

**ON A NON-PARAMETIC ESTIMATION OF THE REGRESSION FUNCTION**

by  
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The regression function is usually estimated by a polynomial. In this paper an other method is investigated, similar to one of the methods of density estimation.

It is the following method: Let  $(\xi_i, \eta_i)$   $i=1, 2, \dots$  be independent identically distributed two-dimensional random variables,  $P(0 \leq \eta_i \leq 1) = 1$ . Let us divide the interval  $[0, 1]$  into  $a_n$  equal parts. We estimate the function  $R(x) = E(\xi | \eta = x)$  by the following  $R_n(x)$

$$(1) \quad R_n(x) = \frac{\sum_{\substack{\eta_i \in \left[ \frac{k}{a_n}, \frac{k+1}{a_n} \right] \\ (i \leq n)}} \xi_i}{\text{the number of } \eta_i - s \text{ (} i \leq n \text{) falling into the interval } \left[ \frac{k}{a_n}, \frac{k+1}{a_n} \right]}$$

$$x \in \left[ \frac{k}{a_n}, \frac{k+1}{a_n} \right] \quad (k = 1, 2, \dots, a_n).$$

We investigate the order of magnitude of  $R_n(x) - R(x)$  in supremum norm. We introduce some notations.  $f(x)$  is the density function of  $\eta_i$ ,

$$\sigma^2(x) = E([\xi_i - E(\xi_i | \eta_i)]^2 | \eta_i = x).$$

Our first statement is the following

**THEOREM 1.** *Let us suppose that  $f(x)$ ,  $\sigma(x)$ ,  $R(x)$  are differentiable,  $|f'(x)| \leq K$ ,  $|\sigma'(x)| \leq K$ ,  $|R'(x)| \leq K$  and  $f(x) > K'$ ,  $\sigma(x) > K'$  for appropriate  $K, K' > 0$  and for every  $x$ . Let us suppose further that  $E(e^{t_0 |\xi_i|} | \eta = x) \leq c$  for appropriate  $t_0 > 0$  and  $c$  for every  $0 \leq x \leq 1$ . If  $n^2 < a_n < n^\beta$ ,  $\frac{1}{3} < \alpha < \beta < 1$  then*

$$(2) \quad P \left( \sup_x \sqrt{\frac{nf(x)}{a_n}} \cdot \frac{|R_n(x) - R(x)|}{\sigma(x)} < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( -\frac{e^{-y/2}}{\sqrt{\pi}} \right)$$

$$(3) \quad P \left( \sup_x \sqrt{\frac{nf(x)}{a_n}} \frac{R_n(x) - R(x)}{\sigma(x)} < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( \frac{-e^{-y/2}}{2\sqrt{\pi}} \right)$$

as  $n \rightarrow \infty$ .

If the functions  $f(x)$ ,  $R(x)$ ,  $\sigma(x)$  are smooth enough, it is worth substituting the estimation  $R_n(x)$  by

$$(4) \quad \bar{R}_n(x) = R_n \left( \frac{k - \frac{1}{2}}{a_n} \right) + \left[ R_n \left( \frac{k + \frac{1}{2}}{a_n} \right) - R_n \left( \frac{k - \frac{1}{2}}{a_n} \right) \right] \left( a_n x - k - \frac{1}{2} \right)$$

for

$$k - \frac{1}{2} < a_n x < k + \frac{1}{2}.$$

Then we have our.

**THEOREM 1'.** *If the conditions of Theorem 1 are fulfilled and, in addition  $f(x)$ ,  $R(x)$  and  $\sigma(x)$  are differentiable twice with bounded second derivatives, then the relations (2) and (3) hold for  $n^\alpha < a_n < n^\beta$ ,  $\frac{1}{5} < \alpha < \beta < 1$ , if we substitute  $R_n(x)$  by  $\bar{R}_n(x)$ .*

Now if we want to construct a "confidence strip" i.e. we want to construct a region  $T$  in the plane such that  $P(R(x) \in T) > 1 - \varepsilon$  with a prescribed  $\varepsilon$ , then we are interested in whether  $f(x)$  and  $\sigma(x)$  in the formulae (2) and (3) can be substituted by their estimations. The answer is in the affirmative.

**THEOREM 2.** *Let*

$$f_n(x) = \frac{a_n}{n} \left\{ \text{the number of } \eta_i \text{-s } (i \leq n) \text{ for which } \eta_i \in \left[ \frac{k}{a_n}, \frac{k+1}{a_n} \right] \right\}$$

$$\sigma_n^2(x) = \frac{a_n}{nf_n(x)} \sum_{\substack{\eta_i \in \left[ \frac{k}{a_n}, \frac{k+1}{a_n} \right] \\ i \leq n}} \xi_i^2 - \left[ \frac{a_n}{nf_n(x)} \sum_{\substack{\eta_i \in \left[ \frac{k}{a_n}, \frac{k+1}{a_n} \right] \\ i \leq n}} \xi_i \right]^2$$

if the condition of Theorem 1 holds

$$x \in \left[ \frac{k}{a_n}, \frac{k+1}{a_n} \right] \quad k = 0, 1, \dots, a_n - 1.$$

Then

$$(2') \quad P \left( \sup_x \sqrt{\frac{nf_n(x)}{a_n}} \cdot \frac{|R_n(x) - R(x)|}{\sigma_n(x)} < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( \frac{-e^{-y/2}}{\sqrt{\pi}} \right)$$

and

$$(3') \quad P \left( \sup_x \sqrt{\frac{nf_n(x)}{a_n}} \cdot \frac{R_n(x) - R(x)}{\sigma_n(x)} < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( \frac{-e^{-y/2}}{2\sqrt{\pi}} \right)$$

if.

