## A CLASS OF NON-PARAMETRIC TESTS FOR HOMOGENEITY AGAINST ORDERED ALTERNATIVES

By Peter V. Tryon<sup>1</sup> and Thomas P. Hettmansperger

The Pennsylvania State University

In this paper, the c-sample location problem with ordered or restricted alternatives is considered. Linear combinations of Chernoff-Savage type two-sample statistics computed among the c(c-1)/2 pairs of samples are proposed as test statistics. It is shown that for each linear combination of two-sample statistics there is another linear combination, using only the c-1 two-sample statistics based on adjacent samples as determined by the alternative, which has the same Pitman efficacy. If the ordered alternative is restricted further by specifying the relative spacings in the alternative, then the weighting coefficients can be chosen to maximize the Pitman efficacy over the class of linear combinations. It is also shown that the statistics proposed by Jonkheere [4] and Puri [9] have maximum Pitman efficacy when the alternative specifies equal spacings.

1. Introduction and summary. Let  $X_{ik}$ ,  $k=1, \cdots n_i$ ,  $i=1, \cdots, c$  be random samples from populations with absolutely continuous distribution functions  $F_i(x) = F(x-\theta_i)$ ,  $i=1, \cdots c$ . This paper is concerned with testing the null hypothesis  $H_0: \theta_1 = \cdots = \theta_c$  against one of the following restricted alternatives:  $H_{1A}: \theta_1 \leq \cdots \leq \theta_c$  with at least one strict inequality or  $H_{1B}: \theta_1 \leq \cdots \leq \theta_c$  with at least one strict inequality and  $\delta' = (\delta_1, \cdots, \delta_{c-1})$  specified where  $\delta_i = (\theta_{i+1} - \theta_i)/(\theta_c - \theta_1)$ .

Let  $N = \sum_{i=1}^{c} n_i$ . For testing  $H_0$  against  $H_{1A}$  Terpstra [10] and Jonckheere [4] proposed the statistic

(1) 
$$J_N = \sum_{i=1}^{c-1} \sum_{i=i+1}^{c} M_{iiN}$$

where  $M_{ijN}$  is the Mann-Whitney statistic [6] computed from the *i*th and *j*th samples for testing the alternative  $\theta_j > \theta_i$ . The Mann-Whitney statistic is one member of a broad class of two-sample statistics studied by Chernoff and Savage [1]. Puri [9] generalized Jonckheere's statistic by replacing  $M_{ijN}$  with any Chernoff-Savage statistic. Following the approach suggested by Hogg [3], Puri's family of statistics is generalized by including weighting coefficients to form arbitrary linear combinations

(2) 
$$T_N = \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} a_{ij} T_{ijN}$$
  $a_{ij} \ge 0$ ,

where  $T_{ijN}$  is any Chernoff-Savage statistic. Denote by  $\Gamma$  the class of statistics

Received January 1972; revised December 1972.

<sup>&</sup>lt;sup>1</sup> This author's research was supported by Ordance Research Laboratory at the Pennsylvania State University under contract with the Naval Ordance Systems Command. This author is now at the National Bureau of Standards, Boulder, Colorado.

Key words and phrases. Tests for ordered alternatives, equally spaced alternatives, linear combinations of two-sample rank tests.

defined by (2). From the results of Puri [9] it follows that statistics in  $\Gamma$ , when properly standardized, are asymptotically normally distributed.

Let  $\Gamma^*$  be the subclass of  $\Gamma$  consisting of linear combinations of  $(T_{12}, T_{23}, \dots, T_{c-1c})$ ; then, assuming equal sample sizes, it is proved that for each  $T_N$  in  $\Gamma$  there corresponds an "equivalent" statistic  $T_N^*$  in  $\Gamma^*$ , where

$$T_N^* = \sum_{k=1}^{c-1} a_k T_{kk+1N}$$
 and  $a_k = \sum_{i=1}^k \sum_{j=k+1}^c a_{ij}$   
 $k = 1, 2, \dots, c-1$ .

The "equivalence" refers to the fact that the difference of  $T_N$  and  $T_N^*$ , when standardized, converges in probability to zero under  $H_0$  and that, for testing  $H_0$  against  $H_{1A}$ , the Pitman efficiency of  $T_N^*$  with respect to  $T_N$  is one. In addition,  $T_N^*$  is a much simpler statistic, requiring the computation of c-1 rather than  $\binom{e}{2}$  two sample statistics.

