

ORDER OF NORMAL APPROXIMATION FOR RANK TEST STATISTICS DISTRIBUTION

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0. Summary. Under suitable assumptions, it is established that the rate of convergence of the cdf (cumulative distribution function) of the simple linear rank statistics

$$S_N = \sum_{i=1}^N C_{Ni} \varphi \left(\frac{R_{Ni}}{N+1} \right)$$

to the normal one is $O(N^{-\frac{1}{2}+\delta})$ for any $\delta > 0$. Here C_{N1}, \dots, C_{NN} are known constants, R_{N1}, \dots, R_{NN} are the ranks of independent observations X_{N1}, \dots, X_{NN} , and φ is a score generating function defined in Section 1.

1. Introduction. Let X_{Ni} , $i = 1, \dots, N$ be independent rvs distributed according to the cdf $F_i(x) = F(x - \Delta d_{Ni})$, $i = 1, \dots, N$. We assumed that $F(x)$ is absolutely continuous having the density function $f(x)$ whose derivative $f'(x)$ exists. Furthermore, $F(x)$ is assumed to have the finite Fisher information, that is,

$$(1.1) \quad I(f) = \int_{-\infty}^{\infty} [f'(x)/f(x)]^2 f(x) dx < \infty.$$

Δ is an unknown parameter, and d_{Ni} , $i = 1, \dots, N$ are known constants. Let R_{Ni} be the rank of X_{Ni} among X_{N1}, \dots, X_{NN} . Setting $u(x) = 1$ if $x \geq 0$, and $u(x) = 0$ otherwise, we can write

$$(1.2) \quad R_{Ni} = \sum_{j=1}^N u(X_{Ni} - X_{Nj}), \quad i = 1, \dots, N.$$

Consider now the simple linear rank statistics

$$(1.3) \quad S_N = \sum_{i=1}^N C_{Ni} a_N(R_{Ni})$$

where C_{N1}, \dots, C_{NN} are known constants, and $a_N(i)$, $i = 1, \dots, N$ are "scores" generated by a function $\varphi(t)$ in the following manner:

$$(1.4) \quad a_N(i) = \varphi \left(\frac{i}{N+1} \right), \quad 1 \leq i \leq N.$$

Statistics of the type (1.3) play an important role in the theory of nonparametric inference. For example, in the two sample problem where $F_1 = \dots = F_m \equiv F$, and

$$F_{m+1} = \dots = F_N \equiv G,$$

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for testing the hypothesis $H_0: F \equiv G$, many rank tests are based on the statistic

$$S_N' = \sum_{i=1}^m a_N(R_{Ni})$$

which is a special case of (1.3) when $C_{N1} = \dots = C_{Nm} = 1$ and $C_{Nm+1} = \dots = C_{NN} = 0$. It is well known (see e.g., Capon (1961)) that the statistics of the form (1.3) for different score functions yield locally most powerful rank tests. Under suitable assumptions on the C 's and the score generating function φ , Hájek (1962) [see also Hájek-Šidák (1967)] established the asymptotic normality of S_N . However, the problem of determining the rate of convergence of the cdf of S_N to the limiting normal distribution has remained open. This problem is investigated in this paper for the case $\Delta = 0$ as well as for $\Delta \neq 0$. In both cases, the rate of convergence is proved to be $O(N^{-\frac{1}{2}+\delta})$ for $\delta > 0$. For the case $\Delta = 0$, the result is valid for the φ functions having the bounded first derivative, and for the case $\Delta \neq 0$, it is necessary to assume the boundedness of the fourth derivative of φ .

