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On the Combination of Independent Two Sample Tests of a General Class

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Title - ON THE COMBINATION OF INDEPENDENT TWO SAMPLE TESTS OF A GENERAL CLASS

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CORRECTIONS:

Page 3: Line 9

From: $y_i n_i$
To: $y_i n_i$

Page 4: Line 10

From: $V^{(i)}_1$
To: $V^{(i)}_1$

Page 5: Line 11 (Assumption 2)

From:

$$
\int_{I_{N_1}} [J_N(H_{N_1}) - J(H_{N_1})] dS_{m_1}(x) = O_p(1/N_1^{1/2})^3; i=1,\ldots,k
$$

To:

$$
\int_{I_{N_1}} [J_N(H_{N_1}) - J(H_{N_1})] dS_{m_1}(x) = o_p \left( \frac{1}{\sqrt{N_1}} \right); i=1,\ldots,k
$$

Page 5: Line 13 (Assumption 3)

From: $J_{N_1}(1) = O(\sqrt{N_1})$
To: $J_{N_1}(1) = o(\sqrt{N_1})$
On the Combination of Independent Two Sample Tests of a General Class

M. L. Puri

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1. Summary

Let $X_{i1}, \ldots, X_{im_i}$ and $Y_{i1}, \ldots, Y_{in_i}$; $i=1, \ldots, k$ be $k$ pairs of samples of mutually independent observations from continuous distribution functions $F_i(x)$ and $G_i(y)$ respectively; $i=1, \ldots, k$. Then for testing the hypothesis $F_i = G_i; i=1, \ldots, k$; test statistics of the form (i) $T = \sum_{i=1}^{k} c_i t_i$ and (ii) $Q = \sum_{i=1}^{k} c_i Q_i$ are considered. Here $c_i$ are the weights which may depend upon the sample sizes, $t_i$ student's t statistic for testing the equality of means between two normal populations with the same variance corresponding to the $i^{th}$ pair of samples and $Q_i$ is the Chernoff-Savage Statistic $^2$ (1958) for the $i^{th}$ pair of samples. Under suitable assumptions, the weights $c_i$ which maximize the local asymptotic powers of the tests (i) and (ii) are obtained. These results are specialized to (a) Pitman's shift alternatives, (b) Lehmann's distribution free alternatives and (c) contaminated alternatives. Finally, the asymptotic efficiencies of $Q$ test relative to some of its parametric as well as non-parametric competitors against the above mentioned alternatives are discussed.

2. Introduction

It frequently happens that several independent test statistics are available for testing the same null hypothesis. These may have arisen from several sets of independent samples which cannot be combined perhaps because they are reported by different investigators or because they have not all been gathered under the same conditions. In such situations, it is often considered reasonable
to combine the various results into a single measure on which an
objective judgment of the evidence as a whole can be based. One
measure is advanced by Fisher (1932). He proposed as a test
statistic the product of the tail errors of the individual tests.
It turns out that -2 times the logarithm of this product has a
chi-square distribution with 2k degrees of freedom when the null
hypothesis is true, k being the number of tests. For detailed
discussion about Fisher's method, the reader is referred to the
paper of Wallis (1942). General discussion of combining indepen-
dent tests can also be found in Birnbaum (1954) and Pearson (1938).
Recently, an interesting technique was advanced by Ph. van
Elteren (1960). He analyses a class of tests based on linear
combinations $\sum_{i=1}^{k} c_i W_i$ of test statistics $W_1, \ldots, W_k$ of k independent
two sample Wilcoxon tests. He considers in particular two special
linear combinations, when (i) $c_i = c/m_i n_i$ and (ii) $c_i = c/(m_i + n_i + 1)$
where c is a positive real number and $m_i, n_i$ are the sample sizes of
of the $i^{th}$ set and shows that the test (i) has a region of consist-
tency independent of sample sizes and the test (ii) has asympto-
tically the maximum power. In this paper, we consider a similar
problem in a more general frame work which includes as a special
case the problem considered by Ph. van Elteren (1960), mentioned
above. Precisely, we consider the following problem.

3. **Problem**

Let $X_{i1}, Y_{i1}; i=1, \ldots, k$ be k pairs of independent stochastic
variables about whose cumulative distribution functions, nothing
\[ H_{1}(x) = \lambda_{1} F_{1}(x) + (1-\lambda_{1}) \hat{G}_{1}(x). \]

Let \( Z_{N, j}^{(1)} = 1 \), if the \( j \)th smallest observation in the combined sample of the \( i \)th pair comes from \( X_{i} \) and otherwise let \( Z_{N, j}^{(1)} = 0 \). Then the Chernoff-Savage statistic (1958) for the \( i \)th pair of samples is

\[ (4.1) \quad Q_{i} = \frac{1}{m_{i}} \sum_{j=1}^{N_{1}} E_{N, j}^{(1)} Z_{N, j}^{(1)} \]

where the \( E_{N, j}^{(1)} \) are given numbers. Note that Wilcoxon's statistic for the \( i \)th pair of samples is obtained from (4.1) by letting \( E_{N, j}^{(1)} = j/N_{i} \) and the normal score statistic for the corresponding samples by letting \( E_{N, j}^{(1)} = E(V_{j}^{(1)}) \) where \( V_{1}^{(1)} < \ldots < V_{N_{1}}^{(1)} \) is an ordered sample of size \( N_{1} \) from a Standard normal distribution.

