ON SEQUENTIAL ESTIMATION OF THE REGRESSION FUNCTION

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ON SEQUENTIAL ESTIMATION OF THE REGRESSION FUNCTION*

By

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1. Introduction and Summary

Let (X, Y) be a two dimensional random variable having a joint density function fand let g be the marginal density function of X. We assume that $E_f Y$ is finite and define the regression function m(x) (for regression of Y on X) by m(x)=E[Y|X=x]. Nadaraya [3] and Watson [7] and Schuster [6] have studied the asymptotic properties of the estimate $\hat{m}_n(x)$ of m(x) defined by

(1)
$$\hat{m}_n(x) = \frac{\sum_{i=1}^n Y_i K\left(\frac{x - X_i}{h_n}\right)}{\sum_{i=1}^n K\left(\frac{x - X_i}{h_n}\right)}$$

where K(u) is a probability density function on $(-\infty, +\infty)$, $\{h_n\}$ is a monotonically decreasing sequence of positive numbers converging to zero and (X_1, Y_1) , (X_2, Y_2) , \cdots , (X_n, Y_n) are *n* independent observations of (X, Y).

In many practical situations the number of observations N_t which we observe in time (0, t] is a random variable. We call N_t a stopping random variable. We assume that $(X_1, Y_1), (X_2, Y_2), \cdots$ are independent observations of (X, Y) and need not be independent of the random variable N_t . In this paper we propose an estimate $m_{N_t}(x)$ of the regression function m(x) based on $(X_1, Y_1), (X_2, Y_2), \cdots, (X_{N_t}, Y_{N_t})$ and given by

(2)
$$m_{N_t}(x) = \frac{\sum_{i=1}^{N_t} \frac{Y_i}{h_i} K\left(\frac{x - X_i}{h_i}\right)}{\sum_{i=1}^{N_t} \frac{1}{h_i} K\left(\frac{x - X_i}{h_i}\right)}$$

We note that the expression for the estimate $m_{N_t}(x)$ is motivated by the recursive type of estimate of a probability density function first proposed by Yamato [8]. Suppose x_1, x_2, \dots, x_l are *l* distinct points. We have shown that under certain regularity conditions $(N_t h_{N_t})^{1/2} \{m_{N_t}(x_1) - m(x_1), \dots, m_{N_t}(x_l) - m(x_l)\}$ is asymptotically normally distributed with mean vector 0 and diagonal covariance matrix $C = \lfloor c_{ij} \rfloor$ with $c_{ii} = \frac{\operatorname{Var} [Y | X = x_i]}{g(x_i)} \nu \int_{-\infty}^{\infty} K^2(u) du$ where $\nu(\nu < 1)$ is as defined in the next section. For simplicity we have proved the theorem for the special case l=2. The method of proof remains valid in the more general case.

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extension of the earlier result due to Schuster [6].

2. Main Result

We assume that the probability density function K and the sequence $\{h_n\}$ are chosen to satisfy the following conditions:

(i) K(u) and |uK(u)| are bounded

(ii)
$$\int_{-\infty}^{\infty} u K(u) du = 0$$

(iii) $\int_{-\infty}^{\infty} u^2 K(u) du < \infty$

(iv)
$$\lim_{n \to \infty} \frac{1}{n} \sum_{j=1}^{n} \left(\frac{h_n}{h_j} \right) = \nu < 1$$

$$(\mathbf{v}) \quad \frac{1}{n} \sum_{j=1}^{n} h_{j}^{2} \leq C_{1} h_{n}^{2} \quad (C_{1} > 0), \ n = 1, \ 2, \ 3, \ \cdots$$

(vi)
$$\lim_{n \to \infty} n h_n^3 = \infty$$
 and $\lim_{n \to \infty} n h_n^5 = 0$

REMARK 1. If K is the standard normal probability density function, then conditions (i), (ii) and (iii) are satisfied.

