

A TEST OF WILCOXON TYPE FOR HOMOGENEITY OF MARGINAL DISTRIBUTIONS AGAINST ORDERED ALTERNATIVES

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1. Introduction.

Let $\mathbf{X}=(X_1, \dots, X_p)$ be a p -dimensional random vector with an absolutely continuous distribution function $G(x_1, \dots, x_p)$ and the marginal distribution function of the i -th component variable X_i be $F_i(x)$ for $i=1, \dots, p$. Let $\mathbf{X}_\alpha=(X_{1\alpha}, \dots, X_{p\alpha})$, $\alpha=1, \dots, n$ be a random sample of size n from the p -variate population with the distribution function G where the forms of G and F_i are unknown. This paper is concerned with the problem of testing the hypothesis

$$H_0: F_1(x) = \dots = F_p(x) \text{ for all } x$$

against the ordered alternatives

$$H_1: F_1(x) \leq \dots \leq F_p(x)$$

where at least one of the inequalities is strict.

Many workers have investigated the nonparametric p -sample problem where the alternatives are ordered. But, most of them have dealt with this problem under the assumption that the components X_1, \dots, X_p are mutually independent, that is,

$$G(x_1, \dots, x_p) = F_1(x_1) \dots F_p(x_p) \text{ for all } \mathbf{x}=(x_1, \dots, x_p).$$

For example, see Jonckheere [3], Tamura [6], Chacho [1] and Puri [4]. The investigations for the case where the independence of X_1, \dots, X_p is violated, can be only found, for $p=2$, in Hollander, Pledger and Lin [2] and Raviv [5]. In this paper, we shall propose a test of Wilcoxon type for this problem where the independence of the component variables is not assumed and $p \geq 2$. And its asymptotic properties will be investigated and we shall find that the proposed test is not strictly distribution-free, but is asymptotically distribution-free.

In what follows, the summation $\sum_{i < j}$ (or $\sum_{i < l}$) extends over all possible $1 \leq i <$

$j \leq p$ (or $1 \leq k < l \leq p$) and $\sum_{\alpha \neq \beta}$ (or $\sum_{\gamma \neq \delta}$) is over all possible $1 \leq \alpha, \beta \leq n, \alpha \neq \beta$ (or $1 \leq \gamma, \delta \leq n, \gamma \neq \delta$).

2. Test statistic and asymptotic distributions.

We first define for $i, j = 1, \dots, p$ and $\alpha, \beta = 1, \dots, n$

$$(2.1) \quad \varphi(X_{i\alpha}, X_{j\beta}) = \begin{cases} 1 & \text{if } X_{i\alpha} > X_{j\beta} \\ 0 & \text{otherwise,} \end{cases}$$

$$(2.2) \quad W_{ij} = \sum_{\alpha \neq \beta} \varphi(X_{i\alpha}, X_{j\beta}) / n(n-1)$$

and

$$(2.3) \quad W = \sqrt{n} \sum_{i < j} (W_{ij} - p_{ij}), \text{ where } p_{ij} = p(X_{i\alpha} > X_{j\beta}) \text{ for } \alpha \neq \beta.$$

Then $E(W_{ij}) = p_{ij} = \int_{-\infty}^{\infty} F_j(x) dF_i(x)$ is easily seen. To derive the variance of W_{ij} , we use the following (2.4) shown by Hollander and others [2] or Raviv [5],

$$(2.4) \quad \lim_{n \rightarrow \infty} E[\sqrt{n} (W_{ij} - p_{ij}) - \frac{1}{\sqrt{n}} \sum_{\alpha=1}^n \{F_j(X_{i\alpha}) + 1 - F_i(X_{j\alpha}) - 2p_{ij}\}]^2 = 0.$$

Then we get (2.5) from both (2.4) and the fact that $F_j(X_{i\alpha}) - F_i(X_{j\alpha}), \alpha = 1, \dots, n$ are independently and identically distributed random variables,

$$(2.5) \quad \lim_{n \rightarrow \infty} \text{Var}\{\sqrt{n} (W_{ij} - p_{ij})\} = \text{Var}\{F_j(X_i) - F_i(X_j)\}.$$

We shall now derive the asymptotic distribution of the statistic W .