Following Chernoff-Savage (1958), we shall use the following equivalent form of \( Q_{i} \):

\[ (4.2) \quad Q_{i} = \int_{-\infty}^{\infty} J_{N}(H_{N_{1}}(x)) dS_{m_{i}}^{(1)}(x); \quad i=1, \ldots, k, \]

where \( E_{N, j}^{(1)} = J_{N}(j/N_{i}) \).

While \( J_{N} \) need be defined only at \( 1/N_{i}, \ldots, N_{i}/N_{i} \) but may have its domain of definition extended to \( (0,1] \) by letting \( J_{N} \) be constant on \( (j/N_{i}, (j+1)/N_{i}] \).

In this paper, we consider the statistics of the form

\[ (4.3) \quad Q = \sum_{i=1}^{k} c_{i} Q_{i} \]

where the \( c \)'s are real positive numbers and may depend upon the sample sizes.
We may test the hypothesis \( H_0: F_1(x) = G_1(x); i=1,\ldots,k \) by means of the critical region \( Q \geq Q_\alpha \) where \( Q_\alpha \) is given by

\[(4.4) \quad P_{H_0}(Q \geq Q_\alpha) = \alpha\]

where \( \alpha \) is the level of significance. If the distribution of \( Q \) under \( H_0 \) is symmetric with respect to the origin, then the corresponding left-sided test will have a critical region: \( Q \leq -Q_\alpha \) and the two sided test will have a critical region \( |Q| \geq Q_{\alpha/2} \).

5. General Properties of the distribution of \( Q \)

In what follows, we make the following assumptions:

(1) \( J(H) = \lim_{N \to \infty} J_N(H) \) exists for \( 0 < H < 1 \) and is not constant.

(2) \( \int_{I_{N_1}} \left[ J_N(H_{N_1}) - J(H_{N_1}) \right] dS_m(x) = 0 \) \( i=1,\ldots,k \)

where \( I_{N_1} = \{ x: 0 < H_{N_1}(x) < 1 \} \).

(3) \( J_{N_1}(1) = 0(\sqrt{N_1}) \)

(4) \( |J^{(r)}(H)| = |\frac{d^r J}{dH^r}| \leq K [H(1-H)]^{-r-(1/2)+\delta} \) for \( r = 0,1,2 \)

and for some \( \delta > 0 \) and some \( K \).

Then, the application of Chernoff-Savage theorem (1958) yields

\[(5.1) \quad \lim_{N_1 \to \infty} P \left( \frac{Q_1 - \mu_1(\theta)}{\sigma_1(\theta)} \leq x \right) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt, \]

where

\[(5.2) \quad \mu_1(\theta) = \int_{-\infty}^{+\infty} J[H_1(x)]dF_1(x) \]

and
(5.3) \[ N_1 \sigma^2_1(\theta) = 2(1-\lambda_1) \left\{ \int_{-\infty}^{\infty} \left[ \int_{-\infty}^{x} q_1(x)[1-q_1(y)]J[H_1(x)]J[H_1(y)] \right] \right. \]
\[ \left. \frac{dF_1(x)}{dx} \frac{dF_1(y)}{dx} \right\} \] 
\[ + \frac{(1-\lambda_1)}{\lambda_1} \left\{ \int_{-\infty}^{\infty} \left[ \right. \right. \] 
\[ \left. \left. \frac{dG_1(x)}{dx} \frac{dG_1(y)}{dx} \right) \right\} \]

provided \( \sigma_1(\theta) \neq 0 \).

Thus
\[ (5.4) \quad \mu(0) = E_{H_0}(Q) = \frac{k}{1} \frac{c_i a_i}{N_1} \]
where
\[ (5.5) \quad a_i = \int_{-\infty}^{+\infty} J[F_1(x)]dF_1(x) \]
\[ (5.6) \quad \sigma^2(0) = \text{var}_{H_0}(Q) = \frac{k}{1} \frac{c_i^2 n_i}{m_i N_1} \]
where
\[ (5.7) \quad A^2 = \int_{0}^{1} J(x)dx - \left( \int_{0}^{1} J(x)dx \right)^2 \]
\[ (5.8) \quad \mu(\theta) = E(Q) = \frac{k}{1} \frac{c_i \mu_1(\theta)}{N_1} \]
\[ (5.9) \quad \var^2(\theta) = \text{var}(Q) = \frac{k}{1} \frac{c_i \sigma^2_1(\theta)}{N_1} \]

where \( \mu_1(\theta) \) and \( \var^2_1(\theta) \) are given by (5.2) and (5.3) respectively.