REMARK 2. If $h_n = n^{-\delta}$, $\frac{1}{5} < \delta < \frac{1}{3}$, then conditions (iv), (v) and (vi) are satisfied. (For a proof see [1], p. 26 and p. 46.)

We define the following:

(3)
$$g(x) = \int_{-\infty}^{\infty} f(x, y) dy$$
$$w(x) = \int_{-\infty}^{\infty} y f(x, y) dy$$
$$v(x) = \int_{-\infty}^{\infty} y^2 f(x, y) dy.$$

Hence,

Var
$$[Y|X=x] = \frac{v(x)}{g(x)} - \frac{w^2(x)}{g^2(x)}$$
.

Suppose x_1 and x_2 are two distinct points. We define for $i=1, 2, \dots, n$ and s=1, 2

$$U_{i}^{*}(x_{s}) = \frac{1}{h_{i}} K \left(\frac{x_{s} - X_{i}}{h_{i}} \right)$$

$$V_{i}^{*}(x_{s}) = Y_{i} U_{i}^{*}(x_{s})$$

$$U_{i}(x_{s}) = h_{n}^{1/2} \{ U_{i}^{*}(x_{s}) - E U_{i}^{*}(x_{s}) \}$$

$$V_{i}(x_{s}) = h_{n}^{1/2} \{ V_{i}^{*}(x_{s}) - E V_{i}^{*}(x_{s}) \}$$

$$\overline{U}_{n}(x_{s}) = \sum_{i=1}^{n} U_{i}(x_{s})$$

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$$(4) \qquad \overline{V}_{n}(x_{s}) = \sum_{i=1}^{n} V_{i}(x_{s}) W_{i} = (U_{i}(x_{1}), V_{i}(x_{1}), U_{i}(x_{2}), V_{i}(x_{2}))' n^{1/2} Z_{n} = (\overline{U}_{n}(x_{1}), \overline{V}_{n}(x_{1}), \overline{U}_{n}(x_{2}), \overline{V}_{n}(x_{2}))' A = \nu \int_{-\infty}^{\infty} K^{2}(u) du \begin{cases} g(x_{1}) \ w(x_{1}) \ 0 \ 0 \\ w(x_{1}) \ v(x_{1}) \ 0 \ 0 \\ 0 \ 0 \ g(x_{2}) \ w(x_{2}) \\ 0 \ 0 \ w(x_{2}) \ v(x_{2}) \end{cases}$$

Let Z be a four variate normal random variable with mean vector 0 and covariance matrix A.

We now prove the following lemmas.

LEMMA 1. Suppose K satisfies conditions (i) and (iii) and the sequence $\{h_n\}$ satisfies condition (iv). Let g', w' and v' exist and be bounded. Then the following results hold for s=1, 2 and r=1, 2.

(a)
$$\lim_{n\to\infty} \operatorname{Var} \{ n^{-1/2} \overline{U}_n(x_s) \} = \nu g(x_s) \int_{-\infty}^{\infty} K^2(u) du$$

(b)
$$\lim_{n \to \infty} \operatorname{Var} \{ n^{-1/2} \overline{V}_n(x_s) \} = \nu v(x_s) \int_{-\infty}^{\infty} K^2(u) du$$

(c)
$$\lim_{n \to \infty} \operatorname{Cov} \left\{ n^{-1/2} \overline{U}_n(x_s), \ n^{-1/2} \overline{V}_n(x_s) \right\} = \nu w(x_s) \int_{-\infty}^{\infty} K^2(u) du$$

(d)
$$\lim_{n \to \infty} \operatorname{Cov} \{ n^{-1/2} \overline{U}_n(x_1), n^{-1/2} \overline{U}_n(x_2) \} = 0$$

(e)
$$\lim_{n \to \infty} \operatorname{Cov} \{ n^{-1/2} \overline{V}_n(x_1), n^{-1/2} \overline{V}_n(x_2) \} = 0$$

