# Some Distribution－free Multiple Comparison Procedures 

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$\S$ 1．Introduction．We shall propose the distribution－free multiple comparison procedures for several treatments with a control which are some nonparametric extension of those discussed by Dunnett 〔4〕and Paulson 〔6〕 respectively under the normal assumption．Nonparametric procedures for some multiple comparison problems have been discussed by Steel［8］and Dunn［3］，but we shall here deal with this problems in more general type．That is，the randomized rank statistics proposed in the theory of testing the hypothesis by Bell－Doksum［1〕 will be available．

We assume that $c$ treatments $\pi_{i}$ with distributions $F_{i}(x)=F\left(x-\Delta_{i}\right)$ ， $i=1, \ldots, c$ ，are given and $\pi_{0}$ is a control whose distribution is $F(x)$ where $F(x)$ is continuous but unknown otherwise．The＂goodness＂of a treatment is characterized by a large value of a translation parameter $\Delta$ ．

Now let $X_{i 1}, \ldots, X_{i n_{i}}$ be the random sample of size $n_{i}$ from $\pi_{i}, i=0,1, \ldots$ ， c．We consider the following two problems（A）and（B）．
（A）．Seperate the treatments which are better than the control $\pi_{0}$ from what are not better under a restriction that a control $\pi_{0}$ should be selected as best when all $\Delta_{i}=0$ with a pre－assiged probability 1－$\alpha$ ．Hence the goal is to accept one of the following $2^{c}$ decisions ：
$D_{0}$ ：a control $\pi_{0}$ is best
$D_{i}: \pi_{i}$ is the only one better than $\pi_{0}, i=1, \ldots, c$
$D_{i j}: \pi_{i}$ and $\pi_{j}$ are the only two better than $\pi_{0}, i, j=1, \ldots, c(i<j)$
$D_{1 \ldots c}$ ：all $\pi_{i}$ are better than $\pi_{0}$
where
（1）$P\left[D_{0}\right.$ is accepted when all $\left.\Delta_{i}=0\right]=1-\alpha$ ．
Dunnett＇s procedure $A_{0}$ is given under the normal $F(x)$ as follows，
accept $D_{0}$ if $\overline{X_{i}}-\overline{X_{0}} \leqq d \sigma\left(N_{i 0} / n_{0} n_{i}\right)^{\frac{1}{2}}$ for all $i \neq 0$
accept $D_{i}$ if $\overline{X_{i}}-\bar{X}_{0}>d \sigma\left(N_{i 0} / n_{0} n_{i}\right)^{\frac{1}{2}}$ and

$$
\bar{X}_{j}-\bar{X}_{0} \leqq d \sigma\left(N_{j 0} / n_{0} n_{i}\right)^{\frac{1}{2}} \text { for all } j \neq i, 0
$$

accept $D_{1 . . . c}$ if $\bar{X}_{i}-\bar{X}_{0}>d \sigma\left(N_{i 0} / n_{0} n_{i}\right)^{\frac{1}{2}}$ for all $i \neq 0$
where $\sigma^{2}$ is the variance of $F(x)$ and $n_{0}+n_{i}=N_{i 0}$ and $\bar{X}_{i}=n_{i}^{-1} \sum_{\alpha=1}^{n i} X_{i \alpha}$.
(B). Determine the best of the $(c+1)$ treatments when comparing $c$ treat ments with a control $\pi_{0}$ under the restriction (1). Hence the goal is to accept one of the $(c+1)$ decisions,
$D_{0}$ : a control $\pi_{0}$ is best
$D_{i}: \pi_{i}$ is best, $i=1, \ldots, c$.
Then Paulson's procedure $B_{0}$ under the normal assumptiom may be expressed by the following,
accept $D_{0}$ if $\bar{X}_{i}-\bar{X}_{0} \leqq d \sigma\left(N_{i 0} / n_{0} n_{i}\right)^{\frac{1}{2}}$ for all $i \neq 0$
accept $D_{i}$ if $\bar{X}_{i}-\bar{X}_{0}>d \sigma\left(N_{i 0} / n_{0} n_{i}\right)^{\frac{1}{2}}$ and $\bar{X}_{i}>\bar{X}_{j}$ for all $j \neq i$.
We propose in the section 2 distribution-free procedures for the problems (A) and (B) and compute in the section 3 the probability that each decision is correct. The section 4 is concerned with the asymptotic relative efficiency of our procedure with respect to that in the normal theory.
$\S$ 2. Distribution free procedures. Now let $X_{i 1}, \ldots, X_{i n_{i}}$ be the random sample of size $n_{i}$ from $F_{i}(x)$ and $R\left(X_{i \alpha}\right)$ be the rank of $X_{i \alpha}$ in the combined sample of size $N=\sum_{i=0}^{c} n_{i}$. Moreover let $Z_{1}, \ldots, Z_{N}$ be the random sample from the standard normal distribution $\Phi(x)$ and $Z(1)<\ldots<Z(N)$ be the order statistics. Bell-Doksum has proposed the new distribution free statistics such as
(2) $T_{N i}=n_{i}^{-1} \sum_{\alpha=1}^{n i} Z\left(R\left(X_{i \alpha}\right)\right), i=0,1, \ldots, c$
in order to construct some nonparametric tests of any exact size where the existing tables as the normal or Chi-square distribution are available. We here apply them for our procedures. Our decision procedures may be formulated as follows.