By the Central Limit Theorem, the distribution of \( Q \) will be approximately normal.

It follows that the critical value \( Q_\alpha \) is approximately equal to
\[ (5.10) \quad Q_\alpha = \mu(0) + \lambda_\alpha A \sqrt{\frac{k}{1} \frac{c_i^2 n_i}{m_i N_1}} \]
where
\[ (5.11) \quad \int_{\lambda_\alpha \sqrt{2\pi}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = \alpha \]
and the power of the Q test with respect to a given set of distribution functions $F_1(x)$ and $G_1(x)$ is approximately equal to

\begin{equation}
\beta_\alpha(\theta) = 1 - \Phi\left(\lambda_\alpha - \frac{\hat{\theta}(\theta) - \mu(0)}{\sigma(0)} \frac{G(0)}{\sigma(0)}\right)
\end{equation}

where $\Phi(x)$ is the standard normal distribution function.

6. **Locally Best Q Test**

From this section onward, we assume that $m_i, n_i$ and $k$ are non-decreasing functions of a natural number $n$ that tends to infinity.

The dependence on $n$ is indicated when necessary, by writing $m_i(n)$, $n_i(n)$, $k(n)$, $\mu(n)(\theta)$, etc. We shall consider the following two special cases:

Case 1: $m_i(n)$ and $n_i(n)$ tend to infinity as $n$ tends to infinity but $\frac{m_i(n)}{n}$ and $\frac{n_i(n)}{n}$ remain bounded away from zero, $k(n) = k$ for each $n$.

Case 2: $m_i(n)$ and $n_i(n)$ remain constants and $k(n)$ tends to infinity as $n$ tends to infinity. For simplicity sake, we assume that $m_i(n) = m_1, n_i(n) = n_1$ and $k(n) = n$.

Furthermore, we make the following assumption:

**Assumption 6.1:**

For sufficiently large $n$,

\[
\sqrt{n}\left[ J \left\{ H_1(x; n) \right\} - J \left\{ F_1(x; n) \right\} \right] / A
\]

remains bounded as $n$ tends to infinity. Then we prove the following

**Theorem 6.1.**

For each index $n$, assume the validity of the case 1 and assumption 6.1. Then the Q test with
(6.1) \[ c_1(n) = c \frac{d_1(n)m_1(n)N_1(n)}{n_1(n)} \]

where

(6.2) \[ d_1(n) = \int_{-\infty}^{+\infty} \left[ J \left\{ H_1(x;n) \right\} - J \left\{ F_1(x;n) \right\} \right] dF_1(x;n) \]

and \( c \) is an arbitrary positive constant, has for \( n \to \infty \), asymptotically the largest power against all alternatives for which \( d_1(n) \) are positive.

Proof. We shall first prove that

\[ \frac{\sigma(n)(0)}{\sigma(n)(\theta)} \to 1 \text{ as } n \to \infty. \]

For this it suffices to show that \( \sigma(n)(\theta) \) is continuous at \( \theta = 0 \), uniformly in \( n \). Consider first, the first integral on the right hand side of (5.3) and let it be denoted by \( A_1(\theta) \). Thus

(6.3) \[ A_1(\theta) = \int_{0<x<y<\infty} G_1(x)[1-G_1(y)]J[H_1(x)]J[H_1(y)] dF_1(x)dF_1(y). \]

Setting \( F_1(x) = u \) and \( F_1(y) = v \), we rewrite (6.3) as

(6.4) \[ A_1(\theta) = \int_{0<u<v<1} G_1^*(u)[1-G_1^*(v)]J[H_1^*(u)]J[H_1^*(v)] dudv \]

where \( G_1^*(u) = G_1[F_1^{-1}(u)] \) and \( H_1^*(u) = \lambda_1 u + (1-\lambda_1)G_1^*(u) \).

It is clear that integrand is continuous at \( \theta = 0 \) for almost all \( u \) and \( v \).

Furthermore, since
\[ G_1^*(u) = \frac{1}{1-\lambda_1} H_1^*(u) \]
\[ 1-G_1^*(v) = \frac{1}{1-\lambda_1} [1-H_1^*(v)] \]
\[ |J[H_1^*(u)]| \leq K[H_1^*(u) \left\{ 1-H_1^*(u) \right\}]^{-3/2+\delta} \]

we have, from (6.4)
\[ (6.5) \quad |G_1^*(u)[1-G_1^*(v)]J[H_1^*(u)]J[H_1^*(v)]| \]
\[ \leq K \frac{1}{(1-\lambda_1)^2} [H_1^*(u)]^{-1/2+\delta}[1-H_1^*(v)]^{-1/2+\delta}[H_1^*(v)]^{-3/2+\delta} \]
\[ [1-H_1^*(u)]^{-3/2+\delta}. \]

We may assume \( \delta < 1/2 \), without loss of generality.