(f)
$$\lim_{n \to \infty} \operatorname{Cov} \{ n^{-1/2} \overline{U}_n(x_s), n^{-1/2} \overline{V}_n(x_\tau) \} = 0, \quad r \neq s.$$

PROOF. We sketch the proof of part (a) and part (d) of the Lemma. The proof of the other parts are similar and will be omitted. To obtain part (a) we have

$$\operatorname{Var} \{n^{-1/2} \overline{U}_n(x_s)\} = \frac{1}{n} \sum_{j=1}^n \left(\frac{h_n}{h_j}\right) \int_{-\infty}^\infty \{K(u)\}^2 g(x_s - h_j u) du$$
$$- \frac{h_n}{n} \sum_{j=1}^n \left\{\int_{-\infty}^\infty K(u) g(x_s - h_j u) du\right\}^2$$
$$= \frac{1}{n} \sum_{j=1}^n \left(\frac{h_n}{h_j}\right) \left[g(x_s) \int_{-\infty}^\infty \{K(u)\}^2 du + O(h_j)\right]$$
$$- \frac{h_n}{n} \sum_{j=1}^n \left[g(x_s) + O(h)\right]_j.$$

Hence,

$$\lim_{n\to\infty}\operatorname{Var}\left\{n^{-1/2}\overline{U}_n(x_s)\right\} = \nu g(x_s) \int_{-\infty}^{\infty} K^2(u) du , \qquad s=1, 2.$$

To prove part (d) we have used the method similar to that of Schuster [6]:

$$E\left[\frac{1}{h_i}K\left(\frac{x_1-X_i}{h_i}\right)K\left(\frac{x_2-X_i}{h_i}\right)\right]=O(h_i).$$

Now,

$$\begin{aligned} \operatorname{Cov}\left\{n^{-1/2}\overline{U}_{n}(x_{1}), \ n^{-1/2}\overline{U}_{n}(x_{2})\right\} &= \frac{1}{n}\sum_{i=1}^{n} E\left\{U_{i}(x_{1})U_{i}(x_{2})\right\} \\ &= \frac{1}{n}\sum_{i=1}^{n} \left[\frac{h_{n}}{h_{i}}E\left\{\frac{1}{h_{i}}K\left(\frac{x_{1}-X_{i}}{h_{i}}\right)K\left(\frac{x_{2}-X_{i}}{h_{i}}\right)\right\}\right] \\ &-h_{n}E\left\{\frac{1}{h_{i}}K\left(\frac{x_{1}-X_{i}}{h_{i}}\right)\right\}E\left\{\frac{1}{h_{i}}K\left(\frac{x_{2}-X_{i}}{h_{i}}\right)\right\}\right] \\ &= \frac{1}{n}\sum_{i=1}^{n} \left[\frac{h_{n}}{h_{i}}\cdot O(h_{i})-h_{n}\left\{g(x_{1})+O(h_{i})\right\}\left\{g(x_{2})+O(h_{i})\right\}\right] \\ &= O(h_{n}). \end{aligned}$$

Hence,

$$\lim_{n \to \infty} \operatorname{Cov} \{ n^{-1/2} \overline{U}_n(x_1), n^{-1/2} \overline{U}_n(x_2) \} = 0.$$

Let $C = (c_1, d_1, c_2, d_2)'$ be any real vector in \mathbb{R}^4 .

LEMMA 2. Suppose K satisfies conditions (i) and (iii) and the sequence $\{h_n\}$ satisfies condition (iv) and $nh_n^3 \to \infty$ as $n \to \infty$. Let $E_f |Y|^3$ be finite and let g', w' and v' exist and be bounded. If $g(x_i) > 0$ for i=1, 2, then $C'Z_n$ converges in distribution to a normal random variable with mean 0 and variance C'AC.

