

ON THE RATE OF CONVERGENCE FOR SEQUENTIAL DENSITY ESTIMATION

By

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Abstract. The density estimator $f_{T_n}(t) = T_n^{-1} \sum_{j=1}^{T_n} h_j^{-1} K((t - X_j)/h_j)$ is considered, where T_n is a random index. A sharp rate of convergence for the uniform distance between the probability of $f_{T_n}(t)$, when properly normed, and the standard normal distribution is obtained. It is shown that for any $\epsilon > 0$, the optimum order of the uniform estimate is $O(n^{-1/3+\epsilon})$. Similar results have been shown by other authors, but under different assumptions on T_n .

1. Introduction

The aim of this study is to show that the asymptotic performance order for the uniform distance between the distribution function of randomly indexed kernel estimators of a probability density function (when properly normed) and standard normal distribution can be extended to include a wider family of stopping rules than heretofore considered. This problem has a number of applications in sequential analysis and, thus, has attracted the attention of several authors. Carroll [2] introduced Wolverton-Wagner-type [8] random kernel estimators to derive the conditions under which they fulfill the central limit theorem. Later, Isogai [3] and Basu and Sahoo [1], by extrapolating the condition on the stopping times proposed by Carroll, provided an exact approximation order of the uniform distance. Our attention here focuses on obtaining the rate of convergence in the central limit theorem for more general, yet realistic, stopping rules.

Throughout this paper, we shall let $\{U_i; i \in N\}$ be a sequence of real-valued independently distributed random variables (i. d. r. v.'s) not necessarily identically distributed on $L_3(\Omega, F, P, \mathbf{R})$, with $E|U|^3 < \infty$. Write $S_0 = 0$ and $S_n = \sum_{j=1}^n U_j$. We assume that $EU_i = 0$, $EU_i^2 = \sigma_i^2$, $E|U_i|^3 = \beta_i^3$, $s_n^2 = \sum_{j=1}^n EU_j^2 = \sum_{j=1}^n \sigma_j^2$, $B_n^3 = \sum_{j=1}^n E|U_j|^3 = \sum_{j=1}^n \beta_j^3$, and $L_n = B_n^3/s_n^3$. Let $\{T_n; n \in N\}$ denote a sequence of integer-valued r. v. s defined on the same probability space $\{\Omega, F, P\}$, not neces-

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sarily independent of the sequence $\{U_i; i \in N\}$, and T is a positive r.v. also defined on $\{\Omega, F, P\}$ and not independent of $\{U_i; i \in N\}$. The symbol " c " denotes a generic positive constant not necessarily the same at each appearance, while $c_i, i=1, 2, \dots$, denote particular versions of c . Define $a_n = O(b_n)$ ($b_n \geq 0$), if $\exists c > 0$, such that $|a_n| \leq cb_n$ for all n . For $x \in \mathbf{R}$, we let $[x] = 1$, if $x \leq 1$ and $[x] = \max\{n \in N: n \leq x\}$, if $x > 1$. $I(E)$ represents the indicator function of the event E , and $\lg_+ x = \max\{1, \log x\}$.

Given a sequence $\{X_i; i \in N\}$ of independently and identically distributed r.v.s with density function $f(t)$, define

$$(1.1) \quad f_{T_n}(t) = \frac{1}{T_n} \sum_{j=1}^{T_n} h_j^{-1} K((t - X_j)/h_j)$$

as a random estimator for $f(t)$. Here, $K(\cdot)$ represents a kernel and $\{h_n; n \in N\}$, a sequence of constants.

We shall deal here with univariate estimators; the extension to a multivariate case is straightforward. Rewriting the estimator given in (1.1) using the notations discussed above, it is clear that

$$(1.2) \quad T_n(f_{T_n}(t) - f(t)) = \sum_{j=1}^{T_n} U_j + Z_{T_n} = S_{T_n} + Z_{T_n} \quad \text{say,}$$

$$\text{where} \quad U_j = h_j^{-1} K((t - X_j)/h_j) - E h_j^{-1} K((t - X_j)/h_j)$$

$$Z_{T_n} = T_n(\hat{f}_{T_n}(t) - f(t)),$$

$$\hat{f}_{T_n}(t) = (1/T_n) \sum_{j=1}^{T_n} E h_j^{-1} K((t - X_j)/h_j).$$

The sequence $\{U_j; j \in N\}$, as defined in (1.2), consists of only i.d.r.v.'s which are not identical.

One of the objectives of this study is to introduce a certain class of stopping rules such that under some sufficient conditions, the uniform distance between the distribution of the random kernel estimator of the density (when properly normed) and standard normal distribution becomes the best possible.

When T is assumed to be constant, it is traditionally used to impose a similar condition to

$$(1.3) \quad P(|s_{T_n}^2 s_{[nT]}^{-2} - 1| > \varepsilon_n) = O(\varepsilon_n^{1/2}), \quad \text{where } n^{-1} \leq \varepsilon_n \rightarrow 0.$$

The reason we use $s_{T_n}^2$ and $s_{[nT]}^2$ here instead of T_n and $[nT]$ respectively, is because U_i 's are just independently distributed not identical. On the other hand, when T is non-constant, an additional assumption on it is required which characterizes its dependence on the process $\{U_i; i \in N\}$. Letting $\sigma(T)$ be the σ -field generated by T , define

$$\rho(\sigma(T), F_n) = \sup_{A \in \sigma(T)} \inf_{B \in F_n} P(A \Delta B)$$

and

$$\Delta(T_n) = \sup_{x \in \mathbf{R}} |P(S_{T_n} + Z_{T_n} \leq x s_{T_n}) - \Phi(x)|,$$

where Φ is the cumulative standard normal distribution function.

If, for some $0 < \alpha \leq 1$ and β ,

$$(1.4) \quad \rho(\sigma(T), F_n) = O(s_n^{-\alpha} (\lg_+ s_n)^\beta).$$

Then, as in Landers and Rogge [6], we shall show that

$$(1.5) \quad \Delta(T_n) = O(\epsilon_n^{1/2}) + O(\delta_n),$$

where δ_n is defined in the following section.

It is worth mentioning that condition (1.4) is legitimate in the form presented. Specifically, if $EU_i = 0$, $E|U_i| = \alpha_i$ and $EU_i^2 = \sigma_i^2 < \infty$ and if the stopping rule T satisfies $E\sum_{i=1}^T \alpha_i < \infty$ and $Es_T < \infty$, for $s_T^2 = \sum_{i=1}^T \sigma_i^2$, then $\rho(\sigma(T), F_n) \leq \sup_{B \in \sigma(T)} P(s_T^2 \in B \Delta(s_T^2 \cap \{s_1^2, \dots, s_n^2\})) = P(s_T^2 > s_n^2) \leq s_n^{-1} Es_T = O(s_n^{-1})$. Also, some of the remarks pointed out by Landers and Rogge [6] for justifying the use of Hausdorff's metric $\rho(\cdot, \cdot)$, and the optimality of the rate in the uniform distance for the i.i.d. case, can be naturally extended to the i.d. case, which this paper deals with.