LEMMA 2.1. W is asymptotically normally distributed with mean 0 and variance A^2 where

$$(2.6) \quad A^2 = \text{Var} \left(\sum_{i < j} \{F_j(X_i) - F_i(X_j)\} \right)$$

PROOF. We first get from (2.4) that

$$\sqrt{n} (W_{ij} - p_{ij}) - \frac{1}{\sqrt{n}} \sum_{\alpha=1}^n \{F_j(X_{i\alpha}) + 1 - F_i(X_{j\alpha}) - 2p_{ij}\} \xrightarrow{(P)} 0 \text{ as } n \rightarrow \infty.$$

Then the following is easily obtained,

$$(2.7) \quad W - \frac{1}{\sqrt{n}} \sum_{i < j} \sum_{\alpha=1}^n \{F_j(X_{i\alpha}) + 1 - F_i(X_{j\alpha}) - 2p_{ij}\} \xrightarrow{(P)} 0 \text{ as } n \rightarrow \infty.$$

Since $Y_\alpha = \sum_{i < j} \{F_j(X_{i\alpha}) + 1 - F_i(X_{j\alpha}) - 2p_{ij}\}$, $\alpha = 1, \dots, n$ are independently and identically distributed random variables with mean 0 and variance A^2 , the central limit theorem leads the asymptotic normality of the statistic

$$\frac{1}{\sqrt{n}} \sum_{\alpha=1}^n Y_\alpha = \frac{1}{\sqrt{n}} \sum_{i < j} \sum_{\alpha=1}^n \{F_j(X_{i\alpha}) + 1 - F_i(X_{j\alpha}) - 2p_{ij}\},$$

where the mean and variance are respectively 0 and A^2 .

The fact that W has the same asymptotic distribution as $\frac{1}{\sqrt{n}} \sum_{\alpha=1}^n Y_\alpha$, proves Lemma 2.1.

Now we shall derive a consistent estimator for A^2 by the similar idea to Raviv [5]. Define for each α ,

$$(2.8) \quad S_\alpha = \sum_{i < j} \sum_{\beta \neq \alpha} \{\varphi(X_{i\alpha}, X_{j\beta}) + \varphi(X_{i\beta}, X_{j\alpha})\} / (n-1)$$

where the summation $\sum_{\beta \neq \alpha}$ is over all possible $1 \leq \beta \leq n$, $\beta \neq \alpha$,

$$(2.9) \quad \hat{A}_n^2 = \sum_{\alpha=1}^n (S_\alpha - \bar{S})^2 / n, \text{ where } \bar{S} = \sum_{\alpha=1}^n S_\alpha / n.$$

LEMMA 2.2. \hat{A}_n^2 is a consistent estimator for A^2 .

PROOF. (i) We first show $E(\hat{A}_n^2) \rightarrow A^2$ as $n \rightarrow \infty$. From (2.8),

$$E(S_\alpha^2) = \frac{1}{(n-1)^2} \sum_{i < j} \sum_{k < l} \sum_{\beta \neq \alpha} \sum_{\gamma \neq \alpha} E[\{\varphi(X_{i\alpha}, X_{j\beta}) + \varphi(X_{i\beta}, X_{j\alpha})\} \\ \times \{\varphi(X_{k\alpha}, X_{l\gamma}) + \varphi(X_{k\gamma}, X_{l\alpha})\}]$$

By using the identity $E\{\varphi(X_{i\alpha}, X_{j\beta}) \varphi(X_{k\alpha}, X_{l\gamma})\} = E\{F_j(X_i) F_l(X_k)\}$ for $\alpha \neq \beta \neq \gamma$, we can get the expression

$$(2.10) \quad E(S_\alpha^2) = \sum_{i < j} \sum_{k < l} E[\{F_j(X_i) + 1 - F_i(X_j)\} \{F_l(X_k) + 1 - F_k(X_l)\}] + O(1/n).$$

We may also write as $\bar{S} = 2 \sum_{i < j} \sum_{\alpha \neq \beta} \varphi(X_{i\alpha}, X_{j\beta}) / n(n-1)$ and we get

$$E(\bar{S}^2) = 4 \sum_{i < j} \sum_{k < l} \sum_{\alpha \neq \beta} \sum_{\gamma \neq \delta} E\{\varphi(X_{i\alpha}, X_{j\beta}) \varphi(X_{k\gamma}, X_{l\delta})\} / n^2(n-1)^2.$$

