A note on extreme values and kernel estimators of sample boundaries

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Abstract

In a previous paper [3], we studied a kernel estimate of the upper edge of a two-dimensional bounded set, based upon the extreme values of a Poisson point process. The initial paper [1] on the subject treats the frontier as the boundary of the support set for a density and the points as a random sample. We claimed in [3] that we are able to deduce the random sample case from the point process case. The present note gives some essential indications to this end, including a method which can be of general interest.

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1 Introduction and main results

As in the early paper of Geffroy [1], we address the problem of estimating a subset D of $\mathbb{R}^2$ given a sequence of random points $\Sigma_n = \{Z_1, ..., Z_n\}$ where the $Z_i = (X_i, Y_i)$ are independent and uniformly distributed on D. The problem is reduced to functional estimation by defining

$$D = \left\{(x, y) \in \mathbb{R}^2 / 0 \le x \le 1; 0 \le y \le f(x)\right\},$$

where f is a strictly positive function. Given an increasing sequence of integers $0 < k_n < n$, $k_n \uparrow \infty$, for $r = 1, ..., k_n$, let $I_{n,r} = [(r-1)/k_n, r/k_n[$ and

$$U_{n,r} = \max\{Y_i / (X_i, Y_i) \in \Sigma_n; X_i \in I_{n,r}\}, \quad (1)$$

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where it is conveniently understood that $\max \varnothing = 0$. Now, let K be a bounded density, which has a support within a compact interval $[-A, A]$, a bounded first derivative and which is piecewise C^2, and $h_n \downarrow 0$ a sequence of positive numbers. Following [3], Section 6, we define the estimate

$$\hat{f}_n(x) = \frac{1}{k_n} \sum_{r=1}^{k_n} K_n(x - x_r) \left(U_{n,r} + \frac{1}{n - k_n} \sum_{s=1}^{k_n} U_{n,s} \right), x \in \mathbb{R}, \tag{2}$$

where x_r is the center of $I_{n,r}$ and, as usually,

$$K_n(t) = \frac{1}{h_n} K\left(\frac{t}{h_n}\right), t \in \mathbb{R}.$$

The perhaps curious second term in brackets in formula (2) is designed for reducing the bias (see [3], Lemma 8). Note that $\hat{f}_n$ can be rewritten as a linear combination of extreme values

$$\hat{f}_n(x) = \frac{1}{k_n} \sum_{r=1}^{k_n} \beta_{n,r}(x) U_{n,r},$$

where

$$\beta_{n,r}(x) = \frac{1}{k_n} K_n(x - x_r) + \frac{1}{k_n(n - k_n)} \sum_{s=1}^{k_n} K_n(x - x_s).$$

In the sequel, we suppose that f is α-Lipschitzian, $0 < \alpha \leq 1$, and strictly positive. Our result is the following:

Theorem 1 *If $h_n k_n \to \infty$, $n = o(k_n^{1/2} h_n^{-1/2-\alpha})$, $n = o(k_n^{5/2} h_n^{3/2})$ and $k_n = o(n/\ln n)$, then for every $x \in]0, 1[$,*

$$\left(n h_n^{1/2}/k_n^{1/2}\right)\left(\hat{f}_n(x) - f(x)\right) \Rightarrow \mathcal{N}\left(0, \sigma^2\right),$$

with $\sigma = \|K\|_2/c$.

