

Web-based Supplementary Material for “Survival Impact Index and Ultrahigh-dimensional Model-free Screening with Survival Outcomes”

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Proofs of Corollaries

Proof of Corollary 1: $1 - \Pr(\mathcal{M}_* \subset \hat{\mathcal{M}}) = \Pr(\exists j \in \mathcal{M}_*, \hat{\xi}_j < bn^{-\alpha}) = 1 - \Pr(\exists j \in \mathcal{M}_*, |\hat{\xi}_j - \xi_j| \geq (c_0 - b)n^{-\alpha}) \leq c_3 |\mathcal{M}_*| \exp(-nc_4(c_0 - b)^2 n^{-2\alpha} - c_5 \log((c_0 - b)n^{-\alpha}))$, which converges to 0, if $\alpha < (1 - c)/2$ and $p = o(\exp(n^c))$. The sure screening property has been established. \square

Proof of Corollary 2: Let $\pi_n := c_3 \exp(-nc_4\nu_n^2 - c_5 \log \nu_n)$. We have

$$\begin{aligned} p\pi_n &= c_3 \exp(-nc_4\nu_n^2 - c_5 \log \nu_n + \log p) \\ &\leq c_3 \exp\left(-nc_4 \frac{\log p + c_5 \log n/2}{c_4 n} - \frac{c_5}{2}(\log(\log p + c_5 \log n/2) - \log n - \log c_4) + \log p\right) \\ &= \frac{c_3 c_4}{(\log p + c_5 \log n/2)^{\frac{c_5}{2}}} < 1. \end{aligned}$$

Since $\binom{p-|\mathcal{M}_*|}{k} \leq p^k$, then we have $\Pr(|\hat{\mathcal{M}} \setminus \mathcal{M}_*| = k) \leq p^k \pi_n^k$, which implies

$$\begin{aligned} \Pr(|\hat{\mathcal{M}} \setminus \mathcal{M}_*| < n^c) &\geq 1 - \sum_{k=n^c}^p (\pi_n p)^k \\ &\geq 1 - \sum_{k=n^c}^p (c_3 \exp(-nc_4\nu_n^2 - c_5 \log \nu_n + \log p))^k \\ &\geq 1 - 2(c_3 \exp(-nc_4\nu_n^2 - c_5 \log \nu_n + \log p))^{n^c} \\ &\geq 1 - 2c_3 p \exp(-nc_4\nu_n^2 - c_5 \log \nu_n), \end{aligned}$$

where the last inequality follows from $p\pi_n < 1$ established above. This completes the proof of Corollary 2. \square

Lemmas

LEMMA 1: For any $0 < \epsilon < 1$,

$$\Pr\left(\sup_{0 \leq x \leq x_0} \left| \hat{S}_j(x) - S_j(x) \right| > \epsilon\right) \leq 12 \exp(-n\epsilon^2/9 - \log \epsilon). \quad (1)$$

Proof: If $|\hat{S}_j(\eta_{k-1}^{(j)}) - S_j(\eta_{k-1}^{(j)})| < \epsilon/3$ and $|\hat{S}_j(\eta_k^{(j)}) - S_j(\eta_k^{(j)})| < \epsilon/3$, then for $\eta_{k-1}^{(j)} \leq x \leq \eta_k^{(j)}$,

$$\hat{S}_j(x) - S_j(x) \leq \hat{S}_j(\eta_{k-1}^{(j)}) - S_j(\eta_{k-1}^{(j)}) + S_j(\eta_k^{(j)}) - S_j(x) \leq 2\epsilon/3,$$