As an immediate consequence of Theorem 1 we get that

$$\sup_x \sqrt{\frac{nf(x)}{2a_n \log a_n}} \cdot \frac{|R_n(x) - R(x)|}{\sigma(x)} \Rightarrow 1$$

where the symbol  $\Rightarrow$  means convergence in probability. The question arises whether this expression is also convergent with probability 1.

THEOREM 3. *Under the conditions of theorem 1 we have*

$$P\left(\limsup_x \sqrt{\frac{nf(x)}{2a_n \log a_n}} \frac{|R_n(x) - R(x)|}{\sigma(x)} = 1\right) = 1$$

$$P\left(\limsup_x \sqrt{\frac{nf(x)}{2a_n \log a_n}} \frac{R_n(x) - R(x)}{\sigma(x)} = 1\right) = 1$$

if

$$n^2 < a_n < n^\beta, \quad \frac{1}{3} < \alpha < \beta < 1.$$

For proving our theorems we need some lemmas:

LEMMA 1. *Let  $\xi_{n1}, \xi_{n2}, \dots, \xi_{nn}, n=1, 2, \dots$  be a double array of random variables independent and identically distributed within a row. Let  $E\xi_{n1}=0, D^2\xi_{n1}=1, Ee^{t|\xi_{n1}|} < c$  for appropriate  $t > 0$  and  $c$ . Then*

$$P(\xi_{n1} + \dots + \xi_{nn} > \sqrt{n} \cdot x_n) \sim 1 - \Phi(x_n) \quad \text{for } x_n = o(\sqrt[6]{n})$$

where  $\Phi(x)$  is the standard normal distribution function.

The proof is essentially the same as in [2] page 517, and we omit it.

LEMMA 2. *Let  $(\xi_i^{(n)}, \eta_i^{(n)})$  be pairs of random variables independent and identically distributed for fixed  $n$ ,*

$$P(\eta_i^{(n)} = k) = p_k^{(n)}, \quad k = 1, 2, \dots, a_n,$$

$$\sum_{k=1}^{a_n} p_k^{(n)} = 1, \quad n^\varepsilon < a_n < n^{1-\varepsilon}, \quad \varepsilon > 0,$$

$$E(\xi_i^{(n)} | \eta_i^{(n)} = k) = 0, \quad E(\xi_i^{(n)2} | \eta_i^{(n)} = k) = \sigma_k^{(n)2}, \quad \frac{c_1}{a_n} < p_k^{(n)} < \frac{c_2}{a_n}$$

$$E(e^{t|\xi_i^{(n)}|} | \eta_i^{(n)}) \leq c, \quad \sigma_k^{(n)} > c'$$

for appropriate  $c_1, c_2, c, t > 0, c'$  for every  $k$  and  $n$ . Then

$$P\left(\max_k \frac{\sqrt{np_k^{(n)}}}{\sigma_k^{(n)}} \cdot \frac{\sum_{i=1}^n \xi_i^{(n)} \cdot I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} < \sqrt{2 \log a_n - \log \log a_n + y}\right) \rightarrow \exp\left(\frac{-e^{-y/2}}{2\sqrt{\pi}}\right)$$

and

$$P \left( \max_k \frac{\sqrt{np_k^{(n)}}}{\sigma_k^{(n)}} \cdot \left| \frac{\sum_{i=1}^n \xi_i^{(n)} \cdot I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} \right| < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( \frac{-e^{-y/2}}{\sqrt{\pi}} \right)$$

where  $I_{(\eta_i^{(n)}=k)} = 1$  if  $\eta_i^{(n)} = k$  and 0 otherwise.

PROOF OF LEMMA 2. In the following we omit the superscript  $n$ . Let us introduce the notations  $s_j = \sum_{i=1}^n \xi_i I_{(\eta_i=j)}$  and  $v_j = \sum_{i=1}^n I_{(\eta_i=j)}$ . Then

$$\begin{aligned} P(s_1 < x_1, \dots, s_{a_n} < x_{a_n} | v_1 = t_1, \dots, v_{a_n} = t_{a_n}) = \\ = P(s_1 < x_1 | v_1 = t_1) \dots P(s_{a_n} < x_{a_n} | v_{a_n} = t_{a_n}) \end{aligned}$$

Let  $\tilde{\xi}_{ij}$ ,  $i=1, 2 \dots j=1, 2 \dots a_n$  be — for fixed  $j$  — independent identically distributed random variables with distribution function  $P(\tilde{\xi}_{ij} < x) = P(\xi_1 = x_1 | \eta_1 = j)$ . Then

$$P(s_j < x_j | v_j = t_j) = P(\tilde{\xi}_{1j} + \dots + \tilde{\xi}_{t_j j} < x_j)$$

Now we prove that

$$(5) \quad P(|v - np_j| > \sqrt{np_j} n^{\frac{1-\varepsilon}{3}}) \leq 2 \exp \left( -\frac{n^{\frac{3}{3}(1-\varepsilon)}}{3} \right)$$

