\omega)$ then*

$$\frac{1}{M_N(u)} \leq \frac{2}{m_N(u)} \quad \text{for all } u \leq T_N. \quad (4.7)$$

Proof. We apply Theorem 3 for the points T_N ($N < N^*$).

By condition (1.2) we may choose an N_1 (independent from ω) such that for $N \geq N_1$ $\bar{G}(N, T_F) > 2^{16} \log N$. Then for $N \geq N_1$

$$m_N(T_N) = \bar{G}(N, T_N) \bar{F}(T_N) = \sqrt{\frac{\log N}{\bar{G}(N, T_F)}} \bar{G}(N, T_N) \geq \sqrt{\log N \bar{G}(N, T_F)} \geq 2^8 \log N$$

hence the condition of Theorem 3 is satisfied. Letting $\lambda = 2$, the result follows by standard Borel-Cantelli argument. \square

Lemma 4.3. *If T_N is defined by (4.6) and (1.2) holds then for almost all ω there exists an $N_0(\omega)$ such that, if $N \geq N_0(\omega)$ then*

$$\sup_{-\infty < u \leq T_N} \left| \frac{M_N(u) - m_N(u)}{\sqrt{m_N(u)}} \right| \leq \sqrt{2^9 \log N}. \quad (4.8)$$

Proof. Apply Theorem 2 with $\varepsilon_N = \sqrt{2^9 \log N}$. (As in Lemma 4.2 it's easy to check that the conditions of Theorem 2 holds if N is big enough.) \square

Lemma 4.4. *Suppose that (1.2) holds, T_N is defined by (4.6) and let $1 \leq \alpha \leq 2$ arbitrary.*

Then for almost all ω there exists an $N_0(\omega)$ such that, for $N > N_0(\omega)$,

$$\sup_{-\infty \leq t \leq T} \left| \int_{-\infty}^t \frac{1}{m_N^\alpha(u)} d(B_N(u) - b_N(u)) \right| \leq \frac{12\sqrt{\log N}}{(m_N(T))^{\frac{1}{2}(2\alpha-1)}} \quad (4.9)$$

for any $T \leq T_N$.

Proof. We prove the statement in two steps. At first we give an exponential bound for fix t and then estimate the sup in $(-\infty, T]$. First observe, that

$$\int_{-\infty}^u \frac{1}{m_N^\alpha(s)} dB_N(s) = \sum_{j=1}^N \frac{\beta_j(u)}{m_N^\alpha(Z_j)} = \sum_{j=1}^N \frac{\beta_j(u)}{\left(\sum_{k=1}^N \bar{H}_k(Z_j)\right)^\alpha}. \quad (4.10)$$

Moreover

$$\int_{-\infty}^u \frac{1}{m_N^\alpha(s)} db_N(s) = \sum_{j=1}^N \int_{-\infty}^u \frac{\bar{G}_j(s^-)}{\left(\sum_{k=1}^N \bar{H}_k(s)\right)^\alpha} dF(s) = \sum_{j=1}^N E \left(\frac{\beta_j(u)}{\left(\sum_{k=1}^N \bar{H}_k(Z_j)\right)^\alpha} \right).$$

Hence introducing the notations

$$\xi_j(u) = \frac{\beta_j(u)}{\left(\sum_{k=1}^N \bar{H}_k(Z_j)\right)^\alpha} \quad \text{and} \quad \xi_j^*(u) = \xi_j(u) - E(\xi_j(u)), \quad (4.11)$$

$$\int_{-\infty}^u \frac{1}{m_N^\alpha(s)} d(B_N(s) - b_N(s)) = \sum_{j=1}^N \xi_j^*(u) \quad (4.12)$$

where $\xi_j^*(u)$ $j=1, \dots, N$ are independent nonidentically distributed zero mean random variables. At first we estimate the probability $P\left(\left|\sum_{j=1}^N \xi_j^*(t)\right| > \varepsilon\right)$ by Lemma 3.1 and then we estimate $P\left(\sup_{-\infty < t \leq u} \left|\sum_{j=1}^N \xi_j^*(t)\right| > \varepsilon\right)$. Using the elementary inequality

$$e^x \leq 1 + x + \frac{x^2}{2} \quad \text{if} \quad |x| \leq \frac{1}{2},$$

$$E(e^{u\xi_j^*(t)}) \leq E(1 + u\xi_j^*(t) + u^2\xi_j^{*2}(t)) = 1 + u^2 E(\xi_j^{*2}(t)) \leq e^{u^2 E(\xi_j^{*2}(t))}$$

if

$$|u\xi_j^*(t)| \leq \frac{1}{2}. \quad (4.13)$$

Observe that for $t \leq T$

$$0 \leq \xi_j(t) = \frac{\beta_j(t)}{\left(\sum_{k=1}^N \bar{H}_k(Z_j)\right)^\alpha} \leq \frac{\beta_j(T)}{\left(\sum_{k=1}^N \bar{H}_k(Z_j)\right)^\alpha}. \quad (4.14)$$