PROOF. We shall establish the asymptotic normality of $C'Z_n$ by showing that

(5)
$$\lim_{n \to \infty} \left\{ \frac{\sum_{i=1}^{n} E[C'W_i]^3}{n^{3/2} (\operatorname{Var}(C'Z_n))^{3/2}} \right\} = 0. \quad \text{(See [2], p. 275.)}$$

Using Lemma 1, we have

(6)
$$\lim_{n \to \infty} \operatorname{Var} (C'Z_n) = \nu \int_{-\infty}^{\infty} K^2(u) du \left[\sum_{s=1}^2 \left\{ c_s^2 g(x_s) + d_s^2 v(x_s) + 2c_s d_s w(x_s) \right\} \right]$$
$$= C'AC > 0.$$

The positive definiteness of the matrix A follows from the fact that $g(x)v(x)-w^2(x)=g^2(x) \operatorname{Var}[Y|X=x]$ and $g(x_i)>0$ for i=1, 2. It now suffices to prove that

$$\lim_{n \to \infty} n^{-3/2} \Big\{ \sum_{i=1}^{n} E |C'W_i|^{s} \Big\} = 0$$

Using the hypothesis and the arguments similar to those in Lemma 1 it can be shown that

$$E|U_{i}(x_{s})|^{3} = O(h_{n}^{3/2}h_{i}^{-2}) = O(h_{n}^{-1/2})$$

and

$$E|V_i(x_s)|^3 = O(h_n^{3/2}h_i^{-3}) = O(h_n^{-3/2}).$$

Hence

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$$n^{-3/2} \left\{ \sum_{i=1}^{n} E |C'W_i|^3 \right\} \leq n^{-3/2} |C|^3 \sum_{i=1}^{n} E |W_i|^3$$
$$\leq 8n^{-3/2} |C|^3 \sum_{i=1}^{n} \max_{s=1,2} \left\{ E |U_i(x_s)|^3, E |V_i(x_s)|^3 \right\}$$
$$= O \left\{ (nh_n^3)^{-1/2} \right\} = o(1).$$

This completes the proof.

We define

$$(7) \qquad Z_n^* = h_n^{1/2} \cdot n^{-1/2} \left\{ \sum_{i=1}^n (U_i^*(x_1) - g(x_1)), \sum_{i=1}^n (V_i^*(x_1) - w(x_1)), \sum_{i=1}^n (U_i^*(x_2) - g(x_2)), \sum_{i=1}^n (V_i^*(x_2) - w(x_2)) \right\}.$$

LEMMA 3. Suppose conditions (i) through (vi) are satisfied. Let $E_f|Y|^3$ be finite and let g', g", w', w" and v' exist and be bounded. If $g(x_i)>0$ for i=1, 2, then $C'Z_n^*$ converges in distribution to a normal random variable with mean 0 and variance C'AC. PROOF. We have

(8)
$$C'Z_n - C'Z_n^* = h_n^{1/2} \cdot n^{-1/2} \sum_{i=1}^n \sum_{s=1}^2 \left[c_s \{ g(x_s) - EU_i^*(x_s) \} + d_s \{ w(x_s) - EV_i^*(x_s) \} \right].$$

Using the hypothesis it can be shown that for $i=1, 2, \dots, n$ and s=1, 2

$$EU_i^*(x_s) = g(x_s) + O(h_i^2)$$

and

$$EV_{i}^{*}(x_{s}) = w(x_{s}) + O(h_{i}^{2}).$$

Hence,

(9)
$$\left|\sum_{i=1}^{n} (g(x_s) - EU_i^*(x_s))\right| = O\left(\sum_{i=1}^{n} h_i^2\right),$$

and

(10)
$$\left|\sum_{i=1}^{n} (w(x_s) - EV_i^*(x_s))\right| = O\left(\sum_{i=1}^{n} h_i^2\right).$$

From (8), (9) and (10) we get

$$C'Z_{n} - C'Z_{n}^{*} = O\left(h_{n}^{1/2} n^{-1/2} \sum_{i=1}^{n} h_{i}^{2}\right)$$
$$= O\left((nh_{n})^{1/2} \frac{1}{n} \sum_{i=1}^{n} h_{i}^{2}\right)$$
$$= O((nh_{n})^{1/2} h_{n}^{2})$$
$$= O((nh_{n}^{5})^{1/2})$$
$$= o(1).$$

The proof now follows from Lemma 2.