Throughout the paper, we shall make the following assumptions on C 's and d 's.

$$(1.5) \quad \sum_{i=1}^N C_{Ni} = \sum_{i=1}^N d_{Ni} = 0, \quad \sum_{i=1}^N C_{Ni}^2 = \sum_{i=1}^N d_{Ni}^2 = 1,$$

$$(1.6) \quad \max_{1 \leq i \leq N} C_{Ni}^2 = O(N^{-1} \log N), \quad \max_{1 \leq i \leq N} d_{Ni}^2 = O(N^{-1} \log N).$$

It may be noted that the assumption (1.5) can be made without any loss of generality. Furthermore, it may be noted [cf. Hájek-Šidák (1967)] that if φ is the difference of two non-decreasing, square integrable functions in $(0, 1)$, then S_N has asymptotically $\eta(0, \sigma^2)$ distribution under $\Delta = 0$, and $\eta(ES_N, \sigma^2)$ or

$$\eta(\Delta \sum_{i=1}^N C_{Ni} d_{Ni} \int_0^1 \varphi(t) \varphi(t, f) dt, \sigma^2)$$

distribution under $\Delta \neq 0$. Here

$$\sigma^2 = \int_0^1 (\varphi(t) - \bar{\varphi})^2 dt, \quad \bar{\varphi} = \int_0^1 \varphi(t) dt, \quad \varphi(t, f) = \frac{-f'(F^{-1}(t))}{f(F^{-1}(t))}$$

and $\eta(\xi, \sigma^2)$ stands for the normal distribution with mean ξ and variance σ^2 .

2. Rate of convergence for $\Delta = 0$. The main result of this section is the following theorem.

THEOREM 2.1. *Let $\Delta = 0$ and the first derivative of $\varphi(t)$ exist and be bounded in $(0, 1)$. Then, under the assumptions of Section 1, corresponding to any $\delta > 0$, there exists a constant $A(\delta) > 0$, and a positive integer N_δ such that for all $N > N_\delta$,*

$$(2.1) \quad \sup_{-\infty < x < \infty} |F_N(x) - \Phi(x)| \leq A(\delta) N^{-(\frac{1}{2}+\delta)}$$

where $F_N(x)$ is the cdf of $\sigma^{-1}S_N$ and $\Phi(x)$ is the standard normal cdf.

The proof of this theorem is based on the following two lemmas, the second of which is a consequence of Theorem 6, Chapter 5 of Petrov (1972).

LEMMA 2.1. *Under the assumptions of Theorem 2.1, corresponding to any positive integer k , where $2k + 1 < N$, there exists a constant $B(k) > 0$ and a positive integer N_k such that for all $N > N_k$,*

$$(2.2) \quad E(S_N - T_N)^{2k} \leq B(k) N^{-k}$$

where

$$(2.3) \quad T_N = \sum_{i=1}^N C_i \varphi(F(X_i)) .$$

LEMMA 2.2. Under assumptions of Section 2 and Theorem 2.1, for any positive integer N ,

$$(2.4) \quad \sup_{-\infty < x < \infty} |F_N^*(x) - \Phi(x)| \leq A \int_0^1 |\varphi(t) - \tilde{\varphi}|^3 dt \cdot \sum_{i=1}^N |C_{Ni}|^3$$

where $A > 0$ is a constant independent of N , and F_N^* is the cdf of $\sigma^{-1}T_N$ under $\Delta = 0$.

In what follows, we shall suppress the subscript N in C_{Ni} , d_{Ni} , R_{Ni} , etc. whenever there is no confusion.

PROOF OF LEMMA 2.1. Set $U_i = F(X_i)$, $i = 1, \dots, N$. Denoting $Y_i = a_N(R_i) - \varphi(U_i)$, $i = 1, \dots, N$, we get

$$(2.5) \quad \begin{aligned} E[(S_N - T_N)^{2k}] &= E[(\sum_{i=1}^N c_i Y_i)^{2k}] \\ &= \sum \frac{(2k)!}{p_1! \cdots p_N!} c_1^{p_1} \cdots c_N^{p_N} E(\prod_{i=1}^N Y_i^{p_i}) \end{aligned}$$

where the sum extends over the set A of vectors (p_1, \dots, p_N) of integers such that $0 \leq p_i \leq 2k$, $i = 1, \dots, N$, $\sum_{i=1}^N p_i = 2k$.

