ON CONSISTENCY OF KERNEL DENSITY ESTIMATORS FOR RANDOMLY CENSORED DATA: RATES HOLDING UNIFORMLY OVER ADAPTIVE INTERVALS

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Abstract

In the usual right-censored data situation, let f_n, $n \in \mathbf{N}$, denote the convolution of the Kaplan-Meier product limit estimator with the kernels $a_n^{-1} K(\cdot/a_n)$, where K is a smooth probability density with bounded support and $a_n \to 0$. That is, f_n is the usual kernel density estimator based on Kaplan-Meier. Let $\bar{f}_n$ denote the convolution of the distribution of the uncensored data, which is assumed to have a bounded density, with the same kernels. For each n, let J_n denote the half line with right end point $Z_{n,n(1-\varepsilon_n)} - a_n$, where $\varepsilon_n \to 0$ and, for each m, $Z_{n,m}$ is the m-th order statistic of the censored data. It is shown that, under some mild conditions on a_n and ε_n, $\sup_{J_n} |f_n(t) - \bar{f}_n(t)|$ converges a.s. to zero as $n \to \infty$ at least as fast as $\sqrt{|\log(a_n \wedge \varepsilon_n)|/(n a_n \varepsilon_n)}$. For ε_n=constant, this rate compares, up to constants, with the exact rate for fixed intervals.

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1. Introduction

Let $X, X_i, i \in \mathbf{N}$, be independent and identically distributed (i.i.d.) random variables with common distribution function (cdf) F, which we assume differentiable, with density f. Let $Y, Y_i,\ i \in \mathbf{N}$, be a second i.i.d. sequence independent of the first, with cdf G, and let $Z = X \wedge Y$, $\delta = I_{X \le Y}$, $Z_i = X_i \wedge Y_i$ and $\delta_i = I_{X_i \le Y_i}$, $i \in \mathbf{N}$. We denote by H the cdf of Z, by $\tau_H = \inf\{x : H(x) = 1\}$ the supremum of the support of H and by H_n and H_n^{-1} respectively the empirical cdf and the empirical quantile function corresponding to $Z_1, \dots, Z_n$, $n \in \mathbf{N}$. Let $\hat{F}_n(x),\ -\infty < x < \tau_H$, be the Kaplan-Meier (1958) product limit estimator of $F(x)$. (See Section 2 for definitions.) A natural nonparametric estimator of f is

$$f_n(t) = \frac{1}{a_n} \int_{-\infty}^{\infty} K\Big(\frac{t-x}{a_n}\Big) d\hat{F}_n(x), \quad n \in \mathbf{N}, \tag{1.1}$$

where K is a probability kernel and a_n is a sequence of positive constants tending to zero. In this article we are interested in the general problem of understanding how well does f_n estimate f. Diehl and Stute (1988) contains an exact law of the iterated logarithm (LIL) for the variable

$$\sup_{t \le T} |f_n(t) - \bar{f}_n(t)|$$

where $T < \tau_H$ is fixed and

$$\bar{f}_n(t) = \frac{1}{a_n} \int_{-\infty}^{\infty} K\Big(\frac{t-x}{a_n}\Big) dF(x) \tag{1.2}$$

is the convolution of f with the approximate identity $a_n^{-1} K(x/a_n) dx$. (The 'bias' $\bar{f} - f$ is ignored as it can always be balanced with the term $f_n - \bar{f}_n$ by calibrating the normalizing sequence $\{a_n\}$, provided enough regularity for K is assumed.) Stute (1994) introduced a.s. bounds for $|\hat{F}_n - F|$ uniform over varying data driven intervals that asymptotically cover the full domain of H, $(-\infty, \tau_H)$, and his analysis was refined in Csörgő (1996) and Giné and Guillou (1999). In view of these developments it is only natural to ask whether the same idea can be applied to kernel density estimation, that is, whether sensible rates of a.s. convergence to zero can be obtained for the random variables

$$\sup_{t \le \tau_n} |f_n(t) - \bar{f}_n(t)| \tag{1.3}$$

with $\tau_n = H_n^{-1}(1 - \varepsilon_n)$, for suitable $\varepsilon_n \to 0$. The object of this article is to provide such rates, which are given in Theorem 3.3 and Corollary 3.4 below. When we take ε_n =constant, our results nearly recover, except for multiplicative constants, the main result in Diehl and Stute (1988), which is optimal.

We should mention here that the upper limit $\tau_n = H_n^{-1}(1 - \varepsilon_n)$ is eventually a.s. dominated by $T_n = H^{-1}(1 - \varepsilon_n/8)$ if $n\varepsilon_n \ge \log n$ for all n large enough (see e.g., any of the last mentioned three articles). Then, in order to obtain an asymptotic upper bound for (1.3), it suffices to obtain one for

$$\sup_{t \le T_n} |f_n(t) - \bar{f}_n(t)|. \tag{1.4}$$

Hence, although our results apply to (1.3), they are stated for (1.4) (our assumptions imply that $n\varepsilon_n$ is indeed asymptotically larger than $\log n$).

This article may be considered as an application to density estimation of the methods and results from Giné and Guillou (1999). As in this last article, the main innovation with respect to previous work consists in using sharp exponential bounds for the empirical process (Alexander (1984), Massart (1986) and Talagrand (1996)). Concretely, we will use a version of Massart's bound obtained from Talagrand's by convenient estimation of the expected value of the supremum of the empirical process, in a way similar to (but different from) Einmahl and Mason (1999). In order to perform 'blocking' as in the classical proofs of the law of the iterated logarithm (LIL) we found a maximal inequality of Montgomery-Smith (1993) very useful, just as in our previous work.

2. An exponential inequality and other preparatory material. The next two propositions use the language of empirical processes. We refer to Giné and Guillou (1999), Lemma 3 and the paragraph before it, for the definition of measurable classes of functions $\mathcal{F}$, VC (Vapnik-Červonenkis) with respect to an envelope F, as well as for the covering numbers $N(T, d, \varepsilon)$ of a metric space (T, d). If $\mathcal{F}$ is VC with respect to $F = \sup\{|f| : f \in \mathcal{F}\}$ then we simply say that $\mathcal{F}$ is a VC class of functions. The functions in $\mathcal{F}$ are assumed to be measurable real functions on a measurable space $(S, \mathcal{S})$, P is a probability measure on $(S, \mathcal{S})$ and ξ_i, $i \in \mathbf{N}$, are the coordinate functions $S^{\mathbf{N}} \mapsto S$, in particular, they are i.i.d. with common law P. $P_n := \sum_{i=1}^n \delta_{\xi_i}/n$ are the empirical measures corresponding to the sequence ξ_i. Finally, $\{\eta_i\}$ is a sequence of independent Rademacher variables, independent of $\{\xi_i\}$, in fact, defined on another factor of a common product probability space. (We recall that a Rademacher variable η is one that satisfies $\Pr\{\eta = 1\} = \Pr\{\eta = -1\} = 1/2$.) Also, $\|\Phi\|_{\mathcal{F}} := \sup_{f\in\mathcal{F}} |\Phi(f)|$.

