

# ON CLASSIFICATION BY THE STATISTICS $R$ AND $Z$

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## 1. Introduction

$$\begin{aligned}
 W &= (\bar{x}^{(2)} - \bar{x}^{(1)})S^{-1}x' - \frac{1}{2}(\bar{x}^{(2)} - \bar{x}^{(1)})S^{-1}(\bar{x}^{(1)} + \bar{x}^{(2)})', \\
 R &= \left(x - \frac{N_1}{N_1 + N_2}\bar{x}^{(1)} - \frac{N_2}{N_1 + N_2}\bar{x}^{(2)}\right)S^{-1}\left(x - \frac{N_1}{N_1 + N_2}\bar{x}^{(1)} - \frac{N_2}{N_1 + N_2}\bar{x}^{(2)}\right)' \\
 &\quad - d\left[\frac{1 + (N_1 + N_2)^{-1}}{N_1^{-1} + N_2^{-1}}\right]^{\frac{1}{2}}(\bar{x}^{(2)} - \bar{x}^{(1)})S^{-1}\left(x - \frac{N_1}{N_1 + N_2}\bar{x}^{(1)} - \frac{N_2}{N_1 + N_2}\bar{x}^{(2)}\right)', \\
 Z &= \frac{N_1}{N_1 + 1}(x - \bar{x}^{(1)})S^{-1}(x - \bar{x}^{(1)})' - \eta \frac{N_2}{N_1 + 1}(x - \bar{x}^{(2)})S^{-1}(x - \bar{x}^{(2)})',
 \end{aligned}$$

where  $\bar{x}^{(k)}$  ( $k=1, 2$ ) is the mean of a sample of size  $N_k$  from population  $P^{(k)}$ ,  $S$  an estimate of the variance-covariance matrix  $\Sigma$  of  $P^{(1)}$  and  $P^{(2)}$ ,  $\eta$  a constant and

$$d = 2\left[\frac{1 + (N_1 + N_2)^{-1}}{N_1^{-1} + N_2^{-1}}\right]^{\frac{1}{2}} \frac{N_1 - N_2}{N_1 + N_2},$$

are three criteria that have been proposed for deciding the population to which an individual, with measurement  $x$ , known to belong to  $P^{(1)}$  or  $P^{(2)}$ , really belongs. If  $P^{(1)}$  and  $P^{(2)}$  are normal,  $W$  is the statistic obtained by replacing the parameters in the logarithm of the likelihood-ratio by estimates of them from random samples; see Anderson (1951). The statistic

$$\begin{aligned}
 &\left(x - \frac{N_1}{N_1 + N_2}\bar{x}^{(1)} - \frac{N_2}{N_1 + N_2}\bar{x}^{(2)}\right)\Sigma^{-1}\left(x - \frac{N_1}{N_1 + N_2}\bar{x}^{(1)} - \frac{N_2}{N_1 + N_2}\bar{x}^{(2)}\right)' \\
 &\quad - d\left[\frac{1 + (N_1 + N_2)^{-1}}{N_1^{-1} + N_2^{-1}}\right]^{\frac{1}{2}}(\bar{x}^{(2)} - \bar{x}^{(1)})\Sigma^{-1}\left(x - \frac{N_1}{N_1 + N_2}\bar{x}^{(1)} - \frac{N_2}{N_1 + N_2}\bar{x}^{(2)}\right)'
 \end{aligned}$$

was proposed by Rao (1954). He showed that it is best for discriminating between alternatives that are close to each other. The statistic  $Z$  is equivalent to a statistic derived by Anderson (1958, p. 142).

[ $Z$  with  $\eta=1$  was considered by John (1960). It was proposed there because it appeared reasonable to give the individual to that population which, on testing, rejects it at a higher level\*. Note that if  $\eta=1$  the two terms, whose difference  $Z$  is, are the criteria used for the tests. We

\* Rao (1954, p. 655) had previously stated this principle.

wish also to mention that A. Kudo (1959) has shown that the procedure of assigning the individual to  $P^{(1)}$  or  $P^{(2)}$  according as

$$\frac{N_1}{N_1+1} (x - \bar{x}^{(1)}) \Sigma^{-1} (x - \bar{x}^{(1)})' - \frac{N_2}{N_2+1} (x - \bar{x}^{(2)}) \Sigma^{-1} (x - \bar{x}^{(2)})' \geq 0$$

is the best of all two-decision rules invariant under translation and rotation of axes.