The remainder of the paper is organized as follows. In section 2, we extend the results of [6] to the sequences of i.d.r.v.s (not identical). The method presented here has some similarities to that of [6]; however, the details in the proofs are considerably different. Section 3 contains the proofs of the results stated in Section 2, and the proofs of certain auxiliary lemmas are delayed to Section 5. The main results on the kernel type estimators are demonstrated in Section 4.

2. The Order of Approximation of the Distribution of S_{T_n} .

In this section, we first exhibit the sufficient conditions for estimating the uniform distance between the distribution of the randomly indexed sum of i.r.v.s and $\Phi(x)$.

Let $\{U_i; i \in N\}$ be a sequence of i.r.v.'s and let $S_n = \sum_{j=1}^n U_j$. The list of conditions are:

$$C1: EU_j = 0, EU_j^2 = \sigma_j^2, E|U_j|^3 = \beta_j^3 < \infty, s_n^2 = \sum_{j=1}^n \sigma_j^2, B_n^3 = \sum_{j=1}^n \beta_j^3$$

and $L_n = B_n^3 / s_n^3$.

$$C2: L_n s_n \text{ tends to infinity as } n \text{ tends to infinity.}$$

Let the sequence of constants $\{\epsilon_i; i \in N\}$ be such that $\epsilon_n^{1/2} \geq L_n$, and let $T_n: \Omega \rightarrow N; n \in N$, and $T: \Omega \rightarrow [c, \infty)$ be F -measurable with $c > 0$. We then assume that

$$C3: P(|s_{T_n}^2 s_{[nT]}^{-2} - 1| > \epsilon_n) = O(\epsilon_n^{1/2}), \quad \text{where } s_{T_n}^2 = \sum_{j=1}^{T_n} \sigma_j^2,$$

$$C4: \rho(\sigma(T), F_n) = O(s_n^{-\alpha} (\lg_+ s_n)^\beta) \quad \text{for } \alpha \in (0, 1], \beta \in \mathbf{R},$$

$$C5: s_n = O(n^\gamma), \quad L_n = O(n^{-\delta}) \quad \text{for } 0 < \delta \leq \gamma < 1$$

with $\delta \leq 1/2$ and $\gamma(1-\alpha) < \delta$, where α is as defined in C4.

Our main result is now summarized in the following theorem.

Theorem 1. *If condition C1-C5 are satisfied, then*

$$(2.1) \quad \Delta(T_n, T) = \sup_{x \in \mathbb{R}} |P(S_{T_n} \leq x s_{[nT_n]}) - \Phi(x)| = O(\epsilon_n^{1/2}) + O(\delta_n), \quad \text{and}$$

$$(2.2) \quad \Delta(T_n) = \sup_{x \in \mathbb{R}} |P(S_{T_n} \leq x s_{T_n}) - \Phi(x)| = O(\epsilon_n^{1/2}) + O(\delta_n),$$

where

$$\delta_n(\alpha, \beta, \gamma, \delta) = \delta_n = \begin{cases} L_n & \alpha = 1, \beta < -3/2, \\ L_n \lg_+ \lg_+ s_n & \alpha = 1, \beta = -3/2, \\ L_n (\lg_+ s_n)^{\beta+3/2} & \alpha = 1, \beta > -3/2, \\ L_n^{1-\gamma(1-\alpha)/\delta} (\lg_+ s_n)^{\beta+\alpha+1/2-\gamma(1-\alpha)} & \alpha < 1, \beta \in \mathbb{R}. \end{cases}$$

The following remarks are in order prior to moving on to the proof of the Theorem.

(i) If we replace C3 by the strongest condition, i. e.,

$$P(|s_{T_n}^2 s_{[nT_n]}^{-2} - 1| > \epsilon_n) = 0,$$

then arguing essentially the same way as [6], we can conclude that a better approximation order than $O(\delta_n)$ for (2.1) or (2.2) cannot be obtained.

(ii) If we replace C3 with a weaker condition, i. e.,

$$P(|s_{T_n}^2 s_{[nT_n]}^{-2} - 1| > \epsilon_n) = O(\epsilon_n^{1/2} \alpha_n),$$

with α_n tending to infinity, then, in general, we can no longer obtain approximation order $O(\epsilon_n^{1/2}) + O(\delta_n)$ for (2.1) and (2.2) as stated in the Theorem.

(iii) If T is a constant, then $\rho(\sigma(T), F_n) = 0$. We cannot obtain a better approximation than $O(\epsilon_n^{1/2})$ for (2.1) and (2.2) under assumption C3. If T is a constant, our result falls into Isogai's approach.

(iv) If $s_n L_n = O(1)$, then the results still hold. This corresponds to the case where the process is "almost identically distributed". In the same class, of course, falls the Landers and Rogge case (i. i. d.).

3. Proofs

This segment of our work has considerable relationship to Landers and Rogge [6], where similar results are proved for the i. i. d. case. For reasons

of convenience, we operate with the same notations as in their work. As mentioned earlier, the proofs of some useful auxiliary lemmas are presented in Section 5.

Proof of (2.2). It can be seen that

$$\begin{aligned}\Delta(T_n) &= \sup_{x \in R} |P(S_{T_n} \leq x S_{T_n}) - \Phi(x)| \\ &= \sup_{x \in R} |P(\xi_n S_{T_n} \leq x S_{[nT]}) - \Phi(x)|,\end{aligned}$$

where $\xi_n = S_{[nT]} S_{T_n}^{-1}$. Consequently, from (2.1), (2.2) may be proved by using Lemma 2 and by showing that $P(|S_{[nT]} S_{T_n}^{-1} - 1| > (2\varepsilon_n)^{1/2}) = O(\varepsilon_n^{1/2})$. It is easy to check that

$$\begin{aligned}P(|\xi_n - 1| > (2\varepsilon_n)^{1/2}) &\leq P(|S_{[nT]}^2 S_{T_n}^{-2} - 1| > 2\varepsilon_n) \\ &\leq P(|S_{T_n}^2 S_{[nT]}^{-2} - 1| > \varepsilon_n) = O(\varepsilon_n^{1/2}).\end{aligned}$$

The proof of (2.2) is now complete.