Proposition 2.1. *Let $\mathcal{F}$ be a measurable uniformly bounded VC class of functions. Let $\sigma^2 \geq \sup_f E_P f^2$ and $U \geq \sup_{f\in\mathcal{F}} \|f\|_\infty$ be such that $0 < \sigma \leq U$. Then there exist A, C dependent on $\mathcal{F}$ but not on P, $A \geq 3\sqrt{e}$, $C > 0$, such that, for all $n \in \mathbf{N}$,*

$$E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)\Big\|_{\mathcal{F}} \leq C\left[U \log\frac{AU}{\sigma} + \sqrt{n}\,\sigma\sqrt{\log\frac{AU}{\sigma}}\,\right]. \tag{2.1}$$

Proof. Since $\mathcal{F}$ is VC, there exists A and v positive such that, if $F := \sup_{f\in\mathcal{F}} |f|$, then for all probability measures P on $(S, \mathcal{S})$ and $0 < \tau < 1$,

$$N\Big(\mathcal{F}, L_2(P), \tau\|F\|_{L_2(P)}\Big) \leq \Big(\frac{A}{\tau}\Big)^v. \tag{2.2}$$

We can assume $A \geq 3\sqrt{e}$. We can also assume that $0 \in \mathcal{F}$. Then, the usual entropy bound for Rademacher processes (e.g., Corollary 5.1.8 in de la Peña and Giné, 1999) gives

$$E_\eta\Big\|\sum_{i=1}^n \eta_i f(\xi_i)/\sqrt{n}\Big\|_{\mathcal{F}} \leq C\int_0^{\|\sum_{i=1}^n f^2(\xi_i)/n\|_{\mathcal{F}}^{1/2}} \sqrt{\log N\Big(\mathcal{F}, L_2(P_n), \tau\Big)}\,d\tau, \tag{2.3}$$

where E_η denotes integration with respect to the Rademacher variables only and C is a universal constant. On the other hand, by Talagrand (1994), Corollary 3.4,

$$E\Big\|\sum_{i=1}^n f^2(\xi_i)\Big\|_{\mathcal{F}} \le n\sigma^2 + 8\ U\ E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)\Big\|_{\mathcal{F}}. \tag{2.4}$$

Then, combining (2.2) and (2.3) and changing variables, we have

$$\begin{aligned} E_\eta\Big\|\sum_{i=1}^n \eta_i f(\xi_i)/\sqrt{n}\Big\|_{\mathcal{F}} &\le ACU \int_{AU/\|\sum_{i=1}^n f^2(\xi_i)/n\|_{\mathcal{F}}^{1/2}}^{\infty} \frac{\sqrt{v\log\tau}}{\tau^2}d\tau \\ &\le C'\Big\|\sum_{i=1}^n f^2(\xi_i)/n\Big\|_{\mathcal{F}}^{1/2}\sqrt{\log\frac{A^2U^2}{\|\sum_{i=1}^n f^2(\xi_i)/n\|_{\mathcal{F}}}} \end{aligned}$$

for another universal constant C'. By Hölder's inequality and concavity of the function $y = x\log\frac{a}{x}$, the above gives

$$E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)/\sqrt{n}\Big\|_{\mathcal{F}} \le C'\sqrt{E\Big\|\sum_{i=1}^n f^2(\xi_i)/n\Big\|_{\mathcal{F}}\log\frac{A^2U^2}{E\|\sum_{i=1}^n f^2(\xi_i)/n\|_{\mathcal{F}}}}\ .$$

Then, inequality (2.4) and the fact that the function $y = x\log\frac{a}{x}$ is increasing for $0 \le x \le \frac{a}{e}$ yield

$$\begin{aligned} &E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)/\sqrt{n}\Big\|_{\mathcal{F}} \\ &\le C'\sqrt{\Big(\sigma^2 + 8\ U\ E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)/n\Big\|_{\mathcal{F}}\Big)\log\frac{A^2U^2}{\sigma^2 + 8\ U\ E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)/n\Big\|_{\mathcal{F}}}} \\ &\le C'\sqrt{\Big(\sigma^2 + \frac{8\ U}{\sqrt{n}}\ E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)/\sqrt{n}\Big\|_{\mathcal{F}}\Big)\log\frac{A^2U^2}{\sigma^2}}\ . \end{aligned}$$

Thus, setting

$$Z = E\Big\|\sum_{i=1}^n \eta_i f(\xi_i)\Big\|_{\mathcal{F}},$$

Z satisfies the inequation

$$Z^2 \le Cn\sigma^2\log\Big(\frac{AU}{\sigma}\Big) + 8CZU\log\Big(\frac{AU}{\sigma}\Big),$$

where C is a universal constant. Hence, Z is between the two roots of the corresponding equation and, since one is negative and $Z \ge 0$, we conclude that

$$\begin{aligned} Z &\le 4\ C\ U\ \log\frac{AU}{\sigma} + \sqrt{16C^2U^2\Big(\log\frac{AU}{\sigma}\Big)^2 + Cn\sigma^2\Big(\log\frac{AU}{\sigma}\Big)} \\ &\le 8\ C\ U\log\frac{AU}{\sigma} + \sqrt{C}\ \sqrt{n}\ \sigma\sqrt{\log\frac{AU}{\sigma}}, \end{aligned}$$

proving Proposition 2.1. □

For a similar proposition with a different proof see Einmahl and Mason (1999), Proposition A.1.

Since

$$E\Big\|\sum_{i=1}^n\Big(f(\xi_i)-Ef(\xi_1)\Big)\Big\|_{\mathcal F}\le 2E\Big\|\sum_{i=1}^n\eta_i\Big(f(\xi_i)-Ef(\xi_1)\Big)\Big\|_{\mathcal F}$$

and since, if $\mathcal F$ is a measurable uniformly bounded VC-type class of functions so is $\tilde{\mathcal F}:=\{f-Ef(\xi_1): f\in\mathcal F\}$, (as is well known and can be seen by a simple estimation of covering numbers), we can apply the previous proposition to $\tilde{\mathcal F}$ with U replaced by $2U$ and σ^2 satisfying instead the requirements $\sigma^2\ge\sup_{f\in\mathcal F}\mathrm{Var}_P f$ and $0<\sigma\le 2U$. We then conclude that there is a universal constant C such that

$$E\Big\|\sum_{i=1}^n\Big(f(\xi_i)-Ef(\xi_1)\Big)\Big\|_{\mathcal F}\le C\left[U\log\frac{AU}{\sigma}+\sqrt{n}\,\sigma\,\sqrt{\log\frac{AU}{\sigma}}\,\right], \tag{2.5}$$

(C may be different from the constant in Proposition 2.1 as it must absorb several numerical factors due to symmetrization and to the change from U to $2U$). Moreover, this and inequality (2.4) applied to $\tilde{\mathcal F}$ yield

$$\begin{aligned}E\Big\|\sum_{i=1}^n(f(\xi_i)-Ef(\xi_1))^2\Big\|_{\mathcal F}&\le n\sigma^2+8CU^2\log\frac{AU}{\sigma}+8CU\sqrt{\log\frac{AU}{\sigma}}\sqrt{n}\,\sigma\\&\le\left(\sqrt{n}\,\sigma+L\,U\sqrt{\log\frac{AU}{\sigma}}\,\right)^2,\end{aligned}\tag{2.6}$$

for some universal constant L.