If the alternative  $H_{1B}$  is considered, the additional information in  $\delta$ , the vector of relative spacings, can be used to choose the weighting coefficients to maximize the Pitman efficacy of statistics in  $\Gamma$ . It is proved that, if the spacings are equal, Puri's family of statistics and their "equivalents" attain the maximum Pitman efficacy within the class  $\Gamma$ . The method of obtaining the optimum weighting coefficients is given.

The alternative  $H_{1B}$  provides a practical alternative to the assumption of equal spacing which is generally made by default in applying Jonckheere's statistic. This alternative requires no more justification than the assumption of equal spacings. Furthermore, the methods developed in this paper provide the means to study the robustness of the Pitman efficacy of the statistics to errors in the choice of relative spacings.

Haller [2] has considered a different class of statistics consisting of a linear combination of the c two-sample statistics formed by comparing each sample against the combined sample. The two-sample statistic used may be of the Chernoff-Savage type. He derives the weighting coefficients which maximize the Pitman efficiency for a specified relative spacing in the ordered alternative. Although the class of statistics considered by Haller and our class  $\Gamma$  are disjoint, Haller has proved that, for equal spacings, the efficiency of Puri's statistic with respect to the optimal statistic in his class is one. It follows that the statistics in  $\Gamma^*$  "equivalent" to Puri's statistics are as efficient in the Pitman sense as Haller's optimal statistic.

2. Equivalent linear combinations of Chernoff-Savage statistics. Let  $N_{ij} = n_i + n_j$ ,  $N = \sum_{i=1}^{c} n_i$  and let  $F_{iN}(x)$  be the empirical distribution function of the sample from the *i*th population. Let  $\gamma_{ij} = (n_j/n_i)^{\frac{1}{2}}$  and  $\lambda_{ij} = n_j/(n_i + n_j)$ .

It is assumed that  $\gamma_{ij}$  is a constant, independent of N and not equal to 0 for any pair i, j. That is, the relative proportions of sample sizes are held constant as N tends to infinity. Let  $H_{ijN}(x) = (1 - \lambda_{ij})F_{iN}(x) + \lambda_{ij}F_{jN}(x)$  be the empirical distribution function of the combined ith and jth samples. Similarly, let

 $H_{ij}(x) = (1 - \lambda_{ij})F_i(x) + \lambda_{ij}F_j(x)$  be the combined population distribution function for the *i*th and *j*th populations. Define

(3) 
$$T_{ijN} = \int_{-\infty}^{\infty} J_{N_{ij}}[H_{ijN}(x)] dF_{jN}(x)$$

where  $J_{N_{ij}}(h)$  is constant on the intervals  $(k/N_{ij}, (k+1)/N_{ij}], k=0,1,\dots, N_{ij}-1$  and depends on i and j only through  $n_i$  and  $n_j$ . This implies that all of the  $\binom{e}{2}$  two-sample statistics are of the same type: Mann-Whitney, Normal Scores, etc.

Let  $\boldsymbol{\tau}_{N}' = (\tau_{12N}, \tau_{13N}, \dots, \tau_{1cN}, \tau_{23N}, \dots, \tau_{2cN}, \dots, \tau_{c-1cN})$  be the  $\binom{c}{2}$  dimensional random vector with elements  $\tau_{ijN}$ ,  $1 \leq i < j < c$ , where

(4) 
$$\tau_{ijN} = n_j^{\frac{1}{2}} (1 - \lambda_{ij})^{-1} \{ T_{ijN} - \int_{-\infty}^{\infty} J[H_{ij}(x)] dF_j(x) \}$$

and suppose  $J(h) = \lim_{N\to\infty} J_{N,j}(h)$  exists for 0 < h < 1.

Suppose that for each pair  $i, j, 1 \le i \le j \le c$  the four conditions of the Chernoff-Savage [1] Theorem 1 hold. Puri [9] in the proof of his Theorem 4.1 proves that for any fixed  $F_i(x)$ ,  $i = 1, 2, \dots, c$  the random vector  $\tau_N$  converges in law to a random vector having a multivariate normal distribution with null mean vector and covariance matrix H.