Using the identities $E\{\varphi(X_{i\alpha}, X_{j\beta}) \varphi(X_{k\gamma}, X_{l\delta})\} = p_{ij} p_{kl}$ for $\alpha \neq \beta \neq \gamma \neq \delta$, $i < j$, $k < l$, we can obtain

$$(2.11) \quad E(\bar{S}^2) = 4 \left(\sum_{i < j} p_{ij} \right)^2 + O(1/n).$$

From (2.10) and (2.11), it holds

$$\begin{aligned} \lim_{n \rightarrow \infty} E(\hat{A}_n^2) &= \sum_{i < j} \sum_{k < l} E[\{F_j(X_i) + 1 - F_i(X_j)\} \{F_l(X_k) + 1 - F_k(X_l)\}] \\ &\quad - 4 \left(\sum_{i < j} p_{ij} \right)^2 \\ &= A^2. \end{aligned}$$

(ii) We next show $\text{Var}(\hat{A}_n^2) \rightarrow 0$ as $n \rightarrow \infty$. First we write \hat{A}_n^2 as

$$(2.12) \quad \hat{A}_n^2 = \sum_{\alpha=1}^n \left(\sum_{\beta, \beta \neq \alpha} u_{\alpha\beta} \right)^2 / n(n-1)^2 - \left(\sum_{\alpha \neq \beta} u_{\alpha\beta} \right)^2 / n^2(n-1)^2,$$

where

$$u_{\alpha\beta} = \sum_{i < j} \{ \varphi(X_{i\alpha}, X_{j\beta}) + \varphi(X_{i\beta}, X_{j\alpha}) \} \text{ for } \alpha \neq \beta.$$

Then $\text{Var}(\hat{A}_n^2)$ is also written as

$$(2.13) \quad \begin{aligned} \text{Var}(\hat{A}_n^2) &= \text{Var} \left(\sum_{\alpha \neq \beta \neq \gamma} u_{\alpha\beta} u_{\alpha\gamma} \right) / n^2(n-1)^4 + \text{Var} \left(\sum_{\alpha \neq \beta \neq \gamma \neq \delta} u_{\alpha\beta} u_{\gamma\delta} \right) / n^4(n-1)^4 \\ &\quad - 2 \text{Cov} \left(\sum_{\alpha \neq \beta \neq \gamma} u_{\alpha\beta} u_{\gamma\alpha}, \sum_{\alpha \neq \beta \neq \gamma \neq \delta} u_{\alpha\beta} u_{\gamma\delta} \right) / n^2(n-1)^4 + O(1/n). \end{aligned}$$

Now, $\text{Var} \left(\sum_{\alpha \neq \beta \neq \gamma} u_{\alpha\beta} u_{\alpha\gamma} \right)$ is the sum of $n^2(n-1)^2(n-2)^2$ terms and among of them, $6! \binom{n}{6}$ terms such as $E[\{u_{\alpha\beta} u_{\alpha\gamma} - E(u_{\alpha\beta} u_{\alpha\gamma})\} \{u_{\alpha'\beta'} u_{\alpha'\gamma'} - E(u_{\alpha'\beta'} u_{\alpha'\gamma'})\}]$ with $\alpha \neq \beta \neq \gamma \neq \alpha' \neq \beta' \neq \gamma' \neq \alpha$ become zero. Therefore the number of non-zero terms in $\text{Var} \left(\sum_{\alpha \neq \beta \neq \gamma} u_{\alpha\beta} u_{\alpha\gamma} \right)$ is at most of order n^5 . Thus the first term in (2.13) tends to zero as $n \rightarrow \infty$. Similarly, the other terms tend to zero as $n \rightarrow \infty$.

The Lemma may be proved from (i) and (ii).

The following theorem is straight from Lemma 2.1 and Lemma 2.2.

THEOREM 2.1. *The asymptotic distribution of $\sqrt{n} \sum_{i < j} (W_{ij} - p_{ij}) / \hat{A}_n$ is normal with mean 0 and variance 1.*

We here propose the test W :

$$\text{If } \sqrt{n} \sum_{i < j} (W_{ij} - \frac{1}{2}) / \hat{A}_n \geq z_\alpha, \text{ reject } H_0,$$

where $1 - \Phi(z_\alpha) = \alpha$ and $\Phi(x)$ is the standard normal distribution function.