Talagrand (1996) proved the following exponential inequality for any measurable, uniformly bounded class of functions $\mathcal F$:

$$\Pr\left\{\left|\Big\|\sum_{i=1}^n f(\xi_i)\Big\|_{\mathcal F}-E\Big\|\sum_{i=1}^n f(\xi_i)\Big\|_{\mathcal F}\right|>t\right\}\le K\exp\left\{-\frac{1}{K}\frac{t}{U}\log\Big(1+\frac{tU}{V}\Big)\right\}, \tag{2.7}$$

valid for all $t>0$, and where K is a universal constant, U is as above and V is any number satisfying $V\ge E\sup_{f\in\mathcal F}\sum_{i=1}^n f^2(\xi_i)$. This inequality applied to $\tilde{\mathcal F}$, together with the estimates (2.5) and (2.6), then gives the following:

Proposition 2.2. *Let $\mathcal F$ be a measurable uniformly bounded VC class of functions, and let σ^2 and U be any numbers such that $\sigma^2\ge\sup_{f\in\mathcal F}\mathrm{Var}_P f$, $U\ge\sup_{f\in\mathcal F}\|f\|_\infty$ and $0<\sigma\le U$. Then, there exist constants C and K, depending only on the VC characteristics A and v of the class $\mathcal F$, such that the inequality*

$$\Pr\left\{\Big\|\sum_{i=1}^n\Big(f(\xi_i)-Ef(\xi_1)\Big)\Big\|_{\mathcal F}>t\right\}$$

$$\leq K \exp\left\{ -\frac{1}{K}\frac{t}{U}\log\left(1+\frac{tU}{K\left(\sqrt{n}\,\sigma+\ U\sqrt{\log\frac{AU}{\sigma}}\ \right)^2}\right)\right\} \tag{2.8}$$

is valid for all

$$t \geq C\left[U\log\frac{AU}{\sigma}+\sqrt{n}\,\sigma\ \sqrt{\log\frac{AU}{\sigma}}\ \right]. \tag{2.9}$$

If in Proposition 2.2 we assume $0 < \sigma \leq cU$ for some $c < 1$ then $\log A \leq d\log(U/\sigma)$ for some $d < \infty$ and we can replace $\log(AU/\sigma)$ by $\log(U/\sigma)$ in both (2.8) and (2.9) at the price of changing the constants K and C (that now depend on c).

The exponential inequality for the empirical process in Proposition 2.2 is comparable to Massart's (1986, Proposition 3.5) and to Inequality A1 in Einmahl and Mason (1999) on a certain range of t's (and is better for t large), and the proof is similar to, but simpler than, the latter.

We will use inequality (2.8) for $0 < \sigma \leq U/2$ and under the additional assumption

$$\sqrt{n}\sigma \geq C_1 U\sqrt{\log\frac{U}{\sigma}} \tag{2.10}$$

and then, with

$$t = C_2\sqrt{n}\ \sigma\ \sqrt{\log\frac{U}{\sigma}}, \tag{2.11}$$

for fixed C_1 and C_2, with C_2 large, in which case, it gives

$$\Pr\left\{\left\|\sum_{i=1}^{n}\Big(f(\xi_i)-Ef(\xi_1)\Big)\right\|_{\mathcal{F}} > C_2\sigma\sqrt{n}\sqrt{\log\frac{U}{\sigma}}\right\} \leq K\exp\left\{-\frac{D}{K}\log\frac{U}{\sigma}\right\}, \tag{2.12}$$

where D can be taken to be $D = C_1C_2\log\big(1+C_2K^{-1}C_1^{-1}(1+C_1^{-1})^{-2}\big)$, as can be easily checked (and therefore, $D\to\infty$ as $C_2\to\infty$ for each C_1 fixed).

As a first application of these inequalities we prove a lemma that will be useful throughout. We recall that the quantile function of H is defined as $H^{-1}(x) = \inf\big[z : H(z) \geq x\big]$ for $x \in (0,1)$, and that $H(H^{-1}(x)-) \leq x \leq H(H^{-1}(x))$. It is convenient to make the following definition: we say that a nonincreasing sequence of numbers $\{\varepsilon_n\}$ is *regular* if there exists a positive constant A such that $\varepsilon_{2n} \geq A\varepsilon_n$ for all n.

Lemma 2.3. *Let $\{\varepsilon_n\}$ be a regular nonincreasing sequence such that*

$$\lim_{n\to\infty}\frac{n\varepsilon_n}{\log\frac{1}{\varepsilon_n}} = \infty. \tag{2.13}$$

Let

$$T_n := H^{-1}(1-\varepsilon_n). \tag{2.14}$$

Then,

$$\sup_{x\leq T_n}\left|\frac{1-H_n(x-)}{1-H(x-)}-1\right| = O\left(\sqrt{\frac{(\log\frac{1}{\varepsilon_n})\vee\log\log n}{n\varepsilon_n}}\right)\quad \text{a.s.} \tag{2.15}$$

and, in particular,

$$\lim_{n\to\infty}\sup_{x\le T_n}\frac{1-H_n(x-)}{1-H(x-)}=1 \quad \text{a.s.} \tag{2.16}$$

Hence, also

$$\sup_{x\le T_n}\left|\frac{1-H(x-)}{1-H_n(x-)}-1\right|=O\left(\sqrt{\frac{\left(\log\frac{1}{\varepsilon_n}\right)\vee\log\log n}{n\varepsilon_n}}\right) \quad \text{a.s.} \tag{2.15$'$}$$

and

$$\lim_{n\to\infty}\sup_{x\le T_n}\frac{1-H(x-)}{1-H_n(x-)}=1 \quad \text{a.s.} \tag{2.16$'$}$$

Proof. We have

$$\frac{1-H_n(x-)}{1-H(x-)}-1=\frac{1}{n}\sum_{i=1}^n\left(\frac{I_{Z_i\ge x}}{1-H(x-)}-E\frac{I_{Z\ge x}}{1-H(x-)}\right):=\sum_{i=1}^n(f_{x,n}(Z_i)-Ef_{x,n}(Z)).$$

For each n, the family of functions $\{f_{x,n}:x\le T_n\}$ is obviously bounded, it is measurable because it is parametrized by a half line and $f_{x,n}(t)$ is jointly measurable in x and t, and it is a VC class because of its monotonicity properties (each function $f_{x,n}$ is the difference of a constant c_x and a function $g_{x,n}$ such that the functions $g_{x,n}$ increase as x increases: see e.g. Lemma 3, b) and c), in Giné and Guillou, loc. cit.). Thus, we can apply the exponential inequalities above, in this case, Talagrand's inequality (2.7) to $\tilde{\mathcal{F}}:=\{f_{x,n}-Ef_{x,n}\}$ in conjunction with the estimate (2.6) of V. We can obviously take $U_n=(n\varepsilon_n)^{-1}$ and, since $Ef_{x,n}^2(Z)=(1-H(x-))^{-1}/n^2$, $x\le T_n$, we can take $\sigma^2=(n^2\varepsilon_n)^{-1}$. Hence,

$$\Pr\left\{\sup_{x\le T_n}\left|\sum_{i=1}^n\big(f_{x,n}(Z_i)-Ef_{x,n}(Z)\big)\right|-E\left(\sup_{x\le T_n}\left|\sum_{i=1}^n\big(f_{x,n}(Z_i)-Ef_{x,n}(Z)\big)\right|\right)\right.$$
$$\left.>C\sqrt{\frac{\log\log n}{n\varepsilon_n}}\right\}$$
$$\le K\exp\left\{-\frac{C}{K}\sqrt{n\varepsilon_n\log\log n}\;\log\left(1+\frac{C\sqrt{\log\log n}/(n\varepsilon_n)^{3/2}}{\left(\frac{1}{\sqrt{n\varepsilon_n}}+2L\frac{1}{n\varepsilon_n}\sqrt{\log\frac{1}{\varepsilon_n}}\right)^2}\right)\right\},$$

which, by (2.13) and (2.14), is dominated by

$$K\exp\left\{-\frac{C^2}{2K}\log\log n\right\}$$

for all n large enough. Also, given the values assigned to U and σ^2, (2.5) shows that the expected value of the sup of the process over $\{x\le T_n\}$ is of the order of