Then, from (6.5)
\[ \left| G_1^*(u)[1-G_1^*(v)]J[H_1^*(u)]J[H_1^*(v)] \right| \]
\[ \leq K \frac{1}{(1-\lambda_1)^2} \lambda_1^{-4+4\delta} u^{-1/2+\delta} (1-v^{-1/2+\delta} (1-u)^{-3/2+\delta} \]

Hence by Cramér ([1957], p. 67) \( A_1(\theta) \) is continuous at \( \theta = 0 \).

Similarly the second integral on the right side of (5.3) is continuous at \( \theta = 0 \). Hence \( \sigma_i^2(n)(\theta) \) and so a fortiori \( \sigma_i^2(n)(\theta) \) is continuous at \( \theta = 0 \).

Next, because of the assumption (6.1)
\[
\frac{\mu(n)(\theta) - \mu(n)(0)}{\sigma(n)(0)} = O(1),
\]

Hence the power of the Q test can be approximated by

\[
1 - \Phi(\lambda_\alpha - \frac{\mu(n)(\theta) - \mu(n)(0)}{\sigma(n)(0)}).
\]

This is maximum, when

\[
\frac{\sum_{i=1}^{k} c_1(n)\int_{-\infty}^{+\infty} \left[ J\left\{ H_1(x;n) \right\} - J\left\{ F_1(x;n) \right\} \right] dF_1(x;n)}{A \sqrt{\sum_{i=1}^{k} [c_1(n)n_1(n)]/m_1(n)N_1(n)}}
\]

is maximum, which is so when \( c_1(n) \) is as defined in (6.1).

This completes the proof of the theorem.

7. Computation of \( d_1(n) \)

The computation of \( d_1(n) \) highly depends upon the sequences of alternatives, we have in mind. In subsequent analysis, we shall concern ourselves with three sequences of admissible alternative hypotheses viz. \( H_n^P \), \( H_n^L \) and \( H_n^C \). The hypothesis \( H_n^P \) specifies that for each \( i=1,\ldots,k; G_i(x) = F(x+\gamma_1+\xi/\sqrt{n}) \), the hypothesis \( H_n^L \) specifies that for each \( i=1,\ldots,k; G_i(x) = [F(x+\gamma_1)] \sqrt{n} \) and the hypothesis \( H_n^C \) specifies that for each \( i=1,\ldots,k; x_i \) has the distribution function \( F(x+\gamma_1) \) and \( y_i \) has the distribution function \( (1/\sqrt{n})F(x+\gamma_1) + \xi/\sqrt{n} G(x+\gamma_1) \); where \( \gamma_1 \) is a real number, \( \xi \) is a finite positive constant independent of \( i \), and \( F_1(x) = F(x+\gamma_1) \). Alternatives of the form \( H_n^P \) were introduced by Pitman, those of the form \( H_n^L \) by Lehmann (1953) in order to study the non-parametric procedures.
when the alternatives themselves are given in a non-parametric form.
For an extensive study of Lehmann's alternatives, the reader is
referred to an interesting paper of Savage (1956). Alternatives of
the form $H_n^c$ are referred to as contaminated alternatives, which
have been considered by Hodges and Lehmann (1956) among others.

We shall, therefore, compute $d_i(n)$ and hence $c_i(n)$ for the
above mentioned classes of alternatives. We shall make use of a
lemma due to Hodges and Lehmann (1961) and the reader is referred
to this reference regarding it. A consequence of this lemma in a
form appropriate for our purpose, may be stated as follows:

Lemma 7.1. (Hodges-Lehmann).

If
(i) $F$ is continuous cumulative distribution function function
differentiable in each of the open intervals $(-\infty, a_1), (a_1, a_2), \ldots,
(a_{s-1}, a_s), (a_s, \infty)$ and the derivative of $F$ is bounded in each of
these intervals and either

(ii) for the alternative $H_n^P$ or $H_n^C$ the function $d[F(x)] dx$
is bounded as $x \to \pm \infty$, or

(ii') for the alternatives $H_n^L$, the function $F(x) \log F(x) d[F(x)] dx$
is bounded as $x \to \pm \infty$, then

(7.1) $\sqrt{n} \ d_i(n) \sim \xi(1-\lambda_1) \int \frac{d[F(x)]}{dx} dF(x)$, in case the hypothesis
$H_n^P$ is valid,

(7.2) $\sqrt{n} \ d_i(n) \sim \xi(1-\lambda_1) \int -F(x) \log F(x) \frac{d[F(x)]}{dx} dx$ in case the
hypothesis $H_n^L$ is valid, and

(7.3) $\sqrt{n} \ d_i(n) \sim \xi(1-\lambda_1) \int [G(x)-F(x)] \frac{d[F(x)]}{dF(x)} dF(x)$ in case the
hypothesis $H_n^c$ is valid.
The proof of this lemma follows by the method used in section 3 and 4 of Hodges-Lehmann (1961).