2 Proofs

If formally the definition of $\hat{f}_n$ is identical here and in [3] the fundamental difference lies in the fact that in [3] the sample is replaced by a homogeneous Poisson point process with a mean measure $\mu_n = nc\lambda 1_D$ where λ is the Lebesgue measure of $\mathbb{R}^2$ and $c^{-1} = \lambda(D)$. Here we denote by $\Sigma_{0,n}$ this point process and we need, for the sake of approximation, two further Poisson point processes $\Sigma_{1,n}$ and $\Sigma_{2,n}$. The point processes $\Sigma_{j,n}$ are constructed as in [2], extending an original idea of J. Geffroy. Given a sequence $\gamma_n \downarrow 0$, consider independent Poisson random variables $N_{1,n}$, $M_{1,n}$, $M_{2,n}$, independent of the sequence (Z_n), with parameters $\mathbb{E}(N_{1,n}) = n(1 - \gamma_n)$ and $\mathbb{E}(M_{1,n}) = \mathbb{E}(M_{2,n}) = n\gamma_n$. Define $N_{0,n} = N_{1,n} + M_{1,n}$, $N_{2,n} = N_{0,n} + M_{2,n}$ and take $\Sigma_{j,n} = \left\{Z_1, ..., Z_{N_{j,n}}\right\}$, $j = 0, 1, 2$. For $j = 0, 1, 2$ we define $U_{j,n,r}$ and $\hat{f}_{j,n}$ by imitating (1) and (2). Finally, let us introduce the event $E_n = \{\Sigma_{1,n} \subseteq \Sigma_n \subseteq \Sigma_{2,n}\}$. The following lemma is the starting point of our "random sandwiching" technique.

Lemma 1 *One always has $\hat{f}_{1,n} \leq \hat{f}_{0,n} \leq \hat{f}_{2,n}$. Moreover, if E_n holds, $\hat{f}_{1,n} \leq \hat{f}_n \leq \hat{f}_{2,n}$.*

Proof : The definition of the random sets $\Sigma_{j,n}$, $j = 0, 1, 2$ implies that $\Sigma_{1,n} \subseteq \Sigma_{0,n} \subseteq \Sigma_{2,n}$. Thus, since $\beta_{n,r}(x) \geq 0$ for all $r = 1, \ldots, k_n$, we have $\hat{f}_{1,n} \leq \hat{f}_{0,n} \leq \hat{f}_{2,n}$. Similarly, E_n implies that $\hat{f}_{1,n} \leq \hat{f}_n \leq \hat{f}_{2,n}$. ■

The success of the approximation between $\hat{f}_n$ and $\hat{f}_{0,n}$ is based upon two lemmas. The first one shows how large is the probability of the event E_n.

Lemma 2 *For n large enough,*

$$\mathbb{P}\left(\Omega \setminus E_n\right) \leq 2\exp\left(-\frac{1}{8}n\gamma_n^2\right).$$

Proof : Using the Laplace transform of a Poisson random variable X with parameter $\lambda > 0$, we get for $\varepsilon/2\lambda$ small enough,

$$\mathbb{P}\left(|X-\lambda| > \varepsilon\right) < \exp\left(-\varepsilon^2/4\lambda\right),$$

see for instance Lemma 1 in [2]. Clearly, $\Omega \setminus E_n = \{N_{1,n} > n\} \cup \{N_{2,n} < n\}$ and thus

$$\mathbb{P}\left(\Omega \setminus E_n\right) \leq \exp\left(-\frac{n\gamma_n^2}{4(1-\gamma_n)}\right) + \exp\left(-\frac{n\gamma_n^2}{4(1+\gamma_n)}\right).$$

The lemma follows. ■

The second lemma is essential to control the approximation obtained when the event E_n holds.

Lemma 3 *If $k_n = o(n/\log n)$ and $n = O\left(k_n^{1+\alpha}\right)$, then uniformly on $r = 1, \ldots, k_n$,*

$$\mathbb{E}\left(U_{2,n,r} - U_{1,n,r}\right) = O\left(\frac{k_n\gamma_n}{n}\right).$$

Proof : Let us define $m_{n,r} = \min_{x\in I_{n,r}} f(x)$ and $M_{n,r} = \max_{x\in I_{n,r}} f(x)$. Then,

$$\begin{aligned}
&\mathbb{E}\left(U_{2,n,r} - U_{1,n,r}\right)\\
=\ & \int_0^{M_{n,r}} \left(\mathbb{P}\left(U_{2,n,r} > y\right) - \mathbb{P}\left(U_{1,n,r} > y\right)\right) dy\\
=\ & \int_0^{m_{n,r}} \left(\mathbb{P}\left(U_{2,n,r} > y\right) - \mathbb{P}\left(U_{1,n,r} > y\right)\right) dy + \int_{m_{n,r}}^{M_{n,r}} \left(\mathbb{P}\left(U_{2,n,r} > y\right) - \mathbb{P}\left(U_{1,n,r} > y\right)\right) dy\\
\stackrel{def}{=}\ & A_{n,r} + B_{n,r}.
\end{aligned}$$