Suppose N_t (t>0) is a stopping random variable such that $\frac{N_t}{t} \xrightarrow{p} \pi$ $(\pi>0)$ as $t \to \infty$. This implies that for any $\varepsilon > 0$, there exists $t_0 = t_0(\varepsilon)$ such that for $t \ge t_0$ we have M. SAMANTA

 $P[|N_t - \pi t| \ge \pi t \varepsilon] < \varepsilon$.

We define

(11)
$$N_1 = N_1(t, \varepsilon) = [\pi t(1-\varepsilon)]$$

and

(12)
$$N_2 = N_2(t, \epsilon) = [\pi t(1+\epsilon)]$$

where [x] is the integral part of x.

We note that for any $0 < \varepsilon < \frac{1}{2}$ and $t > \frac{1}{\pi \varepsilon}$ the numbers N_1 and N_2 defined above satisfy the following inequalities:

$$\frac{N_2}{N_1} < \frac{1 + \varepsilon}{1 - 2\varepsilon}$$

and

$$\frac{N_2-N_1}{N_1} < \frac{3\varepsilon}{1-2\varepsilon} \, .$$

We define

$$\begin{aligned} R_{i} &= \sum_{s=1}^{2} \left\{ c_{s} U_{i}^{*}(x_{s}) + d_{s} V_{i}^{*}(x_{s}) \right\}, \quad i = 1, 2, \cdots \\ \mu &= \sum_{s=1}^{2} \left\{ c_{s} g(x_{s}) + d_{s} w(x_{s}) \right\} \\ S_{n} &= \sum_{i=1}^{n} \left\{ R_{i} - \mu \right\}, \quad n = 1, 2, \cdots \\ Q &= \max_{N_{1} < n \le N_{2}} \left| \sum_{i=N_{1}+1}^{n} \left[R_{i} - E \left\{ R_{i} \right\} \right] \right|. \end{aligned}$$

It can be seen that $h_n^{1/2} n^{-1/2} S_n = C' Z_n^*$. Replacing *n* by N_t in the expressions for $\overline{U}_n(x_s)$, $\overline{V}_n(x_s)$, Z_n and Z_n^* , we define $\overline{U}_{N_t}(x_s)$, $\overline{V}_{N_t}(x_s)$, Z_{N_t} and $Z_{N_t}^*$ respectively.

In order to study the asymptotic distribution of $C'Z_{N_t}^*$ we find it convenient to choose a specific sequence $\{h_n = n^{-\delta}, n = 1, 2, \cdots\}$, where δ is some positive number. With this choice of $\{h_n\}$ we have the following lemma. Let C_1 be a generic constant.

LEMMA 4. Suppose K satisfies conditions (i) and (iii) and $\{h_n = n^{-\delta}\}$, $\delta > 0$. If g' and v' exist and are bounded, then for any $0 < \varepsilon < \frac{1}{2}$, $t > \frac{1}{\pi \varepsilon}$ we have

$$P\left\{Q \!\geq\! \varepsilon^{1/3} \sqrt{\frac{N_1}{h_{N_1}}}\right\} \!<\! \frac{C_1 \varepsilon^{1/3}}{(1\!-\!2\varepsilon)} \left\{\frac{(1\!+\!\varepsilon)}{(1\!-\!2\varepsilon)}\right\}^{\delta}$$

No

PROOF. By Kolmogorov's inequality

(13)
$$P\left[Q \ge \varepsilon^{1/3} \sqrt{\frac{N_1}{h_{N_1}}}\right] \le \frac{\sum_{i=N_1+1}^{\infty} E\left\{R_i^2\right\}}{\varepsilon^{2/3}\left\{\frac{N_1}{h_{N_1}}\right\}}$$