In order to save space the details are omitted.

Now the quantities $\xi \int \frac{dJ[F(x)]}{dx} dF(x)$, $\xi \int -F(x) \log F(x) \frac{dJ[F(x)]}{dx}$ and $\int [G(x)-F(x)] \frac{dJ[F(x)]}{dF(x)} dF(x)$ being constants, can be absorbed into the constant $c$ of (6.1), with the result that we have $c_1(n) = cm_1(n)$. Thus the material discussed in this section coupled with the one discussed in the previous section yields the following.

Theorem 7.1

For each index $n$, assume the validity of the hypotheses $H_n^p$ or $H_n^L$ or $H_n^C$ and the assumptions of lemma 7.1. Then for the case 1, the $Q$ test with weights $c_1(n) = cm_1(n)$, where $c$ is an arbitrary positive constant, has asymptotically the maximum power.

In what follows, we shall denote the locally best Wilcoxon form of $Q$-test by the symbol $Q_W$ and we shall call it locally best $Q_W$ test. Thus

$$Q_W = \sum_{l=1}^{k} cm_1(n)Q_{W_l}$$

where $Q_{W_l}$ is obtained from (4.1) by letting $E_{N,j}^{(1)} = j/N_1$.

8. Relation between Elteren's $W$ test and locally best $Q_W$ test

Let $X_{1,r}$ and $Y_{1,s}$ denote the $r^{th}$ and the $s^{th}$ observations of $X_1$ and $Y_1$ respectively; $r=1,...,m_1$; $s=1,...,n_1$. 
Denote
\[ \text{sgn}(X_{i,r} - Y_{i,s}) = \begin{cases} 
-1, & \text{if } X_{i,r} - Y_{i,s} < 0 \\
0, & \text{if } X_{i,r} - Y_{i,s} = 0 \\
+1, & \text{if } X_{i,r} - Y_{i,s} > 0 
\end{cases} \]
then the Elteren's locally best W test [cf. Elteren, Ph. van (1960)] for case I as well as case II is defined as
\[ (8.1) \quad W = c \sum_{i=1}^{k(n)} \frac{W_i}{[m_i(n) + n_i(n) + 1]} \]
where
\[ (8.2) \quad W_i = \sum_{r=1}^{m_i} \sum_{s=1}^{n_i} \text{sgn}(X_{i,r} - Y_{i,s}) \]
which is equivalent to the Wilcoxon's statistic [cf. Wilcoxon (1945)] for the \( i \)th pair of samples.

It is easy to check that
\[ (8.3) \quad W_i = 2m_iN_iQ_{W_i} - m_i(N_i + 1) \]
so that
\[ (8.4) \quad W = 2c \sum_{i=1}^{k} \frac{m_iN_i}{m_i + n_i + 1} Q_{W_i} - c \sum_{i=1}^{k} m_i. \]
Hence, asymptotically, the following linear relation exists between the W statistic and \( Q_{W} \) statistic.
\[ (8.5) \quad W = 2c Q_W - c \sum_{i=1}^{k} m_i. \]

In our subsequent analysis, we shall use the following expressions connected with the Elteren's W test:
\[ (8.6) \quad \mu(\theta) = E(W) = 2c \sum_{i=1}^{k} \frac{m_iN_i}{m_i + n_i + 1} \int_{-\infty}^{+\infty} \left[ G_1(x) - F_1(x) \right] dF_1(x) \]
\[ (8.7) \quad \sigma^2(\theta) = \text{var}_{H_0}(W) = \frac{1}{2} c^2 \sum_{i=1}^{k} \frac{m_iN_i}{m_i + n_i + 1}. \]
9. On the Combination of Independent Two-Sample tests based on Student's t-statistic.

Let \( F_i(x) \) and \( G_i(x) \) be normal distribution functions with the same variance \( \sigma^2 \). Then the student's t-test for the \( i \)th pair of samples, is based on the statistic

\[
t_i = \frac{(X_i - Y_i)}{\sqrt{\frac{1}{m_i} + \frac{1}{n_i} \sigma^2}}
\]

where

\[
X_i = \frac{m_i}{j=1} X_{ij} / m_i \quad \text{and} \quad Y_i = \frac{n_i}{k=1} Y_{ik} / n_i.
\]

But since the denominator of \( t_i \) tends to one in probability, therefore an asymptotically equivalent statistic is

\[
t_i = (X_i - Y_i) / \sqrt{\frac{1}{m_i} + \frac{1}{n_i} \sigma^2}
\]

which has normal distribution. Now proceeding as in sections 6 and 7, we conclude

Theorem 9.1.