Proof of (2.1). To show (2.1), it is sufficient to obtain that

$$(3.1) \quad I = \sup_{x \in R} |P(S_{[nT]} \leq x S_{[nT]}) - \Phi(x)| = O(\delta_n), \quad \text{and}$$

$$(3.2) \quad \begin{aligned}II &= \sup_{x \in R} (P(\exists \nu \in I_n(\omega) : S_\nu(\omega) \leq x S_{[nT]}) - P(\forall \nu \in I_n(\omega) : S_\nu(\omega) \leq x S_{[nT]})) \\ &= O(\varepsilon_n^{1/2}) + O(\delta_n),\end{aligned}$$

where $I_n(\omega) = \{\nu \in N : (1 - \varepsilon_n) S_{[nT]}^2 \leq S_\nu^2 \leq (1 + \varepsilon_n) S_{[nT]}^2\}$. For convenience, we set $R_n(x)$ to be the event $\{\exists \nu \in I_n(\omega) : S_\nu(\omega) \leq x S_{[nT]}\}$ and $Q_n(x)$ to be the event $\{\forall \nu \in I_n(\omega) : S_\nu(\omega) \leq x S_{[nT]}\}$.

From C3, it follows that $P(T_n \notin I_n(\omega)) = O(\varepsilon_n^{1/2})$ and $[nT] \in I_n(\omega)$. It can be shown that

$$(3.3) \quad P(Q_n(x)) + O(\varepsilon_n^{1/2}) \leq P(S_{T_n} \leq x S_{[nT]}) \leq P(R_n(x)) + O(\varepsilon_n^{1/2}), \quad \text{and}$$

$$(3.4) \quad P(Q_n(x)) \leq P(S_{[nT]} \leq x S_{[nT]}) \leq P(R_n(x)).$$

It follows from (3.3) and (3.4) that

$$(3.5) \quad \begin{aligned}\Delta(T_n, T) &\leq \sup_{x \in R} |P(S_{[nT]} \leq x S_{[nT]}) - \Phi(x)| \\ &\quad + \sup_{x \in R} |P(S_{T_n} \leq x S_{[nT]}) - P(S_{[nT]} \leq x S_{[nT]})| \\ &\leq I + II + O(\varepsilon_n^{1/2}).\end{aligned}$$

The proof is completed, provided (3.1) and (3.2) are true.

Proof of (3.1). Let $N_i = \{2^i; i \in N\}$ and $N_n = \{\nu \in N_i; \nu \leq [n/(c_1 \log n)]\}$, where

$c_1 > 0$ is a fixed constant. Set $j(n) = \max N_n$, and assume that $s_n^2 \geq 3$, and let c_1 be such that $L_\nu^{-2} \leq L_n^{-2}/2$, for any $\nu \in N_n$ and $n \in N$.

For any event $B_m \in F$; $m \in N$, we define $B_m(\nu) = \{P(B_m | F_\nu) > 1/2\} \in F_\nu$. Let $m \geq 2$. We partition the event B_m as follows:

$$(3.6) \quad I(B_m) = I(B_m) - I(B_m(j(m))) + \sum_{\nu \in N_m} (I(B_m(\nu)) - I(B_m(\nu/2))) + I(B_m(1)).$$

We define

$$(3.7) \quad D_\nu = \sup_{x \in \mathcal{R}} |E\{I(S_m \leq x s_m) - \Phi(x)\} \{I(B_m(\nu)) - I(B_m(\nu/2))\}|$$

for $\nu = 1, 2, \dots, j(m)$. With the above definitions in mind, it can be seen that

$$(3.8) \quad \begin{aligned} \Delta_m &= \sup_{x \in \mathcal{R}} |P(S_m \leq x s_m, B_m) - \Phi(x)P(B_m)| \\ &\leq E |I(B_m) - I(B_m(j(m)))| + \sum_{\nu \in N_m \cup \{1\}} D_\nu \\ &\leq d(B_m, F_{j(m)}) + \sum_{\nu \in N_m \cup \{1\}} D_\nu. \end{aligned}$$

The last inequality in (3.8) follows from Lemma 1. Moreover, via Lemma 4, it turns out that

$$(3.9) \quad D_\nu = \sup_{x \in \mathcal{R}} \left| \int (P(S_m \leq x s_m | F_\nu) - \Phi(x)) (I(B_m(\nu)) - I(B_m(\nu/2))) dP \right| \\ \leq c_2 L_m \left\{ s_\nu P(B_m(\nu) \Delta B_m(\nu/2)) + (s_\nu L_\nu)^{-1} \int_{B_m(\nu) \Delta B_m(\nu/2)} |S_\nu| dP \right\}, \text{ and}$$

$$(3.10) \quad D_1 \leq c_3 L_m \left\{ P(B_m(1)) + \int_{B_m(1)} |U_1| dP \right\}.$$

In conjunction with (3.9) and (3.10), (3.8) yields

$$(3.11) \quad \begin{aligned} \Delta_m &\leq d(B_m, F_{j(m)}) + c_3 L_m \left\{ P(B_m(1)) + \int_{B_m(1)} |U_1| dP \right\} \\ &\quad + c_2 L_m \sum_{\nu \in N_m} \left\{ s_\nu P(B_m(\nu) \Delta B_m(\nu/2)) + (s_\nu L_\nu)^{-1} \int_{B_m(\nu) \Delta B_m(\nu/2)} |S_\nu| dP \right\} \\ &\leq d(B_m, F_{j(m)}) + c_3 L_m \left\{ P(B_m(1)) + \int_{B_m(1)} |U_1| dP \right\} \\ &\quad + 2c_2 L_m \sum_{\nu \in N_m} s_\nu d(B_m, F_{\nu/2}) + c_2 L_m \sum_{\nu \in N_m} (s_\nu L_\nu)^{-1} \int_{B_m(\nu) \Delta B_m(\nu/2)} |S_\nu| dP. \end{aligned}$$

The last inequality follows from the fact that

$$P(B_m(\nu) \Delta B_m(\nu/2)) \leq 2d(B_m, F_{\nu/2}).$$

Next, we define $B_m = \{[nT] = m\} \in \sigma(T)$. For our purposes, we shall assume that $nc \geq 3$, for $n \in N$, and that

$$\begin{aligned}
 (3.12) \quad I &= \sup_{x \in \mathcal{R}} |P(S_{[nT]} \leq x S_{[nT]}) - \Phi(x)| \\
 &= \sup_{x \in \mathcal{R}} |\sum_{m \geq nc} (P(S_m \leq x S_m, B_m) - \Phi(x)P(B_m))| \\
 &\leq \sum_{m \geq nc} \sup_{x \in \mathcal{R}} |P(S_m \leq x S_m, B_m) - \Phi(x)P(B_m)|.
 \end{aligned}$$

Invoking (3.11), it is seen as in [6], that for any event $G_\nu = \{\omega \in \Omega : |S_\nu(\omega)| > 2s_\nu(\lg_+ L_\nu^{-1})^{1/2}\}$,

$$(3.13) \quad I \leq \sum_{j=1}^4 R_j(n),$$

where

$$\begin{aligned}
 R_1(n) &= \sum_{m \geq nc} d(B_m, F_{j(m)}), \\
 R_2(n) &= c_4 \sum_{m \geq nc} L_m \left\{ P(B_m(1)) + \int_{B_m(1)} |U_1| dP \right\}, \\
 R_3(n) &= c_5 \sum_{m \geq nc, \nu \in N_m} L_m (4s_\nu^2 \lg_+ L_\nu^{-1})^{1/2} d(B_m, F_{\nu/2}), \quad \text{and} \\
 R_4(n) &= c_6 \sum_{m \geq nc, \nu \in N_m} L_m (L_\nu S_\nu)^{-1} \int_{G_\nu \cap (B_m(\nu) \Delta B_m(\nu/2))} |S_\nu| dP.
 \end{aligned}$$