Procedure $A$ for the problem $A$ :

$$
\begin{array}{ll}
\text { accept } & D_{0} \text { if }\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right) \leqq z_{\alpha} \text { for all } i \neq 0 \\
\text { accept } & D_{i} \text { if }\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right)>z_{\alpha} \text { and } \\
& \quad\left(n_{0} n_{j} / N_{j 0}\right)^{\frac{1}{2}}\left(T_{N j}-T_{N 0}\right) \leqq z_{\alpha} \text { for all } j \neq i, 0
\end{array}
$$

accept $D_{1 . . . c}$ if $\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right)>z_{\alpha}$ for all $i \neq 0$
where $z_{\alpha}$ is determined for a pre-assigned $\alpha$ by the relation
(3) $P\left[D_{0}\right.$ is accepted when all $\left.\Delta_{i}=0\right]=1-\alpha$.

Procedure $B$ for the problem $B$ :
accept $D_{0}$ if $\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right) \leqq z_{\alpha}$ for all $i \neq 0$
accept $D_{i}$ if $\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right)>z_{\alpha}$ and $T_{N i}>T_{N j}$ for all $j \neq i, 0$.
§ 3. Probabilities of correct decisions. The following lemma 1 and 2 are the fundamental properties shown by Bell-Doksum and lemma 3 and 4 are also easily shown from their discussions.

Lemma 1. Assume that all $\Delta_{i}=0$, then it holds that
(i) $Z\left(R\left(X_{i \alpha}\right)\right) i=0,1, \ldots, c ; \alpha=1, \ldots, n_{i}$, have the same joint distribution as the random sample $Z_{i}, i=1, \ldots, N$.
(ii) $T_{N i}$ has the same distribution as $\bar{Y}_{i}=n_{i}^{-1} \sum_{\alpha=1}^{n i} Y_{i \alpha}, i=0,1, \ldots c$ where $Y_{i \alpha}$ is the random sample from $\Phi(x)$.
Lemma 2. When all $\Delta_{i}=0$ or $\Delta_{i}=\delta_{i} / \sqrt{N}$ for all $i$, the statistic $\sqrt{N}$ $\left(T_{N i}-T_{N j}\right)$ converges in probability to the statistic $\sqrt{N}\left(S_{N i}-S_{N j}\right)$ as $N \rightarrow$ $\infty$ where
(4) $S_{N i}=n_{i}^{-1} \sum_{\alpha=1}^{n i} E\left[Z\left(R\left(X_{i \alpha}\right)\right) \mid \Phi\right]$.

When $\Delta_{i}=0$ for all $i$, we easily get that

$$
\begin{aligned}
\operatorname{cov}\left[\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\right. & \left.\left(\overline{\mathrm{Y}}_{i}-\bar{Y}_{0}\right), \quad\left(n_{0} n_{j} / N_{j 0}\right)^{\frac{1}{2}}\left(\bar{Y}_{j}-\bar{Y}_{0}\right)\right] \\
& = \begin{cases}1 & i=j \\
\left(n_{i} n_{j} / N_{i 0} N_{j 0}\right)^{\frac{1}{2}} & i \neq j\end{cases}
\end{aligned}
$$

Hence we get the Lemma 3.
Lemma 3. The joint distribution of $\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right), i=1, \ldots, c$ is the $c$-variate normal under all $\Delta_{i}=0$ with mean vector 0 and covariance matrix $\Sigma$ where
(5) $\quad \Sigma=\left[\sigma_{i j}\right], \quad \sigma_{i j}=\left\{\begin{array}{l}1 \quad i=j \\ \left(n_{i} n_{j} / N_{i 0} N_{j 0}\right)^{\frac{1}{2}}\end{array} \quad i \neq j\right.$.