The three statistics  $W$ ,  $R$  and  $Z$  (with  $\eta=1$ ) are asymptotically equivalent.  $W$  and  $R$  are equivalent if  $N_1=N_2$ .  $Z$  is equivalent to  $W$ , if  $N_1/(N_1+1) = \eta N_2/(N_2+1)$ .]

If  $W$ ,  $R$  or  $Z$  is used to classify individuals, the probability (given  $\bar{x}^{(1)}$ ,  $\bar{x}^{(2)}$  and  $S$ ) of assigning an individual to  $P^{(1)}$  or  $P^{(2)}$  depends on the realised  $S$ ,  $\bar{x}^{(1)}$  and  $\bar{x}^{(2)}$ . John (1961a, 1962) gave the distributions and expected values of these probabilities in the case of  $W$ . With  $R$  and  $Z$  the problems are more difficult. The present paper will indicate what results have been obtained.

## 2. Notation

A glossary of the symbols used is given below. Notations introduced in the previous section are repeated for the sake of completeness.

$P^{(k)}$  ( $k=1, 2$ ): the two parent populations (assumed  $p$ -variate normal) claiming the individual to be classified.

$P$ : a third population (also assumed  $p$ -variate normal).

$p$ : the number of characters used.

$x = (x_1, x_2, \dots, x_p)$ : the vector of measurements on the individual to be classified.

$x \in P$  means that  $x$  is the vector of measurements on an individual from  $P$  (etc).

$\mu^{(k)} = (\mu_1^{(k)}, \mu_2^{(k)}, \dots, \mu_p^{(k)})$ : the mean of  $P^{(k)}$  ( $k=1, 2$ ).

$\mu = (\mu_1, \mu_2, \dots, \mu_p)$ : the mean of  $P$ .

$\Sigma = (\sigma_{ij})$ : the variance-covariance matrix of  $P^{(1)}$ ,  $P^{(2)}$  and  $P$ .

$\delta = [(\mu^{(1)} - \mu^{(2)}) \Sigma^{-1} (\mu^{(1)} - \mu^{(2)})]^{1/2}$ .

$\bar{x}^{(k)}$ : the arithmetic mean of the observations in a random sample of size  $N_k$  from  $P^{(k)}$  ( $k=1, 2$ ).

$S$ : an unbiased estimate of  $\Sigma$ , distributed independently of  $\bar{x}^{(1)}$  and  $\bar{x}^{(2)}$ , and following the Wishart law with  $n$  degrees of freedom.

$N_k$ : size of the sample from  $P^{(k)}$  ( $k=1, 2$ ).

$n$ : the degree of freedom of  $S$ .

$$a_1 = N_1/(N_1 + N_2); \quad a_2 = N_2/(N_1 + N_2).$$

$$a_3 = N_1^{-1} + N_2^{-1}; \quad a_4 = 1 + (N_1 + N_2)^{-1}.$$

$$a_5 = N_1/(N_1 + 1); \quad a_6 = N_2/(N_1 + 1).$$

$$d = 2(a_1/a_2)^{1/2}/(a_1 - a_2).$$

$$W = (\bar{x}^{(1)} - \bar{x}^{(2)})S^{-1}x' - \frac{1}{2}(\bar{x}^{(2)} - \bar{x}^{(1)})S^{-1}(\bar{x}^{(1)} + \bar{x}^{(2)})'$$

$$R = (x - a_1\bar{x}^{(1)} - a_2\bar{x}^{(2)})S^{-1}(x - a_1\bar{x}^{(1)} - a_2\bar{x}^{(2)})' \\ - d(a_1/a_2)^{1/2}(\bar{x}^{(2)} - \bar{x}^{(1)})S^{-1}(x - a_1\bar{x}^{(1)} - a_2\bar{x}^{(2)})'.$$

$$Z = a_3(x - \bar{x}^{(1)})S^{-1}(x - \bar{x}^{(1)})' - \tau a_4(x - \bar{x}^{(2)})S^{-1}(x - \bar{x}^{(2)})'.$$

$W, R, Z$ : respectively the same as  $W, R$  and  $Z$  with  $\Sigma$  substituted for  $S$ .

$$Q = (\bar{x}^{(1)} - \bar{x}^{(2)})\Sigma^{-1}(\bar{x}^{(2)} - \bar{x}^{(1)})'.$$

$$T = (a_1\mu^{(1)} + a_2\mu^{(2)} - \mu)\Sigma^{-1}(\bar{x}^{(2)} - \bar{x}^{(1)})'/C^{1/2}.$$

$$C_1 = (a_1\mu^{(1)} + a_2\mu^{(2)} - \mu)\Sigma^{-1}(a_1\mu^{(1)} + a_2\mu^{(2)} - \mu)'$$

$$C_2 = (a_1\mu^{(1)} + a_2\mu^{(2)} - \mu)\Sigma^{-1}(\mu^{(1)} - \mu^{(2)})'.$$

$$C_3 = \delta^2 - C_2^2/C_1; \quad C_4 = C_2/C_1^{1/2}; \quad C_5 = C_2^{1/2}.$$