The other direction can be shown by the same arguments. Thus, we have $|\hat{S}_j(x) - S_j(x)| < \epsilon$

for any $\eta_{k-1}^{(j)} \leq x \leq \eta_k^{(j)}$. Hence, if $\sup_{0 \leq x \leq x_0} |\hat{S}_j(x) - S_j(x)| > \epsilon$, then for some $0 \leq k \leq L(\epsilon)$, $|\hat{S}_j(\eta_k^{(j)}) - S_j(\eta_k^{(j)})| \geq \epsilon/3$. Thus,

$$\begin{aligned} & Pr \left(\sup_{0 \leq x \leq x_0} |\hat{S}_j(x) - S_j(x)| > \epsilon \right) \leq L(\epsilon) Pr \left(|\hat{S}_j(\eta_k^{(j)}) - S_j(\eta_k^{(j)})| > \epsilon/3 \right) \\ & \leq 2L(\epsilon) \exp \left(\frac{-1}{18} \frac{n^2 \epsilon^2}{n/4 + n\epsilon/9} \right) \leq 12 \exp(-n\epsilon^2/9 - \log \epsilon) \end{aligned}$$

where the second inequality follows from the fact $\text{Var}[1\{X_{ji} > x\} - S_j(x)] \leq 1/4$ and Bernstein's inequality. This completes the proof of (1). Moreover, we have

$$\begin{aligned} & Pr \left(\sup_{1 \leq k \leq L(\epsilon)} |\hat{S}_j(\eta_{k-1}^{(j)}) - \hat{S}_j(\eta_k^{(j)})| > \epsilon \right) \\ & \leq Pr \left(\sup_{1 \leq k \leq L(\epsilon)} |\hat{S}_j(\eta_{k-1}^{(j)}) - S_j(\eta_{k-1}^{(j)})| + |\hat{S}_j(\eta_k^{(j)}) - S_j(\eta_k^{(j)})| > 2\epsilon/3 \right) \\ & \leq L(\epsilon) Pr \left(|\hat{S}_j(\eta_k^{(j)}) - S_j(\eta_k^{(j)})| > \epsilon/3 \right) \\ & \leq 12 \exp(-n\epsilon^2/9 - \log \epsilon). \end{aligned} \tag{2}$$

□

LEMMA 2: Given $x \in [0, x_0]$, for any $24/(n\tau\gamma^4) < \epsilon < \tau/2$, we have

$$\begin{aligned} & Pr \left(\sup_{t \in \mathcal{T}} |\hat{S}_j(t; x) - S_j(t; x)| > \epsilon \right) \\ & \leq 12 \exp(-n\epsilon^2/9 - \log \epsilon) + c_1 \exp(-n\tau\gamma^6\epsilon^2/(2c_2) - \log \epsilon). \end{aligned} \tag{3}$$

Proof: By Foldes and Rejto (1981), we obtain

$$Pr \left(\sup_{t \in \mathcal{T}} |\hat{S}_j(t; x) - S_j(t; x)| > \epsilon | M_{jn}(x) = k \right) \leq c_1 \exp(-k\gamma^6\epsilon^2/c_2 - \log \epsilon), \tag{4}$$

for $12/(k\gamma^4) < \epsilon < 1$. Here, as defined in Appendix, $M_{jn}(x) = \sum_{i=1}^n 1\{X_{ji} > x\}$.

If $24/(n\tau\gamma^4) < \epsilon < \tau/2$, then

$$\begin{aligned}
& Pr \left(\sup_{t \in \mathcal{T}} |\hat{S}_j(t; x) - S_j(t; x)| > \epsilon \right) \\
&= \sum_{k=0}^n Pr \left(\sup_{t \in \mathcal{T}} |\hat{S}_j(t; x) - S_j(t; x)| > \epsilon | M_{jn}(x) = k \right) Pr(M_{jn}(x) = k) \\
&\leq Pr(M_{jn}(x) < nS_j(x) - n\epsilon) \\
&+ \sum_{k \geq nS_j(x) - n\epsilon}^n Pr \left(\sup_{t \in \mathcal{T}} |\hat{S}_j(t; x) - S_j(t; x)| > \epsilon | M_{jn}(x) = k \right) Pr(M_{jn}(x) = k) \\
&\leq Pr \left(|\hat{S}_j(x) - S_j(x)| \geq \epsilon \right) \\
&+ \frac{c_1}{\epsilon} \exp(-(nS_j(x) - n\epsilon)\gamma^6\epsilon^2/c_2) Pr(M_{jn}(x) > nS_j(x) - n\epsilon) \\
&= 12 \exp(-n\epsilon^2/9 - \log \epsilon) + c_1 \exp(-n\tau\gamma^6\epsilon^2/(2c_2) - \log \epsilon), \tag{5}
\end{aligned}$$