Lemma 4. Under $\Delta_{i}=\delta_{i} / \sqrt{N}$ and $n_{i}=\lambda_{i} N$ for all $i$, the asymptotic joint distribution of $\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right)$ is $c$-variate normal with mean vector $\mu$ and covariance matrix $\Sigma$ if the Hodges-Lehmann assumption [5] holds where $\mu=\left(\mu_{1}, \ldots, \mu_{c}\right)$
(6) $\quad \mu_{i}=\left(n_{0} n_{i} / N_{i 0} N\right)^{\frac{1}{2}} \delta_{i} \int_{-\infty} \frac{\stackrel{\infty}{d}}{d F} \Phi^{-1}(F(x)) f(x) d F(x)$.

Proof. $\sqrt{N}\left(T_{N i}-T_{N 0}\right)$ converges in probability as $N \rightarrow \infty$ to $\sqrt{N}\left(S_{N i}-\right.$ $S_{N 0}$ ) from Lemma 2 and $\sqrt{N}\left(S_{N i}-S_{N 0}\right)$ are jointly normally distributed from the works of Puri [7]. Moreover it holds that

$$
N \operatorname{cov}\left(S_{N i}, S_{N j}\right)= \begin{cases}-1+\lambda_{l}^{-1}+O\left(N^{-\frac{1}{2}}\right) & i=j \\ -1+O\left(N^{-\frac{1}{2}}\right) & i \neq j\end{cases}
$$

and

$$
\begin{aligned}
E\left(S_{N i}\right) & =\int_{-\infty}^{\infty} \Phi^{-1}\left(\sum_{\alpha=0}^{c} \lambda_{\alpha} F\left(x-\delta_{\alpha} / \sqrt{N}\right)\right) d F\left(x-\delta_{i} / \sqrt{N}\right) \\
& =\int_{-\infty}^{\infty} \Phi^{-1}(F(x)) d F(x)+\frac{1}{\sqrt{N}}\left(\delta_{i}-\bar{\delta}\right) \int_{\infty-}^{\infty} \frac{d}{d F} \Phi^{-1}(F(x)) f(x) d F(x) \\
& +O(1 / \sqrt{N}) \quad \bar{\delta}=\sum_{\alpha=1}^{c} \lambda_{\alpha} \delta_{\alpha}
\end{aligned}
$$

where the second equality is derived from the Hodges-Lehmann assumption. The discussions above lead to Lemma 4.

Theorem 1. The value of $z_{\alpha}$ is determined by the identity
(7) $1-\alpha=\int_{-\infty}^{z_{\alpha}} \ldots \int_{-\infty}^{z_{\alpha}} n(\mathbf{0}, \Sigma) d x_{1} \ldots d x_{c} \quad\left(=P_{0}\right)$
where $n(\mu, \boldsymbol{\Sigma})$ is the $c$-variate normal density with mean vector $\mu$ and covariance matrix $\mathcal{E}$.

The probabilities that each decision is correct are given by the following.

## Procedure A.

(8) $P_{i}=P\left[D_{i}\right.$ is correct $]$

$$
\sim \int_{z_{\alpha-\mu_{i}}}^{\infty} d x_{i} \int_{-\infty}^{z_{\alpha}-\mu_{1}} \ldots \int_{-\infty}^{z_{\alpha-}-\mu_{c}} n(\mathbf{0}, \Sigma) \prod_{j \neq i} d x_{j}
$$

(9) $P_{i j}=P\left[D_{i j}\right.$ is correct $]$

$$
\sim \int_{z_{\alpha-\mu_{i}}}^{\infty} \int_{z_{\alpha-\mu}}^{\infty} d x_{i} d x_{j} \int_{-\infty}^{z_{\alpha}-\mu_{1}} \ldots \int_{-\infty}^{z_{\alpha}-\mu_{c}} n(\mathbf{0}, \boldsymbol{\Sigma}) \prod_{k \neq i, j} d x_{k} \ldots \ldots
$$

(10) $\quad P_{1 \ldots c}=P\left[D_{1 \ldots c}\right.$ is correct $]$

$$
\sim \int_{z_{\alpha-}-\mu_{1}}^{\infty} \ldots \int_{z_{\alpha-}-\mu_{c}}^{\infty} n(\mathbf{0}, \boldsymbol{\Sigma}) d x_{1} \ldots d x_{c}
$$