The remaining part of the proof of (3.1) is devoted to showing that $R_i(n) = 0(\delta_n)$, for $i=1, 2, 3$ and 4 . It follows from Lemma 1 that

$$(3.14) \quad R_1(n) \leq \sum_{m \geq nc} d(B_m, F_{j([nc])}) \leq 4\rho(\sigma(T), F_{j([nc])}),$$

which, in conjunction with C4 and C5, yields

$$\begin{aligned}
 (3.15) \quad \rho(\sigma(T), F_{j([nc])}) &\leq c_7 (s_n / \log_+ s_n)^{-\alpha} (\lg_+(s_n / \log_+ s_n))^\beta \\
 &\leq c_8 s_n^{-\alpha} (\lg_+ s_n)^{\alpha+\beta} \\
 &\leq c_9 L_n^{1-\gamma(1-\alpha)/\delta} (\lg_+ s_n)^{\beta+\alpha+1/2-\gamma(1-\alpha)} \\
 &\leq c_{10} \delta_n.
 \end{aligned}$$

Next, we proceed with $R_2(n)$. The events $B_m(1)$, for $m \geq nc$, are mutually exclusive. It is deduced that

$$(3.16) \quad R_2(n) = c_4 \sum_{m \geq nc} L_m \left\{ P(B_m(1)) + \int_{B_m(1)} |U_1| dP \right\} \leq c_{11} L_n \leq c_{11} \delta_n.$$

The last statement follows because $E|U_1| < \infty$, $\sum_{m \geq nc} P(B_m(1)) \leq 1$ and $L_{[nc]} = 0(L_n)$. To establish $R_3(n) = 0(\delta_n)$, it can be seen that

$$\begin{aligned}
 (3.17) \quad R_3(n) &= c_5 \sum_{m \geq nc, \nu \in N_m} L_m (4s_\nu^2 \lg_+ L_\nu^{-1})^{1/2} d(B_m, F_{\nu/2}) \\
 &= c_5 \sum_{i \in N_1} \sum_{inc/2 \leq m < inc, \nu \in N_m} L_m (4s_\nu^2 \lg_+ L_\nu^{-1})^{1/2} d(B_m, F_{\nu/2}) \\
 &= c_{12} \sum_{i \in N_1} L_{[inc/2]} \sum_{inc/2 \leq m < inc, \nu \in N_m} (4s_\nu^2 \lg_+ L_\nu^{-1})^{1/2} d(B_m, F_{\nu/2}).
 \end{aligned}$$

As we have pointed out above, the events $B_m \in \sigma(T)$, for $m \geq nc$ and are disjoint. According to Lemma 1 and C2, it follows that $L_\nu^{-1} \leq c_{13} s_\nu$, and

$$\begin{aligned}
 (3.18) \quad R_3(n) &\leq 4c_{12} \sum_{i \in N_1} L_{[inc/2]} \sum_{\nu \in N_{[inc]}} (4s_\nu^2 \lg_+ L_\nu^{-1})^{1/2} \rho(\sigma(T), F_{\nu/2}) \\
 &\leq c_{14} \sum_{i \in N_1} L_{[inc/2]} \sum_{\nu \in N_{[inc]}} (4s_\nu^2 \lg_+ L_\nu^{-1})^{1/2} s_\nu^{-\alpha} (\lg_+ s_\nu)^\beta \\
 &\leq c_{15} \sum_{i \in N_1} L_{[inc/2]} \sum_{\nu \in N_{[inc]}} s_\nu^{1-\alpha} (\lg_+ s_\nu)^{\beta+1/2}.
 \end{aligned}$$

In view of C5 and Lemma 5, (3.18) is deduced to

$$\begin{aligned}
 (3.19) \quad R_3(n) &\leq c_{16} \sum_{i \in N_1} (in)^{-\delta} \sum_{\nu \in N_{[inc]}} \nu^{\gamma(1-\alpha)} (\log \nu)^{\beta+1/2} \\
 &\cong \begin{cases} c_{17} n^{-\delta+\gamma(1-\alpha)} (\log n)^{\beta+1/2-\gamma(1-\alpha)} & \alpha < 1, \beta \in \mathbf{R}, \\ c_{17} n^{-\delta} (\log n)^{\beta/2+\beta} & \alpha = 1, \beta > -3/2, \\ c_{17} n^{-\delta} \log \log n & \alpha = 1, \beta = -3/2, \\ c_{17} n^{-\delta} & \alpha = 1, \beta < -3/2, \end{cases} \\
 &\leq c_{17} \delta_n.
 \end{aligned}$$

It remains to be shown that $R_4(n) = 0(\delta_n)$.

$$\begin{aligned}
 (3.20) \quad R_4(n) &\leq c_6 \sum_{m \geq nc, \nu \in N_1} L_m(L_\nu s_\nu)^{-1} \int_{G_\nu \cap (B_m(\nu) \Delta B_m(\nu/2))} |S_\nu| dP \\
 &\leq c_{18} L_n \sum_{m \geq nc, \nu \in N_1} (L_\nu s_\nu)^{-1} \left(\int_{G_\nu \cap B_m(\nu)} + \int_{G_\nu \cap B_m(\nu/2)} \right) \\
 &\leq c_{19} L_n \sum_{\nu \in N_1} L_\nu^{-1} \int_{G_\nu} |S_\nu^*| dP, \quad \text{where } S_n^* = S_n / s_n.
 \end{aligned}$$

The following arguments are similar to those in [4]. Since $E|X| \leq \sum_{k=0}^{\infty} P(|X| > k)$, then by setting

$$Y = (S_\nu^*/2)(\lg_+ L_\nu^{-1})^{-1/2} I(|S_\nu^*| > 2(\lg_+ L_\nu^{-1})^{1/2}),$$

it follows from Lemma 6 and Markov's inequality that for $\nu > 1$

$$\begin{aligned}
 L_\nu^{-1} \int_{G_\nu} |S_\nu^*| dP &\leq 2(\lg_+ L_\nu^{-1})^{1/2} L_\nu^{-1} \sum_{k=0}^{\infty} P(|S_\nu^*| > 2k(\lg_+ L_\nu^{-1})^{1/2}) \\
 &\leq 2(\lg_+ L_\nu^{-1})^{1/2} L_\nu^{-1} \sum_{k=0}^{\infty} \left\{ c_{20} L_\nu k^{-6} (\lg_+ L_\nu^{-1})^{-3} + \sum_{j=1}^{\nu} P\left(|U_j| > \frac{k}{3} s_\nu (\lg_+ L_\nu^{-1})^{1/2}\right) \right\}.
 \end{aligned}$$

Since $L_\nu = 0(\nu^{-\delta})$ and $i \log 2 \leq \log \nu(i)$ for $\nu \in N_1$, it results from Lemma 6 in [4] that

$$(3.21) \quad R_4(n) \leq c_{22} L_n = 0(\delta_n).$$

By inserting (3.15), (3.16), (3.19) and (3.21) into (3.13), the proof of (3.1) is completed.