For each index \( n \), assume the validity of the hypotheses \( H_n^P \), \( H_n^L \) or \( H_n^C \). Then the t-test with weights \( c_i(n) = c \sqrt{\frac{m_i(n)n_i(n)}{N_1(n)\sigma^2}} \), has for \( n \to \infty \), asymptotically the largest power. (\( c \) is an arbitrary positive constant).

We may note that

(a) Under \( H_n^P \),
(9.4) \( \mu_t(\theta) = \mathbb{E}(t) = \frac{k}{n} \sum_{i=1}^{m} c \frac{m_i(n) n_1(n)}{N(n) \sigma^2} \int \frac{x^{1+\log F(x)}}{\sqrt{2\pi}} \, dx \) \\
(b) Under \( H_n^L \), 
(9.5) \( \mu_t(\theta) = \mathbb{E}(t) = \frac{k}{n} \sum_{i=1}^{m} c \frac{m_i(n) n_1(n)}{N(n) \sigma^2} \int x^{1+\log F(x)} \, dx \) \\
(c) Under \( H_n^C \), 
(9.6) \( \mu_t(\theta) = \mathbb{E}(t) = \frac{k}{n} \sum_{i=1}^{m} c \frac{m_i(n) n_1(n)}{N(n) \sigma^2} \int x^{1+\log F(x)} \, dx \)

and 
(9.7) \( \sigma_t^2(\theta) = \text{var}(t) = \frac{k}{n} \sum_{i=1}^{m} c^2 \frac{m_i(n) n_1(n)}{N(n) \sigma^2} \)

under \( H_n^P, H_n^L, \text{and } H_n^C \).

10. The asymptotic relative efficiencies of the tests

Briefly, the idea of the asymptotic relative efficiency is the following:

Suppose that for testing the hypothesis \( H_0 \) against \( H_n \), two tests \( T \) and \( T' \) require \( N \) and \( N^* \) observations to achieve the same power \( \beta \) at the level of significance \( \alpha \). Then the asymptotic efficiency of \( T \) with respect to \( T^* \) is defined as

\[
N^*/N \to \inf_{T, T'} \mathbb{E}(T; \alpha, \beta, H_0, \{H_n\}).
\]

We shall be interested in studying the asymptotic efficiency of (i) the Elteren's \( W \) test relative to an arbitrary \( Q \) test against (a) Pitman's \( \triangledown \) alternatives and (b) Lehmann's distribution free alternatives, and (ii) the Elteren's \( W \) test relative to the locally best \( t \) test against (a) and (iii) arbitrary \( Q \) test relative to the locally best \( t \) test against contaminated alternatives.
The asymptotic relative efficiency of the Elteren's W test relative to an arbitrary Q test is stated in the following

**Theorem 10.1(a)**

If

(1) for all \( i \), \( \lim_{n \to \infty} \frac{m_i(n)}{n} = r_i \) and \( \lim_{n \to \infty} \frac{n_i(n)}{n} = s_i \) exist and are positive,

(ii) the distribution function \( F \) is such that

\[
\lim_{n \to \infty} \sqrt{n} \int_{-\infty}^{+\infty} \left[ J \left\{ \lambda_1 F_1(x) + (1-\lambda_1) F_1(x+\xi) \right\} \right] \frac{dF_1(x)}{A} \]

exists,

(iii) the hypothesis of lemma 7.1 are assumed,

then

the asymptotic relative efficiency of the Elteren's W test relative to an arbitrary Q test for testing the hypothesis \( H_0 \) against \( H^P_n \) is

\[
e_{W,Q}^P = 12A^2 \left( \frac{\int_{-\infty}^{+\infty} f^2(x) dx}{\int_{-\infty}^{+\infty} \frac{dJ[F(x)]}{dx} dF(x)} \right)^2
\]

where \( f \) is the density of \( F \).

**Proof.**

Let \( n \) index the sample size for the Elteren's W test and \( n^* \) the corresponding index for the Q test. Furthermore, let the level of significance be fixed at \( \alpha \) and the limiting power at \( \beta \). Then the W and Q tests will have the same limiting power, if
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\[
2 \frac{\sum_{i=1}^{k} m_i(n) + m_i(n) + 1}{\sum_{i=1}^{k} m_i(n) + m_i(n) + 1} \int_{-\infty}^{+\infty} [F(x+y_i + \xi \sqrt{n}) - F(x+y_i)] dF(x+y_i)
\]

\[
\sqrt{\frac{1}{2} \sum_{i=1}^{k} m_i(n) + m_i(n) + 1}
\]

\[
= \sum_{i=1}^{k} \frac{m_i(n)}{m_i(n) + m_i(n) + 1}
\]

\[
= \sum_{i=1}^{k} \frac{m_i(n)}{m_i(n) + m_i(n) + 1}
\]

i.e. if

\[(10.2) \quad 2 \sqrt{\frac{1}{2} \sum_{i=1}^{k} \frac{r_i s_i}{r_i + s_i}} \xi \int_{-\infty}^{+\infty} f(x) dF(x) = \frac{1}{A} \sqrt{\frac{1}{2} \sum_{i=1}^{k} \frac{r_i s_i \xi}{r_i + s_i}} \int_{-\infty}^{+\infty} \frac{dF(x)}{d} dF(x)
\]

and the same alternatives, if \( \xi / \sqrt{n} = \xi^* / \sqrt{n^*} \).