Under the null hypothesis  $F_i(x) = F(x)$ ,  $i = 1, 2, \dots c$ , so that the elements of H are

$$h_{ij,lk} = 0 \qquad \text{all subscripts different}$$

$$h_{ij,ij} = \sigma^2 (1 + \gamma_{ij}^2) \qquad i < j$$

$$h_{il,jl} = \sigma^2 \qquad i < l , \quad j < l , \quad i \neq j$$

$$h_{li,lj} = \gamma_{li} \gamma_{lj} \sigma^2 \qquad l < i , \quad l < j , \quad i \neq j$$

$$h_{il,lj} = h_{lj,il} = -\gamma_{lj} \sigma^2 \qquad i < l < j$$

where  $\sigma^2$  depends on the particular Chernoff-Savage statistic in question.

In the remainder of the paper we will assume that the sample sizes are equal. An examination of the non-full rank covariance matrix H for equal sample sizes under  $H_0$  shows that the linear combination  $\tau_{ijN} - \sum_{k=1}^{j-1} \tau_{k}|_{k+1N}$  is asymptotically degenerate. This suggests using  $\sum_{k=1}^{j-1} \tau_{k}|_{k+1N}$  as a replacement for  $\tau_{ijN}$ . Thus, define for

(6) 
$$L_{N} = \mathbf{A}' \boldsymbol{\tau}_{N} = \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} a_{ij} T_{ijN} \qquad a_{ij} \ge 0$$

the random variable  $L_N^*$  where

(7) 
$$L_N^* = \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} a_{ij} \sum_{k=i}^{j-1} \tau_{k} + 1N \qquad a_{ij} \ge 0$$

and  $\tau_{ijN}$  is given by (4).

THEOREM 2.1. An equivalent expression for  $L_N^*$  given in (7) is:

(8) 
$$L_N^* = \sum_{k=1}^{c-1} a_k \tau_{k k+1N}$$
 where  $a_k = \sum_{i=1}^k \sum_{j=k+1}^c a_{ij}$ .

PROOF. The triple summation in (7) is over all triples (i, j, k) such that  $1 \le i \le k$ ,  $i < j \le c$  and  $i \le k < j$  or equivalently  $1 \le i \le k < j \le c$ . From (8) the

triple sum is over all triples (i, j, k) such that  $1 \le k < j$ ,  $1 \le i \le k$  and  $k < j \le c$  or equivalently  $1 \le i \le k < j \le c$ . Thus the summations are identical.

Theorem 2.2. Suppose the sample sizes are equal.  $L_N$  and  $L_N^*$  converge in law to L and  $L^*$  respectively having univariate normal distributions with zero means. Furthermore, under  $H_0$ ,  $L_N - L_N^*$  converges in probability to zero and hence  $\operatorname{Var}(L) = \operatorname{Var}(L^*)$ .

PROOF. Let  $A^{*'}=(a_{12}^*,a_{13}^*,\cdots)$  be the  $\binom{c}{2}$  dimensional vector with elements  $a_{ij}^*=0$  if  $j\neq i+1$  and  $a_{k,k+1}^*=a_k$  defined by (8). From Puri's theorem and the continuity theorem it follows that  $L_N=A'\boldsymbol{\tau}_N$  and  $L_N^*=A^{*'}\boldsymbol{\tau}_N$  converge in law to L and  $L^*$  having univariate normal distributions with zero means and variances A'HA and  $A^{*'}HA^*$ , respectively. Similarly,  $L_N-L_N^*=(A-A^*)'\boldsymbol{\tau}_N$  is asymptotically normally distributed with zero mean and variance  $(A-A^*)'H(A-A^*)$ . Note that  $L_N-L_N^*=A'S$  where  $S_{ij}=\tau_{ijN}-\sum_{k=i}^{j-1}\tau_{k}$  if  $1\leq i< j\leq c$ . Similarly,  $1\leq i< j< c$ . Similarly,  $1\leq i< c$ . Similarly,  $1\leq i< c$ . Similarly,  $1\leq i< c$ . Thus, under  $1\leq i< c$ . From the structure of  $1\leq i< c$ . Thus,  $1\leq i< c$  is an equal to  $1\leq i< c$ . Thus, under  $1\leq i< c$  is an equal to  $1\leq i< c$ . Thus,  $1\leq i< c$  is an equal to  $1\leq i< c$ . Thus,  $1\leq i< c$  is an equal to  $1\leq i< c$ .

Using Theorem 2.1, the weighting coefficients for the "equivalent" form of Jonckheere's statistic  $J_N$  defined by (1) are  $a_k = k(c-k)$ ,  $k = 1, \dots, c-1$  so that  $J_N^* = \sum_{k=1}^{c-1} k(c-k) M_{k,k+1N}$ .

