

## APPLICATION OF THE SKOROKHOD REPRESENTATION THEOREM TO RATES OF CONVERGENCE FOR LINEAR COMBINATIONS OF ORDER STATISTICS

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Rates of convergence for linear combinations of order statistics are obtained. The work is in the spirit of those authors who have used in one form or another the weak convergence of the sample empirical process to a tied-down Wiener process, except that the Skorokhod embedding is explicitly used to obtain a rate of convergence via control on the tail-behavior of the stopping times. The paper concludes with a remark on the limitations of the technique as far as getting the best possible rate is concerned.

**1. Introduction.** Suppose that there are given  $U_{1n}, U_{2n}, \dots, U_{nn}$  ordered observations from a uniform distribution on  $(0,1)$ . Set  $U_{0n} = 0, U_{(n+1)n} = 1$  and let  $F_n^{-1}$  be a version of the inverse of the empirical distribution function of the  $U_{jn}$ 's defined by

$$(1.1) \quad F_n^{-1}(t) = U_{(j-1)n}, \\ (j-1)/(n+1) \leq t < j/(n+1); j = 1, 2, \dots, (n+1). \\ = 1, \quad t = 1.$$

Our purpose is to consider rates of convergence for the asymptotic normality of statistics, appropriately normalized, of the form

$$(1.2) \quad T_n = n^{-1} \sum_{j=1}^n C_{jn} H(X_{jn})$$

where the  $C_{jn}$ 's are specified constants,  $H$  is a real valued Borel measurable function on the real line and  $X_{1n}, X_{2n}, \dots, X_{nn}$  are the order statistics of a sample of size  $n$  from a continuous distribution  $F$ . It is convenient to represent  $T_n$  as

$$(1.3) \quad T_n = \int_0^1 h[F_n^{-1}(t)] d\nu_n(t),$$

where  $h$  is the composition of  $H$  with  $F^{-1}$  i.e.  $h(t) = H[F^{-1}(t)]$ , and  $\nu_n$  is a discrete signed measure defined by

$$(1.4) \quad \nu_n[j/(n+1)] = n^{-1} C_{jn}, \quad j = 1, 2, \dots, n.$$

If  $\nu$  is a signed measure we denote its total variation by  $|\nu|$ . That is  $|\nu| = \nu^+ + \nu^-$  where  $\nu^+, \nu^-$  are the components appearing in the Jordan-Hahn decomposition of  $\nu$ . Pyke in [2] notes that "in most applications the sequence of measure  $\nu_n$  converges suitably to a finite Lebesgue Stieltjes signed measure  $\nu$  in such a way as to allow one to replace  $\nu_n$  by the limiting measure  $\nu$ ." Initially then, we

Received August 21, 1971; revised January 20, 1972.

<sup>1</sup> Research supported in part by N.S.F. Grant GP-11460.

consider not  $T_n$  but the normalized statistic

$$(1.5) \quad \begin{aligned} V_n &= n^{\frac{1}{2}} \int_0^1 \{h[F_n^{-1}(t)] - h(t)\} d\nu(t) \\ &= \int_0^1 A_n(t) D_n(t) d\nu(t) \end{aligned}$$

where

$$(1.6) \quad A_n(t) = \frac{h(F_n^{-1}(t)) - h(t)}{F_n^{-1}(t) - t}, \quad 0 \leq t \leq 1$$

and

$$(1.7) \quad D_n(t) = n^{\frac{1}{2}}(F_n^{-1}(t) - t), \quad 0 \leq t \leq 1.$$

The method depends on using the Skorokhod embedding theorem as in Rosenkrantz [4] to get a speed for the convergence to zero in probability of the maximum distance between a version of the process  $\tilde{D}_n$  and a tied down Wiener process  $W_0(t)$  defined on a common probability space. In Section 2 preliminary results for a special version of  $D_n$  are established in Lemmas 2.1, 2.2 and 2.3. The results on rates are given in Section 3. Theorem 3.1 applies to the statistic  $V_n$ , while Theorem 3.2 gives a result for  $T_n$  in the case that the weights are given by a “scoring” function. Section 4 is a comment on the “right” rate and the limitations of the method used.