where the second inequality follows from (4) and the fact that for all $k \geq nS_j(x) - n\epsilon$,

$$\frac{12}{k\gamma^4} \leq \frac{12}{(nS_j(x) - n\epsilon)\gamma^4} \leq \frac{24}{nS_j(x)\gamma^4} \leq \frac{24}{n\tau\gamma^4} < \epsilon,$$

and the last inequality follows from (1) and $2\epsilon < \tau \leq S_j(x)$. This completes the proof of Lemma 2. \square

LEMMA 3: *For any $0 < \epsilon < \lambda$,*

$$Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} \max_{1 \leq i \leq n} |1\{Y_i \leq t\} n \log V_{ji}(x)| > \frac{2}{\lambda - \epsilon} \right) \leq 2 \exp(-n\epsilon^2/4). \tag{6}$$

Proof:

$$\begin{aligned}
& Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} \max_{1 \leq i \leq n} |1\{Y_i \leq t\}n \log V_{ji}(x)| > \frac{2}{\lambda - \epsilon} \right) \\
&= Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} \max_{1 \leq i \leq n} \left| 1\{Y_i \leq t\}n \log \left(\frac{\sum_{k=1}^n 1\{Y_k > Y_i, X_{jk} > x\}}{\sum_{k=1}^n 1\{Y_k > Y_i, X_{jk} > x\} + 1} \right) \right| > \frac{2}{\lambda - \epsilon} \right) \\
&\leq Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} n \left| \log \left(1 - \frac{1}{\sum_{k=1}^n 1\{Y_k > t, X_{jk} > x\} + 1} \right) \right| > \frac{2}{\lambda - \epsilon} \right) \\
&\leq Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} \frac{2n}{\sum_{k=1}^n 1\{Y_k > t, X_{jk} > x\} + 1} > \frac{2}{\lambda - \epsilon} \right) \\
&\leq Pr \left(\frac{2n}{\sum_{k=1}^n 1\{Y_k > t_0, X_{jk} > x_0\} + 1} > \frac{2}{\lambda - \epsilon} \right) \\
&\leq Pr \left(\left| \frac{\sum_{l=1}^n 1\{Y_l > t_0, X_{jl} > x_0\} + 1}{2n} - \frac{\lambda}{2} \right| > \frac{\epsilon}{2} \right) \\
&\leq 2 \exp(-n\epsilon^2/4),
\end{aligned}$$

where the last inequality follows from Bernstein's inequality. This completes the proof of Lemma 3. \square

LEMMA 4: Let $\{\eta_k^{(j)}, 0 \leq k \leq L(\epsilon)\}$ be the same grid points as constructed in Lemma 1 given $0 < \epsilon < 1$. Then

$$\begin{aligned}
& Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \max_{1 \leq i \leq n} n \left[1\{Y_i \leq t\} \log \left(\frac{V_{ji}(x)}{V_{ji}(\eta_{k-1}^{(j)})} \right) \right] > \frac{8\epsilon}{\lambda^2} \right) \\
&\leq 12 \exp(-n\epsilon^2/9 - \log \epsilon) + 2 \exp(-n\lambda^2/16). \tag{7}
\end{aligned}$$

