

ON A FURTHER ROBUSTNESS PROPERTY OF THE TEST AND ESTIMATOR BASED ON WILCOXON'S SIGNED RANK STATISTIC¹

PRANAB KUMAR SEN

University of North Carolina, Chapel Hill, and University of Calcutta

1. Summary and introduction. The robust-efficiency of the test and estimator based on Wilcoxon's [7] signed rank statistic when the sample observations are drawn from different populations is studied here.

Let X_1, \dots, X_n be n independent random variables distributed according to continuous cumulative distribution functions (cdf) $F_1(x), \dots, F_n(x)$, respectively. Let \mathcal{F} be the class of all continuous cdf's which are symmetric about their medians. If $F_1 = \dots = F_n = F \in \mathcal{F}$, the Wilcoxon's [7] signed rank statistic provides a robust test for and estimator of the median of $F(x)$, (cf. [2], [4], [6], [7]). The asymptotic relative efficiency (ARE) of this test and estimator has been studied by Hodges and Lehmann [1]. The present investigation is concerned with the study of the robust-efficiency of the same when F_1, \dots, F_n are not necessarily identical.

2. The main results. Let us define the sign-function $c(u)$ as 1, $\frac{1}{2}$ or 0 according as u is $>$, $=$ or $<$ 0, and let

$$(2.1) \quad S_i = c(X_i), \quad R_i = \frac{1}{2} + \sum_{j=1}^n c(|X_i| - |X_j|), \quad i = 1, \dots, n.$$

By virtue of the assumed continuity of F_1, \dots, F_n , ties among $|X_i|$, $i = 1, \dots, n$, may be ignored, in probability. Wilcoxon's [7] signed rank statistic may then be defined as

$$(2.2) \quad W_n = [1/n(n+1)] \sum_{i=1}^n S_i R_i - \frac{1}{4}.$$

The main theorem is concerned with the distribution of W_n when F_1, \dots, F_n are not necessarily identical. Let $\{H_n\}$ be a sequence of alternative hypotheses, specified by

$$(2.3) \quad H_n : F_i(x) = F_{in}(x) \text{ is symmetric about } \theta_n = n^{-1}\theta, \quad i = 1, \dots, n;$$

where θ is real and finite, and F_1, \dots, F_n are all assumed to be absolutely continuous having continuous density functions $f_1(x), \dots, f_n(x)$, respectively. It is also assumed that

$$(2.4) \quad \sup_i \int_{-\infty}^{\infty} f_i^2(x) dx < \infty.$$

Instead of dealing with W_n , we shall deal with the allied U -statistic

$$(2.5) \quad U_n = \binom{n}{2}^{-1} \sum_{1 \leq i < j \leq n} \phi(X_i, X_j); \quad \phi(a, b) = c(a+b) - \frac{1}{2}.$$

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It is then easily verified that

$$(2.6) \quad U_n = 2[(n + 1)(n - 1)^{-1}W_n - (n - 1)^{-1}(n^{-1} \sum_{i=1}^n S_i - \frac{1}{2})],$$

and hence,

$$(2.7) \quad |U_n - 2W_n| \leq 2/(n - 1), \quad \text{whatever be } F_1, \dots, F_n.$$

We also define

$$(2.8) \quad \bar{F}_n(x) = n^{-1} \sum_{i=1}^n F_{in}(x), \quad \bar{f}_n(x) = n^{-1} \sum_{i=1}^n f_i(x),$$

$$\delta_n = 2\theta[\int_{-\infty}^{\infty} \bar{f}_n^2(x) dx].$$

THEOREM 2.1. *Under (2.3) and (2.4), $3^{\frac{1}{2}}(n^{\frac{1}{2}}U_n - \delta_n)$ converges in law to a standard normal distribution, uniformly in F_1, \dots, F_n .*