Proof of (3.2). We set $I_n(m) = \{\nu \in N: s_m^2(1 - \epsilon_n) \leq s_\nu^2 \leq s_m^2(1 + \epsilon_n)\}$. It is easy to see that

$$(3.22) \quad P(Q_n(x)) - P(R_n(x)) = \sum_{m \geq nc} (P(Q_n(x) \cap B_m) - P(R_n(x) \cap B_m)) \\ = \sum_{m \geq nc} (P(B_m, \exists \nu \in I_n(m): S_\nu \leq x s_m) - P(B_m, \forall \nu \in I_n(m): S_\nu \leq x s_m)).$$

Let $A_m = \{P(B_m | F_{j(\lfloor nc \rfloor)}) > 1/2\} \in F_{j(\lfloor nc \rfloor)}$. Clearly, $\{A_m, m \geq nc\}$ consists of mutually exclusive events. By Lemma 1, $P(B_m \Delta A_m) = d(B_m, F_{j(\lfloor nc \rfloor)})$. Thus,

$$(3.23) \quad P(Q_n(x)) - P(R_n(x)) \leq 2 \sum_{m \geq nc} d(B_m, F_{j(\lfloor nc \rfloor)}) \\ + \sum_{m \geq nc} (P(A_m, \exists \nu \in I_n(m): S_\nu \leq x s_m) - P(A_m, \forall \nu \in I_n(m): S_\nu \leq x s_m)).$$

From Lemma 1 and (3.15)

$$(3.24) \quad \sum_{m \geq nc} d(B_m, F_{j(\lfloor nc \rfloor)}) \leq 4\rho(\sigma(T), F_{j(\lfloor nc \rfloor)}) \leq 4c_{10}\delta_n.$$

From Lemma 7,

$$(3.25) \quad P(A_m, \exists \nu \in I_n(m): S_\nu \leq x s_m) - P(A_m, \forall \nu \in I_n(m): S_\nu \leq x s_m) \\ = \int_{A_m} P(\exists \nu, l \in I_n(m): S_\nu \leq x s_m < S_l | F_{j(\lfloor nc \rfloor)}) dP \\ \leq c_{23}P(A_m)(\hat{L}_{r(n)} + \{2\epsilon_n s_m^2 / (s_m^2(1 - \epsilon_n) - s_{j(\lfloor nc \rfloor)}^2)\}^{1/2}) \leq c_{24}P(A_m)\epsilon_n^{1/2},$$

where $r(n) = \min\{\nu \in N: s_m^2(1 - \epsilon_n) \leq s_\nu^2 \leq s_m^2(1 + \epsilon_n)\} = \min I_n(m)$. The last inequality in (3.25) follows, since $L_n \leq \epsilon_n^{1/2}$. In view of (3.24) and (3.25), it is observed that

$$(3.26) \quad \Pi \leq 8c_{10}\delta_n + c_{25}\epsilon_n^{1/2} \sum_{m \geq nc} P(A_m) = 0(\delta_n) + 0(\epsilon_n^{1/2}).$$

The proof of Theorem 1 is now complete.

4. An approximation Order of Convergence of the Distribution of $f_{T_n}(t)$

In this section, we exploit the method developed above to obtain the rate of convergence for the uniform distance between the distribution of our random estimator for the p.d.f. and the standard normal distribution.

We first state the conditions for the kernel function, the sequence $\{h_n: n \in N\}$, and the probability density function.

Assume $K(\cdot)$ to be a measurable function with

$$K_1: \sup_{t \in \mathbf{R}} |K(t)| < \infty,$$

$$K_2: \int |K(t)| dt < \infty,$$

$$K_3: \int K(t) dt = 1,$$

$$K_4: \lim_{|t| \rightarrow \infty} |tK(t)| = 0,$$

$$K_5: \int tK(t) dt = 0.$$

For the sequence $\{h_n; n \in \mathbf{N}\}$, we assume that it is a monotone decreasing sequence and

$$H_1: \lim_{n \rightarrow \infty} h_n = 0,$$

$$H_2: \lim_{n \rightarrow \infty} n h_n = \infty,$$

$$H_3: \lim_{n \rightarrow \infty} (h_n^r/n) \sum_{j=1}^n h_j^{-r} = \gamma_r \quad \text{for } r=1, 2.$$

It is traditional in such work to assume that

$$H_4: h_n = n^{-\lambda}, \quad \lambda \in (1/3, 1).$$

As far as the probability density is concerned, we shall assume that

$F_1: f(\cdot)$ is uniform continuous, integrable and bounded
(in order to be a density function),

$F_2: f''(t)$ exists for all $t \in \mathbf{R}$, and $\sup_{t \in \mathbf{R}} |f''(t)| < \infty$.

Adapting the notations presented in Sections 1 and 2, we shall present a result similar to that given by Yamato [9] and Basu and Sahoo [1]. The purpose of this result is two-fold: First, it provides the rate of convergence for the uniform distance between the distribution of Wolverton-Wagner's estimator (when properly normed) and the standard normal distribution (for fixed size sample), and then it states the exact approximation order of L_n , upon which the whole analysis depends.

Theorem 2. *If K_1 – K_4 , H_1 – H_3 and F_1 hold, then for fixed $t \in \mathbf{R}$,*

$$M_n = \sup_{x \in \mathbf{R}} \left| P \left(\frac{f_n(t) - E f_n(t)}{(\text{Var}(f_n(t)))^{1/2}} \leq x \right) - \Phi(x) \right| = O((n h_n)^{-1/2}),$$

where $f_n(t)$ is the fixed-size kernel density estimator.

In addition, if H_4 holds, then $M_n = O(n^{-(1-\lambda)/2})$.

Proof. Since $(f_n(t) - E f_n(t))/(\text{Var}(f_n(t)))^{1/2} = S_n/s_n$, then by Petrov ([7], p.