$\big((\log\varepsilon_n^{-1})/(n\varepsilon_n)\big)^{1/2}$. We then conclude that there exist A, D and n_0 such that

$$\Pr\left\{\sup_{x\le T_n}\left|\frac{1-H_n(x-)}{1-H(x-)}-1\right|>A\sqrt{\frac{(\log\frac{1}{\varepsilon_n})\vee\log\log n}{n\varepsilon_n}}\right\}\le D\exp\{-2\log\log n\} \tag{2.17}$$

for all $n\ge n_0$. Setting, for ease of notation, $B_n^2:=A^2\big[(\log\varepsilon_n^{-1})\vee\log\log n)\big]/(n\varepsilon_n)$, the regularity of the sequence $\{\varepsilon_n\}$ implies that there exists $d>0$ such that $B_{2^k}\le dB_n$ for all $2^{k-1}<n\le 2^k$, for all $k>\log n_0$. Then, by (2.17) and Montgomery-Smith's (1993) maximal inequality (see e.g. de la Peña and Giné, 1999), we have

$$\begin{aligned}
\Pr&\left\{\max_{2^{k-1}<n\le 2^k}B_n^{-1}\sup_{x\le T_n}\left|\frac{1-H_n(x-)}{1-H(x-)}-1\right|>30d\right\}\\
&\le\Pr\left\{\max_{2^{k-1}<n\le 2^k}B_{2^k}^{-1}\sup_{x\le T_{2^k}}\left|\frac{1-H_n(x-)}{1-H(x-)}-1\right|>30\right\}\\
&\le 9\Pr\left\{\sup_{x\le T_{2^k}}\left|\frac{1-H_{2^k}(x-)}{1-H(x-)}-1\right|>B_{2^k}\right\}\\
&\le\frac{9D}{(\log 2)^2}\frac{1}{k^2}.
\end{aligned}$$

Now (2.15) follows by Borel-Cantelli. Condition (2.13) implies $n\varepsilon_n/\log\log n\to\infty$ (because if $\limsup_n n\varepsilon_n/\log\log n\le M<\infty$ then $\limsup_n n\varepsilon_n/\log(\varepsilon_n)^{-1}\le\limsup_n(M\log\log n)/\log n=0$). Therefore the bound in (2.15) is $o(1)$, which implies (2.16) as well as (2.15') and (2.16'). □

The scheme of proof of the previous lemma is used repeatedly throughout. We will refer to the above proof rather than reproduce repetitious arguments.

Next, following Csörgő (1996), we describe a bound for the product limit estimator that follows from the classical expansion of Breslow and Crowley (1974). We need some additional notation, borrowed from Stute (1994) and Csörgő (1996). We set $\tilde H(x)=\Pr\{Z\le x,\delta=1\}$, $-\infty<x\le\tau_H$, and define $\tilde H_n$ to be its empirical counterpart, that is,

$$\tilde H_n(x)=\frac{1}{n}\sum_{i=1}^n I_{\{Z_i\le x,\delta_i=1\}},\quad n\in\mathbf{N},$$

for $-\infty<x\le\tau_H$. (We should recall from the introduction that H is the cdf of Z and that, for each n, $H_n(x)=\sum_{i=1}^n I_{Z_i\le x}/n$.) The obvious facts that $d\tilde H\le dH$ and $d\tilde H_n\le dH_n$ will be used without further mention. We should recall that, with this notation and the notation set up in the Introduction, the cumulative hazard function of X is

$$\Lambda(x)=\int_{-\infty}^x\frac{dF(y)}{1-F(y-)}=\int_{-\infty}^x\frac{d\tilde H(y)}{1-H(y-)},\quad x\in(-\infty,\tau_H),$$

and its Nelson-Aalen estimator (Nelson, 1972, and Aalen, 1976) is

$$\Lambda_n(x) = \int_{-\infty}^{x} \frac{d\tilde{H}_n(y)}{1 - H_n(y-)},$$

defined for $x < \max_{i \le n} Z_i := Z_{n,n}$. The product limit estimator (Kaplan and Meier, 1958) is defined as

$$1 - \hat{F}_n(x) = \prod_{j=1}^{n} \left[1 - \frac{\delta_{j,n} I_{Z_{j,n} \le x}}{n - j + 1} \right]$$

for all $x < Z_{n,n}$, where $Z_{j,n}$ are the order statistics of $Z_1, \dots, Z_n$ and $\delta_{j,n} = \delta_k$ iff $Z_{j,n} = Z_k$. Note that if we take T_n as in the Introduction, $T_n < Z_{n,n}$ a.s. If F is continuous, for any real function h and for all $x < Z_{n,n}$, we have (Csörgő, 1996):

$$\left| \frac{\hat{F}_n(x) - F(x)}{1 - F(x)} - h(x) \right| \le \left| (\Lambda_n(x) - \Lambda(x)) - h(x) \right| + |R_{n,6}(x)| \tag{2.18}$$

where

$$R_{n,6}(x) = \left[\frac{1}{2} |\Lambda_n(x) - \Lambda(x)|^2 + |\ell_n(x)| \exp(|\ell_n(x)|) \right] \exp\big(|\Lambda_n(x) - \Lambda(x)|\big) \tag{2.19}$$

and

$$\ell_n(x) = -\log(1 - \hat{F}_n(x)) - \Lambda_n(x). \tag{2.20}$$

$\Lambda_n - \Lambda$ further decomposes as:

$$\begin{aligned} \Lambda_n(x) - \Lambda(x) &= \int_{-\infty}^{x} \frac{d(\tilde{H}_n - \tilde{H})(y)}{1 - H(y-)} + \int_{-\infty}^{x} \frac{H_n(y-) - H(y-)}{(1 - H_n(y-))(1 - H(y-))} d\tilde{H}_n(y) \\ &:= L_{n,1}(x) + R_n(x). \end{aligned} \tag{2.21}$$

We note that $L_{n,1}$ is only part of the linearization L_n of $\Lambda_n - \Lambda$ considered e.g. in Giné and Guillou, loc. cit.

The probability kernels K we will consider satisfy the following condition:

$$K \textit{ is differentiable with uniformly bounded derivative and vanishes on } [-1,1]^c. \tag{2.22}$$

The case of K vanishing outside $[r, s]$, $-\infty < r < s < \infty$, is not more general as it reduces to K vanishing outside $[-1, 1]$ by translation and dilation. We take the limits -1 and 1 just for convenience. We then have (by (1.1), (1.2), (2.21), (2.22) and integration by parts):

$$\begin{aligned} f_n(t) - \bar{f}_n(t) = &-\frac{1}{a_n} \int_{t-a_n}^{t+a_n} (1 - F(x)) \left(\frac{\hat{F}_n(x) - F(x)}{1 - F(x)} - \big(\Lambda_n(x) - \Lambda(x)\big) \right) dK\left(\frac{t-x}{a_n}\right) \\ &- \frac{1}{a_n} \int_{t-a_n}^{t+a_n} (1 - F(x)) L_{n,1}(x) dK\left(\frac{t-x}{a_n}\right) \\ &- \frac{1}{a_n} \int_{t-a_n}^{t+a_n} (1 - F(x)) R_n(x) dK\left(\frac{t-x}{a_n}\right). \end{aligned} \tag{2.23}$$

The proof of the main result in the next section consists in estimating the sizes of these three terms. We anticipate that the second term dominates.