Proof:

$$\begin{aligned}
& Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \max_{1 \leq i \leq n} n \left[1\{Y_i \leq t\} \log \left(\frac{V_{ji}(x)}{V_{ji}(\eta_{k-1}^{(j)})} \right) \right] > \frac{8\epsilon}{\lambda^2} \right) \\
& \leq Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \max_{1 \leq i \leq n} 2n \left[1\{Y_i \leq t\} \right. \right. \\
& \quad \times \left. \left. \times \frac{\sum_{l=1}^n 1 \left\{ Y_l > Y_i, \eta_{k-1}^{(j)} < X_{jl} < x \right\}}{(\sum_{l=1}^n 1 \{Y_l > Y_i, X_{jl} > x\}) (\sum_{l=1}^n 1 \{Y_l > Y_i, X_{jl} > \eta_{k-1}^{(j)}\})} \right] > \frac{8\epsilon}{\lambda^2} \right) \\
& \leq Pr \left(\sup_{1 \leq k \leq L(\epsilon)} 2n \frac{\sum_{l=1}^n 1 \left\{ \eta_{k-1}^{(j)} < X_{jl} < \eta_k^{(j)} \right\}}{(\sum_{l=1}^n 1 \{Y_l > t_0, X_{jl} > x_0\})^2} > \frac{8\epsilon}{\lambda^2} \right) \\
& \leq Pr \left(\sup_{1 \leq k \leq L(\epsilon)} \left| \hat{S}_j \left(\eta_{k-1}^{(j)} \right) - \hat{S}_j \left(\eta_k^{(j)} \right) \right| > \epsilon \right) + Pr \left(\frac{2n^2}{(\sum_{l=1}^n 1 \{Y_l > t_0, X_{jl} > x_0\})^2} > \frac{8}{\lambda^2} \right) \\
& \leq 12 \exp(-n\epsilon^2/9 - \log \epsilon) + 2 \exp(-n\lambda^2/16),
\end{aligned}$$

where the last inequality follows from (2) and the proof of Lemma 3. This completes the proof of Lemma 4. \square

A useful result

By Foldes and Rejto (1981), for some universal constants c_1 and c_2 , and $12/(n\gamma^4) < \epsilon < 1$.

$$Pr \left(\sup_{t \in \mathcal{T}} |\hat{S}(t) - S(t)| > \epsilon \right) \leq c_1 \exp(-n\gamma^6\epsilon^2/c_2 - \log \epsilon), \quad (8)$$

Hadamard differentiability of $\int_{\Omega^c(\kappa_j)} W_\xi(t, x) | \cdot | dt dx$

For any convergent sequences $u_n \rightarrow 0$ there exists an N , such that for all $n > N$, $|u_n h_n(t; x)| \leq \kappa_j$ uniformly in $\mathcal{T} \times \mathcal{X}$. Then for $n > N$,

$$\begin{aligned} & \int_{\Omega^c(\kappa_j)} W_\xi(t, x) |S_j(t; x) - S(t) + u_n h_n(t, x)| dt dx - \int_{\Omega^c(\kappa_j)} W_\xi(t, x) |S_j(t; x) - S(t)| dt dx \\ &= \int_{\Omega^c(\kappa_j)} W_\xi(t, x) \operatorname{sgn}(S_j(t; x) - S(t)) [S_j(t; x) - S(t) + u_n h_n(t, x)] dt dx \\ &\quad - \int_{\Omega^c(\kappa_j)} W_\xi(t, x) \operatorname{sgn}(S_j(t; x) - S(t)) [S_j(t; x) - S(t)] dt dx \\ &= \int_{\Omega^c(\kappa_j)} W_\xi(t, x) \operatorname{sgn}(S_j(t; x) - S(t)) u_n h_n(t, x) dt dx. \end{aligned}$$

Thus, we have

$$\begin{aligned} & \lim_{n \rightarrow \infty} u_n^{-1} \left(\int_{\Omega^c(\kappa_j)} W_\xi(t, x) |S_j(t; x) - S(t) + u_n h_n(t, x)| dt dx \right. \\ &\quad \left. - \int_{\Omega^c(\kappa_j)} W_\xi(t, x) |S_j(t; x) - S(t)| dt dx \right) \\ &= \int_{\Omega^c(\kappa_j)} W_\xi(t, x) \operatorname{sgn}(S_j(t; x) - S(t)) h(t, x) dt dx, \end{aligned}$$

which implies $\int_{\Omega^c(\kappa_j)} W_\xi(t, x) | \cdot | dt dx$ is Hadamard-differentiable at $S_j(\cdot; \cdot) - S(\cdot)$.