**2. Preliminary results.** For any two functions  $x(\cdot)$  and  $y(\cdot)$  on  $[0, 1]$  let

$$(2.1) \quad d(x, y) = \sup (|x(t) - y(t)|; 0 \leq t \leq 1).$$

The rate of convergence will depend on the choice of a nonnegative sequence  $\epsilon_1, \epsilon_2, \dots$  decreasing to zero for which  $P(d(D_n, W_0) \geq \epsilon_n) \rightarrow 0$ , as  $n \rightarrow \infty$ , at a speed which can be determined. In Section 4 it is shown that a necessary condition on  $\epsilon_n$  is that

$$(2.2) \quad \lim_{n \rightarrow \infty} \epsilon_n n^{\frac{1}{2}} = \infty.$$

To get a version of  $D_n$  for which  $P(d(D_n, W_0) \geq \epsilon_n)$  tends to zero for a suitable choice of  $\epsilon_n$  we use the Skorokhod embedding.

Let  $Y_k = \sum_{j=1}^k X_j$ , where  $X_1, X_2, \dots$  is a sequence of independent, identically distributed random variables with

$$P(X_1 \geq x) = \exp(-x), \quad x \geq 0.$$

It is well known (see e.g. [1] page 285) that the random vectors  $(U_{1n}, U_{2n}, \dots, U_{nn})$  and  $(Y_1/Y_{n+1}, Y_2/Y_{n+2}, \dots, Y_n/Y_{n+1})$  have the same distribution. If  $S_{n+1}(t)$  is the “random broken line” defined by

$$(2.3) \quad \begin{aligned} S_{n+1}(t) &= (Y_j - j)/(n + 1)^{\frac{1}{2}}, \quad j/(n + 1) \leq t < (j + 1)/(n + 1) \\ &= [Y_{n+1} - (n + 1)]/(n + 1)^{\frac{1}{2}}, \quad t = 1 \end{aligned}$$

where  $j = 0, 1, 2, \dots, n$  and  $Z_0 \equiv 0$ , then

$$(2.4) \quad D_n(t) \cong \frac{n^{\frac{1}{2}}(n + 1)^{\frac{1}{2}}}{Y_{n+1}} (S_{n+1}(t) - tS_{n+1}(1)) + n^{\frac{1}{2}}(e_{n+1}(t) - t)$$

where  $\cong$  means that the two processes have the same distribution and  $e_{n+1}(t) = (n + 1)^{-1}[(n + 1)t]$ .

There exists a probability space with a Brownian motion  $W(t)$  and a sequence  $\tau_1, \tau_2, \dots$  of nonnegative, independent and identically distributed random variables with the following properties:

- (2.5) (a) the sequence  $\{(Y_k - k)/n^{\frac{1}{2}}\}, k \geq 1$  is distributed as the sequence  $\{W(\sum_{j=1}^k \tau_j/n)\}$ .
- (b)  $E(\tau_1) = 1, E|\tau_1|^r \leq 4r\Gamma(r)E(|X_1 - 1|^{2r}), r \geq 1$ .

$D_n$  can be represented on the same space as  $W(t)$  since

$$(2.6) \quad D_n(t) \cong \frac{n^{\frac{1}{2}}(n + 1)^{\frac{1}{2}}}{W((n + 1)^{-1} \sum_{j=1}^{n+1} \tau_j)} (\bar{S}_{n+1}(t) - t\bar{S}_{n+1}(1)) + n^{\frac{1}{2}}(e_{n+1}(t) - t)$$

where  $\bar{S}_{n+1}(t)$  is defined in (2.3) but with  $W(\sum_{k=1}^j \tau_k/n+1)$  replacing  $(Y_j - j)/(n+1)^{\frac{1}{2}}$  there.