115), it follows that

$$(4.1) \quad M_n \leq c L_n.$$

If we show that $L_n = o((nh_n)^{-1/2})$, the proof of Theorem 2 is completed. By C_r -inequality,

$$(4.2) \quad B_n^3 = \sum_{j=1}^n E|U_j|^3 \leq 4 \sum_{j=1}^n \{E|Y_j|^3 + |EY_j|^3\}, \quad Y_j = \frac{1}{h_j} K((t - X_j)/h_j).$$

As in [9, (5.8) and (5.9)],

$$(4.3) \quad E|Y_j|^3 \leq \|f\| \int |K(u)|^3 du / h_j^3, \quad \|f\| = \sup_{t \in R} f(t), \quad \text{and}$$

$$(4.5) \quad |EY_j| \leq \|f\| \int |K(u)| du.$$

Consequently, since H3 holds, it is seen that for large n ,

$$(4.6) \quad B_n^3 h_n^2 / n \leq c_2 \gamma_2 \|f\| \int |K(u)|^3 du.$$

We shall now examine the behavior of $\text{Var}(S_n)$. It is clear that

$$(4.7) \quad \text{Var}(S_n) = \sum_{j=1}^n \left\{ h_j^{-2} \int K^2\left(\frac{u}{h_j}\right) f(t-u) du - \left(h_j^{-1} \int K\left(\frac{u}{h_j}\right) f(t-u) du \right)^2 \right\}.$$

Arguments similar to those of [9, Section 3], can be used to show that if $f(t)$ is uniform, continuous, and bounded, and if K_1 - K_4 and H_1 - H_3 hold, then $\text{Var}(S_n) \asymp (n/h_n)$, i. e., $(h_n/n) \text{Var}(S_n)$ is bounded away from zero and infinity.

We conclude, as does Yamato [9, (5.11)], that

$$(4.8) \quad (nh_n)^{1/2} L_n = (B_n^3 h_n^2 / n) (s_n^2 h_n / n)^{-3/2} = o(1).$$

This completes the proof of Theorem 2.

The rest of this section is consigned to the random estimator $f_{T_n}(t)$. Calling upon Theorem 1, the following theorem may also be proved.

Theorem 3. *If conditions C_1, C_3, C_4, K_1 - K_4, H_1 - H_4 and F_1 hold, then for fixed $t \in R$,*

$$\sup_{x \in R} |P(T_n(f_{T_n}(t) - \hat{f}_{T_n}(t)) / s_{[nT]} \leq x) - \Phi(x)| = o(\epsilon_n^{1/2}) + o(\delta_n).$$

Comments. (i) Since $s_n^2 \asymp n^{1+\lambda}$ and $L_n = o(n^{-(1-\lambda)/2})$, it follows that

$$P(|s_{T_n}^2 s_{[nT]}^{-2} - 1| > \epsilon_n) = o(\epsilon_n^{1/2}) \text{ is equivalent to } P(|T_n^{1+\lambda} [nT]^{-1-\lambda} - 1| > \epsilon_n) = o(\epsilon_n^{1/2}).$$

(ii) We note that C_2 and C_5 are always valid because of H_4 and (4.8).

As an extension, the next Theorem asserts that the conclusions of Theorem

3 still hold even if $\hat{f}_{T_n}(t)$ is replaced by $f(t)$.

Theorem 4. *If C1, C3, C4, K1-K5, H1-H4 and F1-F2 hold, then for fixed $t \in \mathbf{R}$,*

$$\sup_{x \in \mathbf{R}} |P(T_n(f_{T_n}(t) - f(t))s_{[nT]}^{-1} \leq x) - \Phi(x)| = O(\epsilon_n^{1/2}) + O(\delta_n).$$

Proof. As pointed out in (1.2), $T_n(f_{T_n}(t) - f(t)) = S_{T_n} + Z_{T_n}$. The asymptotic behavior of S_{T_n} is already known in Theorem 3. Hence, it remains to find out how Z_{T_n} acquires. Using K_1 - K_3 and K_5 , H_4 and F_2 , we see that

$$\begin{aligned} (4.9) \quad |Z_{T_n}| &= \left| \sum_{j=1}^{T_n} K(u)(f(t - h_j u) - f(t)) du \right| \\ &= \left| \sum_{j=1}^{T_n} K(u) \{ h_j u f'(t) + (h_j^2/2) u^2 f''(v) \} du \right| \\ &= c_1 \sum_{j=1}^{T_n} h_j^2 = c_2 T_n^{1-2\lambda} \quad \text{a. e.,} \end{aligned}$$

where v belongs to (t, u) or (u, t) . Since $\epsilon_n^{1/2} \geq L_n = c n^{-(1-\lambda)/2}$ ($\lambda > 1/3$), it follows that

$$\begin{aligned} (4.10) \quad P(T_n(\hat{f}_{T_n}(t) - f(t))s_{[nT]}^{-1} > \epsilon_n^{1/2}) &\leq P(T_n^{1-2\lambda} [nT]^{(\lambda-1)/2} > c_3 \epsilon_n^{1/2}) \\ &\leq P(T_n^{1-2\lambda} [nT]^{2\lambda-1} > c_4 n^{-1+3\lambda}) \\ &\leq (1/2) P(|(T_n^{1+\lambda} [nT]^{-1-\lambda}) - 1| > c_5 n^{-(1+3\lambda)(1+\lambda)/(1-\lambda)} - 1) \\ &\leq (1/2) P(|s_{T_n}^2 s_{[nT]}^{-2} - 1| > \epsilon_n) = O(\epsilon_n^{1/2}). \end{aligned}$$

By Lemma 3 and by choosing $\beta_n = c_6 \epsilon_n^{1/2} + c_7 \delta_n$ and $\alpha_n = c_8 \epsilon_n^{1/2}$, the result is seen immediately.

The next Corollary is a consequence of Theorem 4.

Corollary. *If C1, C3, C4, K1-K5, H1-H4 and F1-F2 hold, then for fixed $t \in \mathbf{R}$,*

$$\sup_{x \in \mathbf{R}} |P(T_n(f_{T_n}(t) - f(t))s_{T_n}^{-1} \leq x) - \Phi(x)| = O(\epsilon_n^{1/2}) + O(\delta_n).$$

5. Auxiliary Results

In this section, we collect all the Lemmas which were used in the proofs of Theorems 1-4.

Lemma 1 ([5]). *Let $F_{(1)}$ and $F_{(2)}$ be subfields of F , then*

(i) *if $\{B_n; n \in \mathbf{N}\}$ is a sequence of disjoint events of $F_{(1)}$, the following result is true*

$$\sum_{n \in \mathbf{N}} d(B_n, F_{(2)}) \leq 4\rho(F_{(1)}, F_{(2)}), \quad \text{and}$$

(ii) if $A \in \mathcal{F}$, and if $B = \{P(A|F_{(1)}) > 1/2\}$, then we have that

$$P(A \Delta B) = d(A, F_{(1)}).$$

The proofs of the following two lemmas are simple and, therefore, are omitted.