Another statistic is defined by  $\bar{R}_N = \sum_{i=1}^c i\bar{R}_{iN}$ . This is Spearman's rho statistic [5], used as a test of correlation between the index i and  $\bar{R}_{iN}$ , the average of the ranks of the items in the ith sample. Now

$$\bar{R}_{N} = \frac{1}{n} \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} (j-i) M_{ijN} + \frac{c(n+1)(c+1)}{4}$$

and hence

$$ar{R}_{\scriptscriptstyle N}{}' = \sum_{i=1}^{c-1} \sum_{j=\imath+1}^{c} (j-i) M_{ijN}$$

may be considered. For this statistic  $a_k = \sum_{i=1}^k \sum_{j=k+1}^c (j-i) = (c/2)k(c-k)$ ; thus, the "equivalent" form for  $\bar{R}_N$  is  $(c/2)J_N^*$ . This shows that the correspondence between a statistic and its "equivalent" is not one to one.

Note that so far the location parameters have been surpressed; the distribution theory is valid for any set of absolutely continuous distribution functions  $F_i(x)$ ,  $i=1,2,\dots,c$ , satisfying the conditions of Puri's theorem. The random vector  $\tau_N$  is not a statistic since it depends on the unknown distribution functions. In the following, the location parameter family is considered and the dependence of the random variables, their moments and the covariance matrix H on  $\theta$ , the vector of locations, is clearly specified.

Only equal sample sizes have been considered because in general the elements of H and thus the weighting coefficients needed for an "equivalent" statistic depend on the  $\binom{e}{2}$  ratios of sample sizes  $\gamma_{ij}$ .

3. Efficiency properties. Let  $\Omega = \{ \boldsymbol{\theta} = (\theta_1, \dots, \theta_c) : \theta_1 \leq \dots \leq \theta_c \}$  be the

parameter space and let  $\omega = \{\boldsymbol{\theta} : \theta_1 = \cdots = \theta_c\}$ ; then the hypotheses to be considered are  $H_0 : \boldsymbol{\theta} \in \omega$  against  $H_{1A} : \boldsymbol{\theta} \in \Omega - \omega$ .

Fix  $\theta \in \Omega - \omega$  and  $\theta_0 \in \omega$  and define  $\theta_N = \theta_0 + N^{-\frac{1}{2}}\theta$ . Note that when  $\theta$  is chosen in  $\Omega - \omega$ , the relative spacings,  $\delta$ , are fixed and remain constant as N increases.

Since  $F_i(x) = F(x - \theta_i)$ ,  $i = 1, \dots, c$  and assuming equal sample sizes, from (6) we can write  $L_N = \mathbf{A}'\boldsymbol{\tau}_N = 2(N/c)^{\frac{1}{2}}(T_N - \mu(\boldsymbol{\theta}))$  where  $\mu(\boldsymbol{\theta}) = \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} a_{ij} \mu_{ij}(\boldsymbol{\theta})$  and

(9) 
$$\mu_{ij}(\boldsymbol{\theta}) = \int_{-\infty}^{\infty} J\left(\frac{F(x) + F(x + \theta_j - \theta_i)}{2}\right) dF(x) .$$

Now,  $L_N$  is asymptotically normally distributed with mean 0 and variance  $\eta^2(\boldsymbol{\theta}) = \mathbf{A}'H(\boldsymbol{\theta})\mathbf{A}$ . The Pitman efficacy for such statistics is discussed by Puri [8]. The reader is referred to his paper for definitions.

THEOREM 3.1. If the statistic  $T_N$  in  $\Gamma$  and its "equivalent"  $T_N^*$  in  $\Gamma^*$  satisfy the conditions for Pitman efficiency, then their relative Pitman efficiency is 1.