Moreover, if $Z_j \leq T$ then $\beta_j(T) \leq 1$ and $\bar{H}_k(Z_j) \geq \bar{H}_k(T)$. On the other hand if $Z_j > T$ then $\beta_j(T) = 0$. Consequently

$$0 \leq \xi_j(t) \leq \frac{1}{\left(\sum_{k=1}^N \bar{H}_k(T)\right)^\alpha} = \frac{1}{(m_N(T))^\alpha} \quad \text{for any} \quad t \leq T.$$

Hence (4.13) valid if $0 \leq u \leq \frac{(m_N(T))^\alpha}{2}$.

For any $t \leq T$ we have

$$\begin{aligned} \sum_{j=1}^N E(\xi_j^{*2}(t)) &\leq \sum_{j=1}^N E(\xi_j^2(t)) \\ &= \sum_{j=1}^N E\left(\frac{\beta_j^2(t)}{\left(\sum_{k=1}^N \bar{H}_k(Z_j)\right)^{2\alpha}}\right) = \sum_{j=1}^N E\left(\frac{\beta_j(t)}{\left(\sum_{k=1}^N \bar{H}_k(Z_j)\right)^{2\alpha}}\right) \\ &\leq \frac{1}{\left(\sum_{k=1}^N \bar{G}_k(T)\right)^{2\alpha-1}} \int_{-\infty}^t \frac{\sum_{j=1}^N \bar{G}_j(s^-)}{\bar{F}^{2\alpha}(s) \left(\sum_{k=1}^N \bar{G}_k(s)\right)} dF(s) \\ &\leq \frac{1}{(\bar{G}(N, T))^{2\alpha-1}} \int_{-\infty}^t \frac{\bar{G}(N, s^-)}{\bar{F}^{2\alpha}(s) \bar{G}(N, s)} dF(s) \\ &= \frac{1}{(2\alpha-1)(\bar{G}(N, T))^{2\alpha-1}} \left(\frac{1}{(\bar{F}(t))^{2\alpha-1}} - 1\right) \\ &\leq \frac{1}{(\bar{G}(N, T) \bar{F}(T))^{2\alpha-1}} = \frac{1}{(m_N(T))^{2\alpha-1}}. \end{aligned}$$

Hence using the notations of Lemma 3.1, with

$$U = \frac{(m_N(T))^\alpha}{2}, \quad A = \sum_{j=1}^N \lambda_j = \frac{2}{(m_N(T))^{2\alpha-1}}, \quad UA = 1$$

we have for any $0 \leq \varepsilon \leq 1$ and any $t \leq T$

$$P\left(\left|\sum_{j=1}^N \xi_j^*(t)\right| > \varepsilon\right) \leq 2 \exp\left\{-\frac{\varepsilon^2 (m_N(T))^{2\alpha-1}}{4}\right\}.$$

To estimate the supremum in $(-\infty, T)$ observe that

$$\eta_N(t) = \sum_{j=1}^N \xi_j(t) = \int_{-\infty}^t \frac{1}{m_N^\alpha(u)} dB_N(u), \quad l_N(t) = \sum_{j=1}^N E(\xi_j(t)) = \int_{-\infty}^t \frac{1}{m_N^\alpha(u)} db_N(u)$$

are both monotone nondecreasing functions of t . Suppose that $m_N(T) > 1$ then $l_N(t) \leq |\log \bar{F}(t)|$. (As by $m_N(T) \geq 1$, $1 \leq \alpha \leq 2$, $l_N(t) = \int_{-\infty}^t \frac{1}{m_N^\alpha(t)} db_N(t) \leq \int_{-\infty}^t \frac{1}{m_N(t)} db_N(t) = |\log \bar{F}(t)|$.) For a fix $0 < \varepsilon < 1$ consider a partition of the interval $(-\infty, T)$ $-\infty = u_0 < u_1 \dots < u_{L(\varepsilon)} = T$ such that

$$l_N(u_i) - l_N(u_{i-1}) < \frac{\varepsilon}{3} \quad i = 1, 2, \dots, L(\varepsilon) \quad \text{and} \quad L(\varepsilon) \leq \frac{3|\log \bar{F}(T)|}{\varepsilon} + 1. \quad (4.14)$$