PROOF. We essentially follow the line of proof of Theorem 8.1 of Hoeffding [3], pp. 310-313), and let

$$(2.9) \quad \psi_{1(i)j}(x_i) = E\{\phi(x_i, X_j)\} - E\{\phi(X_i, X_j)\}, \quad i \neq j = 1, \dots, n;$$

$$(2.10) \quad \psi_{1(i)}(X_i) = (n - 1)^{-1} \sum_{j=1, j \neq i}^n \psi_{1(i)j}(X_i), \quad i = 1, \dots, n;$$

$$\bar{\psi}_n = n^{-1} \sum_{i=1}^n \psi_{1(i)}(X_i).$$

Then, it follows from the boundedness of $\phi(X_i, X_j)$'s that

$$(2.11) \quad n^{\frac{1}{2}}\{[U_n - E(U_n)] - 2\bar{\psi}_n\} = R_n; \quad E(R_n^2) = O(n^{-1}),$$

uniformly in F_1, \dots, F_n . Also, from (2.3), (2.4) and (2.5), we obtain

$$(2.12) \quad |n^{\frac{1}{2}}E\{U_n | H_n\} - \delta_n| = o(1), \quad \text{uniformly in } F_1, \dots, F_n.$$

So, it suffices to show that $(12n)^{\frac{1}{2}}\bar{\psi}_n$ converges in law to a standard normal distribution (under $\{H_n\}$). Using (2.5), (2.8), (2.9) and (2.10), we obtain

$$(2.13) \quad \psi_{1(i)}(X_i) = (n - 1)^{-1}\{n[\{\frac{1}{2} - \bar{F}_n(-X_i)\} - \int_{-\infty}^{\frac{1}{2}} \{\frac{1}{2} - \bar{F}_n(-x)\} dF_{in}(x)] - [\{\frac{1}{2} - F_{in}(-X_i)\} - \int_{-\infty}^{\frac{1}{2}} \{\frac{1}{2} - F_{in}(-x)\} dF_{in}(x)]\}, \quad i = 1, \dots, n.$$

Also, under H_n in (2.3)

$$(2.14) \quad [\frac{1}{2} - F_{in}(-x)] = [F_{in}(x + 2n^{-\frac{1}{2}}\theta) - \frac{1}{2}], \quad i = 1, \dots, n.$$

Hence, from (2.13) and (2.14), we obtain, on using (2.4) and (2.8), that

$$(2.15) \quad V\{n^{\frac{1}{2}}\bar{\psi}_n | H_n\} = \frac{1}{12} + o(1), \quad \text{uniformly in } F_1, \dots, F_n.$$

Upon noting that $\{\psi_{1(i)}(X_i), i = 1, \dots, n\}$ are independent and bounded valued random variables, the rest of the proof follows from the Berry-Esseen theorem (cf. [5], p. 288). Hence the theorem.

REMARK. As is pointed out by the referee, a proof of Theorem 2.1 for the particular case of symmetry about 0 (i.e., $\theta = 0$ in (2.3),) is contained on page

12 of Chapter 3 of the preliminary version of J. W. Pratt's book on nonparametric statistics. The same result also follows directly from the sign-invariance permutation arguments of Sen and Puri [6a], which does not require the identity of F_1, \dots, F_n .

If the cdf $F_i(x)$ has a finite variance σ_i^2 ($i = 1, \dots, n$), and we define $\bar{\sigma}_n^2 = n^{-1} \sum_{i=1}^n \sigma_i^2$, it is easy to show that according to the usual definition of ARE (cf. [1]), the ARE of the Wilcoxon's signed rank test with respect to Student's t -test is

$$(2.16) \quad e_{w_n/t_n} = 12\bar{\sigma}_n^2 [\int_{-\infty}^{\infty} \bar{f}_n^2(x) dx]^2.$$

Since, $\bar{f}_n(x)$ is also a continuous cdf with the variance $\bar{\sigma}_n^2$, it follows that the lower bound to the ARE of Wilcoxon's test with respect to t -test (viz. 0.864), considered by Hodges and Lehmann [1], is also valid when F_1, \dots, F_n are not necessarily identical. For a class of cdf's, (2.16) provides sharper bounds to e_{w_n/t_n} . Let $\mathfrak{F}_0 (\subset \mathfrak{F})$ be a class of cdf's, such that if F_1, F_2 both belong to \mathfrak{F}_0 , then

$$(2.17) \quad \int_{-\infty}^{\infty} f_1(x) dF_2(x) \geq (\int_{-\infty}^{\infty} f_1(x) dF_1(x)) (\int_{-\infty}^{\infty} f_2(x) dF_2(x)) \cdot \{\frac{1}{2} ((\int_{-\infty}^{\infty} f_1(x) dF_1(x))^2 + (\int_{-\infty}^{\infty} f_2(x) dF_2(x))^2)\}^{-\frac{1}{2}} > 0.$$