$F(Q, T)$ : the joint density of  $Q$  and  $T$ .

$$L(r, s) = \frac{\Gamma(r+s)}{\Gamma(r)\Gamma(s)} \int_0^1 z^{r-1}(1-z)^{s-1} dz.$$

$$J_p(\chi^2; \lambda) = \frac{e^{-\lambda}}{2^{(1/2)p}} \sum_{r=0}^{\infty} \frac{(\frac{1}{2}\lambda)^r}{\Gamma(\frac{1}{2}p+r)r!} (\chi^2)^{(1/2)p+r-1} e^{-(1/2)\chi^2}.$$

A random variable having  $J_p(\chi^2; \lambda)$  as the density function of its distribution will be spoken of as a non-central chi-square with  $p$  degrees of freedom and non-centrality  $\lambda$ .

$L_p(\alpha, z)$ : the value of  $\lambda$  satisfying the equation  $\int_0^1 J_p(\chi^2; \lambda) d\chi^2 = z$ .

$e_k(\bar{x}^{(1)}, \bar{x}^{(2)}; S)$ : the probability, given  $\bar{x}^{(1)}, \bar{x}^{(2)}$  and  $S$ , of assigning an individual from  $P$  to  $P^{(k)}$  ( $k=1, 2$ ), if individuals are assigned to  $P^{(1)}$  or  $P^{(2)}$  according as  $R \notin c$ .

$e_k'(\bar{x}^{(1)}, \bar{x}^{(2)}; S)$ : the probability, given  $\bar{x}^{(1)}, \bar{x}^{(2)}$  and  $S$ , of assigning an individual from  $P$ , to  $P^{(k)}$  ( $k=1, 2$ ), if individuals are assigned to  $P^{(1)}$  or  $P^{(2)}$  according as  $Z \notin c$ .

$$e_k(\bar{x}^{(1)}, \bar{x}^{(2)}) = e_k(\bar{x}^{(1)}, \bar{x}^{(2)}; \Sigma) \quad (k=1, 2).$$

$$e_k'(\bar{x}^{(1)}, \bar{x}^{(2)}) = e_k'(\bar{x}^{(1)}, \bar{x}^{(2)}; \Sigma) \quad (k=1, 2).$$

The symbol for a random variable preceded by  $E$  denotes its expected value.

Let  $Y = (y_{ij})$  be a  $m \times \nu$  random matrix whose elements are independent normal variables with unit variance. Let  $E y_{ij} = \theta_{ij}$

( $i=1, 2, \dots, m; j=1, 2, \dots, \nu$ ). Let  $A = \left( \sum_{j=1}^{\nu} \theta_{ij} \theta_{j'}$  ). We shall call any random matrix having the same distribution as  $Y' Y'$  a non-central Wishart matrix of order  $m$ , degree of freedom  $\nu$  and non-centrality  $\frac{1}{2}A$ . In case  $A$  is the null matrix, we shall call the random matrix simply a Wishart matrix of order  $m$  and degree of freedom  $\nu$ .

### 3. Distribution of the probability when the statistic is $R$

If  $N_1 = N_2$ ,  $R$  is equivalent to  $W$ . In what follows we shall, therefore, assume that  $N_1 \neq N_2$ . Whether individuals assigned to  $P^{(1)}$  should be those for whom  $R_1 \leq c$  depends on whether  $N_1 \leq N_2$ . For the sake of definiteness, we assume that  $N_1 > N_2$ . Suppose that the individuals assigned to  $P^{(1)}$  are those with  $R_1 \geq c$ . We denote the probability, given  $\bar{x}^{(1)}$  and  $\bar{x}^{(2)}$ , of assigning an individual from  $P$  to  $P^{(1)}$  by  $e_i(\bar{x}^{(1)}, \bar{x}^{(2)})$ . Since  $e_i(\bar{x}^{(1)}, \bar{x}^{(2)}) = 1 - e_i(\bar{x}^{(2)}, \bar{x}^{(1)})$ , we consider only  $e_i(\bar{x}^{(1)}, \bar{x}^{(2)})$ .