Since $p_{ij} = \frac{1}{2}$ under H_0 , it is seen from Theorem 2.1 that the test W has asymptotically level α of significance.

3. Asymptotic properties of the test W .

In this section, we shall restrict ourselves to the translation model as

$$(3.1) \quad F_i(x) = F(x - \Delta_i), \quad i = 1, \dots, p.$$

Then the hypothesis and the alternatives are respectively expressed as follows,

$$H_0: \Delta_1 = \dots = \Delta_p, \quad H_1: \Delta_1 \geq \dots \geq \Delta_p.$$

In addition, we adopt the alternatives H_1^* converging to the hypothesis, in order to discuss the asymptotic power and Pitman relative efficiency,

$$(3.2) \quad H_1^*: \Delta_i = \Delta + \theta_i/\sqrt{n}, \quad \theta_1 = 0 \geq \theta_2 \geq \dots \geq \theta_p$$

THEOREM 3.1. *Under the model (3.1) and the alternatives (3.2), the asymptotic power of the test W is given by*

$$(3.3) \quad 1 - \Phi(z_\alpha - \left(\int_{-\infty}^{\infty} f^2(x) dx \right) \sum_{i < j} (\theta_i - \theta_j) / A_0),$$

where $f(x)$ is the density of $F(x)$ and

$$(3.4) \quad A_0^2 = p(p^2 - 1)/36 + 2 \sum_{i < j} c_{ij} \text{Cov}_0(F(X_i), F(X_j))$$

$$c_{ij} = (p - 2i + 1)(p - 2j + 1)$$

and Cov_0 is the covariance under the hypothesis H_0 .

PROOF. The asymptotic power of the test W is written as

$$(3.5) \quad \lim_{n \rightarrow \infty} P[\sqrt{n} \sum_{i < j} (W_{ij} - \frac{1}{2}) / \hat{A}_n \geq z_\alpha | H_1^*]$$

$$= \lim_{n \rightarrow \infty} P[\sqrt{n} \sum_{i < j} (W_{ij} - p_{ij}) / A \geq z_\alpha - \sqrt{n} \sum_{i < j} (p_{ij} - \frac{1}{2}) / A | H_1^*],$$

$$= 1 - \Phi(\lambda_\alpha)$$

where

$$\lambda_\alpha = z_\alpha - \lim_{n \rightarrow \infty} \sqrt{n} \sum_{i < j} (p_{ij} - \frac{1}{2}) / A.$$

Since it holds under H_1^*

$$p_{ij} = \frac{1}{2} + \left(\int_{-\infty}^{\infty} f^2(x) dx \right) (\theta_i - \theta_j) / \sqrt{n} + O(1/n),$$

we get

$$(3.6) \quad \lim_{n \rightarrow \infty} \sqrt{n} \sum_{i < j} (p_{ij} - \frac{1}{2}) = (\int_{-\infty}^{\infty} f^2(x) dx) \sum_{i < j} (\theta_i - \theta_j).$$

To derive $\lim_{n \rightarrow \infty} A^2$, we first note that

$$\text{Cov}(F_j(X_i), F_l(X_k)) = \text{Cov}_0(F(X_i), F(X_k)) + O(1/\sqrt{n})$$

and therefore,

$$\lim_{n \rightarrow \infty} A^2 = \text{Var}_0(\sum_{i < j} \{F(X_i) - F(X_j)\}),$$

where Var_0 is the variance under H_0 .

In $\text{Var}_0(\sum_{i < j} \{F(X_i) - F(X_j)\})$, we can show that the coefficient of $\text{Cov}_0(F(X_i), F(X_j))$ becomes $(p-2i+1)(p-2j+1)$ for $1 \leq i \leq j \leq p$ after elementary but some tedious calculations. Thus we can obtain the following by using $\text{Var}_0(F(X_i)) = 1/12$ and $\sum_{i=1}^p (p-2i+1)^2 = p(p^2-1)/3$,

$$(3.7) \quad \begin{aligned} & \text{Var}_0(\sum_{i < j} \{F(X_i) - F(X_j)\}) \\ &= p(p^2-1)/36 + 2 \sum_{i < j} c_{ij} \text{Cov}_0(F(X_i), F(X_j)) \\ &= A_0^2 \end{aligned}$$

The relations (3.4), (3.5) and (3.7) prove the Theorem 3.1.