Really

$$\begin{aligned} P(v_j - np_j > \sqrt{np_j} n^{\frac{1-\varepsilon}{3}}) &= P \left( \sum_{i=1}^n [I_{(\eta_i=j)} - p_j] > \sqrt{np_j} n^{\frac{1-\varepsilon}{3}} \right) = \\ &= P \left( \exp \left( n^{\frac{1-\varepsilon}{3}} \sum_{i=1}^n \frac{I_{(\eta_i=j)} - p_j}{\sqrt{np_j}} \right) > \exp(n^{\frac{3}{3}(1-\varepsilon)}) \right) \leq \\ &\leq \frac{\left( E \left[ \exp \left( n^{\frac{1-\varepsilon}{3}} \frac{I_{(\eta_1=j)} - p_j}{\sqrt{np_j}} \right) \right] \right)^n}{\exp(n^{\frac{3}{3}(1-\varepsilon)})} \leq \frac{\left[ 1 + \frac{2}{3} n^{\frac{3}{3}(1-\varepsilon)} E \left( \frac{I_{(\eta_1=j)} - p_j}{\sqrt{np_j}} \right)^2 \right]^n}{\exp(n^{\frac{3}{3}(1-\varepsilon)})} \leq \\ &\leq \frac{\exp \left[ \frac{2}{3} (1-p_j) n^{\frac{3}{3}(1-\varepsilon)} \right]}{\exp(n^{\frac{3}{3}(1-\varepsilon)})} \leq \exp \left( -\frac{n^{\frac{3}{3}(1-\varepsilon)}}{3} \right) \end{aligned}$$

and similarly

$$P(v_j - np_j < -\sqrt{np_j} n^{\frac{1-\varepsilon}{3}}) = \exp \left( -\frac{n^{\frac{3}{3}(1-\varepsilon)}}{3} \right).$$

Thus (5) is valid.

Now, by lemma 1 and by the relation  $\frac{1}{\sqrt{2\pi}x} e^{-x^2/2} \sim 1 - \Phi(x)$  for  $x \rightarrow \infty$  we have

$$\begin{aligned} & P\left(\frac{\sqrt{np_j}}{\sigma_j} \cdot \frac{s_j}{v_j} > \sqrt{2 \log a_n - \log \log a_n + y} \mid v_j = t\right) = \\ & = P\left(\frac{\xi_{1j} + \dots + \xi_{tj}}{\sigma_j \sqrt{t}} > \sqrt{\frac{t}{np_j}} \sqrt{2 \log a_n - \log \log a_n + y}\right) \sim \\ & \sim \sqrt{\frac{np_j}{2\pi t}} \cdot \frac{1}{\sqrt{2 \log a_n - \log \log a_n + y}} \cdot e^{-\frac{np_j}{2t}(2 \log a_n - \log \log a_n + y)} \sim \frac{e^{-y/2}}{2\sqrt{\pi} a_n} \end{aligned}$$

if

$$|t - np_j| < \sqrt{np_j} n^{\frac{1-\varepsilon}{3}}$$

On the other hand from (5) we have

$$P(|v_k - np_k| > \sqrt{np_k} n^{\frac{1-\varepsilon}{3}} \text{ for some } k) \equiv 2a_n \exp\left(-\frac{n^{\frac{1-\varepsilon}{3}}}{3}\right) = o(1)$$

Thus

$$\begin{aligned} & P\left(\max_k \frac{\sqrt{np_k}}{\sigma_k} \cdot \frac{s_k}{v_k} < \sqrt{2 \log a_n - \log \log a_n + y}\right) = \\ & = \left[1 - \frac{e^{-y/2}}{2\sqrt{\pi} a_n} (1 + o(1))\right]^{a_n} P(|v_k - np_k| < \sqrt{np_k} n^{\frac{1-\varepsilon}{3}} \text{ for every } k) + o(1) = \\ & = \exp\left(-\frac{e^{-y/2}}{2\sqrt{\pi}}\right) + o(1) \end{aligned}$$

as we have stated.

The second relation of lemma 2 can be proved in the same way.

LEMMA 3. Under the conditions of lemma 2

$$\begin{aligned} & P\left(\max_k \frac{\sqrt{np_k^{(n)}}}{\sigma_k^{(n)}} \cdot \frac{\sum_{i=1}^n \xi_i^{(n)} I_{(n_i^{(n)})=k}}{\sum_{i=1}^n I_{(n_i^{(n)})=k}} < \sqrt{2 \log a_n - 3 \log \log a_n - 2 \log 2\sqrt{\pi} c}\right) = \frac{1}{a_n^{c+o(1)}} \\ & P\left(\max_k \frac{\sqrt{np_k^{(n)}}}{\sigma_k^{(n)}} \cdot \left| \frac{\sum_{i=1}^n \xi_i^{(n)} I_{(n_i^{(n)})=k}}{\sum_{i=1}^n I_{(n_i^{(n)})=k}} \right| < \sqrt{2 \log a_n - 3 \log \log a_n - 2 \log \sqrt{\pi} c}\right) = \frac{1}{a_n^{c+o(1)}} \end{aligned}$$

The proof is similar to that of Lemma 2.

LEMMA 4. Under the conditions of Lemma 2 we have

$$\begin{aligned}
 P \left( \max_k \frac{\sqrt{np_k^{(n)}}}{\sigma_k^{(n)}} \left( 1 + o \left( \frac{1}{\log a_n} \right) \right) \cdot \frac{\sum_{i=k}^n I_{(\eta_i^{(n)}=k)} \left[ \xi_i^{(n)} + o \left( \sqrt{\frac{a_n}{n \log a_n}} \right) \right]}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} \right. \\
 \left. < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( -\frac{e^{-y/2}}{2\sqrt{\pi}} \right) \\
 P \left( \max_k \frac{\sqrt{np_k^{(n)}}}{\sigma_k^{(n)}} \left( 1 + o \left( \frac{1}{\log a_n} \right) \right) \cdot \left| \frac{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)} \left[ \xi_i^{(n)} + o \left( \sqrt{\frac{a_n}{n \log a_n}} \right) \right]}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} \right| \right. \\
 \left. < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( -\frac{e^{-y/2}}{\sqrt{\pi}} \right).
 \end{aligned}$$

Lemma 4 is an easy consequence of Lemma 2.