PROOF. Let

$$\begin{split} \eta^*(\pmb{\theta}) &= \mathbf{A}^{*\prime} H(\pmb{\theta}) \mathbf{A}^* \;, \\ b_l^* &= (c^{\frac{1}{2}} \eta^*(\pmb{\theta}_0))^{-1} \int_{-\infty}^{\infty} J'(F(z)) F'(z) \; dF(z) [a_{l-1} - a_l] \qquad \text{and} \\ b_l &= (c^{\frac{1}{2}} \eta(\pmb{\theta}_0))^{-1} \int_{-\infty}^{\infty} J'(F(z)) F'(z) \; dF(z) [\sum_{i=1}^{l-1} a_{il} = \sum_{j=l+1}^{c} a_{lj}] \end{split}$$

where, for convenience,  $a_0 = a_c = 0$  and  $a_{11} = a_{cc+1} = 0$ . The Pitman efficiency of  $L_N^*$  with respect to  $L_N$  is  $e_p(L_N^*, L_N) = [\sum_{l=1}^c b_l^* \theta_l / \sum_{l=1}^c b_l \theta_l]^2$ . However

$$\begin{array}{c} \sum_{l=1}^{c} \theta_{l}(a_{l-1}-a_{l}) = \sum_{l=1}^{c-1} a_{l}(\theta_{l+1}-\theta_{l}) & \text{and} \\ \sum_{l=1}^{c} \theta_{l} \left[ \sum_{i=1}^{l-1} a_{il} - \sum_{j=l+1}^{c} a_{lj} \right] = \sum_{i=1}^{c-1} \sum_{j=i+1}^{c} a_{ij}(\theta_{j}-\theta_{i}) \ . \end{array}$$

From Theorem 2.2., since  $\eta(\boldsymbol{\theta}_0) = \eta^*(\boldsymbol{\theta}_0)$ ,

$$e_{p}(L_{\scriptscriptstyle N}{}^{*},\,L_{\scriptscriptstyle N}) = [\,\sum_{l=1}^{c-1} a_{l}(\theta_{\,l+1}\,-\,\theta_{\,l})/\sum_{i=1}^{c-1}\,\sum_{j\,=\,i+1}^{c} a_{ij}(\theta_{\,j}\,-\,\theta_{\,i})\,]^{2}\,.$$

Recall that  $a_l = \sum_{i=1}^l \sum_{j=l+1}^c a_{ij}$  and observe that  $(\theta_j - \theta_i) = \sum_{l=1}^{j-1} (\theta_{l+1} - \theta_l)$ . Making these substitutions yields

$$e_p(L_N^*,L_N) = \sum_{l=1}^{c-1} \sum_{i=1}^l \sum_{j=l+1}^c a_{ij} (\theta_{l+1}-\theta_l) / \sum_{i=1}^{c-1} \sum_{j=i+1}^c \sum_{l=i}^{j-1} a_{ij} (\theta_{l+1}-\theta_l)^2.$$
 In Theorem 2.1 it was proved that these summations are equal. Thus  $e_p(L_N^*,L_N) = 1$  independent of  $\boldsymbol{\theta}$ .

We now consider the alternative hypothesis  $H_{1B}$ . Recall that  $H_{1B}$  specifies  $\boldsymbol{\theta} \in \Omega$  and  $\boldsymbol{\delta} = (\delta_1, \cdots, \delta_{c-1})$ , where  $\delta_j = (\theta_{j+1} - \theta_j)/(\theta_c - \theta_1)$ , is assumed to be known. It has been shown that for any linear combination of Chernoff-Savage statistics  $L_N$ , in  $\Gamma$  there is an "equivalent" linear combination,  $L_N^*$ , in  $\Gamma^*$ . The statistic  $L_N^*$  has Pitman efficiency one with respect to  $L_N$ . For this reason, only the class of statistics  $\Gamma^*$  need be considered in deriving the weighting coefficients  $a_k$ ,  $k=1,2,\cdots,c-1$ , which give maximum Pitman efficacy for testing alternatives  $H_{1B}$ .

The Pitman efficiency of one statistic with respect to another is the ratio of two efficacies. The Pitman efficacy of  $L_N^*$  is  $e(L_N^*) = (\sum_{l=1}^c \theta_l b_l^*)^2$  where  $b_l^*$  is given in Theorem 3.1. The efficacy of  $L_N^*$  will be considered as a function of the vector  $\mathbf{A}' = (a_1, a_2, \cdots, a_{e-1})$  and maximized by selecting the appropriate vector  $\hat{\mathbf{A}}$ . From the proof of Theorem 3.1 it follows that