Each point of A could have at most $2k$ positive components. Noting this fact, we may decompose A into $2k$ disjoint parts such that the j th part consists of those points which have just j positive components. Thus we may rewrite (2.5) as

$$(2.6) \quad \begin{aligned} E[(S_N - T_N)^{2k}] &= \sum_{i=1}^N c_i^{2k} E Y_i^{2k} + \cdots \\ &+ \sum_{1 \leq p_1, \dots, p_m < 2k, p_1 + \dots + p_m = 2k} \frac{(2k)!}{p_1! \cdots p_m!} \\ &\times \sum_{i_1, \dots, i_m=1, \text{different}}^N c_{i_1}^{p_1} \cdots c_{i_m}^{p_m} E(Y_{i_1}^{p_1} \cdots Y_{i_m}^{p_m}) + \cdots \\ &+ \sum_{i_1, \dots, i_{2k}=1, \text{different}}^N c_{i_1} \cdots c_{i_{2k}} E(Y_{i_1} \cdots Y_{i_{2k}}) . \end{aligned}$$

In view of (1.5) and (1.6), it follows that

$$(2.7) \quad |\sum_{i_1, \dots, i_m=1, \text{different}}^N c_{i_1}^{p_1} \cdots c_{i_m}^{p_m}| \leq K \quad \text{for } N > N_k$$

for any $m = 1, \dots, 2k$ and any p_i , $0 < p_i < 2k$, $i = 1, \dots, m$, $\sum_{i=1}^m p_i = 2k$, $K > 0$ is a constant dependent only on k . Actually, if $p_i \geq 2$ for $i = 1, \dots, m$, then

$$|\sum_{i_1, \dots, i_m=1, \text{different}}^N c_{i_1}^{p_1} \cdots c_{i_m}^{p_m}| \leq |\prod_{j=1}^m (\sum_{i=1}^N |c_i|^{p_j})| \leq \max_{1 \leq i \leq N} |c_i|^{2(k-m)} .$$

On the other hand, suppose that some of p_i 's are equal to one, say $p_m = 1$. Then in view of (1.5)

$$(2.8) \quad \begin{aligned} \sum_{i_1, \dots, i_m=1, \text{different}}^N c_{i_1}^{p_1} \cdots c_{i_m}^{p_m} \\ = \sum_{i_1, \dots, i_{m-1}=1, \text{different}}^N c_{i_1}^{p_1} \cdots c_{i_{m-1}}^{p_{m-1}} (-c_{i_1} - \cdots - c_{i_{m-1}}) \end{aligned}$$

so that we get $m - 1$ sums of similar type; each of them sums the products of $(m - 1)$ factors. Considering any of these sums, we may have again two cases:

either all exponents are at least two, so that we are in the first case; or some of them equal one and we may write an equality analogous to (2.8). We continue in this way until after a finite number of steps (in which we decompose the original expression into at most $m!$ sums) we get only the sums with exponents greater than or equal to two. Actually, the extreme case is the sum of the type

$$\sum_{i_1, i_2=1, i_1 \neq i_2}^N c_{i_1}^{2k-1} c_{i_2} = - \sum_{i_1=1}^N c_{i_1}^{2k},$$

so that (2.7) is proved.

Further, using the generalized Cauchy-Schwarz inequality

$$(2.9) \quad E|\prod_{i=1}^n Z_i| \leq (\prod_{i=1}^n E|Z_i|^n)^{1/n}, \quad n = 2, 3, \dots$$

we see that

$$(2.10) \quad E|Y_{i_1}^{p_1} \dots Y_{i_m}^{p_m}| \leq (\prod_{j=1}^m E|Y_{i_j}^{p_j}|)^{1/m} < (\prod_{j=1}^m E|Y_{i_j}^{2kp_j}|)^{1/2k} \\ = (\prod_{j=1}^m E|a_N(R_1) - \varphi(U_1)|^{2kp_j})^{1/2k}$$

holds for any $m = 1, \dots, 2k$ and any p_i , $0 < p_i \leq 2k$, $\sum_{i=1}^m p_i = 2k$. Finally, the expression

$$(2.11) \quad \sum_{m=1}^{2k} \sum_{1 \leq p_1, \dots, p_m \leq 2k, p_1 + \dots + p_m = 2k} \frac{(2k)!}{p_1! \dots p_m!}$$

depends only on k .