Detailed arguments of Theorem 2

Step 1: We consider $\sup_{t \in \mathcal{T}, 0 \leq k \leq L(\epsilon)} \left| \hat{S}_j \left(t; \eta_k^{(j)} \right) - S_j \left(t; \eta_k^{(j)} \right) \right|$ first. By Lemma 2, we obtain that for any $24/(n\tau\gamma^4) < \epsilon < \tau/2$,

$$\begin{aligned} & Pr \left(\sup_{t \in \mathcal{T}, 0 \leq k \leq L(\epsilon)} \left| \hat{S}_j \left(t; \eta_k^{(j)} \right) - S_j \left(t; \eta_k^{(j)} \right) \right| > \epsilon \right) \\ &\leq L(\epsilon) Pr \left(\sup_{t \in \mathcal{T}} \left| \hat{S}_j \left(t; \eta_k^{(j)} \right) - S_j \left(t; \eta_k^{(j)} \right) \right| > \epsilon \right) \\ &\leq 72 \exp(-n\epsilon^2/9 - 2\log\epsilon) + 6c_1 \exp(-n\tau\gamma^6\epsilon^2/(2c_2) - 2\log\epsilon). \end{aligned} \tag{9}$$

Step 2: Next, we consider $\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1} < x < \eta_k} |S_j(t; x) - S_j(t; \eta_{k-1})|$. If $\eta_{k-1}^{(j)} < x < \eta_k^{(j)}$,

$$\begin{aligned} |S_j(t; x) - S_j(t; \eta_{k-1}^{(j)})| &= \left| \frac{Pr(T > t, X_j > x)}{Pr(X_j > x)} - \frac{Pr(T > t, X_j > \eta_{k-1}^{(j)})}{Pr(X_j > \eta_{k-1}^{(j)})} \right| \\ &\leq \frac{Pr(T > t, X_j > x) \left| Pr(X_j > \eta_{k-1}^{(j)}) - Pr(X_j > x) \right|}{Pr(X_j > x) Pr(X_j > \eta_{k-1}^{(j)})} \\ &\quad + \frac{Pr(X_j > x) \left| Pr(T > t, X_j > x) - Pr(T > t, X_j > \eta_{k-1}^{(j)}) \right|}{Pr(X_j > x) Pr(X_j > \eta_{k-1}^{(j)})} \\ &\leq \frac{\epsilon/3}{\tau} + \frac{\epsilon/3}{\tau} = \frac{2\epsilon}{3\tau}. \end{aligned}$$

Therefore, we obtain

$$\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} |S_j(t; x) - S_j(t; \eta_{k-1}^{(j)})| < \frac{2\epsilon}{3\tau}. \quad (10)$$

Step 3: Then we deal with $\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} |\hat{S}_j(t; x) - \hat{S}_j(t; \eta_{k-1}^{(j)})|$. For any $0 < u, v \leq 1$, we have $|u - v| \leq |\log u - \log v|$. Therefore,