3. The order of magnitude of $f_n - \bar{f}_n$. In what follows we assume that $\{\varepsilon_n\}$ and $\{a_n\}$ are nonincreasing regular sequences such that $a_n \to 0$ and both,

$$\lim_{n\to\infty} \frac{na_n\varepsilon_n}{\log \frac{1}{a_n \wedge \varepsilon_n}} = \infty \tag{3.1}$$

and

$$\lim_{n\to\infty} \frac{\log \frac{1}{a_n \wedge \varepsilon_n}}{\log\log n} = \infty. \tag{3.2}$$

In particular, $\{\varepsilon_n\}$ satisfies hypothesis (2.13) from Lemma 2.3. We assume, in addition, two conditions which may seem less natural but that nevertheless are not too restrictive, namely, that

$$\liminf_n \frac{n\varepsilon_n}{d_n \log n} > 0 \tag{3.3}$$

where $d_n \nearrow \infty$ is such that $\sum \big[kd_{2^k}\log k\big]^{-1} < \infty$ (such as, for instance, $d_n = (\log\log\log n)^{1+\delta}$ for some $\delta > 0$), and that

$$a_n \left(\log \frac{1}{\varepsilon_n}\right)^2 \to 0. \tag{3.4}$$

Condition (3.4) is obviously satisfied if $a_n \le \varepsilon_n$, and, since by (3.3) $\log \varepsilon_n^{-1} < \log n$ for all n large enough, it also holds if $a_n(\log n)^2 \to 0$.

We also set

$$T_n = H^{-1}(1 - \varepsilon_n). \tag{2.14}$$

Then, condition (3.3) implies that $n\varepsilon_n/\log n \to \infty$ and therefore, as mentioned in the introduction, it follows e.g. by Remark 3 in Giné and Guillou, loc. cit., that T_n dominates $H_n^{-1}(1-3\varepsilon_n)$ eventually a.s., hence also $Z_{n(1-3\varepsilon_n),n}$ if the numbers $3n\varepsilon_n$ are integers. So, although the results that follow are stated in terms of T_n they are really results on the sup of $|f_n - \bar{f}_n|$ over adaptive random intervals that tend to τ_H. Finally, we also assume that

$$F \text{ and } G \text{ are differentiable and } F' := f \text{ is uniformly bounded.} \tag{3.5}$$

Lemma 3.1. *Let F and G be cdf's satisfying condition (3.5), let K be a probability kernel satisfying condition (2.22), and let $\{\varepsilon_n\}$ and $\{a_n\}$ be two nonincreasing regular sequences satisfying $a_n \to 0$ and conditions (3.1) and (3.2). We assume also that $\{\varepsilon_n\}$ satisfies (3.3). Then,*

$$\sup_{t \le T_n - a_n} \frac{1}{a_n}\left| \int_{t-a_n}^{t+a_n} (1-F(x))\left(\frac{\hat{F}_n(x) - F(x)}{1-F(x)} - \big(\Lambda_n(x) - \Lambda(x)\big)\right) dK\left(\frac{t-x}{a_n}\right)\right| \tag{3.6}$$

$$= o\left(\frac{\log \frac{1}{a_n \wedge \varepsilon_n}}{na_n\varepsilon_n}\right) \text{ a.s.}$$

Proof. Taking $h(x) = \Lambda_n(x) - \Lambda(x)$ in (2.18) gives

$$\left| \frac{\hat{F}_n(x) - F(x)}{1 - F(x)} - \big(\Lambda_n(x) - \Lambda(x)\big) \right| \le \big|R_{n,6}(x)\big|,$$

and therefore,

$$\sup_{t \le T_n - a_n} \frac{1}{a_n} \left| \int_{t-a_n}^{t+a_n} (1 - F(x)) \left(\frac{\hat{F}_n(x) - F(x)}{1 - F(x)} - \big(\Lambda_n(x) - \Lambda(x)\big) \right) dK\left(\frac{t-x}{a_n}\right) \right|$$
$$\le \frac{2}{a_n} \|K'\|_\infty \sup_{t \le T_n} \big|R_{n,6}(t)\big|.$$

Now, Theorem 6 in Giné and Guillou, loc. cit., gives

$$\sup_{t \le T_n} \big(\Lambda_n(t) - \Lambda(t)\big)^2 = O\left(\frac{\log\log n}{n\varepsilon_n}\right) \quad \text{a.s.}$$

on account of (3.3) and the regularity of the sequence $\{\varepsilon_n\}$. Moreover, by Lemma 1 in Breslow and Crowley (1974), if $x \le T_n$,

$$0 < \ell_n(t) = -\log(1 - \hat{F}_n(t)) - \Lambda_n(t) \le \frac{H_n(t-)}{n(1 - H_n(t-))} \quad \text{a.s.}$$

and, by Lemma 2.3,

$$\sup_{t \le T_n} \frac{H_n(t-)}{n(1 - H_n(t-))} \le \frac{1}{n(1 - H(T_n))} \frac{1 - H(T_n)}{1 - H_n(T_n-)} = O\left(\frac{1}{n\varepsilon_n}\right) \quad \text{a.s.}$$

Then, since these bounds tend to zero by (3.1) and (3.2), combining them with (2.19) and (2.20) yields

$$\sup_{t \le T_n} \big|R_{n,6}(t)\big| = O\left(\frac{\log\log n}{n\varepsilon_n}\right) \quad \text{a.s.}$$

Now the result follows from condition (3.2). □

Lemma 3.2. *Under the assumptions of Lemma 3.1 plus condition (3.4) for $\{a_n\}$, we have*

$$\sup_{t \le T_n - a_n} \frac{1}{a_n} \left| \int_{t-a_n}^{t+a_n} (1 - F(x)) R_n(x) dK\left(\frac{t-x}{a_n}\right) \right| = o\left(\sqrt{\frac{\log \frac{1}{a_n \wedge \varepsilon_n}}{n a_n \varepsilon_n}}\right) \quad \text{a.s.} \qquad (3.7)$$

Proof. Changing variables, we can write

$$\frac{1}{a_n}\int_{t-a_n}^{t+a_n}(1-F(x))R_n(x)dK\left(\frac{t-x}{a_n}\right)$$
$$=\frac{1}{a_n}\int_{-1}^{1}\big(1-F(t-a_nu)\big)\big(R_n(t-a_nu)-R_n(t)\big)K'(u)du$$
$$+\frac{1}{a_n}R_n(t)\int_{-1}^{1}\big(1-F(t-a_nu)\big)K'(u)du$$
$$=(I_n)+(II_n).$$

Order of magnitude of (II_n). K being a probability kernel, by integration by parts we have

$$\sup_{t\le T_n-a_n}|(II_n)|\le\frac{1}{a_n}\left(\sup_{t\le T_n}|R_n(t)|\right)\left(\sup_{t\le T_n-a_n}\left|\int_{-1}^{1}K(u)d(1-F(t-a_nu))\right|\right)$$
$$\le\|f\|_\infty\sup_{t\le T_n}|R_n(t)|. \tag{3.8}$$

We consider two cases according as to whether $a_n\ge\varepsilon_n$ or $a_n<\varepsilon_n$. First, we assume $a_n\ge\varepsilon_n$ for all n (strictly, we should just consider the subsequence of those integers n for which $a_n\ge\varepsilon_n$ but, for ease of notation, we will assume that this subsequence is $\mathbf{N}$ as the changes in the proof if it is not all of $\mathbf{N}$ are only formal). In this case it is convenient to use the bound

$$\sup_{t\le T_n}|R_n(t)|\le\sup_{t\le T_n}\left|\frac{H_n(t-)-H(t-)}{1-H(t-)}\right|\int_{-\infty}^{T_n}\frac{d\tilde{H}_n(y)}{1-H_n(y-)}. \tag{3.9}$$