Rosenkrantz [4] showed that for a version of  $D_n$  almost like that in (2.6)

$$(2.7) \quad P(d(D_n, W_0) \geq 12(\log n)n^{-\frac{1}{2}}) = O(n^{-\frac{1}{2}}),$$

where  $W_0(t) = W(t) - tW(1)$ . Slight modifications to the methods in [4] will yield (2.7) for  $D_n$  exactly as in (2.6). However, this result can be improved if in place of the estimate (27) in Rosenkrantz [3] one uses

$$(2.8) \quad P(\max_{1 \leq k \leq (n+1)} |\sum_{j=1}^k (\tau_j - 1)| \geq (n + 1)^{\frac{1}{2}} \log n) = O(n^{-1}).$$

This gives in place of Lemma 6 of [3], with  $\epsilon_n = 2(\log n)n^{-\frac{1}{2}}$  and  $\delta_n = n^{-\frac{1}{2}} \log n$ ,

$$(2.9) \quad P(\sup_{0 \leq t \leq 1} |W_{n+1}(t) - \bar{S}_{n+1}(t)| \geq \epsilon_n) = O(n^{-1}),$$

where

$$\begin{aligned} W_{n+1}(t) &= W(j/(n + 1)), & j/(n + 1) \leq t < (j + 1)/(n + 1) \\ &= W(1), & t = 1. \end{aligned}$$

Lemma 8 of [4] can now be sharpened in an obvious way to get

LEMMA 2.1. *There exists a probability space with a Brownian motion  $W(t)$  and  $\tau_1, \tau_2, \dots$  satisfying (2.5) so that for  $D_n$  as in (2.6)*

$$(2.10) \quad P(d(D_n, W_0) \geq 12(\log n)n^{-\frac{1}{2}}) = O(n^{-\frac{1}{2}}).$$

PROOF. This has been indicated above, apart from (2.8) which is established by a reasonably straightforward truncation argument which we will not give here.

We require two additional preliminary results.

LEMMA 2.2.  $P(\sup_{0 \leq t \leq 1} |D_n(t)| \geq 12(\log n)^{\frac{1}{2}}) = O(n^{-\frac{1}{2}})$ .

PROOF. From (2.4) it follows that,

$$\begin{aligned}
 &P(\sup_{0 \leq t \leq 1} |D_n(t)| \geq 12(\log n)^{\frac{1}{2}}) \\
 &\leq P(\sup_{0 \leq t \leq 1} |S_{n+1}(t) - tS_{n+1}(1)| \geq 12(\log n)^{\frac{1}{2}} Y_{n+1}/(n+1)) \\
 (2.11) \quad &\leq P(\sup_{0 \leq t \leq 1} |S_{n+1}(t) - tS_{n+1}(1)| \geq 12(\log n)^{\frac{1}{2}}(1 - \alpha_n)) \\
 &\quad + P\{|Y_{n+1} - (n+1)| \geq (n+1)\alpha_n\} \\
 &= P_n^{(1)} + P_n^{(2)}, \text{ say.}
 \end{aligned}$$

Choose  $\alpha_n = 3(\log n)^{\frac{1}{2}}/(n+1)^{\frac{1}{2}}$ . Then by Lemma 4(i) of [4] it follows immediately that

$$(2.12) \quad P_n^{(2)} = O(n^{-\frac{1}{2}}).$$

Since for sufficiently large  $n$ ,  $(1 - \alpha_n) \geq \frac{2}{3}$  it follows that

$$\begin{aligned}
 &P_n^{(1)} \leq P\{\sup_{0 \leq t \leq 1} |S_{n+1}(t) - tS_{n+1}(1)| \geq 8(\log n)^{\frac{1}{2}}\} \\
 &\leq P\{\max_{1 \leq k \leq 1} |\sum_{j=1}^k (X_j - 1)/(n+1)^{\frac{1}{2}}| \geq 4(\log n)^{\frac{1}{2}}\} \\
 (2.13) \quad &\leq 2P\{|Y_{n+1} - (n+1)| \geq 4[(n+1) \log n]^{\frac{1}{2}} - (2(n+1))^{\frac{1}{2}}\} \\
 &\leq 2P\{|Y_{n+1} - (n+1)| \geq (n+1)\alpha_n\} \quad \text{for large enough } n, \\
 &= O(n^{-\frac{1}{2}}), \quad \text{by Lemma 4(i) of [4].}
 \end{aligned}$$

The result follows from (2.11), (2.12) and (2.13).