$$\begin{aligned} &Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} |\hat{S}_j(t; x) - \hat{S}_j(t; \eta_{k-1}^{(j)})| > \frac{4\epsilon}{\lambda} + \frac{8\epsilon}{\lambda^2} \right) \\ &\leq Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} |\log \hat{S}_j(t; x) - \log \hat{S}_j(t; \eta_{k-1}^{(j)})| > \frac{4\epsilon}{\lambda} + \frac{8\epsilon}{\lambda^2} \right) \\ &\leq Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \left| \sum_{i=1}^n \log V_{ji}(x) \right. \right. \\ &\quad \times \left. \left(1 \{ \delta_i = 1, Y_i \leq t, X_{ji} > x \} - 1 \{ \delta_i = 1, Y_i \leq t, X_{ji} > \eta_{k-1}^{(j)} \} \right) \right| > \frac{4\epsilon}{\lambda} \right) \\ &\quad + Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \sum_{i=1}^n 1 \{ \delta_i = 1, Y_i \leq t, X_{ji} > \eta_{k-1}^{(j)} \} \right. \\ &\quad \quad \quad \times \left. \log \left(\frac{V_{ji}(x)}{V_{ji}(\eta_{k-1}^{(j)})} \right) > \frac{8\epsilon}{\lambda^2} \right) \end{aligned}$$

where the last inequality follows from the decomposition:

$$\begin{aligned} & \log \hat{S}_j(t; x) - \log \hat{S}_j\left(t; \eta_{k-1}^{(j)}\right) \\ &= \sum_{i=1}^n \left[1\{\delta_i = 1, Y_i \leq t, X_{ji} > x\} - 1\{\delta_i = 1, Y_i \leq t, X_{ji} > \eta_{k-1}^{(j)}\} \right] \log V_{ji}(x) \\ &+ \sum_{i=1}^n 1\{\delta_i = 1, Y_i \leq t, X_{ji} > \eta_{k-1}^{(j)}\} \left[\log V_{ji}(x) - \log V_{ji}\left(\eta_{k-1}^{(j)}\right) \right]. \end{aligned}$$

Then we have,

$$\begin{aligned} & Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \left| \sum_{i=1}^n \log V_{ji}(x) \right. \right. \\ & \quad \times \left. \left(1\{\delta_i = 1, Y_i \leq t, X_{ji} > x\} - 1\{\delta_i = 1, Y_i \leq t, X_{ji} > \eta_{k-1}^{(j)}\} \right) \right| > \frac{4\epsilon}{\lambda} \right) \\ & \leq Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} \max_{1 \leq i \leq n} |1\{Y_i \leq t\} n \log V_{ji}(x)| \right. \\ & \quad \times \left. \sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon)} \frac{\sum_{i=1}^n 1\{\delta_i = 1, Y_i \leq t, \eta_{k-1}^{(j)} < X_{ji} < \eta_k^{(j)}\}}{n} > \frac{4\epsilon}{\lambda} \right) \\ & \leq Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} \max_{1 \leq i \leq n} |1\{Y_i \leq t\} n \log V_{ji}(x)| \sup_{1 \leq k \leq L(\epsilon)} [\hat{S}_j(\eta_{k-1}^{(j)}) - \hat{S}_j(\eta_k^{(j)})] > \frac{4\epsilon}{\lambda} \right) \\ & \leq Pr \left(\sup_{(t,x) \in \mathcal{T} \times \mathcal{X}} \max_{1 \leq i \leq n} |1\{Y_i \leq t\} n \log V_{ji}(x)| > \frac{4}{\lambda} \right) \\ & + Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon)} [\hat{S}_j(\eta_{k-1}^{(j)}) - \hat{S}_j(\eta_k^{(j)})] > \epsilon \right) \\ & \leq 2 \exp(-n\lambda^2/16) + 12 \exp(-n\epsilon^2/9 - \log \epsilon), \end{aligned}$$

following from Lemma 3 and (2). On the other hand, by Lemma 4.