The inequality  $R_1 \geq c$  is equivalent to the inequality

$$V \geq c + \frac{1}{2} a_i d^2 Q / a_i, \quad (3.1)$$

where

$$V = [x - a_i \bar{x}^{(1)} - a_i \bar{x}^{(2)} - \frac{1}{2} d(a_i/a_i)^{1/2} (\bar{x}^{(2)} - \bar{x}^{(1)})] \Sigma^{-1} [x - a_i \bar{x}^{(1)} - a_i \bar{x}^{(2)} - \frac{1}{2} d(a_i/a_i)^{1/2} (\bar{x}^{(2)} - \bar{x}^{(1)})]'. \quad (3.2)$$

Given  $\bar{x}^{(1)}$  and  $\bar{x}^{(2)}$ ,  $V$  is distributed as a non-central chi-square with  $p$  degrees of freedom and non-centrality

$$\frac{1}{2} [\mu - a_i \bar{x}^{(1)} - a_i \bar{x}^{(2)} - \frac{1}{2} d(a_i/a_i)^{1/2} (\bar{x}^{(2)} - \bar{x}^{(1)})] \Sigma^{-1} [\mu - a_i \bar{x}^{(1)} - a_i \bar{x}^{(2)} - \frac{1}{2} d(a_i/a_i)^{1/2} (\bar{x}^{(2)} - \bar{x}^{(1)})]' = V' \quad (\text{say}). \quad (3.3)$$

Therefore

$$e_i(\bar{x}^{(1)}, \bar{x}^{(2)}) = \int_{c + (1/2) a_i d^2 Q / a_i}^{\infty} J_p(\chi^2; V') d\chi^2. \quad (3.4)$$

Hence,

$$\Pr[e_i(\bar{x}^{(1)}, \bar{x}^{(2)}) < z] = \Pr[V' < L_p(c + \frac{1}{2} a_i d^2 Q / a_i, z)]. \quad (3.5)$$

To find  $\Pr[V' < L_p(c + \frac{1}{2} a_i d^2 Q / a_i, z)]$ , we first find

$$\Pr[V' < L_p(c + \frac{1}{2} a_i d^2 Q / a_i, z) | \bar{x}^{(2)} - \bar{x}^{(1)}].$$

Given  $\bar{x}^{(2)} - \bar{x}^{(1)}$ ,  $2(N_1 + N_2)V'$  is distributed as a non-central chi-square with  $p$  degrees of freedom and non-centrality

$$\frac{1}{2} (N_1 + N_2) [\frac{1}{2} (a_i/a_i) d^2 Q + d(C_i a_i/a_i)^{1/2} T + C_i] = V'' \quad (\text{say}). \quad (3.6)$$

Therefore,

$$\begin{aligned} & \Pr[V' < L_p(c + \frac{1}{2}a_1 d^1 Q/a_1, z)] \bar{x}^{(1)} - \bar{x}^{(2)} \\ &= \int_{c \leq x^1 \leq (N_1 + N_2) \int_{c + (1/2)a_1 d^1 Q/a_1, z}} D_p(x^1; V'') d\chi^1, \end{aligned} \quad (3.7)$$

a function of  $z$ ,  $Q$  and  $T$ , which we shall denote by the symbol  $\Omega(z; Q, T)$ . Let  $F(Q, T)$  denote the joint density of  $Q$  and  $T$ . Then

$$\Pr[V' < L_p(c + \frac{1}{2}a_1 d^1 Q/a_1, z)] = \iint \Omega(z; Q, T) F(Q, T) dQ dT, \quad (3.8)$$

where the domain of integration is the entire domain of variation of  $Q$  and  $T$ . That is,

$$\Pr[e_i(\bar{x}^{(1)}, \bar{x}^{(2)}) < z] = \iint \Omega(z; Q, T) F(Q, T) dQ dT. \quad (3.9)$$

The joint density of  $Q$  and  $T$  was required in the solution of problems connected with  $W$ , and will again be required when we consider the statistic  $Z$ . John (1962) shows that

$$\begin{aligned} F(Q, T) &= \frac{(Q - T^2)^{1/2(p-2)}}{(2a_1)^{(1/2)p} \sqrt{\pi}} \exp\left[-\frac{1}{2a_1}(Q - 2CT + \delta^2)\right] \\ &= \sum_{k=0}^{\infty} \frac{(\frac{1}{2}C_1/a_1)^{2k} (Q - T^2)^k}{k! \Gamma(\frac{1}{2}p + k - \frac{1}{2})} (-Q^{1/2} \leq T \leq Q^{1/2}), \end{aligned} \quad (3.10)$$

if  $C_1 \neq 0$ ; if  $C_1 = 0$ ,  $\Omega(z; Q, T)$  does not involve  $T$ , and, therefore, in equation (3.9),  $F(Q, T)$  may be replaced by the density function of  $Q$ ; the density function of  $Q$  is  $a_1^{-1} D_p(Q/a_1; \frac{1}{2} \delta^2/a_1)$ .