Now, if $a_N(i) = \varphi(i/(N+1))$, $i = 1, \dots, N$, where φ has a bounded derivative we get the inequality

$$(2.12) \quad E[a_N(R_1) - \varphi(U_1)]^{2kp_j} \leq B_2(k)E\left[\frac{R_1}{N+1} - U_1\right]^{2kp_j}$$

which is varied for $j = 1, \dots, m$; $m = 1, \dots, 2k$.

U_1 being fixed, R_1 is the sum of independent zero-one random variables (see (1.2)) so that

$$(2.13) \quad E\left(\frac{R_{N1}}{N+1} - U_{N1}\right)^{2kp_j} \leq B_3(k)N^{-kp_j}.$$

(2.6), (2.7), (2.10), (2.11), (2.12) and (2.13) then prove the lemma.

PROOF OF THEOREM 2.1. Since for any $\varepsilon > 0$ and any N , we have

$$(2.14) \quad P\{\sigma^{-1}S_N \leq x\} \leq P\{\sigma^{-1}T_N \leq x + \varepsilon\} + P\{\sigma^{-1}|S_N - T_N| \geq \varepsilon\}$$

and analogously

$$(2.15) \quad P\{\sigma^{-1}S_N \leq x\} \geq P\{\sigma^{-1}T_N \leq x - \varepsilon\} - P\{\sigma^{-1}|S_N - T_N| \geq \varepsilon\},$$

it follows using Lemmas 2.1 and 2.2, that

$$(2.16) \quad \sup_{-\infty < x < \infty} |F_N(x) - \Phi(x)| \leq (\varepsilon\sigma)^{-2k} B(k)N^{-k} + c_2 \sum_{i=1}^N |c_{Ni}|^3 + O(\varepsilon)$$

holds for any $\varepsilon > 0$, any k and for $N > N_k$.

For $\delta > 0$ being fixed, take k such that $2k+1 > 1/2\delta \geq 2k$ and put $\varepsilon = N^{-\frac{1}{2}(1-1/(2k+1))}$. The theorem then follows from (2.13) and from the assumption (1.6).

3. Rate of convergence for $\Delta \neq 0$. Without loss of generality, we assume that $\Delta > 0$. For convenience we shall use the following representation in this section. Let X_{Ni} , $i = 1, \dots, N$ be independent and identically distributed rvs each having the cdf $F(x)$ such that $I(f) < \infty$. Let R_{Ni}^A be the rank of $X_{Ni} + \Delta d_{Ni}$, that is

$$R_{Ni}^A = \sum_{j=1}^N u(X_{Ni} - X_{Nj} + \Delta(d_{Ni} - d_{Nj})).$$

Consider now the statistics

$$S_{\Delta N} = \sum_{i=1}^N c_{Ni} \varphi \left(\frac{R_{Ni}^A}{N+1} \right).$$

The asymptotic distribution of $S_{\Delta N} - S_{0N}$ was investigated by Jurečková for Wilcoxon scores in (1973a) and for general score function φ in (1973b). In the case of general scores function φ , it was assumed that the φ function has the four bounded derivatives in $(0, 1)$.

Suppose now that the vectors (c_{N1}, \dots, c_{NN}) and (d_{N1}, \dots, d_{NN}) satisfy (1.5), (1.6) and the following:

$$(3.1) \quad \lim_{N \rightarrow \infty} \sum_{i=1}^N c_{Ni} d_{Ni} = a^2, \quad 0 < a^2 < \infty,$$

$$(3.2) \quad \lim_{N \rightarrow \infty} [\max_{1 \leq i \leq N} (c_{Ni}^2 d_{Ni}^2) (\sum_{i=1}^N c_{Ni}^2 d_{Ni}^2)^{-1}] = 0,$$

and

$$(3.3) \quad \lim_{N \rightarrow \infty} [N^{-1} (\sum_{i=1}^N c_{Ni} d_{Ni})^2 (\sum_{i=1}^N c_{Ni}^2 d_{Ni}^2)^{-1}] = \gamma \geq 0.$$