Since $l_N(t)$ is continuous such a partition easily can be constructed. If

$$|\eta_N(u_{i-1}) - l_N(u_{i-1})| \leq \frac{\varepsilon}{3} \quad \text{and} \quad |\eta_N(u_i^-) - l_N(u_i)| \leq \frac{\varepsilon}{3},$$

then by the monotonicity of $n_N(t)$ and $l_N(t)$ and (4.14) for any $u_i \leq t < u_{i+1}$,

$$|\eta_N(t) - l_N(t)| \leq \frac{\varepsilon}{3} + 2\frac{\varepsilon}{3} = \varepsilon.$$

Consequently, if $\sup_{-\infty < t \leq T} |\eta_N(t) - (-\log \bar{F}(t))| > \varepsilon$ then for some $0 \leq i \leq L(\varepsilon)$

$$|\eta_N(u_i) - l_N(u_i)| > \frac{\varepsilon}{3} \quad \text{or} \quad |\eta_N(u_i^-) - l_N(u_i)| > \frac{\varepsilon}{3}.$$

Thus we have¹ that if $m_N(T) \geq 1$

$$\begin{aligned} P \left(\sup_{-\infty < t \leq T} \left| \int_{-\infty}^t \frac{1}{m_N^\alpha(s)} dB_N(s) - \int_{-\infty}^t \frac{1}{m_N^\alpha(s)} db_N(s) \right| > \varepsilon \right) \\ \leq 2 \cdot 2L(\varepsilon) \exp \left\{ -\frac{\varepsilon^2 m_N^{2\alpha-1}(T)}{4 \cdot 3^2} \right\} \\ \leq 4 \left(\frac{3|\log \bar{F}(T)|}{\varepsilon} + 1 \right) \exp \left\{ -\frac{\varepsilon^2 m_N^{2\alpha-1}(T)}{36} \right\}. \end{aligned} \quad (4.15)$$

Consider now the sequence T_N defined by (4.6). Observe that

$$m_N(T_N) = \bar{G}(N, T_N) \bar{F}(T_N) = \bar{G}(N, T_N) \sqrt{\frac{\log N}{\bar{G}(N, T_N)}} \geq \sqrt{\log N \bar{G}(N, T_N)} > 1 \quad (4.16)$$

if $N \geq N_1 (\geq N^*)$ by (1.2).

Consequently for any $T \leq T_N$, $m_N(T) > 1$, if $N \geq N_1$. Thus (4.15) is valid for any $T \leq T_N$, if $N \geq N_1$.

Let $\varepsilon_N = \frac{\sqrt{4 \cdot 36 \log N}}{(m_N(T))^{\frac{1}{2}(2\alpha-1)}}$. Then for any $T \leq T_N$

$$4 \left(\frac{3|\log \bar{F}(T)|}{\varepsilon_N} + 1 \right) \leq 4 \left(\frac{3|\log \bar{F}(T_N)|}{\varepsilon_N} + 1 \right) \leq 4 \left(\frac{3 \log N}{\sqrt{4 \cdot 36 \log N}} N^{\frac{2\alpha-1}{2}} + 1 \right) \leq N^2$$

if $N \geq N_2 (\geq N_1)$ (as $m_N(t) \leq N$ for any t , $\bar{G}(N, T) \leq N$, for any T , $\alpha \leq 2$, and by the definition of T_N $|\log \bar{F}(T_N)| \leq \log N$, if N is big enough). Consequently for any $T \leq T_N$ we have

$$\begin{aligned} \sum_{N \geq N_2} P \left(\sup_{-\infty < t \leq T} \left| \int_{-\infty}^t \frac{1}{m_N^\alpha(s)} d(B_N(s) - b_N(s)) \right| > \frac{12\sqrt{\log N}}{(m_N(T))^{\frac{1}{2}(2\alpha-1)}} \right) \\ \leq \sum_{N \geq N_2} N^2 \exp\{-4 \log N\} < +\infty \end{aligned}$$

which proves our statement. \square

¹ A similar but weaker inequality is proved in [4]