$$\begin{split} e(L_N^*) &= \frac{1}{c\mathbf{A}'H^*\mathbf{A}} \left( \int_{-\infty}^{\infty} J'(F(z))F'(z) \, dF(z) \right)^2 \left[ \sum_{l=1}^{c-1} a_l (\theta_{l+1} - \theta_l) \right]^2 \\ &= \frac{(\theta_c - \theta_1)^2}{c\mathbf{A}'H^*\mathbf{A}} \left( \int_{-\infty}^{\infty} J'(F(z))F'(z) \, dF(z) \right)^2 \mathbf{A}' \boldsymbol{\delta} \boldsymbol{\delta}' \mathbf{A} \\ &= R \, \frac{\mathbf{A}' \boldsymbol{\delta} \boldsymbol{\delta}' \mathbf{A}}{\mathbf{A}'H^*\mathbf{A}} \end{split}$$

where R is a constant independent of A,  $H^*$  is the full rank asymptotic covariance matrix of  $(\tau'_{12N}, \dots, \tau'_{c-1cN})$  and  $\delta = (\delta_1, \dots, \delta_{c-1})$  the known vector of relative spacings specified by  $H_{1B}$ .

THEOREM 3.2. A vector  $\hat{\mathbf{A}}$  which maximizes  $e(L_N^*)$  for a given vector  $\boldsymbol{\delta}$  is  $\hat{\mathbf{A}} = H^{*-1}\boldsymbol{\delta}$ .

PROOF. This result is a standard result in matrix theory.

Theorem 3.3. When  $H_0$  is true and when the sample sizes are equal  $\alpha H^{*-1}$  is given by

$$h_{ij}^{-1} = 2i(c-j)/c$$
  $i \le j$   
=  $2j(c-i)/c$   $i \ge j$  where  $\alpha$  is a constant.

For c=3 the solution for an arbitrary vector  $\boldsymbol{\delta}$  can be easily obtained. Let  $\boldsymbol{\delta}'=(\gamma,1-\gamma),\ 0<\gamma<1$ . Note that  $\sum_{i=1}^{c-1}\delta_i=1$ . However, it is convenient to normalize  $\boldsymbol{\delta}$  to place a 1 in the first position to obtain  $\boldsymbol{\delta}'=(1,\alpha),\ 0<\alpha<\infty$ . Thus,  $\hat{\mathbf{A}}'=((4+2a)/3,(2+4a)/3)$ . Note that for equally spaced alternatives a=1 and  $\hat{\mathbf{A}}'=(2,2)$ . This is the test equivalent to Puri's or Jonckheere's statistics where each of the 3 two-sample statistics carried equal weight.

In the special case of equal spacings,  $\delta' = (1, 1, \dots, 1)$ , the vector  $\hat{\mathbf{A}}$  can be determined.

THEOREM 3.4. When  $\delta' = (1, 1, \dots, 1)$ , the vector  $\hat{\mathbf{A}}$  has elements  $a_k = k(c - k)$ ,  $k = 1, 2, \dots, c - 1$ .

COROLLARY. In the class  $\Gamma$  of statistics, linear combinations with equal weightings proposed by Jonckheere [3] and more generally by Puri [8] for testing  $H_0$  against  $H_{1A}$  with equal spacings have maximum Pitman efficacy for the Chernoff–Savage statistic used.

Note that the statistic with maximum Pitman efficacy in  $\Gamma^*$  is unique up to a multiplicative constant but is not unique in  $\Gamma$ . For example, if linear combinations of Mann-Whitney statistics are considered then  $J_N$ ,  $J_N^*$ , and  $\bar{R}_N'$  defined at the end of Section 3 have the maximum Pitman efficacy in  $\Gamma$  for equal

spacings. Note also that the class  $\Gamma$  is defined for an arbitrary, but fixed, type of parent Chernoff–Savage statistic; however, the optimum weighting coefficients are independent of the two sample statistics used.

Let  $\delta'=(0,1,0)$ . That is, it is hypothesized that for c=4 the first two locations are equal and the last two are both equal but greater than the first pair. The optimum weighting coefficients are A=(1,2,1) which specifies weighting the statistic  $\tau_{23N}$  twice as heavily as  $\tau_{12N}$  and  $\tau_{34N}$  which are weighted equally. In this case an intuitive approach is interesting. The hypothesis suggests pooling the samples from the first two and last two pairs of samples and computing a single two-sample statistic. If this is done for the Mann-Whitney statistic, the result is  $M_{1+2,3+4}=M_{13}+M_{23}+M_{14}+M_{24}$  which, in the latter form, is in  $\Gamma$  and has the "equivalent" form with weights (2,4,2) which, when normalized, corresponds to the previous result. The Pitman efficiency of the optimum statistic in  $\Gamma^*$  with respect to Puri's statistic is 1.25.