$$\begin{aligned} & Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \sum_{i=1}^n 1\{\delta_i = 1, Y_i \leq t, X_{ji} > \eta_{k-1}^{(j)}\} \right. \\ & \quad \times \left. \log \left(\frac{V_{ji}(x)}{V_{ji}(\eta_{k-1}^{(j)})} \right) > \frac{8\epsilon}{\lambda^2} \right) \\ & \leq Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \max_{1 \leq i \leq n} n \left[1\{Y_i \leq t\} \log \left(\frac{V_{ji}(x)}{V_{ji}(\eta_{k-1}^{(j)})} \right) \right] > \frac{8\epsilon}{\lambda^2} \right) \\ & \leq 12 \exp(-n\epsilon^2/9 - \log \epsilon) + 2 \exp(-n\lambda^2/16). \end{aligned}$$

Thus,

$$\begin{aligned} & Pr \left(\sup_{t \in \mathcal{T}, 1 \leq k \leq L(\epsilon), \eta_{k-1}^{(j)} < x < \eta_k^{(j)}} \left| \hat{S}_j(t; x) - \hat{S}_j(t; \eta_{k-1}^{(j)}) \right| > \frac{4\epsilon}{\lambda} + \frac{8\epsilon}{\lambda^2} \right) \\ & \leq 24 \exp(-n\epsilon^2/9 - \log \epsilon) + 4 \exp(-n\lambda^2/16). \end{aligned} \quad (11)$$

Combining (9), (10) and (11) yields,

$$\begin{aligned} & Pr \left(\sup_{t \in \mathcal{T}, 0 \leq x \leq x_0} |\hat{S}_j(t; x) - S_j(t; x)| > \epsilon + \frac{2\epsilon}{3\lambda} + \frac{4\epsilon}{\lambda} + \frac{8\epsilon}{\lambda^2} \right) \\ & \leq 72 \exp(-n\epsilon^2/9 - 2\log \epsilon) + 6c_1 \exp(-n\tau\delta^6\epsilon^2/(2c_2) - 2\log \epsilon) \\ & \quad + 24 \exp(-n\epsilon^2/9 - \log \epsilon) + 4 \exp(-n\lambda^2/16), \end{aligned} \quad (12)$$

for any $24/(n\tau\gamma^4) < \epsilon < \lambda \wedge \tau/2$. This and (8) together imply

$$\begin{aligned} & Pr \left(\sup_{t \in \mathcal{T}, 0 \leq x \leq x_0} \left| \hat{S}_j(t; x) - \hat{S}(t) - (S_j(t; x) - S(t)) \right| > \epsilon \right) \\ & \leq c_3 \exp(-nc_4\epsilon^2 - c_5 \log \epsilon), \end{aligned} \quad (13)$$

for any $c_6 n^{-1} < \epsilon < 1$, where c_3, c_4, c_5, c_6 are some constant depending only on τ, γ , and λ , and n is sufficiently large.

Since

$$|\hat{\xi}_j - \xi_j| \leq \int_0^{x_0} \int_0^{t_0} W_\xi(t, x) \left| \hat{S}_j(t; x) - \hat{S}(t) - S_j(t; x) + S(t) \right| dt dx,$$

then by (13),

$$\begin{aligned} & Pr \left(|\hat{\xi}_j - \xi_j| > \epsilon \right) \\ & \leq Pr \left(\int_0^{x_0} \int_0^{t_0} W_\xi(t, x) \left| \hat{S}_j(t; x) - \hat{S}(t) - S_j(t; x) + S(t) \right| dt dx > \epsilon \right) \\ & \leq Pr \left(\sup_{t \in \mathcal{T}, 0 \leq x \leq x_0} \left| \hat{S}_j(t; x) - \hat{S}(t) - (S_j(t; x) - S(t)) \right| > \epsilon \right) \\ & \leq c_3 \exp(-nc_4\epsilon^2 - c_5 \log \epsilon). \end{aligned} \quad (14)$$

and hence

$$Pr \left(\max_{1 \leq j \leq p} |\hat{\xi}_j - \xi_j| > \epsilon \right) \leq c_3 \exp(-nc_4\epsilon^2 - c_5 \log \epsilon + \log p). \quad (15)$$

References

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