LEMMA 2.3. For some  $0 < \lambda < 1$  and  $0 < \alpha \leq \frac{1}{2}$ , let

$$(2.14) \quad \alpha_n = 12(1 - \lambda)^{-1}(\log n/n)^{\frac{1}{2}}$$

and

$$\begin{aligned}
 (2.15) \quad &q_\alpha(t) = t^{\frac{1}{2}-\alpha}, \quad 0 \leq t \leq \frac{1}{2} \\
 &= q_\alpha(1 - t), \quad \frac{1}{2} \leq t \leq 1.
 \end{aligned}$$

For any constant  $C > 0$ ,

$$(2.16) \quad P(\sup_{0 \leq t \leq \alpha_n} (|W_0(t)|/q_\alpha(t)) \geq C(\log n)^{3/4+\alpha/2}n^{-\alpha/2}) = O(n^{-1}).$$

PROOF.

$$\begin{aligned}
 &P\{|W_0(t)| \geq C(\log n)^{3/4+\alpha/2}n^{-\alpha/2}q_\alpha(t) \text{ for some } 0 \leq t \leq \alpha_n\} \\
 &\leq P\left\{|W(t)| \geq \frac{C}{2}(\log n)^{3/4+\alpha/2}n^{-\alpha/2}q_\alpha(t) \text{ for some } 0 \leq t \leq \alpha_n\right\} \\
 &\quad + P\left\{|W(1)| \geq \frac{C}{2}(\log n)^{3/4+\alpha/2}n^{-\alpha/2}\alpha_n^{-\frac{1}{2}-\alpha}\right\} \\
 &= P_n^{(1)} + P_n^{(2)}, \text{ say.}
 \end{aligned}$$

Let  $C_n = \frac{1}{2}C(\log n)^{3/4+\alpha/2}n^{-\alpha/2}$ . Then

$$(2.17) \quad P_n^{(1)} \leq 2P\{W(t) \geq C_n t^{\frac{1}{2}-\alpha} \text{ for some } 0 < t \leq \alpha_n\}.$$

Let  $r$  be a real number between 0 and 1 and let  $k(\alpha_n)$  denote the largest integer  $k$  such that  $r^k \geq \alpha_n$ . Then

$$\begin{aligned}
 P_n^{(1)} &\leq 2 \sum_{k \geq k(\alpha_n)} P\{\max_{r^{k+1} \leq t \leq r^k} W(t) \geq C_n r^{(k+1)(\frac{1}{2}-\alpha)}\} \\
 (2.18) \quad &\leq 2 \sum_{k \geq k(\alpha_n)} P\{\max_{0 \leq t \leq r^k} W(t) \geq C_n r^{(k+1)(\frac{1}{2}-\alpha)}\} \\
 &\leq 4 \sum_{k \geq k(\alpha_n)} P\{W(1) \geq C_n r^{(k+1)(\frac{1}{2}-\alpha)-k/2}\} \\
 &\leq [4(2\pi)^{-\frac{1}{2}}/C_n] \sum_{k \geq k(\alpha_n)} r^{k\alpha - (\frac{1}{2}-\alpha)} \exp\{-\frac{1}{2}(C_n^2 r^{-2k\alpha+2(\frac{1}{2}-\alpha)})\}.
 \end{aligned}$$

The last sum is bounded by the following integral,

$$(2.19) \quad [4(2\pi)^{-\frac{1}{2}}/C_n] \int_{k(\alpha_n)-1}^{\infty} r^{x\alpha - (\frac{1}{2}-\alpha)} \exp\{-\frac{1}{2}(C_n^2 r^{-2x\alpha+2(\frac{1}{2}-\alpha)})\} dx.$$

Make the change of variable  $y = f(x)$  where

$$(2.20) \quad f(x) = C_n r^{-x\alpha + (\frac{1}{2}-\alpha)}.$$

A routine calculation transforms (2.17) into

$$(2.21) \quad 4(2\pi)^{-\frac{1}{2}} \int_{\beta_n}^{\infty} y^{-2} \exp(-y^2) dy,$$

where

$$(2.22) \quad \beta_n = f[k(\theta_n) - 1] \geq (\log n)^{\frac{1}{2}} \quad \text{for large enough } n.$$

It is clear then that (2.21), and hence  $P_n^{(1)}$ , is  $O(n^{-1})$ .  $P_n^{(2)}$  is easily estimated to be  $O(n^{-1})$ .