PROOF OF THEOREM 1. Let us divide the interval [0,1] into  $a_n$  equal parts. Obviously

$$m_k^{(n)} = E \left( \xi_i \left| \frac{k-1}{a_n} \leq \eta_i < \frac{k}{a_n} \right. \right) = \frac{\int_{\frac{k-1}{a_n}}^{\frac{k}{a_n}} R(y)f(y) dy}{\int_{\frac{k-1}{a_n}}^{\frac{k}{a_n}} f(y) dy}$$

and

$$D_k^{2(n)} = D^2 \left( \xi_i \left| \frac{k-1}{a_n} \leq \eta_i < \frac{k}{a_n} \right. \right) = \frac{\int_{\frac{k-1}{a_n}}^{\frac{k}{a_n}} [\sigma^2(y) + R^2(y)]f(y) dy}{\int_{\frac{k-1}{a_n}}^{\frac{k}{a_n}} f(y) dy} - [m_k^{(n)}]^2.$$

Let us define the random variables  $(\xi_i^{(n)}, \eta_i^{(n)})$   $i=1, 2 \dots n$  in the following way:

$$\eta_i^{(n)} = k \quad \text{and} \quad \xi_i^{(n)} = \frac{\xi_i - m_k^{(n)}}{D_k^{(n)}} \cdot \sigma \left( \frac{k - \frac{1}{2}}{a_n} \right)$$

if

$$\frac{k-1}{a_n} \leq \eta_i < \frac{k}{a_n} \quad i = 1, 2, \dots, n \quad k = 1, 2, \dots, a_n.$$

Then the conditions of Lemma 2 are satisfied for the sequence  $(\xi_i^{(n)}, \eta_i^{(n)})$ . Indeed,

$$p_k^{(n)} = \int_{\frac{k-1}{a_n}}^{\frac{k}{a_n}} f(y) dy, \text{ thus } \frac{c_1}{a_n} < p_k^{(n)} < \frac{c_2}{a_n} \text{ since } f(x) \text{ is bounded both from above and}$$

below.  $E(\xi_i^{(n)} | \eta_i^{(n)} = k) = 0, (\sigma_k^{(n)})^2 = D^2(\xi_i^{(n)} | \eta_i^{(n)} = k) = \sigma^2 \left( \frac{k - \frac{1}{2}}{a_n} \right)$  is bounded from

below.  $\frac{D_k^{(n)}}{\sigma \left( \frac{k - \frac{1}{2}}{a_n} \right)}$  is bounded from below and

$$E \left( \exp \left( t_0 \frac{D_k^{(n)}}{\sigma \left( \frac{k - \frac{1}{2}}{a_n} \right)} |\xi_i^{(n)}| \right) \middle| \eta_i^{(n)} = k \right) \cong c \exp(t_0 m_k^{(n)})$$

is also bounded as required. By the Taylor formula

$$f(y) = f(x) + (y - x) \cdot f'(x + \theta(y - x))$$

$$R(y) = R(x) + (y - x) \cdot R'(x + \theta'(y - x)) \quad 0 < \theta, \theta', \theta'' < 1$$

$$\sigma(y) = \sigma(x) + (y - x) \cdot \sigma'(x + \theta''(y - x))$$

The first derivatives of  $f(x), R(x), \sigma(x)$  are bounded and so it can be seen easily that  $m_k^{(n)} = R(x) + O\left(\frac{1}{a_n}\right), p_k^{(n)} = \frac{f(x)}{a_n} + O\left(\frac{1}{a_n^2}\right), D^2(\xi_i^{(n)} | \eta_i^{(n)} = k) = \sigma^2(x) + O\left(\frac{1}{a_n}\right)$

if  $x \in \left[ \frac{k-1}{a_n}, \frac{k}{a_n} \right]$ . Since  $n^2 < a_n$  and  $\alpha > \frac{1}{3}, \frac{1}{a_n} = o\left(\sqrt{\frac{a_n}{n \log a_n}}\right)$  and

$$\sqrt{\frac{nf(x)}{a_n}} \frac{1}{\sigma(x)} = \frac{\sqrt{np_k^{(n)}}}{\sigma_k^{(n)}} \left( 1 + o\left(\frac{1}{\log a_n}\right) \right) \text{ for } x \in \left[ \frac{k-1}{a_n}, \frac{k}{a_n} \right].$$

Hence Lemma 4 can be applied, and we get

$$P \left( \sup_k \sup_{k \in \left[ \frac{k-1}{a_n}, \frac{k}{a_n} \right]} \sqrt{\frac{nf(x)}{a_n}} \frac{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)} [\xi_i - R(x)]}{\sigma(x) \sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} < \sqrt{2 \log a_n - \log \log a_n + y} \right) \rightarrow \exp \left( -\frac{e^{-y/2}}{2\sqrt{\pi}} \right)$$

which is identical to formula (3). The second statement of lemma 4 gives formula (4).