Lemma 2. Let $\{\xi_n; n \in \mathbb{N}\}$ and $\{Y_n; n \in \mathbb{N}\}$ be sequences of r.v.s and let $W_n = \xi_n Y_n$. Suppose that $\{\alpha_n; n \in \mathbb{N}\}$ and $\{\beta_n; n \in \mathbb{N}\}$ are two sequences of positive constants which tend to zero as n tends to infinity. If

$$\sup_{x \in \mathbb{R}} |P(Y_n \leq x) - \Phi(x)| = o(\beta_n) \quad \text{and} \quad P(|\xi_n - 1| > \alpha_n) = o(\beta_n),$$

then $\sup_{x \in \mathbb{R}} |P(W_n \leq x) - \Phi(x)| = o(\beta_n) + o(\alpha_n)$.

Lemma 3. Let $\{Z_n; n \in \mathbb{N}\}$ and $\{Y_n; n \in \mathbb{N}\}$ be sequences of r.v.s and let $W_n = Z_n + Y_n$, for $n = 1, 2, \dots$. Suppose that for any sequence $\{\beta_n; n \in \mathbb{N}\}$ of positive constants, we have that

$$\sup_{x \in \mathbb{R}} |P(Z_n \leq x) - \Phi(x)| = o(\beta_n).$$

Then, for any sequence of positive constants $\{\alpha_n; n \in \mathbb{N}\}$, it follows that

$$\sup_{x \in \mathbb{R}} |P(W_n \leq x) - \Phi(x)| = o(\alpha_n) + o(\beta_n) + P(|Y_n| > \alpha_n).$$

Lemma 4. Let $\{U_i; i \in \mathbb{N}\}$ be a sequence of i.r.v.s such that $EU_i = 0$, $EU_i^2 = \sigma_i^2$ and $E|U_i|^3 < \infty$. Let $\{S_n; n \in \mathbb{N}\}$ be a sequence of partial sums with $s_n^2 = \sum_{j=1}^n \sigma_j^2$, $B_n^3 = \sum_{j=1}^n \beta_j^3$ and $L_n = B_n^3 / s_n^3$. Define $F_k = \sigma(U_1, U_2, \dots, U_k)$, then for any $2L_k^{-1} \leq L_n^{-1}$ we have P-a. e.

$$\sup_{x \in \mathbb{R}} |P(S_n \leq x s_n | F_k) - \Phi(x)| = c L_n \{s_k + (s_k L_k)^{-1} |S_k|\}.$$

Proof. We note that

$$\begin{aligned} \Delta_n(F_k) &= \sup_{x \in \mathbb{R}} |P(S_n \leq x s_n | F_k) - \Phi(x)| \\ &= \sup_{x \in \mathbb{R}} |P(S_k + (S_n - S_k) \leq x s_n | F_k) - \Phi(x)| \\ &= \sup_{x \in \mathbb{R}} \left| P\left(\frac{S_n - S_k}{(s_n^2 - s_k^2)^{1/2}} \leq x \frac{s_n}{(s_n^2 - s_k^2)^{1/2}} - \frac{S_k}{(s_n^2 - s_k^2)^{1/2}} \mid F_k\right) - \Phi(x) \right| \\ &\leq \sup_{x \in \mathbb{R}} |P(S_n - S_k \leq x(s_n^2 - s_k^2)^{1/2}) - \Phi(x)| \\ &\quad + \sup_{x \in \mathbb{R}} \left| \Phi\left(x \frac{s_n}{(s_n^2 - s_k^2)^{1/2}} - \frac{S_k}{(s_n^2 - s_k^2)^{1/2}}\right) - \Phi(x) \right| \\ &= T_1 + T_2, \quad \text{say.} \end{aligned}$$

It is clear ([7], p. 114) that

$$T_2 \leq (s_n(s_n^2 - s_k^2)^{-1/2} - 1) / \sqrt{2\pi e} + |S_k| (s_n^2 - s_k^2)^{-1/2} / \sqrt{2\pi}$$

$$\leq c_1 \{s_k^2 / (s_n^2 - s_k^2) + |S_k| / (s_n^2 - s_k^2)^{1/2}\},$$

since $2s_k^3/B_k^3 \leq s_n^3/B_n^3$ implies that $2B_n^3/B_k^3 \leq s_n^3/s_k^3$. But $B_n^3/B_k^3 \geq 1$, hence $2^{2/3}s_k^2 \leq s_n^2$. And since $s_k^2/s_n^2 < 1$, it follows that $s_k^2/s_n^2 < s_k/s_n$. Under these considerations, we obtain that $T_2 \leq c_2 s_n^{-1} \{s_k + |S_k|\}$. Since s_n is a monotone increasing with respect to n , and $s_n L_n$ tends to infinity, T_2 can be bounded by $T_2 \leq c_3 L_n \{s_k + (s_k L_k)^{-1} |S_k|\}$. From [7, p. 115], and since $2^{2/3}s_k^2 \leq s_n^2$, it follows that $T_1 \leq c_4 (B_n^3 - B_k^3)(s_n^2 - s_k^2)^{-3/2} \leq c_5 L_n$. This completes the proof of the lemma.

Lemma 5 ([6]). *Let $N_1 = \{2^\nu; \nu \in N\}$ and $N_n = \{\nu \in N_1: \nu \leq [n/\log n]\}$. Then*

$$\sum_{\nu \in N_n} \nu^\epsilon (\log \nu)^\delta = \begin{cases} 0(1) & \text{if } \epsilon = 0, \delta < -1, \\ 0(\log \log n) & \text{if } \epsilon = 0, \delta = -1, \\ 0((\log n)^{\delta+1}) & \text{if } \epsilon = 0, \delta > -1, \\ 0(n^\epsilon (\log n)^{\delta-\epsilon}) & \text{if } \epsilon > 0, \delta \in R. \end{cases}$$

Lemma 6. *Let $\{U_i; i \in N\}$ be a sequence of i.r.v.'s with $EU_i = 0, EU_i^2 = \sigma_i^2$ and $E|U_i|^3 = \beta_i^3 < \infty$. Let $\{S_n; n \in N\}$ be a sequence of partial sums with $s_n^2 = \sum_{j=1}^n \sigma_j^2, B_n^3 = \sum_{j=1}^n \beta_j^3$ and $L_n = B_n^3/s_n^3$. Then, for all $t > 0$ with $t^2 \geq 4 \log_+ L_n^{-1}$ we have*

$$(5.1) \quad P(|S_n| > s_n t) \leq c_1 L_n t^{-6} + R_n,$$

where $R_n = \sum_{k=1}^n P(|U_k| > c_2 t s_n), c_2 = 1/6$.