Procedure. B
(11) $P_{i}=P\left[D_{i}\right.$ is correct $]$

$$
\sim \int_{z_{\alpha-\nu}}^{\infty} d x_{i} \int_{-\nu_{i_{1}}}^{\infty} \ldots \int_{-\nu i c}^{\infty} n\left(\mathbf{0}, \Sigma_{i}\right) \prod_{j \neq i} d x_{j}
$$

where $\Sigma_{i}$ is the submatrix of $c \times c$ by delating the $i$-th row and column of $\Sigma^{\prime}=\left[\sigma^{\prime}{ }_{j k}\right]_{j, k=0,1, \ldots, c}$
(12) $\quad \sigma^{\prime}{ }_{j k}= \begin{cases}1 & j=k \\ \left(n_{j} n_{i} / N_{i j} N_{i k}\right)^{\frac{1}{2}} & j \neq k\end{cases}$
and

$$
\begin{equation*}
\nu_{i \mathrm{k}}=\left(n_{i} n_{k} / N_{i k} N\right)^{\frac{1}{2}}\left(\delta_{i}-\delta_{k}\right) \int_{-\infty}^{\infty} \frac{d}{d x} \Phi^{-1}(F(x)) d F(x), \quad k \neq i . \tag{13}
\end{equation*}
$$

Proof. (7) is evident from Lemma 3. For (8), we get

$$
\begin{aligned}
P_{i}= & P\left[\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right)>z_{\alpha}, \quad\left(n_{0} n_{j} / N_{j 0}\right)^{\frac{1}{2}}\left(T_{N j}-T_{N 0}\right) \leqq z_{\alpha}\right. \\
& \text { for all } \left.j \neq i \mid \delta_{i}>0, \delta_{j} \leqq 0 \text { for all } j \neq i\right] \\
& \sim \int_{z_{\alpha-}-\mu_{i}}^{\infty} d x_{-\infty} \int_{-\infty}^{z_{\alpha-\mu_{1}}} \ldots \int_{-\infty}^{z_{\alpha-}-\mu_{c}} n(0, \Sigma) \prod_{j \neq i} d x_{j}
\end{aligned}
$$

where the second equality is followed from Lemma 4.
The other relations (9) and (10) are proved similarly. For $B$, we first notice that $\left(n_{i} n_{j} / N_{i j}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N j}\right)$ for $j \neq i$ are jointly normally distributed as $n\left(\nu_{\boldsymbol{i}}, \boldsymbol{\Sigma}_{\boldsymbol{i}}\right.$ (where $\nu_{\boldsymbol{i}}=\left(\nu_{i 0}, \ldots, \nu_{i c}\right)$ except $\nu_{i i}$.

Then

$$
\begin{aligned}
P_{i}= & P\left[\left(n_{0} n_{i} / N_{i 0}\right)^{\frac{1}{2}}\left(T_{N i}-T_{N 0}\right)>z_{\alpha}, T_{N i}-T_{N j}>0 \text { for all } j \neq i\right. \\
& \left.\mid \delta_{i}>0, \delta_{j} \leqq 0 \text { for all } j \neq i\right] \\
& \sim \int_{z_{\alpha-\nu} \nu_{0}}^{\infty} d x_{-i_{1}} \int_{-\nu_{i c}}^{\infty} \ldots \int_{j}^{\infty} n\left(\mathbf{0}, \boldsymbol{\Sigma}_{i}\right) \prod_{j \neq i} d x_{j} .
\end{aligned}
$$

Now assuming $n_{i}=n, i=1, \ldots, c$, we get $\Sigma=\boldsymbol{\Sigma}_{\mathbf{0}}=\left[\sigma_{i i}^{0}\right], \sigma_{i i}^{0}=\left\{\begin{array}{cc}1 & i=j \\ \frac{1}{2} & i \neq j\end{array}\right.$ and hence
(14) $1-\alpha=\int_{-\infty}^{z_{\alpha}} \ldots \int_{-\infty}^{z_{\alpha}} n\left(\mathbf{0}, \Sigma_{0}\right) d x_{1} \ldots d x_{c}$.

Then a constant $z_{\alpha}$ may be obtained from an existing table such as that of Dunnett, that is for $\alpha=0.05$,

| $\mathbf{c}$ | 1 | 2 | 3 | 4 | 5 | 6 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $z_{\alpha}$ | 1.64 | 1.92 | 2.06 | 2.16 | 2.23 | 2.29 |

§4. Asymptotic relative efficiency. We first define the asymptotic relative efficiency of our procedure with respect to the normal procedure discussed by Dunnett or Paulson. As for the $\operatorname{ARE} e_{A, A_{0}}$ of $A$ with respect to $A_{0}$, we assume that $m_{i}=\rho_{i} N$ and $n_{0} / n_{i} \sim m_{0} / m_{i}$ as $N \rightarrow \infty$ where $m$ and $n$ express the sample size for the normal and distribution-free procedures. Then $e_{A, A_{0}}$ is defined by the common limit (if existing) of $m_{i} / n_{i}$ as $N \rightarrow \infty$, satisfying the $2^{c}-1$ equations $P_{i}=P_{i}^{0}, P_{i j}=P_{i j}^{0}, \ldots, P_{1 \ldots c}=P_{1 \ldots c}^{0}$ under $P_{0}=P_{0}^{0}$ and $\Delta_{i}=$ $\delta_{i} / \sqrt{N}$ where $P^{0 \prime} s$ are the values in the procedure $A_{0}$ corresponding to $P^{\prime} s$ in the procedure $A$. The definition is quite analogious for $e_{B, B_{0}}$.