Introducing $\lambda_{n,r} = \int_{I_{n,r}} f(x)dx$, we can write $A_{n,r}$ as

$$A_{n,r} = \int_0^{m_{n,r}} \exp\left(\frac{n(1-\gamma_n)}{k_n}\left(y - k_n\lambda_{n,r}\right)\right) dy - \exp\left(\frac{n(1+\gamma_n)}{k_n}\left(y - k_n\lambda_{n,r}\right)\right) dy.$$

Now, $A_{n,r}$ is expanded as a sum $A_{1,n,r} + A_{2,n,r}$ with

$$\begin{aligned}
A_{1,n,r} &= \frac{k_n}{n(1-\gamma_n)}\exp\left(\frac{n(1-\gamma_n)}{k_n}\left(m_{n,r} - k_n\lambda_{n,r}\right)\right) - \frac{k_n}{n(1+\gamma_n)}\exp\left(\frac{n(1+\gamma_n)}{k_n}\left(m_{n,r} - k_n\lambda_{n,r}\right)\right),\\
A_{2,n,r} &= \frac{k_n}{n(1+\gamma_n)}\exp\left(-n(1+\gamma_n)\lambda_{n,r}\right) - \frac{k_n}{n(1-\gamma_n)}\exp\left(-n(1-\gamma_n)\lambda_{n,r}\right).
\end{aligned}$$

The part $A_{2,n,r}$ is easily seen to be a $o\left(n^{-s}\right)$ where s is a arbitrarily large exponent under the condition $k_n = o(n/\log n)$. Now, If a, b, x, y are real numbers such that $x < y < 0 < b < a$, we have $0 < ae^y - be^x < (a-b) + b\,(y-x)$. Applying to $A_{1,n,r}$ this inequality yields

$$A_{1,n,r} \leq \frac{k_n}{n}\frac{2\gamma_n}{\left(1-\gamma_n^2\right)} + \left(M_{n,r} - m_{n,r}\right)\frac{2\gamma_n}{(1+\gamma_n)}.$$

Under the hypothesis that f is $\alpha-$Lipschitzian, and the condition $n = O\left(k_n^{1+\alpha}\right)$, we have $(M_{n,r} - m_{n,r}) = O(k_n/n)$, so that $A_{n,r} = A_{1,n,r}+A_{2,n,r} = O\left(k_n\gamma_n/n\right)$. Now, for $m_{n,r} \leq y \leq M_{n,r}$, it is easily seen that

$$\mathbb{P}\left(U_{2,n,r} > y\right) - \mathbb{P}\left(U_{1,n,r} > y\right) \leq 2\gamma_n \frac{n}{k_n}(M_{n,r} - m_{n,r}),$$

and thus

$$B_{n,r} \leq 2\gamma_n \frac{n}{k_n}\left(M_{n,r} - m_{n,r}\right)^2 = O\left(\frac{k_n}{n}\gamma_n\right).$$

Clearly, the bounds on $A_{n,r}$ and $B_{n,r}$ are uniform in $r = 1, ..., k_n$, and thus we obtain the result.

■

We quote a technical lemma.