By Lemma 2.3,

$$\sup_{t\le T_n}\left|\frac{H_n(t-)-H(t-)}{1-H(t-)}\right|=O\left(\sqrt{\frac{\big(\log\frac{1}{\varepsilon_n}\big)\vee\log\log n}{n\varepsilon_n}}\right)\quad\text{a.s.} \tag{3.10}$$

Since, also by Lemma 2.3, $\sup_{t\le T_n}\big|(1-H(t-))/(1-H_n(t-))\big|=O(1)$ a.s., we have

$$\int_{-\infty}^{T_n}\frac{d\tilde{H}_n(y)}{1-H_n(y-)}\asymp\int_{-\infty}^{T_n}\frac{d\tilde{H}_n(y)}{1-H(y-)}\quad\text{a.s.}, \tag{3.11}$$

where $A_n\asymp B_n$ means that A_n/B_n and B_n/A_n are $O(1)$ a.s. We will estimate the right hand side of (3.11) using Prohorov's inequality (for convenience, Talagrand's applied to a single function) and then will proceed as in the proof of Lemma 2.3. The last integral in (3.11) is dominated as follows:

$$\int_{-\infty}^{T_n}\frac{d\tilde{H}_n(y)}{1-H(y-)}\le\int_{-\infty}^{T_n}\frac{dH_n(y)}{1-H(y-)}=\frac{1}{n}\sum_{i=1}^{n}\frac{I_{Z_i\le T_n}}{1-H(Z_i)}.$$

The expected value of this average is

$$E\frac{I_{Z\le T_n}}{1-H(Z)} = \int_{-\infty}^{T_n}\frac{dH}{1-H} = \log\frac{1}{\varepsilon_n},$$

and the parameters U and V in Talagrand's inequality (2.7) can be taken to be respectively $U_n := (n\varepsilon_n)^{-1}$ and

$$\frac{1}{n}E\left(\frac{I_{Z\le T_n}}{1-H(Z)}\right)^2 = \frac{1}{n}\int_{-\infty}^{T_n}\frac{dH}{(1-H)^2} \le \frac{1}{n\varepsilon_n} =: V_n.$$

Since condition (2.13) holds (as noted above, (2.13) is implied by (3.1)), Talagrand's (or Prohorov's) inequality shows that there exists $C<\infty$ such that

$$\begin{aligned}\Pr\left\{\max_{2^{k-1}<n\le 2^k}\int_{-\infty}^{T_n}\frac{dH_n(y)}{1-H(y-)} > 2\log\frac{1}{\varepsilon_{2^k}} + 2C\sqrt{\frac{\log\frac{1}{\varepsilon_{2^k}}}{2^k\varepsilon_{2^k}}}\right\}&\\ \le \Pr\left\{\int_{-\infty}^{T_{2^k}}\frac{dH_{2^k}(y)}{1-H(y-)} > \log\frac{1}{\varepsilon_{2^k}} + C\sqrt{\frac{\log\frac{1}{\varepsilon_{2^k}}}{2^k\varepsilon_{2^k}}}\right\}&\\ \le \Pr\left\{\left|\int_{-\infty}^{T_{2^k}}\frac{d(H_{2^k}-H)(y)}{1-H(y-)}\right| > C\sqrt{\frac{\log\frac{1}{\varepsilon_{2^k}}}{2^k\varepsilon_{2^k}}}\right\}&\\ \le K\exp\left\{-\log\frac{1}{\varepsilon_{2^k}}\right\}&\end{aligned}$$

for all k. By hypothesis (3.2) and the assumption $a_n \ge \varepsilon_n$,

$$\sum \exp\left\{-\log\frac{1}{\varepsilon_{2^k}}\right\} < \infty,$$

and therefore, Borel-Cantelli and the regularity of the sequence $\{\varepsilon_n\}$ imply that

$$\int_{-\infty}^{T_n}\frac{dH_n(y)}{1-H(y-)} = O\left(\log\frac{1}{\varepsilon_n} + C\sqrt{\frac{\log\frac{1}{\varepsilon_n}}{n\varepsilon_n}}\right)\quad \text{a.s.}$$

The term $\log\varepsilon_n^{-1}$ dominates (as $\varepsilon_n \le a_n \to 0$ and, by (3.1), $n\varepsilon_n\to\infty$) and we have

$$\int_{-\infty}^{T_n}\frac{d\tilde{H}_n(y)}{1-H(y-)} \le \int_{-\infty}^{T_n}\frac{dH_n(y)}{1-H(y-)} = O\left(\log\frac{1}{\varepsilon_n}\right)\quad \text{a.s.} \tag{3.12}$$

Combining (3.8)-(3.12) with (3.4), proves that

$$\sup_{t\le T_n-a_n}|(II_n)| = o\left(\sqrt{\frac{\log\frac{1}{a_n\wedge\varepsilon_n}}{na_n\varepsilon_n}}\right)\quad \text{a.s.} \tag{3.13}$$

assuming $a_n \geq \varepsilon_n$. Let now $a_n < \varepsilon_n$ (again, without real loss of generality, we assume this holds for all $n \in \mathbf{N}$). Then, we write

$$\sup_{t \leq T_n} |R_n(t)| \leq \sup_{t \leq T_n} |H_n(t-) - H(t-)| \int_{-\infty}^{T_n} \frac{d\tilde{H}_n(y)}{(1 - H_n(y-))(1 - H(y-))}. \tag{3.14}$$

Since $H_n - H$ is the regular empirical process for the sequence $\{Z_i\}$, it is classical that

$$\sup_{-\infty < t < \infty} |H_n(t-) - H(t-)| = O\left(\sqrt{\frac{\log\log n}{n}}\right) \text{ a.s.} \tag{3.15}$$

By Lemma 2.3, we can replace $1 - H(y-)$ in the integral (3.14) by $1 - H_n(y-)$ (as in (3.11), where the opposite replacement is made) and then we can apply Lemma 2.1 from Stute (1994) to the effect that

$$\int_{-\infty}^{T_n} \frac{d\tilde{H}_n(y)}{(1 - H_n(y-))^2} \leq \int_{-\infty}^{T_n} \frac{dH_n(y)}{(1 - H_n(y-))^2} \leq \frac{2}{1 - H_n(T_n-)}.$$

By (2.16) in Lemma 2.3 and the definition of T_n, this random variable is $O(\varepsilon_n^{-1})$ a.s. Hence,

$$\int_{-\infty}^{T_n} \frac{d\tilde{H}_n(y)}{(1 - H_n(y-))(1 - H(y-))} = O\left(\frac{1}{\varepsilon_n}\right) \text{ a.s.} \tag{3.16}$$

Since $\varepsilon_n \geq \sqrt{a_n \varepsilon_n}$, combining (3.8), (3.14)-(3.16) with condition (3.2) yields

$$\sup_{t \leq T_n - a_n} |(II_n)| = o\left(\sqrt{\frac{\log \frac{1}{a_n \wedge \varepsilon_n}}{n a_n \varepsilon_n}}\right) \text{ a.s.} \tag{3.17}$$

for $a_n < \varepsilon_n$. Hence, by (3.13) and (3.17), we have that in all cases, the lemma is proved for the component (II_n) of the left side variable in (3.7).