Using the hypothesis it can be shown that

(14)
$$E\{R_i^2\} = O\left(\frac{1}{h_i}\right) = O\left(\frac{1}{h_{N_2}}\right) \quad \text{if} \quad N_1 < i \le N_2.$$

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From (13) and (14), we get

$$P\left[Q \ge \varepsilon^{1/3} \sqrt{\frac{N_1}{h_{N_1}}}\right] \le \frac{C_1(N_2 - N_1)}{3\varepsilon^{2/3}N_1} \left(\frac{h_{N_1}}{h_{N_2}}\right)$$
$$\le \frac{C_1 \varepsilon^{1/3}}{(1 - 2\varepsilon)} \left(\frac{1 + \varepsilon}{(1 - 2\varepsilon)}\right)^{\delta}.$$

LEMMA 5. Suppose K satisfies conditions (ii), and (iii) and $\{h_n = n^{-\delta}\}, \delta > 0$. If g', g", w' and w" exist and are bounded and if $0 < \varepsilon < \frac{1}{2}, t > \frac{1}{\pi \varepsilon}$ and $\frac{1}{5} < \delta$, then for all $N_1 < n \leq N_2$,

$$\left|\sqrt{\frac{h_{N_1}}{N_1}}\sum_{i=N_1+1}^n \left[E\left\{R_i\right\}-\mu\right]\right| < \frac{C_1\varepsilon}{(1-2\varepsilon)}$$

PROOF. Using computations similar to those in Lemma 3, we obtain for all n such that $N_1 < n \leq N_2$

$$\left|\sum_{i=N_{1}+1}^{n} \left[E\left\{R_{i}\right\}-\mu\right]\right| \leq \frac{C_{1}}{3} (N_{2}-N_{1}) \sum_{i=N_{1}+1}^{n} h_{i}^{2}$$
$$\leq \frac{C_{1}}{3} (N_{2}-N_{1}) h_{N_{1}}^{2}.$$

Hence,

$$\begin{split} \left| \sqrt{\frac{h_{N_1}}{N_1}} \sum_{i=N_1+1}^n [E\{R_i\} - \mu] \right| &\leq \frac{C_1 (N_2 - N_1)}{3N_1} (N_1 h_{N_1}^5)^{1/2} \\ &= \frac{C_1 (N_2 - N_1)}{3N_1} (N_1^{1-5\delta})^{1/2} \\ &\leq \frac{C_1 \varepsilon}{(1-2\varepsilon)} \,. \end{split}$$

LEMMA 6. Suppose K satisfies conditions (i), (ii) and (iii) and $\{h_n = n^{-\delta}\}$, $\frac{1}{5} < \delta < \frac{1}{3}$ and $\frac{N_t}{t} \xrightarrow{p} \pi$ ($\pi > 0$) as $t \to \infty$. Let $E_f |Y|^3$ be finite and let g', g", w', w" and v' exist and be bounded. If $x_1 \neq x_2$, $g(x_i) > 0$ for i=1, 2, then $C'Z_{N_t}^*$ converges in distribution to a normal random variable with mean 0 and variance C'AC as t tends to infinity.

PROOF. The proof resembles that of Theorem 1 in Renyi [5]. Let $\varepsilon \left(\varepsilon < \frac{1}{2}\right)$ be an arbitrarily small positive number. Let $t \ge t_0$ where $t_0 = t_0(\varepsilon) > \frac{1}{\pi \varepsilon}$ and let N_1 and N_2 be chosen as before.