Lemma 4.5. *If T_N is defined by (4.6), $1 < \alpha \leq 2$ arbitrary, and (1.2) holds, then for almost all ω there exists an $N_0^*(\omega)$ such that for $N \geq N_0^*(\omega)$*

$$\int_{-\infty}^T \frac{1}{m_N^\alpha(u)} dB_N(u) \leq \frac{2}{(\alpha-1)m_N^{\alpha-1}(T)} \quad \text{for any } T \leq T_N.$$

Proof.

$$\int_{-\infty}^T \frac{1}{m_N^\alpha(u)} dB_N(u) = \int_{-\infty}^T \frac{1}{m_N^\alpha(u)} d(B_N(u) - b_N(u)) + \int_{-\infty}^T \frac{1}{m_N^\alpha(u)} db_N(u). \quad (4.17)$$

The first term of (4.17) can be estimated by Lemma 4.4. On the other hand

$$\begin{aligned} \int_{-\infty}^T \frac{1}{m_N^\alpha(u)} db_N(u) &= \int_{-\infty}^T \frac{\bar{G}(N, u^-)}{(\bar{F}(u) \bar{G}(N, u))^\alpha} dF(u) \\ &\leq \frac{1}{(\bar{G}(N, T))^{\alpha-1}} \int_{-\infty}^T \frac{1}{\bar{F}^\alpha(u)} dF(u) \\ &\leq \frac{1}{(\bar{G}(N, T))^{\alpha-1} (\alpha-1) \bar{F}^{\alpha-1}(T)} = \frac{1}{(\alpha-1)m_N^{\alpha-1}(T)}. \end{aligned} \quad (4.18)$$

From (4.17), (4.18) and Lemma 4.4 for almost all ω there exists an $N_0(\omega)$ ($\geq N^*$) such that for $N \geq N_0(\omega)$, for any $T \leq T_N$

$$\begin{aligned} \int_{-\infty}^T \frac{1}{m_N^\alpha(u)} dB_N(u) &\leq \frac{12\sqrt{\log N}}{m_N(T)^{\frac{1}{2}(2\alpha-1)}} + \frac{1}{(\alpha-1)m_N^{\alpha-1}(T)} \\ &\leq \frac{1}{(\alpha-1)m_N^{\alpha-1}(T)} \left(1 + \frac{12\sqrt{\log N}}{m_N(T)^{\frac{1}{2}}} \right). \end{aligned}$$

By condition (1.2) there exists an N_0^* ($\geq N_0$) such that if $N \geq N_0^*$ then $\frac{12\sqrt{\log N}}{m_N(T)^{\frac{1}{2}}} \leq 1$, which proves the Lemma. \square

Proof of Theorem 1. First observe that

$$\begin{aligned} \sup_{-\infty < u < +\infty} |F_N^*(u) - F(u)| &\leq \sup_{-\infty < u \leq T_N} |F_N^*(u) - F(u)| + \sup_{T_N < u < +\infty} |F_N^*(u) - F(u)| \\ &\leq \sup_{-\infty < u \leq T_N} |F_N^*(u) - F(u)| + \sup_{T_N \leq u < +\infty} |\bar{F}_N^*(u) - \bar{F}(u)| \leq \sup_{-\infty < u \leq T_N} |F_N^*(u) - F(u)| \\ &\quad + |\bar{F}_N^*(T_N) - \bar{F}(T_N)| + \bar{F}(T_N) \leq 2 \sup_{-\infty < u \leq T_N} |F_N^*(u) - F(u)| + \bar{F}(T_N) \end{aligned}$$

as both \bar{F}_N^* and \bar{F} are monotone nonincreasing. By the definition of T_N it's enough to consider

$$\sup_{-\infty < u \leq T_N} |F_N^*(u) - F(u)|.$$

Using Lemma 4.1 and applying the same argument for (4.4) which was used in [3] (Lemma 2.2, (2.7) in Lemma 2.3, and Lemma 2.5) we get that under conditions (1.2) if,

$$\sup_{-\infty < u \leq T_N} |R_N(u) - R(u)| \leq \frac{2}{3} \quad \text{a.s.}, \quad (5.1)$$

then

$$\begin{aligned} \sup_{-\infty < u \leq T_N} |F_N^*(u) - F(u)| &\leq 4 \int_{-\infty}^{T_N} \frac{1}{M_N^2(s)} dB_N(s) \\ &\quad + 2 \sup_{-\infty < u \leq T_N} \bar{F}(u) |R_N(u) - R(u)| \quad \text{a.s.} \end{aligned} \quad (5.2)$$