Then, [cf. Jurečková (1973b)] for φ having four bounded derivatives in $(0, 1)$, the asymptotic distribution of

$$(3.4) \quad A_N^{-1}(S_{\Delta N} - S_{0N} - \Delta a_N - \Delta^2 b_N)$$

is $\eta(0, \Delta^2 \rho^2)$ where

$$(3.5) \quad A_N^{-2} = \sum_{i=1}^N c_{Ni}^2 d_{Ni}^2 + 3N^{-1} (\sum_{i=1}^N c_{Ni} d_{Ni})^2$$

$$(3.6) \quad a_N = \sum_{i=1}^N c_{Ni} d_{Ni} \int \varphi'(F(x)) f^2(x) dx = \sum_{i=1}^N c_{Ni} d_{Ni} \int_0^1 \varphi(t) \varphi(t, f) dt$$

$$(3.7) \quad b_N = \frac{1}{2} \sum_{i=1}^N c_{Ni} d_{Ni} \int \varphi''(F(x)) f^3(x) dx$$

and

$$(3.8) \quad \begin{aligned} \rho^2 = & \int [\varphi'(F(x))]^2 f^3(x) dx - (\int [\varphi'(F(x))]^2 f^2(x) dx)^2 + 2\gamma(1 + 3\gamma)^{-1} \\ & \times [\int \int_{x < y} F(x)(1 - F(y)) \varphi''(F(x)) \varphi''(F(y)) f^2(x) f^2(y) dx dy \\ & + \int \int_{x < y} \varphi'(F(x)) \varphi''(F(y)) f^2(x) f^2(y) dx dy \\ & - \int \varphi'(F(x)) f(x) dx \cdot \int \varphi''(F(x)) F(x) f^2(x) dx. \end{aligned}$$

Let $F_{N\Delta}$ denote the cdf of $\sigma^{-1}(S_{\Delta N} - \Delta a_N)$. Then we have the following theorem.

THEOREM 3.1. Suppose that c_{Ni} , d_{Ni} , $i = 1, \dots, N$ satisfy (1.5), (1.6), (3.1)—(3.3) and that the score-generating function has four bounded derivatives on $(0, 1)$.

Then

$$(3.9) \quad \sup_x |F_{N\Delta}(x) - \Phi(x)| = O(N^{-\frac{1}{2}+\delta})$$

holds for any $\delta > 0$ and any fixed Δ .

PROOF. We may write for any $\varepsilon > 0$ and for any x

$$(3.10) \quad \begin{aligned} P\{\sigma^{-1}(S_{\Delta N} - \Delta a_N - \Delta^2 b_N) \leq x\} \\ \leq P\{\sigma^{-1}S_{0N} \leq x + \varepsilon\} \\ + P\{\sigma^{-1}|S_{\Delta N} - S_{0N} - \Delta a_N - \Delta^2 b_N| \geq \varepsilon\} \end{aligned}$$

and analogously

$$\begin{aligned} P\{\sigma^{-1}(S_{\Delta N} - \Delta a_N - \Delta^2 b_N) \leq x\} \\ \geq P\{\sigma^{-1}S_{0N} \leq x - \varepsilon\} - P\{\sigma^{-1}|S_{\Delta N} - S_{0N} - \Delta a_N - \Delta^2 b_N| \geq \varepsilon\}. \end{aligned}$$

Then by Theorem 2.1,

$$(3.11) \quad \begin{aligned} \sup_x |F_{N\Delta}(x + \sigma^{-1}\Delta^2 b_N) - \Phi(x)| \\ \leq C \cdot \varepsilon + P\{\sigma^{-1}|S_{\Delta N} - S_{0N} - \Delta a_N - \Delta^2 b_N| \geq \varepsilon\} \\ + A(\delta)N^{-\frac{1}{2}+\delta} \end{aligned}$$

holds for any $\delta > 0$ and $N > N_\delta$.