**3. Rates of convergence.** For  $0 < \lambda < 1$  define  $V_n(\lambda)$  by

$$(3.1) \quad V_n(\lambda) = n^{\frac{1}{2}} \int_{\alpha_n}^{1-\alpha_n} \{h[F_n^{-1}(t)] - h(t)\} d\nu(t),$$

with  $\alpha_n = 12(1 - \lambda)^{-1}(\log n/n)^{\frac{1}{2}}$ . Let  $G_n(\lambda; x)$  denote the distribution function of  $V_n(\lambda)$ . That is

$$G_n(\lambda; x) = P(S_n(\lambda) \leq x).$$

Denote by  $\Phi$  the standard normal distribution function. Let

$$q_\alpha'(t) = \{t(1 - t)\}q_\alpha(t).$$

Our first result is

**THEOREM 3.1.** *Suppose  $h'(t)$  exists on  $(0, 1)$  and that for some  $0 < \alpha \leq \frac{1}{2}$  and  $0 < \lambda < 1$  the following conditions are satisfied.*

$$(3.2) \quad \int_0^1 |h'(t)|q_\alpha(t) d|\nu| < \infty.$$

$$(3.3) \quad |h'(t_1) - h'(t_2)| \leq K_\lambda(t)|t_1 - t_2| \quad \text{for } t_1, t_2 \text{ in } [\lambda t, 1 - \lambda(1 - t)], \\
 0 < t < 1,$$

where  $K$  is a nonnegative function, non-increasing on  $[0, \frac{1}{2}]$ , with  $K(t) = K(1 - t)$  and

$$(3.4) \quad \int_0^1 K_\lambda(t)q_\alpha'(t) d|\nu| < \infty,$$

where

$$(3.5) \quad \begin{aligned} K_\lambda(t) &= K(\lambda t), & 0 < t \leq \frac{1}{2} \\ &= K[\lambda(1 - t)], & \frac{1}{2} \leq t < 1. \end{aligned}$$

Then

$$(3.6) \quad \max_{-\infty < x < \infty} |G_n(\lambda; x) - \Phi(x/\sigma)| = O\{(\log n)^{3/4+\alpha/2} n^{-\alpha/2}\}$$

where  $\sigma$  is defined by

$$(3.7) \quad \sigma^2 = \int_0^1 \int_0^t h'(t)h'(s)s(1-t) d\nu(s) d\nu(t).$$

PROOF. Let  $b_n = C(\log n)^{3/4+\alpha/2} n^{-\alpha/2}$  where

$$C = 36 \max (\int_0^1 |h'(t)|q_\alpha(t) d|\nu|, \int_0^1 K_\lambda(t)q_\alpha'(t) d|\nu|).$$

The first step in the proof is to show that

$$(3.8) \quad P(|V_n(\lambda) - \int_0^1 h'(t)W_0(t) d\nu| \geq b_n) = O(n^{-1/2}).$$

The left-hand side of (3.8) is bounded above by  $P_n^{(1)} + P_n^{(2)} + P_n^{(3)}$  where

$$(3.9) \quad \begin{aligned} P_n^{(1)} &= P\{d(D_n, W_0)(\alpha_n)^{-\frac{3}{2}+\alpha} \int_{\alpha_n}^{1-\alpha_n} |A_n - h'(t)|q_\alpha'(t) d|\nu| \geq b_n/3\}, \\ P_n^{(2)} &= P\{|\int_{\alpha_n}^{1-\alpha_n} (\Delta_n - h')W_0 d\nu| \geq b_n/3\} \\ P_n^{(3)} &= P\{d_{q_\alpha}(I_n D_n, W_0) \int_0^1 |h'(t)|q_\alpha(t) d|\nu| \geq b_n/3\}, \end{aligned}$$

where  $I_n$  is the indicator function of the interval  $[\alpha_n, 1 - \alpha_n]$ , and

$$(3.10) \quad d_{q_\alpha}(x, y) = \sup (|x(t) - y(t)|/q_\alpha(t); 0 \leq t \leq 1).$$