As an example of optimum weights and the resulting increased efficiency Table 1 shows the weights for 5 different alternative spacings and the Pitman efficiencies relative to Puri's statistic (optimum for equal spacings) for values of c = 4, 5, 6, 7. The alternative spacings considered are: (A) equal spacings,

TABLE 1
Optimal weighting coefficients
(the number in parenthesis is the Pitman efficiency of the optimal test to the test of Puri)

	Α	В	С	D	E
c = 4	1.00	1.00	1.00	1.00	1.00
	1.33	1.50	1.38	1.60	1.64
	1.00	1.00	1.06	1.40	1.55
	(1.000)	(1.020)	(1.002)	(1.050)	(1.087)
c = 5	1.00	1.00	1.00	1.00	1.00
	1.50	1.58	1.55	1.75	1.81
	1.50	1.75	1.59	2.00	2.23
	1.00	1.08	1.09	1.50	1.88
	(1.000)	(1.018)	(1.003)	(1.056)	(1.148)
c=6	1.00	1.00	1.00	1.00	1.00
	1.60	1.67	1.65	1.83	1.89
	1.80	2.00	1.91	2.31	2.58
	1.60	1.67	1.74	2.29	2.84
	1.00	1.00	1.12	1.57	2.26
	(1.000)	(1.012)	(1.004)	(1.059)	(1.219)
c = 7	1.00	1.00	1.00	1.00	1.00
	1.67	1.71	1.71	1.88	1.94
	2.00	2.13	2.11	2.50	2.77
	2.00	2.25	2.17	2.75	3.36
	1.67	1.79	1.86	2.50	3.48
	1.00	1.04	1.14	1.63	2.68
	(1.000)	(1.010)	(1.005)	(1.061)	(1.298)

 $\delta_i=1$   $i=1,2,\cdots,c-1;$  (B)  $\delta_{c/2}=2$  if c is even or  $\delta_{(c+1)/2}=2$  if c is odd and  $\delta_i=1$  otherwise; (C)  $\delta_i=1+.1(i-1)$   $i=1,2,\cdots,c-1;$  (D)  $\delta_i=1+(i-1)$   $i=1,2,\cdots,c-1;$  (E)  $\delta_1=1,\delta_i=2\delta_{i-1}$   $i=2,3,\cdots,c-1.$  The spacings (B) represent the occurrence of a missing sample interior to an otherwise equal spacing situation. The alternatives (C), (D) and (E) represent increasingly more severe examples of increasing the relative spacings.

For ease in comparison the coefficients have been normalized so that the first weight is unity. It is noted that, with the exception of the case mentioned earlier, the optimal weights defy intuition.

It is further noted that Puri's statistic seems quite robust against the violation of equal spacings. Only for alternative (E), where the spacings are doubling, is the optimal statistic a significant improvement.

In conclusion, the use of statistics in  $\Gamma^*$  equivalent to Puri's family are suggested for simplicity of calculation. Further adjustment of weighting coefficients need only be considered if the assumption of equal spacings is grossly inadequate.

**4.** The exact and approximate null distribution of  $J^*$ . Under the null hypothesis, the means, variances and covariances of the Mann-Whitney statistics  $M_{ij}$ ,  $i=1,2,\dots,c-1$ ,  $j=i+1,\dots,c$  computed from the c samples are  $EM_{ij}=n_in_j/2$ ,  $Var(M_{ij})=n_in_j(n_i+n_j+1)/12$ ,  $Cov(M_{ij},M_{kl})=0$  if all i,j,k,l are different and if i,j,k are all different

$$\begin{split} & \text{Cov} \left( M_{ij}, \, M_{ik} \right) = \text{Cov} \left( M_{ji}, \, M_{ki} \right) = n_i n_j n_k / 12 \\ & \text{Cov} \left( M_{ij}, \, M_{ki} \right) = \text{Cov} \left( M_{ji}, \, M_{ik} \right) = -n_i n_j n_k / 12 \; . \end{split}$$

Tryon [11] has given an elementary derivation of the covariances. It is now easy to calculate the mean and variance of  $J^*$ . These are listed in Table 2 for c=3,4,5,6 assuming equal sample sizes along with the necessary weights  $a_k$ , to construct  $J^*$ . For equal sample sizes, under the null hypothesis  $EJ^*=n^2(c^3-c)/12$  and  $Var J^*=n^2(c^3-c)(10n+c^2+1)/360$ .