Lemma 4 *If $k_n = o\left(n\right)$ and $h_n k_n \to \infty$ when $n \to \infty$,*

$$\lim_{n\to\infty} \sum_{r=1}^{k_n} \beta_{n,r}(x) = 1.$$

Proof : Remarking that

$$\sum_{r=1}^{k_n} \beta_{n,r}(x) = \frac{n}{n-k_n}\frac{1}{k_n}\sum_{r=1}^{k_n} K_n(x - x_r),$$

the result follows from the well-known property

$$\lim_{n\to\infty} \frac{1}{k_n}\sum_{r=1}^{k_n} K_n(x - x_r) = 1,$$

see for instance [3], Corollary 2. ■

The next proposition is the key tool to extend the results obtained on Poisson processes to samples.

Proposition 1 *If $k_n = o(n/\log n)$, $h_n k_n \to \infty$, and $n = O\left(k_n^{1+\alpha}\right)$, then, for every $x \in \left]0,1\right[$,*

$$(nh_n^{1/2}/k_n^{1/2})\mathbb{E}\left(\left|\hat{f}_n(x) - \hat{f}_{0,n}(x)\right|\right) \to 0.$$

Proof : From Lemma 1, we have

$$\begin{aligned}
\mathbb{E}\left(\left|\hat{f}_n(x) - \hat{f}_{0,n}(x)\right| \mathbf{1}_{E_n}\right) &\leq \mathbb{E}\left(\hat{f}_{2,n}(x) - \hat{f}_{1,n}(x)\right) \\
&= \sum_{r=1}^{k_n} \beta_{n,r}(x)\mathbb{E}(U_{2,n,r} - U_{1,n,r}) \\
&\leq \sum_{r=1}^{k_n} \beta_{n,r}(x) \max_{1\leq s\leq k_n} \mathbb{E}(U_{2,n,s} - U_{1,n,s}) \\
&= O\left(\frac{k_n\gamma_n}{n}\right),
\end{aligned}$$

in view of Lemma 3 and Lemma 4. As a consequence,

$$(nh_n^{1/2}/k_n^{1/2})\mathbb{E}\left(\left|\hat{f}_n(x)-\hat{f}_{0,n}(x)\right|\mathbf{1}_{E_n}\right)=O\left(k_n^{1/2}h_n^{1/2}\gamma_n\right). \tag{3}$$

Now, let $M=\sup\{f(x), x\in[0,1]\}$. Then, applying Lemma 4 again,

$$\max\left\{\hat{f}_n(x),\hat{f}_{0,n}(x)\right\}\leq M\sum_{r=1}^{k_n}\beta_{n,r}(x)=O(1),$$

and therefore, from Lemma 2,

$$\begin{aligned}(nh_n^{1/2}/k_n^{1/2})\mathbb{E}\left(\left|\hat{f}_n(x)-\hat{f}_{0,n}(x)\right|\mathbf{1}_{\Omega\setminus E_n}\right) &= (nh_n^{1/2}/k_n^{1/2})O(1)\mathbb{P}\left(\Omega\setminus E_n\right)\\ &= o(n)\exp\left(-\frac{1}{8}n\gamma_n^2\right)\\ &= o(1)\exp\left(-\frac{n}{k_n}\left(\frac{1}{8}k_n\gamma_n^2-\frac{k_n}{n}\log n\right)\right). \end{aligned}\tag{4}$$

From (3) and (4) it suffices to take $\gamma_n=k_n^{-1/2}$ to obtain the desired result. ■

The main theorem is now obtained without difficulty.

Proof of Theorem 1. Under the conditions $h_nk_n\to\infty$, $n=o(k_n^{1/2}h_n^{-1/2-\alpha})$, $n=o(k_n^{5/2}h_n^{3/2})$ and $k_n=o(n/\ln n)$, Theorem 5 of [3] asserts that

$$\left(nh_n^{1/2}/k_n^{1/2}\right)\left(\hat{f}_{0,n}(x)-f(x)\right)\Rightarrow\mathcal{N}\left(0,\sigma^2\right),$$

while from Proposition 1,

$$\left(nh_n^{1/2}/k_n^{1/2}\right)\left(\hat{f}_{0,n}(x)-\hat{f}_n(x)\right)\xrightarrow{\mathbb{P}}0.$$

Thus, the result is an immediate application of Slutsky's theorem. ■

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