Order of magnitude of (I_n). If in (I_n) we replace the factor $1 - F(t - a_n u)$ by $1 - F(t + a_n)$, the difference is dominated by

$$\frac{4}{a_n} \sup_{t \leq T_n} |R_n(t)| \|K'\|_\infty \sup_{t \in \mathbf{R}, |u| \leq 1} |F(t - a_n u) - F(t + a_n)| \leq 8 \|f\|_\infty \|K'\|_\infty \sup_{t \leq T_n} |R_n(t)|,$$

which is $o\big(\sqrt{(n a_n \varepsilon_n)^{-1} \log(a_n \wedge \varepsilon_n)^{-1}}\big)$ a.s. by the first part of this proof. Hence, K' being bounded, it suffices to prove that

$$\frac{1}{a_n} \sup_{\substack{t \leq T_n - a_n \\ -1 \leq u \leq 1}} \big|(1 - F(t + a_n))(R_n(t - a_n u) - R_n(t))\big| = o\left(\sqrt{\frac{\log \frac{1}{a_n \wedge \varepsilon_n}}{n a_n \varepsilon_n}}\right). \tag{3.18}$$

So, we must look at the process

$$\frac{1}{a_n}(1 - F(t + a_n)) \int_{t - a_n u}^{t} \frac{H_n(y-) - H(y-)}{(1 - H_n(y-))(1 - H(y-))} d\tilde{H}_n(y)$$

on the parameter set $-\infty < t \le T_n - a_n, -1 \le u \le 1$. For ease of notation, we will only consider $-1 \le u \le 0$. By factoring out

$$\sup_{y \le T_n} \left| \frac{H_n(y-) - H(y-)}{1 - H(y-)} \right| = O\left(\sqrt{\frac{(\log \frac{1}{\varepsilon_n}) \vee \log\log n}{n\varepsilon_n}} \right) \quad \text{a.s.} \tag{3.19}$$

(by Lemma 2.3) it suffices to consider the process

$$\frac{1}{a_n}(1 - F(t + a_n)) \int_t^{t+a_n u} \frac{d\tilde{H}_n(y)}{1 - H_n(y-)}, \quad -\infty < t \le T_n - a_n, \ 0 \le u \le 1,$$

which, again by Lemma 2.3, is of the same order as

$$\begin{aligned} \frac{1}{a_n}(1 - F(t + a_n)) \int_t^{t+a_n u} \frac{d\tilde{H}_n(y)}{1 - H(y)} &\le \frac{1}{a_n} \int_t^{t+a_n u} \frac{d\tilde{H}_n(y)}{1 - G(y)} \\ &= \frac{1}{na_n} \sum_{i=1}^n \frac{I_{X_i \in [t, t+a_n u]} I_{X_i \le Y_i}}{1 - G(X_i)} \end{aligned}$$

(on the same parameter set). The expected value of this process for each t and u satisfies

$$\left| \frac{1}{na_n} E \sum_{i=1}^n \frac{I_{X_i \in [t, t+a_n u]} I_{X_i \le Y_i}}{1 - G(X_i)} \right| = \left| \frac{1}{a_n} \int_t^{t+a_n u} \frac{1 - G(x)}{1 - G(x)} dF(x) \right| \le \|f\|_\infty,$$

and we will apply the proof of Lemma 2.3 to show that, in fact, the sup of the difference between the process and its expected value is asymptotically negligible. The corresponding class of functions is a bounded measurable VC class and we can take

$$U_n = \frac{1}{na_n\varepsilon_n}, \quad \sigma_n^2 = \|f\|_\infty \frac{1}{n^2 a_n \varepsilon_n} \ge \frac{1}{n^2 a_n^2} E\left(\frac{I_{X \in [t, t+a_n u]}(1 - G(X))}{(1 - G(X))^2} \right).$$

Condition (2.10) holds for these parameters so that we can use inequality (2.12) and proceed as in the proof of Lemma 2.3. Here are the details: Combining Montgomery-Smith maximal inequality and inequality (2.12), and setting

$$B_n = C \sqrt{\frac{\log \frac{1}{a_n \varepsilon_n}}{na_n\varepsilon_n}}$$

for a conveniently chosen large constant C (note $na_nB_n \ge c2^k a_{2^k} B_{2^k}$ for some $c > 0$ and $2^{k-1} < n \le 2^k$), we obtain

$$\begin{aligned} &\Pr\left\{ \max_{2^{k-1} < n \le 2^k} \sup_{\substack{t \le T_n - a_n \\ 0 \le u \le 1}} \left| \frac{1}{na_nB_n} \sum_{i=1}^n \left(\frac{I_{X_i \in [t, t+a_n u]} I_{X_i \le Y_i}}{1 - G(X_i)} - \int_t^{t+a_n u} dF(x) \right) \right| > 1 \right\} \\ &\le \Pr\left\{ \max_{2^{k-1} < n \le 2^k} \sup_{\substack{\{(t,v): t \le T_{2^k} - a_{2^k} \\ 0 \le v \le a_{2^{k-1}}, t+v \le T_{2^k}\}}} \left| \frac{1}{2^k a_{2^k} B_{2^k}} \sum_{i=1}^n \left(\frac{I_{X_i \in [t, t+v]} I_{X_i \le Y_i}}{1 - G(X_i)} - \int_t^{t+v} dF(x) \right) \right| > c \right\} \end{aligned}$$

$$\leq 9\,\Pr\Bigg\{\sup_{\substack{\{(t,v):t\leq T_{2^k}-a_{2^k}\\ 0\leq v\leq a_{2^{k-1}},t+v\leq T_{2^k}\}}}\Bigg|\frac{1}{2^k a_{2^k}}\sum_{i=1}^{2^k}\bigg(\frac{I_{X_i\in[t,t+v]}I_{X_i\leq Y_i}}{1-G(X_i)}-\int_t^{t+v}dF(x)\bigg)\Bigg|>\frac{c}{30}B_{2^k}\Bigg\}$$

$$\leq K\exp\Bigg\{-\log\frac{1}{a_{2^k}\varepsilon_{2^k}}\Bigg\}. \tag{3.20}$$

Since $\log(a_n\varepsilon_n)^{-1}\simeq\log(a_n\wedge\varepsilon_n)^{-1}$, condition (3.2) implies that this is the general term of a convergent series, hence, by Borel-Cantelli, the process under consideration is a.s. of the order of the sup of its expected values (bounded by $\|f\|_\infty$, which is finite), that is,

$$\sup_{\substack{t\leq T_n-a_n\\ 0\leq u\leq 1}}\frac{1}{a_n}(1-F(t+a_n))\int_t^{t+a_nu}\frac{d\tilde{H}_n(y)}{1-H_n(y-)}=O(1)\quad\text{a.s.} \tag{3.21}$$

Now, (3.18) follows from (3.19) and (3.21) because, by (3.2), $(\log\varepsilon_n^{-1})\vee\log\log n$ is asymptotically smaller than $\log(a_n\wedge\varepsilon_n)^{-1}$ and $a_n\to 0$. This shows that the component (I_n) of the left hand side of (3.7) is of the prescribed order, which completes the proof of the lemma. □

We can now proceed to prove the LIL result for densities.