Substituting \( \xi^* = \xi \sqrt{n^*/n} \) in (10.2) yields the desired result.

It may be remarked that (10.1) agrees with the result found by Chernoff-Savage (1958), Hodges-Lehmann (1961) for the two-sample problem and Puri (1962) for the c-sample problem. Hence the efficiency results of this paper as well as those mentioned above apply directly to the present problem.

Proofs of theorems 10.1(b) to 10.1(d) are similar to those of theorem 10.1(a) and are therefore omitted.

Theorem 10.1(b).

If
(i) For all \( i \), \( \lim_{n \to \infty} \frac{m_i(n)}{n} = r_i \) and \( \lim_{n \to \infty} \frac{n_i(n)}{n} = s_i \) exist and are positive.

(ii) The distribution function \( F \) is such that

\[
\lim_{n \to \infty} \frac{1}{\sqrt{n}} \int_{-\infty}^{\infty} [J \left\{ \lambda F_1(x) + (1-\lambda_1)[F_1(x)]^{1-\xi}/\sqrt{n} \right\} - J \left\{ F_1(x) \right\} ] dF_1(x)/A
\]

exists.

(iii) The hypotheses of Lemma 7.1 are satisfied, then,

The asymptotic relative efficiency of the Elteren's \( W \) test relative to an arbitrary \( Q \) test for testing the hypothesis \( H_0 \) against \( H_n^{L} \) is

\[
e_{W, Q} = \left( \frac{3}{4} \right)^2 \left( \frac{1}{\int_{-\infty}^{+\infty} x \log \Phi(x) d\Phi(x)} \right) \]

In particular when \( J = \Phi^{-1} \), where \( \Phi \) is the cumulative normal distribution function,

\[
e_{W, Q}(F(x)) = \left( \frac{3}{4} \right)^2 \left( \frac{1}{\int_{-\infty}^{+\infty} x \log \Phi(x) d\Phi(x)} \right)
\]

= .927 by numerical evaluation.

We may remark that (10.4) agrees with the result found by Puris (1962) for the \( c \)-sample problem.

Theorem 10.1 (c).

If

(i) For all \( i \), \( \lim_{n \to \infty} \frac{m_i(n)}{n} = r_i \) and \( \lim_{n \to \infty} \frac{n_i(n)}{n} = s_i \) exist and are positive,
the distribution function $F$ and $G$ are such that
\[
\lim_{n \to \infty} \sqrt{n} \int_{-\infty}^{+\infty} \left[ J \left\{ \lambda_1 F(x+\gamma_1) + (1-\lambda_1) \left\{ (1-\theta)F(x+\gamma_1) + \theta G(x+\gamma_1) \right\} \right\} - J \left\{ F(x+\gamma_1) \right\} \right] dF(x+\gamma_1)/A
\]
exists,

the hypotheses of lemma 7.1 are assumed,

then,

the asymptotic relative efficiency of an arbitrary $Q$ test relative to locally best $T$ test for testing the hypothesis $H_0$ against $H_n^c$ is

\[
e_{Q,T}^c(F,G) = \frac{2}{A^2} \left( \frac{\int_{-\infty}^{+\infty} [F(x)-G(x)] dF(x) \int_{-\infty}^{+\infty} [F(x)-G(x)] dF(x)}{\int_{-\infty}^{+\infty} [F(x)-G(x)] dx} \right)^2.
\]

If, in particular, $J(u) = u$, then $Q$ test becomes Elteren's $W$ test and we have

\[
e_{W,T}^c = 12 \sigma^2 \left( \frac{\int_{-\infty}^{+\infty} [F(x)-G(x)] dF(x)}{\int_{-\infty}^{+\infty} [F(x)-G(x)] dx} \right)^2.
\]

We may remark that the result (10.6) agrees with the result found by Hodges, Lehmann (1956) for the two sample problem. Hence their general comments regarding the merits of the performance of Wilcoxon test relative to $t$ test against contaminated alternatives may be carried along the present situation.

Theorem 10.1(d).