Hence using the standard normal table and a continuity correction the observed significance level for  $J^*$  can be approximated. The exact distribution of  $J^*$  under  $H_0$  has been calculated by R. E. Odeh (in a personal communication) for various combinations of c and n. Exact probabilities nearest .05 and .01 are given in Table 3 along with the normal approximation. The approximation is useful for very small values of c and n. From Table 3 it appears that for  $J^*$ , under most circumstances, the asymptotic distribution is adequate for constructing tests.

TABLE 2

С	Weights for $J^*$	$E(J^*)$	$V(J^*)$
3	2, 2	$2n^2$	$n^2(8n+8)/12$
4	3, 4, 3	$5n^2$	n²(20n + 34)/12
5	4, 6, 6, 4	and the same of th	

TABLE 3						
Exact values for $P(J^* \ge k)$ under $H_0$						
[the number in brackets is the normal approximation]						

c						
n	k					
n	3	4	5	6		
3	28(.0345)	59(.0525)	112(.0516)	189(.0488)		
	[.0329]	[.0537]	[.0485]	[.0495]		
	32(.0048)	66( <b>.00</b> 94)	122(.0097)	203(.0094)		
	[.0041]	[.0073]	[.0075]	[.0082]		
4	46(.0384)	101(.0471)	192(.0489)	324(.0518)		
	[.0375]	[.0485]	[.0465]	[.0526]		
	50(0.115)	110(.0098)	206(.0094)	344(.0101)		
	[.0096]	[.0084]	[.0075]	[.0089]		
5	68 (.0449)	153(.0492)	292(.0510)			
	[.0446]	[.0495]	[.0495]			
	76 (.0076)	165 (.0104)	310(.0107)	_		
	[.0062]	[.0091]	[.0091]			
6	94(.0524)	216(.0488)	414(.0491)			
	[.0526]	[.0495]	[.0485]	*********		
	104(.0098)	232(.0095)	438(.0093)			
	[.0084]	[.0082]	.[0079]	Minimized		

5. Acknowledgment. We are indebted to Dr. Joan R. Rosenblatt for the result in Theorem 3.2. Her result greatly simplifies the calculation of the optimal weighting coefficients. We are also indebted to Dr. Robert E. Odeh for his calculation of the exact probabilities of  $J^*$ . A more extensive table for the exact distribution in Table 3 may be obtained from Dr. Odeh, Department of Mathematics, University of Victoria, Victoria, B. C.

## **REFERENCES**

- [1] Chernoff, H. and Savage, I. R. (1958). Asymptotic normality and efficiency of certain nonparametric test statistics. *Ann. Math. Statist.* 29 972-994.
- [2] HALLER, H. S. Jr. (1968). Optimal c-sample rank-order procedures for selection and tests against slippage and ordered alternatives. Dissertation, Case Institute of Technology.
- [3] Hogg, R. V. (1965). On models and hypotheses with restricted alternatives. J. Amer. Statist. Assoc. 60 1153-1162.
- [4] JONCKHEERE, A. R. (1954). A distribution free k-sample test against ordered alternatives. Biometrika 41 133-145.
- [5] KENDALL, M. G. and Stuart, A. (1961). Advanced Theory of Statistics, 2. Hafer Publishing Company, New York.
- [6] MANN, H. B. and WHITNEY, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *Ann. Math. Statist.* 18 50-60.
- [7] NOETHER, G. E. (1955). On a theorem of Pitman. Ann. Math. Statist. 26 64-68.
- [8] Puri, M. L. (1964). Asymptotic efficiency of a class of c-sample tests. Ann. Math. Statist. 35 102-121.

- [9] Puri, M. L. (1965). Some distribution free K-sample rank tests of homogeneity against ordered alternatives. Comm. Pure Appl. Math. 18 51-63.
- [10] TERPSTRA, T. J. (1952). The asymptotic normality and consistency of Kendall's test against trend when ties are present in one ranking. Nederl. Akad. Wetensch. Indag. Math. 55 327-333.
- [11] TRYON, P. V. (1972). Covariances of two sample rank sum statistics. J. Res. Nat. Bur. Standards Sect. B 76B.

NATIONAL BUREAU OF STANDARDS BOULDER, COLORADO 80302 DEPARTMENT OF STATISTICS
PENNSYLVANIA STATE UNIVERSITY
UNIVERSITY PARK, PENNSYLVANIA 16802