The PROOF of Theorem 1' is almost the same. By the Taylor expansion up to 2 terms

$$\begin{aligned} R(x) &= R\left(\frac{k-\frac{1}{2}}{a_n}\right) + R'\left(\frac{k-\frac{1}{2}}{a_n}\right)\left(x - \frac{k-\frac{1}{2}}{a_n}\right) + \\ &+ \frac{1}{2}R''\left(\frac{k-\frac{1}{2}}{a_n} + \theta\left(x - \frac{k-\frac{1}{2}}{a_n}\right)\right)\left(x - \frac{k-\frac{1}{2}}{a_n}\right)^2 \\ f(x) &= f\left(\frac{k-\frac{1}{2}}{a_n}\right) + f'\left(\frac{k-\frac{1}{2}}{a_n}\right)\left(x - \frac{k-\frac{1}{2}}{a_n}\right) + \\ &+ \frac{1}{2}f''\left(\frac{k-\frac{1}{2}}{a_n} + \theta'\left(x - \frac{k-\frac{1}{2}}{a_n}\right)\right)\left(x - \frac{k-\frac{1}{2}}{a_n}\right)^2 \\ \sigma(x) &= \sigma\left(\frac{k-\frac{1}{2}}{a_n}\right) + \sigma'\left(\frac{k-\frac{1}{2}}{a_n}\right)\left(x - \frac{k-\frac{1}{2}}{a_n}\right) + \\ &+ \frac{1}{2}\sigma''\left(\frac{k-\frac{1}{2}}{a_n} + \theta''\left(x - \frac{k-\frac{1}{2}}{a_n}\right)\right)\left(x - \frac{k-\frac{1}{2}}{a_n}\right)^2 \end{aligned}$$

where  $0 < \theta, \theta', \theta'' < 1$ . It implies that

$$m_k^{(n)} = R\left(\frac{k-\frac{1}{2}}{a_n}\right) + O\left(\frac{1}{a_n^2}\right), \quad p_k^{(n)} = \frac{f\left(\frac{k-\frac{1}{2}}{a_n}\right)}{a_n} + O\left(\frac{1}{a_n^3}\right)$$

and

$$D^2(\xi_i^{(n)} | \eta_i^{(n)} = k) = \sigma^2\left(\frac{k-\frac{1}{2}}{a_n}\right) + O\left(\frac{1}{a_n^2}\right),$$

and these imply, just as in Theorem 1, the limit relation

$$\begin{aligned} P\left(\sup_k \left| \frac{nf\left(\frac{k-\frac{1}{2}}{a_n}\right) R_n\left(\frac{k-\frac{1}{2}}{a_n}\right) - R\left(\frac{k-\frac{1}{2}}{a_n}\right)}{a_n \sigma\left(\frac{k-\frac{1}{2}}{a_n}\right)} < \sqrt{2 \log a_n - \log \log a_n + y} \right.\right) \rightarrow \\ \rightarrow \exp\left(\frac{-e^{-y/2}}{2\sqrt{\pi}}\right). \end{aligned}$$

Now by

$$R(x) = R\left(\frac{k-\frac{1}{2}}{a_n}\right) + \left[R\left(\frac{k+\frac{1}{2}}{a_n}\right) - R\left(\frac{k-\frac{1}{2}}{a_n}\right)\right]\left(a_n x - k - \frac{1}{2}\right) + O\left(\frac{1}{a_n^2}\right)$$

for  $x \in \left[\frac{k-\frac{1}{2}}{a_n}, \frac{k+\frac{1}{2}}{a_n}\right]$  and (4) the statement of Theorem 1' is valid.



PROOF OF THEOREM 2. Since we have already proved Theorem 1, it is sufficient to prove that

$$P\left(\sup_x \frac{\sqrt{f(x)}}{\sigma(x)} \frac{\sigma_n(x)}{\sqrt{f_n(x)}} > 1 + \frac{\delta_n}{\sqrt{\log a_n}}\right) \rightarrow 0$$

and

$$P\left(\inf_x \frac{\sqrt{f(x)}}{\sigma(x)} \frac{\sigma_n(x)}{\sqrt{f_n(x)}} > 1 - \frac{\delta_n}{\sqrt{\log a_n}}\right) \rightarrow 0$$

for an appropriate sequence  $\delta_n \rightarrow 0$ , i.e.  $\frac{\sqrt{f(x)}}{\sigma(x)}$  and  $\frac{\sqrt{f_n(x)}}{\sigma_n(x)}$  are near to each other.

We shall estimate  $f_n(x) - f(x)$  and  $\sigma_n(x) - \sigma(x)$ . This will be similar to the proof of Lemma 2.

$$f(x) - a_n p_k^{(n)} = O\left(\frac{1}{a_n}\right) \quad x \in \left[\frac{k+1}{a_n}, \frac{k+1}{a_n}\right]$$

and

$$f_n(x) - a_n p_k^{(n)} = \frac{a_n}{n} \sum_{i=1}^n [I_{(\eta_i^{(n)}=k)} - \mathbb{E}I_{(\eta_i^{(n)}=k)}].$$

Thus, exactly the same way as in proving estimation (5) we get that

$$P\left(|f_n(x) - f(x)| > n^{\frac{1-\alpha}{3}} \frac{\sqrt{n}}{a_n \sqrt{p_k^{(n)}}}\right) = O(\exp(-n^{\frac{1-\alpha}{3}})).$$

$n^{\frac{1-\alpha}{3}} \frac{\sqrt{n}}{a_n \sqrt{p_k^{(n)}}} < K \cdot n^{-\frac{1-\alpha}{6}}$  for an appropriate constant  $K$ . Thus

$$P(\sup_x |f_n(x) - f(x)| > K \cdot n^{-\frac{1-\alpha}{6}}) \leq a_n O(\exp(-n^{\frac{1-\alpha}{3}})) \rightarrow 0$$