Theorem 2. The ARE $e_{A, A_{0}}$ or $e_{B, B_{0}}$ is given by the following,

$$
\begin{equation*}
e_{A, A_{0}}=e_{B, B_{0}}=\sigma^{2}\left[\int_{-\infty}^{\infty} \frac{d}{d x} \Phi^{-1}(F(x)) d F(x)\right]^{2} \tag{15}
\end{equation*}
$$

Proof. The probabilities $P^{0 \prime} s$ in the procedure $A_{0}$ are easily computed by noticing that the correlation of $\bar{X}_{i}-\bar{X}_{0}$ and $\bar{X}_{j}-\bar{X}_{0}$ is $\left(m_{i} m_{j} / M_{i 0} M_{j 0}\right)^{\frac{1}{2}}$ and $m_{i} / M_{i 0} \sim n_{i} / N_{i 0}$. First

$$
\begin{align*}
P_{0}^{0} & =P\left[\bar{X}_{i}-\overline{\mathrm{X}}_{0} \leqq d \sigma\left(M_{i 0} / m_{i} m_{0}\right)^{\frac{1}{2}} \text { for all } i \mid \text { all } \Delta_{i}=0\right]  \tag{16}\\
& \sim \int_{-\infty}^{d} \ldots \int_{-\infty}^{d} n(\mathbf{0}, \Sigma) d x_{1} \ldots d x_{c}
\end{align*}
$$

Hence we get $P_{0}=P_{0}^{0}$ from (7) and (16) by taking $d=z_{\alpha}$. Similarly we get under $\Delta_{i}=\delta_{i} / V \bar{N}$

$$
P_{i}^{0} \sim \int_{d-s i}^{\infty} d x_{i} \int_{-\infty}^{d-s 1} \ldots \int_{-\infty}^{d-s c} n(\mathbf{0}, \boldsymbol{\Sigma}) \prod_{j \neq i} d x_{j}
$$

$$
\begin{equation*}
P_{i j}^{0} \sim \int_{d-s i}^{\infty} \int_{d-s j}^{\infty} d x_{i} d x_{j} \int_{-\infty}^{d-s 1} \ldots \int_{-\infty}^{d-s c} n(\mathbf{0}, \quad \Sigma) \prod_{k \neq i, j} d x_{k} \tag{17}
\end{equation*}
$$

$$
P_{1 \ldots c}^{0} \sim \int_{d-s 1}^{\infty} \ldots \int_{d-s c}^{\infty} n(\mathbf{0}, \boldsymbol{\Sigma}) d x_{1} \ldots d x_{c}
$$

where
(18) $s_{i}=\sigma^{-1} \delta_{i}\left(m_{0} m_{i} / M_{i 0} N\right)^{\frac{1}{2}}$.

From the relations（8），（9），（10）and（17），$e_{A, A_{0}}$ is given by the limiting value of $m_{i} / n_{i}$ satisfying $\mu_{i}=s_{i}$ ．Thus we get（15）by（6）and（18）． The value of $e_{B, B 0}$ is also obtained by noticing

$$
\begin{equation*}
P_{i}^{0} \sim \int_{z \alpha-w i 0}^{\infty} d x_{i} \int_{-w i 1}^{\infty} \ldots \int_{-w i c}^{\infty} n\left(\mathbf{0}, \Sigma_{i}\right) \prod_{i \neq i} d x_{j} \tag{19}
\end{equation*}
$$

where

$$
\begin{equation*}
w_{i k}=\sigma^{-1}\left(\delta_{i}-\delta_{k}\right)\left(m_{i} m_{k} / M_{i k} N\right)^{\frac{1}{2}} . \tag{20}
\end{equation*}
$$

The expression（15）is known to be the ARE of the two－sample normal scores test respective to the Student t －test and is always $\geqq 1$ as shown by Chernoff－Savage［2］．Lastly we shall add that some multivariate extensions of these procedures are now preparing by the author along the line of Tamura ［9］．

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