#### 4. Distribution of the probability when the statistic is $Z$

Suppose individuals are assigned to  $P^{(1)}$  or  $P^{(2)}$  according as  $Z_i \geq c$ . We denote the probability, given  $\bar{x}^{(1)}$  and  $\bar{x}^{(2)}$ , of assigning the individuals to  $P^{(k)}$  ( $k=1, 2$ ) by  $e_k(\bar{x}^{(1)}, \bar{x}^{(2)})$ . Since  $e_1(\bar{x}^{(1)}, \bar{x}^{(2)}) = 1 - e_2(\bar{x}^{(1)}, \bar{x}^{(2)})$ , we shall consider only  $e_2(\bar{x}^{(1)}, \bar{x}^{(2)})$ .

The inequality  $Z_i \geq c$  is equivalent to

$$\begin{aligned} [x - \bar{x}^{(1)} + \alpha(\bar{x}^{(2)} - \bar{x}^{(1)})] \Sigma^{-1} [x - \bar{x}^{(1)} + \alpha(\bar{x}^{(2)} - \bar{x}^{(1)})]' \\ \geq \alpha(\alpha + 1)Q + c' \end{aligned} \quad (4.1)$$

according as  $a_1 \geq \eta a_2$ ;

$$\alpha = \frac{N_1(N_1 + 1)\eta}{N_1(N_1 + 1) - N_2(N_2 + 1)\eta}; \quad (4.2)$$

$$c' = \frac{\alpha(N_1 + 1)(N_1 + 1)}{N_1(N_1 + 1) - N_2(N_2 + 1)\eta}. \quad (4.3)$$

For the sake of definiteness, we shall assume that  $a_1 > \gamma a_2$ . (If  $a_2 = \gamma a_1$ ,  $Z_1$  is equivalent to  $W_1$ .) Then  $e_1''(\bar{x}^{(1)}, \bar{x}^{(2)})$  is the probability, given  $\bar{x}^{(1)}$  and  $\bar{x}^{(2)}$ , of the inequality (4.1) with the upper inequality sign being satisfied. It is easily seen to be equal to

$$\int_{c + (\alpha + 1)Q + c'}^{\infty} A_p(\chi^2; v) d\chi^2, \quad (4.4)$$

where

$$v = \frac{1}{2}[\mu - \bar{x}^{(1)} + \alpha(\bar{x}^{(2)} - \bar{x}^{(1)})] \Sigma^{-1}[\mu - \bar{x}^{(1)} + \alpha(\bar{x}^{(2)} - \bar{x}^{(1)})]'. \quad (4.5)$$

By methods similar to those of the previous section we can show that

$$\Pr\{e_1''(\bar{x}^{(1)}, \bar{x}^{(2)}) < z\} = \iint \mathcal{O}'(z; Q, T) F(Q, T) dQ dT, \quad (4.6)$$

where

$$\mathcal{O}'(z; Q, T) = \int_{0 \leq v^2 \leq N_1 + N_2, \int_{c + (\alpha + 1)Q + c'}^{\infty} A_p(\chi^2; v') d\chi^2; \quad (4.7)$$

$$v' = \frac{1}{2}(N_1 + N_2)[\beta^2 Q - 2\beta C_1^{1/2} T + C_1]; \quad (4.8)$$

$$\beta = \alpha + a_1. \quad (4.9)$$

If  $C_1 = 0$ ,  $\mathcal{O}'$  does not involve  $T$ , and, therefore, in equation (4.6),  $F(Q, T)$  may be replaced by the density function of  $Q$ ; i.e., by  $a_1^{-1} A_p(Q/a_1; \frac{1}{2}\delta^2/a_1)$ .

## 5. Expected values

If individuals are assigned to  $P^{(1)}$  or  $P^{(2)}$  according as  $R_1 \leq c$  ( $Z_1 \leq c$ ), the expected probability of assigning the individual to  $P^{(1)}$  is clearly equal to the integral of the density function of  $R_1$  ( $Z_1$ ) from  $c$  to  $\infty$ . The density function of  $R_1$  for  $x \in P^{(1)}$ , together with that of  $W_1$  and another statistic, was given by John (1960). They all have the form