We have

$$\sigma^2(x) - D_k^{(n)2} = O\left(\frac{1}{a_n}\right) \quad \text{and} \quad \sigma_n^2(x) = \frac{\sum_{i=1}^n \zeta_i^2 I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} - \left[ \frac{\sum_{i=1}^n \zeta_i I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} \right]^2$$

for

$$x \in \left[\frac{k-1}{a_n}, \frac{k}{a_n}\right].$$

Now we estimate

$$P\left(\left| \frac{\sum_{i=1}^n \zeta_i I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} - m_k^{(n)} \right| > \frac{n^{\frac{1-\alpha}{3}}}{\sqrt{n p_k^{(n)}}}\right).$$

Let  $\xi_1, \dots, \xi_n \dots n=1, 2, \dots$  be independent identically distributed random variables having the distribution

$$P(\xi_i < x) = P(\xi_1 - m_k^{(n)} < x | \eta_1^{(n)} = k)$$

Then

$$P \left( \left| \frac{\sum_{i=1}^n \xi_i I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} - m_k^{(n)} \right| > \frac{n^{\frac{1-\alpha}{3}}}{\sqrt{np_k^{(n)}}} \left| \sum_{i=1}^n I_{(\eta_i^{(n)}=k)} = t \right. \right) =$$

$$= P \left( \left| \frac{\xi_1 + \dots + \xi_t}{\sqrt{t}} \right| < n^{\frac{1-\alpha}{3}} \sqrt{\frac{t}{np_k^{(n)}}} \right) = O(\exp(-n^{\frac{1-\alpha}{3}}))$$

for  $|t - np_k^{(n)}| < n^{\frac{1-\alpha}{3}} \sqrt{np_k^{(n)}}$ . On the other hand

$$P \left( \left| \sum_{i=1}^n I_{(\eta_i^{(n)}=k)} - np_k^{(n)} \right| > n^{\frac{1-\alpha}{3}} \sqrt{np_k^{(n)}} \right) = O(\exp(-n^{\frac{1-\alpha}{3}}))$$

Thus

$$P \left( \left| \frac{\sum_{i=1}^n \xi_i I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} - m_k^{(n)} \right| > \frac{n^{\frac{1-\alpha}{3}}}{\sqrt{np_k^{(n)}}} \text{ for some } k \right) \leq a_n O(\exp(-n^{\frac{1-\alpha}{3}})) \rightarrow 0$$

The relation

$$P \left( \left| \frac{\sum_{i=1}^n \xi_i^2 I_{(\eta_i^{(n)}=k)}}{\sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} - \frac{\int_{\frac{k-1}{a_n}}^{\frac{k}{a_n}} [\sigma^2(y) + R^2(y)] f(y) dy}{\int_{\frac{k-1}{a_n}}^{\frac{k}{a_n}} f(y) dy} \right| > \frac{n^{\frac{1-\alpha}{3}}}{\sqrt{np_k^{(n)}}} \text{ for some } k \right) \rightarrow 0$$

can be proved in the same way. From these estimations it follows that  $|f_n(x) - f(x)|$  and  $|\sigma_n(x) - \sigma(x)|$  are less than  $n^{-c}$  for appropriate  $c > 0$  with a probability near 1. Thus Theorem 2 is valid.

PROOF OF THEOREM 3. First we prove that

$$P \left( \limsup_x \sqrt{\frac{nf(x)}{2a_n \log a_n}} \frac{|R_n(x) - R(x)|}{\sigma(x)} > 1 - \varepsilon \right) = 1$$

for arbitrary  $\varepsilon > 0$ .

It is easy to check the validity of the conditions of Lemma 2 for the sequence  $(\xi_i^{(n)}, \eta_i^{(n)})$ , therefore by Lemma 3 we can state that

$$P \left( \max_k \sqrt{np_k^{(n)}} \left| \frac{\sum_{i=1}^n \xi_i^{(n)} I_{(\eta_i^{(n)}=k)}^{\sim}}{\sigma \left( \frac{k-\frac{1}{2}}{a_n} \right) \sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} \right| > \sqrt{2 \log a_n - 3 \log \log a_n - 2 \log \sqrt{\pi} c} \right) = \\ = \frac{1}{a_n^{c+o(1)}}$$

Thus, choosing  $n_0$  large enough, by the Borel—Cantelly lemma we obtain

$$\max_k \sqrt{np_k^{(n)}} \left| \frac{\sum_{i=1}^n \xi_i^{(n)} I_{(\eta_i^{(n)}=k)}}{\sigma \left( \frac{k-\frac{1}{2}}{a_n} \right) \sum_{i=1}^n I_{(\eta_i^{(n)}=k)}} \right| < \\ < \sqrt{2 \log a_n - 3 \log \log a_n - 2 \log \sqrt{\pi} c} \quad \text{for } n > n_0(\omega)$$

with probability 1. Since

$$\sqrt{np_k^{(n)}} = \sqrt{\frac{nf(x)}{a_n}} \left( 1 + O \left( \frac{1}{a_n} \right) \right), \quad \sigma \left( \frac{k-\frac{1}{2}}{a_n} \right) = \sigma(x) + O \left( \frac{1}{a_n} \right)$$

and

$$\xi_i^{(n)} I_{(\eta_i^{(n)}=k)} = \left[ \xi_i - R(x) + O \left( \frac{1}{a_n} \right) \right] I_{(\eta_i^{(n)}=k)} \left[ 1 + O \left( \frac{1}{a_n} \right) \right]$$

if  $x \in \left[ \frac{k-1}{a_n}, \frac{k}{a_n} \right]$ , our statement follows.