Let us consider the third member of the right-hand side of (3.11). We shall use the following theorem:

THEOREM 3.2 (Petrov). *Let $H(x)$ be any cdf and $\Phi(x)$ cdf of the normal $(0, 1)$ distribution.*

Let

$$\nu = \sup_{-\infty < x < \infty} |H(x) - \Phi(x)|$$

and let M_p denote the set of distribution functions possessing the finite absolute moment of order $p > 0$. Then, if $0 < \nu \leq e^{-\frac{1}{2}}$ and $H(x) \in M_p$, there exists a constant C_p depending on p only such that

$$(3.12) \quad |H(x) - \Phi(x)| \leq \frac{C_p \nu \left(\log \frac{1}{\nu}\right)^{p/2} + \lambda_p}{1 + |x|^p}$$

holds for all real x ; here

$$\lambda_p = \int |x|^p dH(x) - \int |x|^p d\Phi(x).$$

For the proof, see Petrov (1972).

Let us denote by $G_{N\Delta}$ the cdf of $\Delta^{-1}A_N^{-1}\rho^{-1}(S_{\Delta N} - S_{0N} - \Delta a_N - \Delta^2 b_N)$. On account of the boundedness of φ , $G_{N\Delta}$ has finite absolute moments of any order for any fixed N and any fixed Δ . On the other hand, it follows from Theorem 2.1 of [6] (see (3.1)–(3.8) of the present paper) that $\lim_{N \rightarrow \infty} \sup_x |G_{N\Delta}(x) - \Phi(x)| = 0$ for any fixed Δ and that for $N > N_\Delta$

$$\sup_x |G_{N\Delta}(x) - \Phi(x)| < e^{-\frac{1}{2}}.$$

The assumptions of Theorem 3.2 are satisfied for any $p = k = 1, 2, \dots$, so that there exists a constant C_k^* to any k such that

$$(3.13) \quad |G_{N\Delta}(x) - \Phi(x)| \leq C_k^*(1 + |x|^k)^{-1}$$

holds for all $x \in (-\infty, \infty)$.

We have

$$(3.14) \quad P\{\sigma^{-1}|S_{\Delta N} - S_{0N} - \Delta a_N - \Delta^2 b_N| \geq \varepsilon\} = 2[1 - G_{N\Delta}(\Delta^{-1}\rho^{-1}\sigma A_N^{-1}\varepsilon)]$$

so that (3.13) implies that

$$(3.15) \quad \begin{aligned} P\{\sigma^{-1}|S_{\Delta N} - S_{0N} - \Delta a_N - \Delta^2 b_N| \geq \varepsilon\} \\ \leq 2[1 - \Phi(\Delta^{-1}\rho^{-1}\sigma A_N^{-1}\varepsilon)] + 2C_k^*[1 + (\Delta^{-1}\rho^{-1}\sigma)^k A_N^{-k}\varepsilon^k]^{-1} \end{aligned}$$

holds for any $\varepsilon > 0$, any $k = 1, 2, \dots$ and for $N > N_\Delta$.

Let us fix δ , $\delta > 0$ and put $\varepsilon = A_N \cdot N^{\delta/2}$. Then in view of (3.15) and Lemma 2, Chapter VII of Feller (1957) we have that for any $N > N_\Delta$ and sufficiently large k

$$(3.16) \quad \sup |F_{N\Delta}(x + \sigma^{-1}\Delta^2 b_N) - \Phi(x)| \leq C_\delta'' N^{-\frac{1}{2}+\delta} + O(N^{-1+2\delta}).$$

Thus

$$(3.17) \quad \begin{aligned} \sup_{-\infty < x < \infty} |F_{N\Delta}(x) - \Phi(x)| \\ \leq \sup_x |F_{N\Delta}(x) - \Phi(x + \sigma^{-1}\Delta^2 b_N)| \\ + \sup_x |\Phi(x + \sigma^{-1}\Delta^2 b_N) - \Phi(x)| \\ \leq \sup_x |F_{N\Delta}(x - \sigma^{-1}\Delta^2 b_N) - \Phi(x)| + K \cdot \sigma^{-1}\Delta^2 b_N. \end{aligned}$$

(3.16) and (3.17) together with assumption (1.5) complete the proof of the Theorem.

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