If

(i) for all $i$, $\lim_{n \to \infty} \frac{m_i(n)}{n} = r_i$ and $\lim_{n \to \infty} \frac{n_i(n)}{n} = s_i$ exist and are positive.
(ii) the hypotheses of lemma 7.1 are satisfied, then,

the asymptotic relative efficiency of the Elteren's $W$ test relative to the locally best $T$ test for testing the hypothesis $H_0$ against $H_n^L$ is

\begin{equation}
(10.7) \quad e_{W',T}^L(F(x)) = \frac{3}{4} \sigma^2 \left( \int_{-\infty}^{+\infty} x [1 + \log F(x)] dF(x) \right)^2
\end{equation}

which agrees with the result obtained by the author (1962) for the $c$-sample problem.

Similarly, it can be shown that

\begin{equation}
(10.8) \quad e_{W',T}^P(F(x)) = 12 \sigma^2 \left( \int_{-\infty}^{+\infty} f^2(x) dx \right)^2
\end{equation}

which is known to be the asymptotic efficiency of the two sample Wilcoxon test relative to the student's $t$ test. Hodges and Lehmann (1956) have shown that always $e_{W',t}^P(F(x)) \leq 0.864$. In case $F(x)$ is normal distribution function, this is $3/\pi$.

We now consider the case II. Let $m_1(n) = m_1$, $n_1(n) = n_1$ and suppose that the number, say $v$, of pair of samples tend to infinity in such a way that the limits:

\begin{align*}
L &= \lim_{v \to \infty} \frac{1}{v} \sum_{i=1}^{v} \frac{m_i n_1}{m_1 + n_i + 1} \\
M &= \lim_{v \to \infty} \frac{1}{v} \sum_{i=1}^{v} \frac{m_i n_1}{m_1 + n_i}
\end{align*}

exist. Then subject to the conditions that underlying distributions satisfy some general regularity conditions, it can be shown that
As a special case, suppose that \( N \) repetitions of \( k \) blocks are needed for Elteren's locally best \( W \) test and \( N^* \) for the locally best \( T \) test. Then we shall have

\[
e_{W,T}(F(x)) = 12 \sigma^2 \frac{\left( \int_{-\infty}^{+\infty} f^2(x) \, dx \right)^2}{M} \tag{10.9}
\]

In particular, where \( m_i = n_i = 1 \)

\[
e_{W,T}(F(x)) = 8 \sigma^2 \left( \int_{-\infty}^{+\infty} f^2(x) \, dx \right)^2 \tag{10.11}
\]

which is the asymptotic efficiency of the sign test relative to the student's test, a quantity which is usually expressed as

\[
e_{S,T}(F(x)) = 4 \sigma^2 f^2(0) \tag{10.12}
\]

see in this connection Hodges-Lehmann (1956) and Noether (1958).

It is interesting to note that the asymptotic relative efficiency (10.10) depends on the number of blocks as well as their sizes. When the sample sizes are equal from block to block, say \( m_i = n_i = m \), then the asymptotic efficiency (10.10) depends only on the block size \( 2m \). In the special case where \( F(x) \) is normal distribution function \( \Phi(x) \), we have
(10.13) \[ e_{w,t}^P(F(x)) = \frac{3}{\pi} \frac{2m}{2m+1} \]

some values of this expression are tabulated below:

(10.14) \[ \begin{array}{cccccccccc}
m & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 \ldots\infty \\
\frac{1}{e_{w,t}^p(F)} & .637 & .764 & .818 & .849 & .863 & .881 & .891 & .898 & .904 & .909 & .955 \\
\end{array} \]

In conclusion, we may mention that the results given here are valid for large number of replications.

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Footnotes

1. This paper was prepared with the support of the Office of Naval Research (Nonr - 222(43) and Nonr - 285(38)). Reproduction in whole or in part is permitted for the purpose of the United States Government.

2. Chernoff and Savage use the symbol $T_N$ instead of $Q_N$.

3. If $\{x_n\}$ is a sequence of random variables and $\{r_n\}$ a sequence of positive numbers, we write $x_n = o_p(r_n)$, if $x_n/r_n$ tends to zero in probability, or equivalently, if, for each $\varepsilon > 0$, $P_n\{ |x_n| r_n \leq \varepsilon \} \rightarrow 1$ as $n \rightarrow \infty$. 
Sur la combinaison de tests indépendantes d'une classe générale pour deux échantillons.

Dans cet article, on analyse des tests qui sont basées sur des combinaisons linéaires de k statistiques indépendantes pour deux échantillons. On compare deux classes de ces tests, où les statistiques employées sont d'une part du type de Chernoff et Savage [1] et de l'autre part du type de "Student". Sous certaines conditions, on obtient les coefficients de ces combinaisons linéaires qui donnent les plus grandes puissances asymptotiques locales de ces tests. Ces résultats sont particulièrement au cas où les hypothèses alternatives sont les hypothèses (non paramétriques) de Pitman ou de Lehmann ou des moyennes pondérées souvent appelées "distributions contaminées". Enfin on discute les efficacités asymptotiques du test Q relatives à quelques-uns de ses compétiteurs paramétriques ainsi que compétiteurs non-paramétriques en relation avec alternatives mentionnées ci-devant.
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