The proof of the relation

$$P \left( \overline{\lim}_x \sup \sqrt{\frac{nf(x)}{2a_n \log a_n}} \frac{|R_n(x) - R(x)|}{\sigma(x)} < 1 - \varepsilon \right) = 1$$

is more involved.

Set

$$\bar{\xi}_i = \frac{\xi_i - E(\xi_i | \eta_i)}{D(\xi_i | \eta_i)}.$$

Let us define the random variable

$$T_n(x) = \sum_{\substack{i \leq n \\ \eta_i \leq x}} \bar{\xi}_i \quad 0 \leq x \leq 1.$$

We want to prove that

$$(6) \quad P(A_n) = P \left( \sup_{\substack{y-x \leq \frac{1}{a_n} \\ 0 \leq x < y \leq 1}} \frac{1}{\sqrt{f(x)}} |T_n(x) - T_n(y)| > \left(1 + \varepsilon + \frac{\sqrt{\varepsilon}}{2}\right) \sqrt{\frac{2n \log a_n}{a_n}} \right) \leq \frac{12}{\varepsilon \cdot a_n^\varepsilon}.$$

First we estimate, for fixed  $x$ , the probability

$$P \left( \sup_{x \leq y \leq x + \frac{3+\varepsilon}{3a_n}} \frac{1}{\sqrt{f(x)}} |T_n(x) - T_n(y)| > (1 + \varepsilon) \sqrt{\frac{2n \log a_n}{a_n}} \right).$$

Let us order the  $\eta_i$ -s falling into the interval  $\left[ x, x + \frac{3+\varepsilon}{3a_n} \right]$  in increasing order  $x \leq \eta_1^* < \eta_2^* \dots < \eta_t^* < x + \frac{3+\varepsilon}{3a_n}$  and denote by  $\bar{\xi}_i^*$  the  $\bar{\xi}_i$  which is the pair of  $\eta_j^*$ . Then

$$\sup_{x < y < x + \frac{3+\varepsilon}{3a_n}} |T_n(y) - T_n(x)| = \sup_{k \leq t} \left| \sum_{j=1}^k \bar{\xi}_j^* \right|$$

We can state that

$$(7) \quad P \left( \sup_{k \leq t} \sum_{j=1}^k \bar{\xi}_j^* > (1 + \varepsilon) \sqrt{\frac{2nf(x) \log a_n}{a_n}} \left| \begin{array}{l} \text{the number of } \eta_i\text{-s } i \leq n \text{ falling} \\ \text{into the interval } \left[ x, x + \frac{3+\varepsilon}{3a_n} \right] \\ \text{is } t, \eta_1^* = x_1, \dots, \eta_t^* = x_t \end{array} \right. \right) =$$

$$= P \left( \sup_{k \leq t} \sum_{j=1}^k \zeta_j > (1 + \varepsilon) \sqrt{\frac{2nf(x) \log a_n}{a_n}} \right)$$

where  $\zeta_1, \zeta_2, \dots, \zeta_t$  are independent and  $P(\zeta_j < y) = P(\bar{\xi}_1 < y | \eta_1 = x_j)$ . Now the sequence  $\sum_{j=1}^k \zeta_j, k=1, 2, \dots, t$  forms a martingale, so  $\exp(t \sum_{j=1}^k \zeta_j)$  is a semimartingale for arbitrary  $t$ , and by a well-known martingale inequality see [1] p. 314.,

$$(8) \quad P \left( \sup_{k \leq t} \sum_{j=1}^k \zeta_j > (1 + \varepsilon) \sqrt{\frac{2nf(x) \log a_n}{a_n}} \right) =$$

$$= P \left( \sup_{k \leq t} \exp \left( \sqrt{\frac{2a_n \log a_n}{nf(x)}} \sum_{j=1}^k \zeta_j \right) > \exp(2(1 + \varepsilon) \log a_n) \right) \leq$$

$$\leq \frac{\prod_{i=1}^t E \exp \left( \sqrt{\frac{2a_n \log a_n}{nf(x)}} \zeta_i \right)}{a_n^{2(1+\varepsilon)}}$$

Now

$$(9) \quad \begin{aligned} E \exp \left( \sqrt{\frac{2a_n \log a_n}{nf(x)}} \zeta_i \right) &\cong 1 + E \sqrt{\frac{2a_n \log a_n}{nf(x)}} \zeta_i + \\ + E \left[ \frac{a_n \log a_n}{nf(x)} \zeta_i^2 \exp \left| \sqrt{\frac{2a_n \log a_n}{nf(x)}} \zeta_i \right| \right] &\cong 1 + \left( 1 + \frac{\varepsilon}{2} \right) \frac{a_n \log a_n}{nf(x)} \cong \\ &\cong \exp \left[ \left( 1 + \frac{\varepsilon}{2} \right) \frac{a_n \log a_n}{nf(x)} \right] \end{aligned}$$

It can be proved in the same way as relation (5) that

$$P \left( \left| t - \frac{n \left( 1 + \frac{\varepsilon}{3} \right)}{a_n} \cdot f(x) \right| > n^{\frac{1-\alpha}{3}} \sqrt{\frac{n}{a_n}} f(x) \right) = O(\exp(-n^{3(1-\alpha)}))$$

( $t$  is the number of  $\eta_i$ -s ( $i \leq n$ ) falling into the interval  $\left[ x, x + \frac{3+\varepsilon}{3a_n} \right]$ ), and so by (7), (8) and (9)

$$P \left( \sup_{x < y < x + \frac{3+\varepsilon}{3a_n}} (T_n(y) - T_n(x)) > (1 + \varepsilon) \sqrt{\frac{2nf(x) \log a_n}{a_n}} \right) < \frac{1}{a_n^{1+\varepsilon}}$$