$$\exp[-\lambda_1 - \lambda_2 - \frac{1}{2}(b_1 - b_2)\theta] \sum_{r=0}^{\infty} \sum_{s=0}^{\infty} \frac{\lambda_1^r \lambda_2^s}{r! s!} \frac{b_1^{(1/2)p+s} b_2^{(1/2)p+s}}{\Gamma(\frac{1}{2}p+r)} \left( \frac{\theta}{2b_1 + 2b_2} \right)^{1/2(p+r+s)} \theta^{-1} W_{1,n}(\frac{1}{2}[b_1 + b_2]\theta) \quad (5.1)$$

for  $\theta \geq 0$  and the form

$$\exp[-\lambda_1 - \lambda_2 - \frac{1}{2}(b_1 - b_2)\theta] \sum_{r=0}^{\infty} \sum_{s=0}^{\infty} \frac{\lambda_1^r \lambda_2^s}{r! s!} \frac{b_1^{(1/2)p+s} b_2^{(1/2)p+s}}{\Gamma(\frac{1}{2}p+s)} \left( \frac{-\theta}{2b_1 + 2b_2} \right)^{1/2(p+r+s)} \theta^{-1} W_{-1,n}(-\frac{1}{2}[b_1 + b_2]\theta) \quad (5.2)$$

for  $\theta < 0$ . Here

$$l = \frac{1}{2}(r-s), \quad m = \frac{1}{2}(r+s+p-1); \quad (5.3)$$

$W_{l,m}$  is Whittaker's confluent hypergeometric function defined by the equation

$$W_{l,m}(\theta) = \frac{\theta^{m+(1/2)}}{\Gamma(m-l+\frac{1}{2})} e^{-(1/2)\theta} \int_0^\infty e^{-\alpha} \alpha^{m-1-(1/2)\theta} (1+\alpha)^{m+(1/2)} d\alpha.$$

The density functions of  $W_0$ ,  $R_0$  and  $Z_0$  retain the form given above even if  $x \in P$ . If in (5.1) and (5.2) we take  $\theta = R_0$ ,

$$\begin{aligned} \lambda_1 = & \frac{1}{2} \left[ \frac{\{\sqrt{(1+d^2)}+1\}^{1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu - a_1 \mu^{(1)} - a_2 \mu^{(2)}) \right. \\ & \left. - \frac{d \{\sqrt{(1+d^2)}+1\}^{-1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu^{(1)} - \mu^{(2)}) \right] \Sigma^{-1} \\ & \left[ \frac{\{\sqrt{(1+d^2)}+1\}^{1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu - a_1 \mu^{(1)} - a_2 \mu^{(2)}) \right. \\ & \left. - \frac{d \{\sqrt{(1+d^2)}+1\}^{-1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu^{(1)} - \mu^{(2)}) \right]'. \end{aligned} \quad (5.4)$$

$$\begin{aligned} \lambda_2 = & \frac{1}{2} \left[ \frac{\{\sqrt{(1+d^2)}-1\}^{1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu - a_1 \mu^{(1)} - a_2 \mu^{(2)}) \right. \\ & \left. + \frac{d \{\sqrt{(1+d^2)}-1\}^{-1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu^{(1)} - \mu^{(2)}) \right] \Sigma^{-1} \\ & \left[ \frac{\{\sqrt{(1+d^2)}-1\}^{1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu - a_1 \mu^{(1)} - a_2 \mu^{(2)}) \right. \\ & \left. + \frac{d \{\sqrt{(1+d^2)}-1\}^{-1/2}}{(1+d^2)^{1/4}(2a_1)^{1/2}} (\mu^{(1)} - \mu^{(2)}) \right]'. \end{aligned} \quad (5.5)$$

$$b_1 = (2/a_1) / [\sqrt{(1+d^2)}+1], \quad b_2 = (2/a_1) / [\sqrt{(1+d^2)}-1], \quad (5.6)$$

we shall get the density function of  $R_0$  (for  $x \in P$ ). To get the density function of  $Z_0$  (for  $x \in P$ ) we should take, in (5.1) and (5.2),  $\theta = Z_0$ ,

$$\begin{aligned} \lambda_1 = & \frac{1}{2} \{ [a_2^{1/2}(\gamma_1 + \gamma_2)(\mu - \mu^{(1)}) + (\gamma a_1)^{1/2}(\gamma_1 - \gamma_2)(\mu - \mu^{(2)})] \Sigma^{-1} \\ & [a_2^{1/2}(\gamma_1 + \gamma_2)(\mu - \mu^{(1)}) + (\gamma a_1)^{1/2}(\gamma_1 - \gamma_2)(\mu - \mu^{(2)})] \}' \div (2\gamma_1 \gamma_2 - 2\eta + 2), \end{aligned} \quad (5.7)$$