Proof. The idea here is to show that $P(S_n \geq s_n t)$ is bounded above by the R.H.S. of (5.1). Next, replacing the U_k by $-U_k$ and repeating the proof of the latter case, we establish that $P(S_n < -s_n t)$ is also bounded above by the same expression as in (5.1). This confirms that (5.1) is true. We proceed by showing that

$$P(S_n \geq s_n t) \leq c_1 L_n t^{-6} + R_n.$$

We define $U_k^* = U_k I(|U_k| \leq c_2 t s_n), c_2 = 1/6, k = 1, 2, \dots, n$, and $S_n^* = \sum_{j=1}^n U_j^*$. It is easy to check that

$$(5.2) \quad P(S_n \geq t s_n) \leq P(S_n^* \geq t s_n) + \sum_{j=1}^n P(|U_j| > c_2 t s_n).$$

Set $h = (s_n t)^{-1} \{2 \log_+ L_n^{-1} + 12 \log_+ t\}$. Via Markov's inequality and independence,

$$(5.3) \quad P(S_n^* > t s_n) \leq \exp(-h s_n t) E \exp(h S_n^*)$$

$$\leq L_n^{-2} t^{-12} \prod_{j=1}^n E \exp(h U_j^*).$$

Since $hU_j^* \leq (2 \lg_+ L_n^{-1} + 12 \lg_+ t) c_2 = d_n$, a. e., it follows that

$$(5.4) \quad \begin{aligned} \exp(hU_j^*) &= 1 + hU_j^* + (hU_j^*)^2/2 + ((hU_j^*)^3/6)(1 + hU_j^*/3 + \dots) \\ &\leq 1 + hU_j^* + (hU_j^*)^2/2 + (h^3/6) |U_j^*|^3 \exp(d_n). \end{aligned}$$

Taking the expectations from both sides of (5.4), it can be seen that

$$E \exp(hU_j^*) \leq \exp(hEU_j^* + (h^2/2)EU_j^{*2} + (h^3/6)E|U_j^*|^3 \exp(d_n)).$$

Now, since $EU_j = 0$, it implies that

$$(5.5) \quad |hEU_j^*| \leq hE|U_j^*| I(|U_j| > c_2 s_{nt}) \leq h\sigma_j^2 / (c_2 s_{nt}) \leq c_4 \sigma_j^2 / s_n^2,$$

and

$$(5.6) \quad h^3 \exp(d_n) E|U_j^*|^3 \leq L_n^{-1/3} t^2 (s_{nt})^{-3} \{2 \lg_+ L_n^{-1} + \lg_+ t\}^3 \beta_j^3.$$

In conjunction with (5.5) and (5.6), (5.3) becomes

$$P(S_n^* > t s_n) \leq L_n^{-2} t^{12} \exp(c_4 + (1/2)h^2 s_n^2 + L_n^{2/3} t \{s \lg_+ L_n^{-1} + \lg_+ t\}^3).$$

But for sufficiently large n , $L_n^{2/3} t \{s \lg_+ L_n^{-1} + \lg_+ t\}^3$ is bounded above by a constant c_5 , say, and $(1/2)h^2 s_n^2$ is bounded by $\lg_+ L_n^{-1} + 6 \lg_+ t$. This confirms that $P(S_n^* > t s_n) \leq c_1 L_n t^{-6}$, which completes the proof of the lemma, by noticing that

$$R_n = \sum_{j=1}^n P(|U_j| > c_2 s_{nt}) \leq \sum_{j=1}^n E|U_j|^3 / (c_2 s_{nt})^3 \leq c_8 L_n t^{-3}.$$

Lemma 7. Let $\{U_i; i \in N\}$ be a sequence of i. r. v.'s with $EU_i = 0$, $EU_i^2 = \sigma_i^2$ and $E|U_i|^3 = \beta_i^3 < \infty$. Let $\{S_n; n \in N\}$ be a sequence of partial sums with $s_n^2 = \sum_{j=1}^n \sigma_j^2$, $B_n^3 = \sum_{j=1}^n \beta_j^3$ and $L_n = B_n^3 / s_n^3$. Then for $I([p, q]) = \{\nu \in N; s_p^2 \leq s_\nu^2 \leq s_q^2\}$ ($p \leq q$), we have that

$$(i) \quad \sup_{x \in R} P(\exists \mu, \nu \in I([p, q]): S_\nu \leq x < S_\mu) \leq c_1 L_p + c_2 (s_q^2 - s_p^2)^{1/2} s_p^{-1}$$

and for $F_k \equiv \sigma(U_1, \dots, U_k)$ ($k < p \leq q$), we have that

$$(ii) \quad \sup_{x \in R} P(\exists \mu, \nu \in I([p, q]): S_\nu \leq x < S_\mu | F_k) \leq c_1 \hat{L}_p + c_2 (s_q^2 - s_p^2)^{1/2} (s_p^2 - s_k^2)^{-1/2},$$

where $\hat{L}_p = (B_p^3 - B_k^3) (s_p^2 - s_k^2)^{-3/2}$.

Proof. We shall first show (i). It is not hard to see that

$$\begin{aligned} &P(\exists \mu, \nu \in I([p, q]): S_\nu \leq x < S_\mu) \\ &= P(\exists \nu \in I([p, q]): S_\nu \leq x < S_p) + P(\exists \mu \in I([p, q]): S_p \leq x < S_\mu). \end{aligned}$$

Since we can replace X_i by $-X_i$, it suffices to show that

$$P(S_p \leq x < \max_{p < j \leq q} S_j) \leq c_1 L_p + c_2 (s_q^2 - s_p^2)^{1/2} s_p^{-1}.$$

Set $H = \max_{p < j \leq q} (S_j - S_p)$, then using [7, p. 115] it follows that

$$\begin{aligned}
P(S_p \leq x < \max_{p < j \leq q} S_j) &\leq P(x - H \leq S_p \leq x) \\
&= \int P(x - h \leq S_p \leq x) dP(H \leq h) \\
&\leq c_1 L_p + \int |\Phi(x/s) - \Phi((x-h)/s_p)| dP(H \leq h) \\
&\leq c_1 L_p + c_2 E|H|/s_p \\
&\leq c_1 L_p + c_2 (EH^2)^{1/2}/s_p \\
&\leq c_1 L_p + c_3 (s_q^2 - s_p^2)^{1/2}/s_p.
\end{aligned}$$

The last statement follows from the Marcinkiewicz-Zygmund Inequality for independent variables.

To show (ii), we have that *P*-a. e.

$$\begin{aligned}
P(S_p \leq x < \max_{p < j \leq q} S_j | F_k) &\leq P(x - H - S_k \leq S_p - S_k \leq x - S_k | F_k) \\
&= \int P(x - h - S_k \leq S_p - S_k \leq x - S_k | F_k) dP(H \leq h) \\
&\leq c_1 \hat{L}_p + \int |\Phi((x - S_k)(s_p^2 - s_k^2)^{-1/2}) - \Phi((x - S_k - h)(s_p^2 - s_k^2)^{-1/2})| dP(H \leq h) \\
&\leq c_1 \hat{L}_p + c_2 (s_q^2 - s_p^2)^{1/2} (s_p^2 - s_k^2)^{-1/2}.
\end{aligned}$$

This completes the proof of Lemma 7.

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