We have for y > 0

$$P[C'Z_{N_{t}}^{*} < y] = \sum_{n=1}^{\infty} P[C'Z_{n}^{*} < y ; N_{t} = n]$$
$$= \sum_{|n-\pi t| < \pi t \in} P[C'Z_{n}^{*} < y ; N_{t} = n]$$
$$+ \sum_{|n-\pi t| < \pi t \in} P[C'Z_{n}^{*} < y ; N_{t} = n]$$
$$\leq \sum_{|n-\pi t| < \pi t \in} P[C'Z_{n}^{*} < y ; N_{t} = n] + \varepsilon$$

Hence,

(15)
$$|P[C'Z_{N_t}^* < y] - \sum_{|n-\pi| < \pi t \in} P[C'Z_n^* < y; N_t = n]| < \varepsilon.$$

Introducing the random variables $R_i,\,S_n$ and Q as defined in (11), we have for any n such that $N_1\!<\!n\!\leq\!N_2$

$$(16) \qquad P[C'Z_{n}^{*} < y ; N_{t} = n] = P\left[\sqrt{\frac{h_{n}}{n}} \left\{ \sum_{i=1}^{N_{1}} (R_{i} - \mu) + \sum_{i=N_{1}+1}^{n} (R_{i} - E(R_{i})) + \sum_{i=N_{1}+1}^{n} (E(R_{i}) - \mu) \right\} < y ; N_{t} = n \right] \\ \leq P\left[S_{N_{1}} < y\sqrt{\frac{N_{2}}{h_{N_{2}}}} - \sum_{i=N_{1}+1}^{n} (E(R_{i}) - \mu) + Q ; N_{t} = n \right] \\ = P\left[\sqrt{\frac{h_{N_{1}}}{N_{1}}} S_{N_{1}} < y\sqrt{\frac{N_{2}}{N_{1}}} \left(\frac{h_{N_{1}}}{h_{N_{2}}}\right) - \sqrt{\frac{h_{N_{1}}}{N_{1}}} \sum_{i=N_{1}+1}^{n} \{E(R_{i}) - \mu\} \right. \\ \left. + \sqrt{\frac{h_{N_{1}}}{N_{1}}} Q ; N_{t} = n \right] \\ \leq P\left[C'Z_{N_{1}}^{*} < y\sqrt{\left(\frac{N_{2}}{N_{1}}\right)^{1+\delta}} + \frac{C_{1}\varepsilon}{(1-2\varepsilon)} + \sqrt{\frac{h_{N_{1}}}{N_{1}}} Q ; N_{t} = n \right],$$

by Lemma 5. Hence,

(17)

$$\sum_{|n-\pi t|<\pi t\varepsilon} P[C'Z_n^* < y ; N_t = n]$$

$$\leq P\Big[C'Z_{N_1}^* < y\sqrt{\left(\frac{N_2}{N_1}\right)^{1+\delta}} + \frac{C_1\varepsilon}{(1-2\varepsilon)} + \sqrt{\frac{h_{N_1}}{N_1}}Q ; |N_t - \pi t| < \pi t\varepsilon\Big]$$

$$\leq P\Big[C'Z_{N_1}^* < y\left(\frac{1+\varepsilon}{(1-2\varepsilon)}\right)^{(1+\delta)/2} + \frac{C_1\varepsilon}{(1-2\varepsilon)} + \varepsilon^{1/3};$$

$$Q < \varepsilon^{1/3}\sqrt{\frac{N_1}{h_{N_1}}}; |N_t - \pi t| < \pi t\varepsilon\Big] + P\Big[Q \ge \varepsilon^{1/3}\sqrt{\frac{N_1}{h_{N_1}}}\Big]$$

$$\leq P\Big[C'Z_{N_1}^* < y\left(\frac{1+\varepsilon}{1-2\varepsilon}\right)^{(1+\delta)/2} + \frac{C_1\varepsilon}{(1-2\varepsilon)} + \varepsilon^{1/3}\Big] + \frac{C_1\varepsilon^{1/3}}{(1-2\varepsilon)}\left(\frac{1+\varepsilon}{1-2\varepsilon}\right)^{\delta},$$

by Lemma 4.