$$\begin{aligned} \lambda_2 = & \frac{1}{2} \{ [a_2^{1/2}(\gamma_1 - \gamma_2)(\mu - \mu^{(1)}) + (\gamma a_1)^{1/2}(\gamma_1 + \gamma_2)(\mu - \mu^{(2)})] \Sigma^{-1} \\ & [a_2^{1/2}(\gamma_1 - \gamma_2)(\mu - \mu^{(1)}) + (\gamma a_1)^{1/2}(\gamma_1 + \gamma_2)(\mu - \mu^{(2)})] \}' \div (2\gamma_1 \gamma_2 + 2\eta - 2), \end{aligned} \quad (5.8)$$

$$b_1 = 2 \{ [(1+\eta)^2 - 4a_1 a_2 \eta]^{1/2} + 1 - \eta \}^{-1}, \quad (5.9)$$

and

$$b_2 = 2 \{ [(1+\eta)^2 - 4a_1 a_2 \eta]^{1/2} + \eta - 1 \}^{-1}; \quad (5.10)$$

$$\gamma_1 = [1 + \eta - 2(\gamma a_1 a_2)^{1/2}]^{1/2}; \quad \gamma_2 = [1 + \eta + 2(\gamma a_1 a_2)^{1/2}]^{1/2}. \quad (5.11)$$

John (1961a, 1962) has given an expression of the form

$$e^{-\lambda_1 + \lambda_2} \left[ \sum_{r=0}^{\infty} \sum_{s=0}^{\infty} \frac{\lambda_1^r \lambda_2^s}{r! s!} \left\{ 1 - I_{\lambda_1 / (\lambda_1 + \lambda_2)} \left( \frac{1}{2} p + r, \frac{1}{2} p + s \right) \right\} \right. \\ \left. + \sum_{r=0}^{\infty} \sum_{s=0}^{\infty} \frac{\lambda_1^r \lambda_2^s}{r! s!} I_{\lambda_2 / (\lambda_1 + \lambda_2)} \left( \frac{1}{2} p + s, \frac{1}{2} p + r \right) \right] \quad (5.12)$$

for  $\Pr(W_s \geq 0)$  and has shown that it is approximately equal to

$$\int_{-\infty}^a \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt, \quad (5.13)$$

where

$$a = \frac{2[b_1^{1/2} r_1^{-1/2}(1+\theta_1) - b_2^{1/2} r_2^{-1/2}(1+\theta_2)] + 9[(r_1 b_1)^{1/2} - (r_2 b_2)^{1/2}]}{(18)^{1/2} [b_1^{1/2} r_1^{-1/2}(1+\theta_1) + b_2^{1/2} r_2^{-1/2}(1+\theta_2)]^{1/2}}; \quad (5.14)$$

$$r_i = p + 2\lambda_i \quad (i=1, 2); \quad (5.15)$$

$$\theta_i = 2\lambda_i / (p + 2\lambda_i) \quad (i=1, 2). \quad (5.16)$$

Since the density functions of  $R_s$  and  $Z_s$  are the same as that of  $W_s$  in form, these same expressions will be equal to  $\Pr(R_s > 0)$  or  $\Pr(Z_s > 0)$  according as  $\lambda_1$ ,  $\lambda_2$ ,  $b_1$ ,  $b_2$  and  $\theta_1$ ,  $\theta_2$  are as in equations (5.4) to (5.6) or as in equations (5.7) to (5.10)\*.

We shall now give some results regarding  $R$  and  $Z$ . John (1961b) shows that  $R$  is distributed as

$$(n\alpha_1/\chi^2) \{ B_{11} - d [B_{11} - (n-p+2)^{-1/2} t |B|^{1/2}] \}, \quad (5.17)$$

where

$$B = \begin{pmatrix} B_{11} & B_{12} \\ B_{12} & B_{22} \end{pmatrix},$$

$t$  and  $\chi^2$  are independent random variables distributed as follows:  $B$  has the non-central Wishart distribution with  $p$  degrees of freedom and, if we let

$$\frac{1}{2} A = \frac{1}{2} \begin{pmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{12} & \lambda_{22} \end{pmatrix}$$

denote its non-centrality matrix, with

$$\lambda_{11} = (\mu - \alpha_1 \mu^{(1)} - \alpha_2 \mu^{(2)}) \Sigma^{-1} (\mu - \alpha_1 \mu^{(1)} - \alpha_2 \mu^{(2)})' / \alpha_1, \quad (5.18)$$

$$\lambda_{12} = (\mu - \alpha_1 \mu^{(1)} - \alpha_2 \mu^{(2)}) \Sigma^{-1} (\mu^{(1)} - \mu^{(2)})' / (\alpha_2 \alpha_1)^{1/2} \text{ and } \lambda_{22} = \delta^2 / \alpha_2;$$