We are now in a position to make large sample comparison between the test W and the normal theory competitor based on Student statistic,

$$(3.8) \quad T = \sqrt{n} \sum_{i < j} (\bar{X}_i - \bar{X}_j), \quad \bar{X}_i = \sum_{\alpha=1}^n X_{i\alpha}/n \text{ for } i=1, \dots, p.$$

Then the procedure of the test T is as follows,

$$\text{if } T/\sqrt{\text{Var}_0(T)} \geq z_\alpha, \text{ reject } H_0.$$

THEOREM 3.2. *The Pitman's asymptotic relative efficiency of the test W relative to the test T is the following,*

$$(3.9) \quad e_{W,T} = B_0^2 (\int_{-\infty}^{\infty} f^2(x) dx)^2 / A_0^2,$$

$$(3.10) \quad B_0^2 = p(p^2-1)\sigma^2/3 + 2 \sum_{i < j} c_{ij} \text{Cov}_0(X_i, X_j),$$

where σ^2 is the variance of X_i and c_{ij} is given in (3.4).

PROOF. We first show the asymptotic normality of T . We represent T as

$$T = \sum_{\alpha=1}^n \left(\sum_{i < j} (X_{i\alpha} - X_{j\alpha}) \right) / \sqrt{n}. \text{ Since } Z_\alpha = \sum_{i < j} (X_{i\alpha} - X_{j\alpha}), \alpha = 1, \dots, n$$

are independently and identically distributed random variables, we get the asymptotic normality of $T = \sum_{\alpha=1}^n Z_\alpha / \sqrt{n}$ by the central limit theorem. It is evident that $E(T) = \sum_{i < j} (\theta_i - \theta_j)$ or 0 under H_1^* or H_0 and $\text{Cov}_0(\sqrt{n} \bar{X}_i, \sqrt{n} \bar{X}_j) = \text{Cov}_0(X_i, X_j)$. By the similar discussions to A_0^2 in Theorem 3.1, we obtain

$$\begin{aligned} \lim_{n \rightarrow \infty} \text{Var}(T) &= \text{Var}_0(T) \\ &= p(p^2 - 1)\sigma^2/3 + 2 \sum_{i < j} c_{ij} \text{Cov}_0(X_i, X_j) \end{aligned}$$

Thus the asymptotic power of the test T is given by

$$(3.11) \quad 1 - \Phi(z_\alpha - \sum_{i < j} (\theta_i - \theta_j) / B_0).$$

From Theorem 3.1 and (3.11), we can get (3.9) as the asymptotic efficiency of the test W relative to the test T .

Finally, we consider the model with more strong restriction than (3.1), that is, we assume in addition to (3.1) that

$$(3.12) \quad P[X_i \leq x, X_j \leq y] = K(x - \Delta_i, y - \Delta_j) \text{ for } i, j = 1, \dots, p.$$

We here note that the multivariate normal distribution with covariance matrix $\|\sigma_{ij}\|$ where $\sigma_{ij} = \sigma^2$ or $\rho\sigma^2$ for $i = j$ or $i \neq j$ is a special case of the model above. Then we get

COROLLARY 3.1. Under the model (3.1), (3.2) and (3.12), the Pitman relative efficiency $e_{W,T}^*$ of the test W relative to the test T is given by

$$(3.13) \quad e_{W,T}^* = 12\sigma^2 \left(\int_{-\infty}^{\infty} f^2(x) dx \right)^2 (1 - \rho_0(X_i, X_j)) / (1 - \rho_0(F(X_i), F(X_j))),$$

where ρ_0 is the correlation coefficient under H_0 .

PROOF. Under the model above, $\text{Cov}_0(F(X_i), F(X_j))$ and $\text{Cov}_0(X_i, X_j)$ have respectively the same values for all $1 \leq i < j \leq p$ and moreover we get $2 \sum_{i < j} c_{ij} = p(1 - p^2)/3$. Hence, we get

$$A_0^2 = p(p^2 - 1)(1 - \rho_0(F(X_i), F(X_j)))/36 \text{ and } B_0^2 = p(p^2 - 1)\sigma^2(1 - \rho_0(X_i, X_j))/3.$$

These show (3.13).

It should be noted that the form (3.13) of $e_{W,T}^*$ consists with that in Raviv [5] where the problem has been dealt for $p=2$.

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