Theorem 3.3. *Assuming: a) F and G satisfy condition (3.5), b) the probability kernel K sastisfies condition (2.22) and c) the sequences $\{\varepsilon_n\}$ and $\{a_n\}$ are regular, nonincreasing, satisfy conditions (3.1)-(3.4) and $a_n\to 0$; letting $T_n=H^{-1}(1-\varepsilon_n)$ and letting f_n and $\bar{f}_n$ be as defined by equations (1.1) and (1.2), we have*

$$\sup_{t\leq T_n-a_n}|f_n(t)-\bar{f}_n(t)|=O\Bigg(\sqrt{\frac{\log\frac{1}{a_n\wedge\varepsilon_n}}{na_n\varepsilon_n}}\Bigg)\quad a.s. \tag{3.22}$$

Proof. By the decomposition (2.23) and Lemmas 3.1 and 3.2, it suffices to show

$$\sup_{t\leq T_n-a_n}\frac{1}{a_n}\bigg|\int_{t-a_n}^{t+a_n}(1-F(x))L_{n,1}(x)dK\Big(\frac{t-x}{a_n}\Big)\bigg|=O\Bigg(\sqrt{\frac{\log\frac{1}{a_n\wedge\varepsilon_n}}{na_n\varepsilon_n}}\Bigg). \tag{3.23}$$

We decompose this integral as in the proof of Lemma 3.2:

$$\begin{aligned}\frac{1}{a_n}&\int_{t-a_n}^{t+a_n}(1-F(x))L_{n,1}(x)dK\Big(\frac{t-x}{a_n}\Big)\\ &=\frac{1}{a_n}\int_{-1}^{1}\big(1-F(t-a_nu)\big)\big(L_{n,1}(t-a_nu)-L_{n,1}(t)\big)K'(u)du\\ &\qquad+\frac{1}{a_n}L_{n,1}(t)\int_{-1}^{1}\big(1-F(t-a_nu)\big)K'(u)du\\ &=(I_n)+(II_n),\end{aligned}$$

and proceed to bound the two resulting terms.

By integration by parts, we see that the absolute value of the last term is dominated by $|L_{n,1}(t)|\|f\|_\infty$. By Theorem 5 in Giné and Guillou, loc. cit. (actually by its proof since $L_{n,1}$ is one of the two components of L_n there, each treated separately), we then obtain, owing to the regularity of $\{\varepsilon_n\}$ and to (3.3), that

$$\sup_{t\le T_n-a_n}|(II_n)| = O\left(\sqrt{\frac{\log\log n}{n\varepsilon_n}}\right) \quad \text{a.s.}$$

Hence, since $a_n\to 0$ and (3.2) holds,

$$\sup_{t\le T_n-a_n}|(II_n)| = o\left(\sqrt{\frac{\log\frac{1}{a_n\wedge\varepsilon_n}}{na_n\varepsilon_n}}\right) \quad \text{a.s.} \tag{3.24}$$

If in (I_n) we replace $1-F(t-a_nu)$ by $1-F(t+a_n)$, the difference is dominated by

$$\frac{4}{a_n}\sup_{t\le T_n}|L_{n,1}(t)|\|K'\|_\infty \sup_{\substack{t\in\mathbf{R}\\ -1\le u\le 1}}|F(t-a_nu)-F(t+a_n)| \le 8\|f\|_\infty\|K'\|_\infty\sup_{t\le T_n}|L_{n,1}(t)|$$
$$= o\left(\sqrt{\frac{\log\frac{1}{a_n\wedge\varepsilon_n}}{na_n\varepsilon_n}}\right) \quad \text{a.s.} \tag{3.25}$$

as in (3.24). Hence, we need only prove

$$\frac{1}{a_n}\sup_{\substack{t\le T_n-a_n\\ -1\le u\le 1}}(1-F(t+a_n))\big|L_{n,1}(t-a_nu)-L_{n,1}(t)\big| = O\left(\sqrt{\frac{\log\frac{1}{a_n\wedge\varepsilon_n}}{na_n\varepsilon_n}}\right) \quad \text{a.s.} \tag{3.26}$$

Again, for ease of notation, we restrict to $u\in[0,1]$ (as the part of this sup corresponding to $u\in[-1,0)$ can be dealt with in the same way). If we define

$$W_n(t,u) := \frac{1}{a_n}\frac{1}{n}\sum_{i=1}^n \frac{I_{X_i\in[t-a_nu,t]}I_{X_i\le Y_i}(1-F(t+a_n))}{(1-F(X_i))(1-G(X_i))},\ t\le T_n-a_n,\ 0\le u\le 1,$$

then the left hand side of (3.26), with the restriction to $u\in[0,1]$, just becomes

$$\sup_{\substack{t\le T_n-a_n\\ 0\le u\le 1}}|W_n(t,u)-EW_n(t,u)|.$$

The corresponding class $\mathcal{F}$ is bounded measurable VC and we have

$$\sup_{\substack{t\le T_n-a_n\\ 0\le u\le 1}}\frac{1}{a_n}\frac{1}{n}\frac{I_{X\in[t-a_nu,t]}I_{X\le Y}(1-F(t+a_n))}{(1-F(X))(1-G(X))} \le \frac{1}{na_n(1-G(T_n))} \le \frac{1}{na_n\varepsilon_n}$$

and

$$\frac{1}{a_n^2n^2}E\left[\frac{I_{X\in[t-a_nu,t]}I_{X\le Y}(1-F(t+a_n))}{(1-F(X))(1-G(X))}\right]^2 \le \frac{1}{a_n^2n^2}E\left[\frac{I_{X\in[t-a_nu,t]}}{1-G(X)}\right]$$
$$\le \|f\|_\infty\frac{1}{n^2a_n\varepsilon_n}.$$

Hence the parameters U_n and σ_n^2 can be taken to be

$$U_n = \frac{1}{na_n\varepsilon_n}, \quad \sigma_n^2 = \|f\|_\infty \frac{1}{n^2 a_n\varepsilon_n},$$

and they satisfy inequality (2.10). Then we can apply inequality (2.12) and proceed as in the last part of the proof of Lemma 2.3 (see also (3.20) for more details on how to apply Montgomery-Smith's maximal inequality) to obtain

$$\sup_{\substack{t\le T_n-a_n\\ 0\le u\le 1}} |W_n(t,u) - EW_n(t,u)| = O\left(\sqrt{\frac{\log\frac{1}{a_n\wedge\varepsilon_n}}{na_n\varepsilon_n}}\right).$$

The same applies to $-1 \le u \le 0$, proving (3.26) and, therefore, the theorem. □

The previous proof and the Kolmogorov $0-1$ law show the following:

Corollary 3.4. *Under the hypotheses of Theorem 3.3, there exists a finite constant C such that*

$$\begin{aligned}
&\limsup_{n\to\infty} \sqrt{\frac{na_n\varepsilon_n}{\log\frac{1}{a_n\wedge\varepsilon_n}}} \sup_{t\le T_n-a_n} |f_n(t) - \bar{f}_n(t)| \\
&= \limsup_{n\to\infty} \sqrt{\frac{na_n\varepsilon_n}{\log\frac{1}{a_n\wedge\varepsilon_n}}} \sup_{t\le T_n-a_n} \frac{1}{a_n}(1-F(t+a_n))\left|\int_{-1}^{1}(L_{n,1}(t-a_nu) - L_{n,1}(t))K'(u)du\right| \\
&= C \quad \text{a.s.} \qquad (3.27)
\end{aligned}$$

Corollary 2 in Diehl and Stute (1988) shows that the constant C is not zero if ε_n is a constant independent of n and f is bounded away from zero on an interval with right end strictly larger than $H^{-1}(1-\varepsilon_n)$. We do not know if $C \ne 0$ for $\varepsilon_n \to 0$ as well and, although we believe this to be the case in general (or at least if $1-G(t)$ is of the same order as $1 - H(t)$ for large t and if ε_n is eventually larger than a_n), this remains an open question.

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