From (16) we get in a similar manner

(18)

$$\sum_{|n-\pi t| < \pi t \in} P[C'Z_n^* < y; N_t = n]$$

$$\geq P\Big[C'Z_{N_1}^* < y - \frac{C_1\varepsilon}{(1-2\varepsilon)} - \sqrt{\frac{h_{N_1}}{N_1}}Q; |N_t - \pi t| < \pi t\varepsilon\Big]$$

$$\geq P\Big[C'Z_{N_1}^* < y - \frac{C_1\varepsilon}{(1-2\varepsilon)} - \varepsilon^{1/3}; Q < \varepsilon^{1/3}\sqrt{\frac{N_1}{h_{N_1}}}; |N_t - \pi t| < \pi t\varepsilon\Big]$$

$$\geq P\Big[C'Z_{N_1}^* < y - \frac{C_1\varepsilon}{(1-2\varepsilon)} - \varepsilon^{1/3}\Big] - P\Big[Q \ge \varepsilon^{1/3}\sqrt{\frac{N_1}{h_{N_1}}}\Big] - P[|N_t - \pi t| \ge \pi t\varepsilon]$$

$$\geq P\Big[C'Z_{N_1}^* < y - \frac{C_1\varepsilon}{(1-2\varepsilon)} - \varepsilon^{1/3}\Big] - \frac{C_1\varepsilon^{1/3}}{(1-2\varepsilon)}\Big(\frac{1+\varepsilon}{1-2\varepsilon}\Big)^{\delta} - \varepsilon.$$

From (15), (17) and (18) we conclude that for $t \ge t_0$

$$P[C'Z_{N_{l}}^{*} < y] \leq P\left[C'Z_{N_{1}}^{*} < y\left(\frac{1+\varepsilon}{1-2\varepsilon}\right)^{(1+\delta)/2} + \frac{C_{1}\varepsilon}{(1-2\varepsilon)} + \varepsilon^{1/3}\right] + \frac{C_{1}\varepsilon^{1/3}}{(1-2\varepsilon)}\left(\frac{1+\varepsilon}{1-2\varepsilon}\right)^{\delta} + \varepsilon^{1/3}\left(\frac{1+\varepsilon}{1-2\varepsilon}\right)^{\delta} +$$

and

$$P[C'Z_{N_{t}}^{*} < y] \ge P\Big[C'Z_{N_{1}}^{*} < y - \frac{C_{1}\varepsilon}{(1-2\varepsilon)} - \varepsilon^{1/3}\Big] - \frac{C_{1}\varepsilon^{1/3}}{(1-2\varepsilon)}\Big(\frac{1+\varepsilon}{1-2\varepsilon}\Big)^{\delta} - 2\varepsilon .$$

Similar statements hold for y < 0. We now invoke Lemma 3 and the continuity of the distribution function of a normal random variable to complete the proof.

We are now in a position to prove the main theorem of this paper.

THEOREM. Suppose K satisfies conditions (i), (ii) and (iii), and $\{h_n=n^{-\delta}\}, \frac{1}{5} < \delta < \frac{1}{3}$ and $\frac{N_t}{t} \xrightarrow{p} \pi$ ($\pi > 0$) as $t \to \infty$. Let $E_f |Y|^3$ be finite and let g', g'', w', w'' and v' exist and be bounded. If $x_1 \neq x_2$, $g(x_i) > 0$ for i=1, 2, then $(N_t h_{N_t})^{1/2}(m_{N_t}(x_1)-m(x_1), m_{N_t}(x_2)$ $-m(x_2))'$ converges in distribution to Z* as t tends to infinity where Z* is a bivariate normal random variable with mean vector 0 and diagonal covariance matrix $C=[c_{ij}]$ where

$$c_{ii} = \frac{\operatorname{Var}[Y|X=x_i]}{g(x_i)} \nu \int_{-\infty}^{\infty} K^2(u) du \qquad i=1, 2.$$

PROOF. Using the Cramér-Wold theorem (Theorem (xi) on page 123 of [4]) we conclude from Lemma 6 that $Z_{N_t}^*$ converges in distribution to Z as t tends to infinity. The proof of the theorem now immediately follows from this result in conjunction with Theorem (iii) on page 388 of [4].

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