Let  $B_n$  be the event that  $\sup |F_n^{-1}(t) - t| < 12(\log n/n)^{1/2}$ . Then on  $B_n$  for all  $t$  in  $[\alpha_n, 1 - \alpha_n]$ ,

$$(3.11) \quad |A_n(t) - h'(t)| \leq K_\lambda(t)|F_n^{-1}(t) - t| \leq K_\lambda(t)12(\log n/n)^{1/2}$$

so that, by Lemma 2.2,

$$(3.12) \quad \begin{aligned} P_n^{(1)} &\leq P\{d(D_n, W_0) \geq 12(\log n)n^{-1/2}\} + O(n^{-1/2}) \\ &= O(n^{-1/2}) \end{aligned} \quad \text{by Lemma 2.1.}$$

Similarly, by intersecting the event of  $P_n^{(2)}$  with the event  $B_n$  one obtains

$$(3.13) \quad \begin{aligned} P_n^{(2)} &\leq P\{12(\log n/n)^{1/2}(\alpha_n)^{-1+\alpha} |\int_0^1 K_\lambda(t)W_0(t)t^{1-\alpha} d\nu| \geq b_n/3\} + O(n^{-1/2}) \\ &\leq P\{|\int_0^1 K_\lambda(t)W_0(t)t^{1-\alpha} d\nu| \geq (\log n)^{3/2}\} + O(n^{-1/2}) \\ &= O(n^{-1/2}) \end{aligned}$$

since by condition (3.4)  $\int_0^1 K_\lambda(t)W_0(t)t^{1-\alpha} d\nu$  is a well-defined normal random variable with zero mean. Now

$$(3.14) \quad \begin{aligned} P_n^{(3)} &\leq P\{d(D_n, W_0) \geq 12(\log n)^{3/4+\alpha/2} n^{-\alpha/2} q_\alpha(\alpha_n)\} \\ &\quad + P\{|W_0(t)| \geq Cq_\alpha(t)b_n \text{ for some } 0 < t \leq \alpha_n\} \\ &= P\{d(D_n, W_0) \geq 12(\log n)n^{-1/2}\} + O(n^{-1}), \quad \text{by Lemma 2.3} \\ &= O(n^{-1/2}), \quad \text{by Lemma 2.1.} \end{aligned}$$

Hence (3.8) holds. The limiting random variable  $\int_0^1 h'(t)W_0(t) d\nu(t)$  is clearly normal with mean 0 and variance  $\sigma^2$  given by (3.7). Now

$$(3.15) \quad |\Phi(x_1/\sigma) - \Phi(x_2/\sigma)| \leq (2\pi\sigma^2)^{-1/2}|x_1 - x_2|$$

and this together with (3.8) yields

$$(3.16) \quad \Phi(x/\sigma) - r(n) \leq G_n(\lambda; x) \leq \Phi(x/\sigma) + r(n)$$

where

$$(3.17) \quad \begin{aligned} r(n) &= O(n^{-\frac{1}{2}}) + (2\pi\sigma^2)^{-\frac{1}{2}}b_n \\ &= O[(\log n)^{3/4+\alpha/2}n^{-\alpha/2}]. \end{aligned}$$

The authors are indebted to one of the referees for pointing out that the ‘‘right’’ exponent of  $t$  in the function  $q_\alpha'(t)$  is  $\frac{3}{2} - \alpha$  rather than the authors’ original  $1 - \alpha$ . Also the idea of the ‘‘shifted’’ function  $K_\lambda$  is due to Shorack in [5].