$t$  follows Student's law with  $n-p+2$  degrees of freedom;  $\chi^2$  has the

\* In my 1960 paper (1960a), another expression is given for  $\Pr\{Z_s > 0\}$  for  $x \in P^{(1)}$ . A similar expression can be given for  $x \in P$  also, but will be less simple than what is given here.



chi-square distribution with  $n-p+1$  degrees of freedom\*. From this it follows that

$$E e_i'(\bar{x}^{(1)}, \bar{x}^{(2)}; S) = E \Pr[\chi^2 \leq (na_i/c) \{B_{11} - d B_{11} + d(n-p+2)^{-1/2} |B|^{1/2} t\}] \quad (5.19)$$

according as  $c \geq 0$ . If  $c=0$ , we can write

$$E e_i'(\bar{x}^{(1)}, \bar{x}^{(2)}; S) = E \Pr[t > (n-p+2)^{1/2} |B|^{-1/2} \{B_{11} - B_{11}/d\}]. \quad (5.20)$$

These results will facilitate the evaluation of  $E e_i'(\bar{x}^{(1)}, \bar{x}^{(2)}; S)$  by Monte Carlo methods. Similarly, it has been shown there that  $Z$  has the distribution of

$$(n/\chi^2) \{ (1-\eta)B_{11} + 2(\eta - a_s a_s \eta)^{1/2} [B_{11} - (n-p+2)^{-1/2} |B|^{1/2} t] \}, \quad (5.21)$$

where  $B_{11}$ ,  $B_{11}$ ,  $B_{11}$ ,  $t$  and  $\chi^2$  have the same joint distribution as in the case of  $R$  except that

$$\lambda_{11} = \{ [a_s^{1/2}(\mu - \mu^{(1)}) - (\eta a_s)^{1/2}(\mu - \mu^{(2)})] \Sigma^{-1} [a_s^{1/2}(\mu - \mu^{(1)}) - (\eta a_s)^{1/2}(\mu - \mu^{(2)})]' \} \div [1 + \eta - 2(\eta a_s a_s)^{1/2}], \quad (5.22)$$

$$\lambda_{12} = \{ [a_s^{1/2}(\mu - \mu^{(1)}) - (\eta a_s)^{1/2}(\mu - \mu^{(2)})] \Sigma^{-1} [\beta_1(\mu - \mu^{(1)}) + \beta_2(\mu - \mu^{(2)})]' \} \div [1 + \eta - 2(\eta a_s a_s)^{1/2}]^{1/2}, \quad (5.23)$$

$$\lambda_{22} = [\beta_1(\mu - \mu^{(1)}) + \beta_2(\mu - \mu^{(2)})] \Sigma^{-1} [\beta_1(\mu - \mu^{(1)}) + \beta_2(\mu - \mu^{(2)})]' ; \quad (5.24)$$

$$\beta_1 = \frac{a_s^{1/2} [2\eta - 2(a_s a_s \eta)^{1/2}]}{2(\eta - a_s a_s \eta)^{1/2} [1 + \eta - 2(a_s a_s \eta)^{1/2}]^{1/2}} ; \quad (5.25)$$

$$\beta_2 = \frac{(\eta a_s)^{1/2} [2 - 2(\eta a_s a_s)^{1/2}]}{2(\eta - a_s a_s \eta)^{1/2} [1 + \eta - 2(a_s a_s \eta)^{1/2}]^{1/2}} . \quad (5.26)$$

Hence it follows that

$$E e_i'(\bar{x}^{(1)}, \bar{x}^{(2)}; S) = E \Pr[\chi^2 \leq (n/c) \{ (1-\eta)B_{11} + 2(n/c)(\eta - a_s a_s \eta)^{1/2} [B_{11} - (n-p+2)^{-1/2} |B|^{1/2} t] \}] \quad (5.27)$$

according as  $c \geq 0$ . If  $c=0$ , we can write

$$E e_i'(\bar{x}^{(1)}, \bar{x}^{(2)}; S) = E \Pr[t < (n-p+2)^{1/2} |B|^{-1/2} \{ B_{11} + \frac{1}{2}(\eta - a_s a_s \eta)^{-1/2} (1-\eta)B_{11} \}]. \quad (5.28)$$

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\* This result is similar to that of Bowker (1960) for  $W$ . Some implications of this representation of  $R$  and that of  $Z$ , given below, will be developed elsewhere.

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