Using this relation for the sequence  $(-\xi_1, \eta_1), \dots, (-\xi_n, \eta_n)$  we get that

$$P \left( \sup_{x < y < x + \frac{3+\varepsilon}{3a_n}} |T_n(x) - T_n(y)| > (1 + \varepsilon) \sqrt{\frac{2nf(x) \log a_n}{a_n}} \right) < \frac{2}{a_n^{1+\varepsilon}}$$

In the same way ( $x$  is fixed) we find

$$P \left( \sup_{x < y < x + \frac{\varepsilon}{3a_n}} |T_n(y) - T_n(x)| > \frac{\sqrt{\varepsilon}}{2} \sqrt{\frac{2nf(x) \log a_n}{a_n}} \right) < \frac{2}{a_n^{1+\varepsilon}}$$

Thus

$$P \left( \sup_{\substack{x < y < x + \frac{3+\varepsilon}{3a_n} \\ x = \frac{k\varepsilon}{3a_n} \left( k = 0, 1, \dots, \frac{3a_n}{\varepsilon} \right)}} \frac{1}{\sqrt{f(x)}} |T_n(y) - T_n(x)| > (1 + \varepsilon) \sqrt{\frac{2n \log a_n}{a_n}} \right) < \frac{6}{\varepsilon a_n^\varepsilon}$$

and

$$P \left( \sup_{\substack{x < y < x + \frac{\varepsilon}{3a_n} \\ x = \frac{k\varepsilon}{3a_n} \left( k = 0, 1, \dots, \frac{3a_n}{\varepsilon} \right)}} \frac{1}{\sqrt{f(x)}} |T_n(y) - T_n(x)| > \frac{\sqrt{\varepsilon}}{2} \sqrt{\frac{2n \log a_n}{a_n}} \right) < \frac{6}{\varepsilon a_n^\varepsilon}$$

Let us now consider an arbitrary interval  $[u, v]$  such that  $0 < v - u \leq \frac{1}{a_n}$ . Choose the integer  $k$  in such a way that for the number  $x = \frac{k\varepsilon}{3a_n}$  the inequality  $0 < u - x < \frac{\varepsilon}{3a_n}$  hold. Then

$$|T_n(v) - T_n(u)| \leq \sup_{x < y < x + \frac{3+\varepsilon}{3a_n}} |T_n(y) - T_n(x)| + \sup_{x < y < x + \frac{\varepsilon}{3a_n}} |T_n(y) - T_n(x)|,$$

and therefore (6) follows from the last two inequalities. Choosing a  $c > \frac{6}{\varepsilon}$  we get

$P(A_{l^c}) < \frac{1}{l^2}$ , and by the Borel—Cantelli lemma

$$(10) \quad \lim_{l \rightarrow \infty} A_{l^c} = \emptyset$$

Given a number  $n$  it determines a unique  $l$  for which  $l^c \leq n < (l+1)^c$ . Then  $n - l^c < c(l+1)^{c-1} < 2cn^{c-1}$ . By similar calculations as before we get

$$P\left(\sum_{i=1}^n \xi_i I_{(\eta_i^{(n)}=k)} > \varepsilon \sqrt{\frac{2nf(x)\log a_n}{a_n}}\right) < \exp(-Dn^{1/c})$$

with appropriate  $D > 0$  for  $k=1, 2, \dots, a_n$ ,  $x \in \left[\frac{k-1}{a_n}, \frac{k}{a_n}\right]$  and

$$P(B_n) = P\left(\sup_{x \in \left[\frac{k-1}{a_n}, \frac{k}{a_n}\right]} \left| \frac{1}{\sqrt{f(x)}} \sum_{i=1}^n \xi_i I_{(\eta_i^{(n)}=k)} \right| > \varepsilon \sqrt{\frac{2n \log a_n}{a_n}}\right) < a_n \exp(-Dn^{1/c})$$

This yields the relation

$$(11) \quad \lim B_n = \emptyset.$$

By the definition of  $A_n$  and  $B_n$  and relations (10) and (11) we have with probability 1

$$(12) \quad \left| \sup \frac{1}{\sqrt{f(x_k)}} \sum_{i=1}^n \xi_i I_{(\eta_i^{(n)}=k)} \right| < \left(1 + 2\varepsilon + \frac{\sqrt{\varepsilon}}{2}\right) \sqrt{\frac{2n \log a_n}{a_n}}$$

for

$$x_k \in \left[\frac{k-1}{a_n}, \frac{k}{a_n}\right]$$

for every large  $n$ .

An easy computation shows that with probability one

$$(13) \quad \sum_{i=1}^n I_{(\eta_i^{(n)}=k)} > (1-\varepsilon) \frac{nf(x_k)}{a_n}, x_k \in \left[\frac{k-1}{a_n}, \frac{k}{a_n}\right]$$

for every large  $n$  and  $k=1, 2, \dots, a_n$ . Since  $R(x)$ ,  $\sigma(x)$  and  $f(x)$  are smooth enough

$$P \left( \limsup_n \sup_x \sqrt{\frac{nf(x)}{2a_n \log a_n}} \frac{|R_n(x) - R(x)|}{\sigma(x)} < \frac{1 + 2\varepsilon + \frac{\sqrt{\varepsilon}}{2}}{1 - \varepsilon} \right) = 1$$

from the relations (12) and (13). Since it is true for arbitrary small  $\varepsilon > 0$ , the first statement of theorem 3 is valid. The second statement can be proved in the same way.

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