From Lemma 4.2 and Lemma 4.5 follows that

$$\int_{-\infty}^{T_N} \frac{1}{M_N^2(s)} dB_N(s) \leq 2^2 \int_{-\infty}^{T_N} \frac{1}{m_N^2(s)} dB_N(s) = O\left(\frac{1}{m_N(T_N)}\right) \leq O\left(\frac{1}{\sqrt{\log N \bar{G}(N, T_F)}}\right) \quad \text{a.s.} \quad (5.3)$$

as by (4.16)

$$m_N(T_N) \geq \sqrt{\log N \bar{G}(N, T_F)}, \quad \text{if } N > N_1 (\geq N^*).$$

Considering the difference $|R_N(u) - R(u)|$ apply Lemma 4.2, 4.3 and 4.5 with $\alpha = \frac{3}{2}$ for the first term of (4.5) and for the second term apply Lemma 4.4 with $\alpha = 1$. Then for any $u \leq T_N$

$$\begin{aligned} |R_N(u) - R(u)| &\leq \int_{-\infty}^u \frac{2|M_N(s) - m_N(s)|}{m_N^2(s)} dB_N(s) + \sup_{-\infty < t \leq u} \left| \int_{-\infty}^t \frac{1}{m_N(s)} d(B_N(s) - b_N(s)) \right| \\ &\leq 2\sqrt{2^9 \log N} \int_{-\infty}^u \frac{1}{m_N^{3/2}(s)} dB_N(s) + \sup_{-\infty < t \leq u} \left| \int_{-\infty}^t \frac{1}{m_N(s)} d(B_N(s) - b_N(s)) \right| \\ &\leq 2^3 \sqrt{2^9 \log N} \frac{1}{\sqrt{m_N(u)}} + \frac{12\sqrt{\log N}}{\sqrt{m_N(u)}} = O\left(\sqrt{\frac{\log N}{m_N(u)}}\right) \quad \text{a.s.} \end{aligned} \quad (5.4)$$

Hence by (4.16)

$$\sup_{-\infty < u \leq T_N} |R_N(u) - R(u)| = O\left(\sqrt{\frac{\log N}{m_N(T_N)}}\right) \leq O\left(\left(\frac{\log N}{\bar{G}(N, T_F)}\right)^{\frac{1}{4}}\right) \quad \text{a.s.} \quad (5.5)$$

Hence (5.1) holds if $N \geq N_1$.

From (5.2), (5.3), (5.5)

$$\begin{aligned} \sup_{-\infty < u \leq T_N} |F_N^*(u) - F(u)| &\leq O\left(\frac{1}{\sqrt{\log N \bar{G}(N, T_F)}}\right) + \sup_{-\infty < u \leq T_N} \bar{F}(u) O\left(\sqrt{\frac{\log N}{m_N(u)}}\right) \\ &\leq O\left(\frac{1}{\sqrt{\log N \bar{G}(N, T_F)}}\right) + \sup_{-\infty < u \leq T_N} \bar{F}(u) O\left(\sqrt{\frac{\log N}{F(u) \bar{G}(N, u)}}\right) \leq O\left(\frac{1}{\sqrt{\log N \bar{G}(N, T_F)}}\right) \\ &\quad + \sup_{-\infty < u \leq T_N} \sqrt{\bar{F}(u)} O\left(\sqrt{\frac{\log N}{\bar{G}(N, u)}}\right) \leq O\left(\frac{1}{\sqrt{\log N \bar{G}(N, T_F)}}\right) + O\left(\sqrt{\frac{\log N}{\bar{G}(N, T_F)}}\right) \\ &= O\left(\sqrt{\frac{\log N}{\bar{G}(N, T_F)}}\right) \quad \text{a.s.} \end{aligned}$$

and the theorem follows. \square

Remark 1. From our proof it is clear that we may give a concrete bound instead of using the O symbol. But this bound would be very crude.

Remark 2. Corollary 1 easily follows from Theorem 1. For this it's enough to observe that all of the lemmas and statements are valid for $(-\infty, t]$ using conditions of the corollary instead of the conditions of Theorem 1.

Remark 3. Corollary 2 covers the i.i.d. censoring case ($\alpha=1$) and gives slightly weaker result then (1.1).

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Received June 13, 1980; in revised form May 2, 1981