It may be noted that for F_1, \dots, F_n being all normal or all double exponential distributions, differing only in scale parameters, (2.17) is satisfied; \mathfrak{F}_0 may also hold some other distributions (viz., convex exponential cdf's with strictly positive density everywhere). Let then

$$(2.18) \quad e_i = 12\sigma_i^2 (\int_{-\infty}^{\infty} f_i^2(x) dx)^2; \quad g_{in} = \sigma_i^2 / (\sum_{j=1}^n \sigma_j^2), \quad i = 1, \dots, n.$$

THEOREM 2.2. *If F_1, \dots, F_n all belong to \mathfrak{F}_0 ,*

$$(2.19) \quad e_{w_n/t_n} \geq [\sum_{i=1}^n g_{in}/e_i]^{-1},$$

where the equality sign holds only when $\int_{-\infty}^{\infty} f_i(x) dF_j(x) = \text{constant}$, for all $i, j = 1, \dots, n$.

PROOF. Using the elementary inequalities between the arithmetic and harmonic means and between the sum of powers, we have

$$(2.20) \quad \begin{aligned} (\int_{-\infty}^{\infty} \bar{f}_n^2(x) dx)^2 &= (n^{-2} \sum_{i=1}^n \sum_{j=1}^n \int_{-\infty}^{\infty} f_i(x) f_j(x) dx)^2 \\ &\geq (n^{-2} \sum_{i=1}^n \sum_{j=1}^n [1/\int_{-\infty}^{\infty} f_i(x) f_j(x) dx]^{-2})^{-2} \\ &\geq (n^{-2} \sum_{i=1}^n \sum_{j=1}^n [1/\int_{-\infty}^{\infty} f_i(x) f_j(x) dx]^2)^{-1}, \end{aligned}$$

where the equality sign holds only when $\int_{-\infty}^{\infty} f_i(x) dF_j(x) = \text{constant}$, for all $i, j = 1, \dots, n$. Since, F_1, \dots, F_n all belong to \mathfrak{F}_0 , on using (2.17), (2.20) reduces to

$$(2.21) \quad \begin{aligned} (\int_{-\infty}^{\infty} \bar{f}_n^2(x) dx)^2 &\geq \{(2n^2)^{-1} \sum_{i=1}^n \sum_{j=1}^n (\int_{-\infty}^{\infty} f_i^2(x) dx)^{-2} \\ &\quad + (\int_{-\infty}^{\infty} f_j^2(x) dx)^{-2}\}^{-1} \\ &= (n^{-1} \sum_{i=1}^n [\int_{-\infty}^{\infty} f_i^2(x) dx]^{-2})^{-1} \\ &= (12n^{-1} \sum_{i=1}^n \sigma_i^2/e_i)^{-1}. \end{aligned}$$

The rest of the proof follows from (2.16), (2.18), (2.19) and (2.21). Hence, the theorem.

If the cdf's F_1, \dots, F_n differ only in scale parameters $\sigma_1, \dots, \sigma_n$, it is easy to show that $e_1 = \dots = e_n = e$, and hence, under the condition of Theorem 2.2 we obtain

$$(2.22) \quad e_{w_n/t_n} \geq e,$$

where the equality sign holds only when $\sigma_1 = \dots = \sigma_n$. In particular, if F_i is normal with variance σ_i^2 , $i = 1, \dots, n$, it is easily seen that

$$(2.23) \quad e_{w_n/t_n} = 3\pi^{-1} \bar{\sigma}_n^2 (n^{-2} \sum_{i=1}^n \sum_{j=1}^n (2/(\sigma_i^2 + \sigma_j^2))^{\frac{1}{2}})^2 \geq 3/\pi$$

where the equality sign holds only when $\sigma_1 = \dots = \sigma_n$. Further, by varying $\sigma_1, \dots, \sigma_n$ arbitrarily, (2.23) can be made arbitrarily large. This clearly indicates the robust-efficiency of the signed rank test when the variables are not identically distributed.

Since, the same efficiency results also apply to the (point as well as confidence interval) estimator of the median obtained by using the signed rank statistic, (cf. [2], [4], [6]), the conclusions of Theorems 2.1 and 2.2 are true for the estimation case too.

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