In some applications the weights are given by  $C_{jn} = J(j/n + 1)$ ,  $1 \leq j \leq n$ ,  $n > 1$ , for some Borel measurable function  $J$  on  $(0, 1)$ . Let  $G_n(x)$  be the distribution function of the normalized statistic  $n^\lambda(\bar{T}_n - \mu_n)$  where for some  $0 < \lambda < 1$ ,

$$(3.18) \quad \mu_n = \int_{\alpha_n}^{1-\alpha_n} h(t)J(t) dt.$$

**THEOREM 3.2.** *Suppose that for some  $0 < \alpha \leq \frac{1}{2}$  and  $0 < \lambda < 1$  the conditions of Theorem 3.1 hold with  $\nu$  defined by*

$$(3.19) \quad \nu((a, b]) = \int_a^b J(t) dt.$$

*If in addition there exist nonnegative functions  $\bar{h}$  and  $\bar{J}$ , increasing on  $[\frac{1}{2}, 1]$  and symmetric about  $\frac{1}{2}$  such that  $|h(t)| \leq \bar{h}(t)$  a.s.  $|\nu|$  and*

$$|J(t_1) - J(t_2)| \leq \bar{J}_\lambda(t)|t_1 - t_2| \quad \text{for } t_1, t_2 \text{ in } [\lambda t, 1 - \lambda(1 - t)]$$

and

$$(3.20) \quad \begin{aligned} \int_0^1 \bar{h}_\lambda(t)\bar{J}_\lambda(t)[t(1-t)]^{\frac{1}{2}} dt &< \infty \\ \int_0^1 \bar{h}_\lambda(t)J(t)[t(1-t)]^{\frac{1}{2}} dt &< \infty \end{aligned}$$

then

$$(3.21) \quad \max_{-\infty < x < \infty} |G_n(x) - \Phi(x/\sigma)| = O(n^{-\alpha/2}(\log n)^{3/4+\alpha/2}).$$

**PROOF.**

$$(3.22) \quad n^\lambda(T_n - \mu_n) = S_n(\lambda) + R_n$$

where

$$(3.23) \quad R_n = n^\lambda \int_{\alpha_n}^{1-\alpha_n} h[F_n^{-1}(t)][(n+1)/nJ_n(t) - J(t)] dt.$$

Let  $b_n$  be as in the proof of Theorem 2. Then

$$(3.24) \quad \begin{aligned} P\{|n^\lambda(T_n - \mu_n) - \int_0^1 h'(t)W_0(t)J(t) dt| \geq 2b_n\} \\ \leq P\{|S_n(\lambda) - \int_0^1 h'(t)W_0(t)J(t) dt| \geq b_n\} + P\{|R_n| \geq b_n\} \\ = O[n^{-\alpha/2}(\log n)^{3/4+\alpha/2}] + P\{|R_n| \geq b_n\}, \quad \text{by Theorem 3.1.} \end{aligned}$$

It is now a fairly straightforward matter to see that the additional conditions in the hypothesis of the theorem imply

$$(3.25) \quad P(|R_n| \geq b_n) = O(n^{-\frac{1}{2}}).$$

The theorem follows from (3.24) and (3.25).

If  $h = [t(1 - t)]^{-a}$  and  $d\nu = J = [t(1 - t)]^{-\frac{1}{2}+a+2\alpha}$  then with  $\bar{h} = h$  and  $\bar{J} = J'$ ,  $K = h''$  the conditions of Theorem (3.2) hold.

**4. The “right” rate.** In general the rate of convergence will depend on the weight function. However, one may conjecture that at least in some situations the “right” rate is  $n^{-\frac{1}{2}}$ . Our methods yield a rate  $n^{-\frac{1}{2}}$  when the conditions of Theorems 3.1 and 3.2 are satisfied for  $\alpha = \frac{1}{2}$ . This will be the case, for example, when the extreme order statistics are given zero weight; that is, for some  $0 < \delta < \frac{1}{2}$ ,  $\nu((\delta, 1 - \delta)') = 0$ . Moreover,  $n^{-\frac{1}{2}}$  is the largest possible rate that can be obtained by these methods. This is so because the rate is bounded by the sequence of constants  $\epsilon_n$  for which  $P(d(D_n, W_0) \geq \epsilon_n) \rightarrow 0$  for any constant  $\epsilon > 0$

$$(4.1) \quad \liminf_{n \rightarrow \infty} P(d(D_n, W_0) \geq \epsilon n^{-\frac{1}{2}}) > 0.$$

To show that (4.1) holds it is sufficient to establish the corresponding result for  $\bar{S}_n$  and  $W$ . Using the notation of Rosenkrantz [3] let

$$Z_{nk} = \sum_{j=1}^k (T_j - 1)/n$$

and  $B_n$  denote the event:

$$B_n = \left\{ \max_{1 \leq k \leq n} \left| W\left(\frac{k}{n} + Z_{nk}\right) - W\left(\frac{k}{n}\right) \right| \geq \epsilon n^{-\frac{1}{2}} \right\}$$

and note  $B_n = B_{n1} \cup B_{n2}$  where

$$B_{n1} = B_n \cap \{ \max_{1 \leq k \leq n} |Z_{nk}| \leq \delta_n \}$$

and

$$B_{n2} = B_n \cap \{ \max_{1 \leq k \leq n} |Z_{nk}| > \delta_n \}$$

where  $\delta_n > 0$  is a sequence whose dependence on  $n$  will be specified later. Now

$$(4.2) \quad \begin{aligned} P(d(\bar{S}_n, W) \geq \epsilon n^{-\frac{1}{2}}) &= P(B_n) \\ &\geq P(B_{n2}) \\ &\geq P(\bar{S}_n(1) - W(1) \geq \epsilon n^{-\frac{1}{2}}, Z_{nn} < -\delta_n) \\ &= \int_{-\delta_n}^{\infty} P(W(1+t) - W(1) \geq \epsilon n^{-\frac{1}{2}} / Z_{nn} = t) F_n(dt), \end{aligned}$$

where  $F_n(t) = P(Z_{nn} \leq t)$ . Use the strong Markov property for Brownian motion to write the right-hand side of (4.2) as

$$(4.3) \quad \begin{aligned} &\int_{-\delta_n}^{\infty} P(W(1+t) - W(1) \geq \epsilon n^{-\frac{1}{2}}) F_n(dt) \\ &= (2\pi)^{-\frac{1}{2}} \int_{-\delta_n}^{\infty} \int_{\epsilon n^{-\frac{1}{2}}(-t)^{-\frac{1}{2}}}^{\infty} e^{-s^2/2} ds F_n(dt) \\ &\geq (2\pi)^{-\frac{1}{2}} \int_0^C e^{-s^2/2} P\left(Z_{nn} \leq -\frac{\epsilon^2 n^{-\frac{1}{2}}}{s^2}\right) ds \end{aligned}$$

for  $\delta_n$  chosen so that  $\epsilon^2 n^{-\frac{1}{2}} / \delta_n \rightarrow \infty$  and  $n$  large enough that  $\epsilon^2 n^{-\frac{1}{2}} / \delta_n > C$ , where  $C$  is an arbitrary constant. By the central limit theorem,



$$(4.4) \quad P\left(Z_{nn} \leq -\frac{\varepsilon^2 n^{-\frac{1}{2}}}{s^2}\right) \rightarrow \Phi(-\varepsilon^2/\gamma s^2),$$

where  $\gamma^2$  is the variance of  $\tau_1$ . By the dominated convergence theorem the right-hand side of (4.3) tends as  $n \rightarrow \infty$  to

$$(4.4) \quad (2\pi)^{-\frac{1}{2}} \int_0^\infty e^{-s^2/2} \Phi(-\varepsilon^2/\gamma s^2) ds > 0.$$

It follows from (4.2), (4.3) and (4.4) that

$$(4.5) \quad \liminf_{n \rightarrow \infty} P(d(\bar{S}_n, W) \geq \varepsilon n^{-\frac{1}{2}}) \geq (2\pi)^{-\frac{1}{2}} \int_0^\infty e^{-s^2/2} \Phi(-\varepsilon^2/\gamma s^2) ds$$

where the right side of (4.5) is strictly greater than zero.

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