

# NOTE ON A MULTIDIMENSIONAL LINEAR DISCRIMINANT FUNCTION

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## 1. Introduction and summary

When  $p$  measurements  $x_1, x_2, \dots, x_p$  are available on an individual belonging to one of  $s$  ( $\geq 2$ ) groups, to allot the individual to one of these groups a linear discriminant function is formed, say,  $y = \sum_{i=1}^p a_i x_i$ . The coefficients  $a$ 's are determined by a certain procedure, see e.g., Kendall and Stuart ([3], pp. 316-318, 44.6-44.7), so that the linear function will minimize the probability of misclassification. Hayashi [1] in his studies of quantification theory proposed an alternative method for determining the coefficients  $a$ 's by maximizing the observed correlation ratio  $\eta^2 = \sigma_b^2 / \sigma^2$ , where  $\sigma^2$  is the estimated variance of  $y$  and  $\sigma_b^2$  is the estimated variance of  $y$  between the groups. In many situations it becomes necessary to carry on the discrimination by more than a single discriminant function, see e.g., Radcliffe [4]. Let then these simultaneous  $m$  linear discriminant functions be

$$(1) \quad y_i = \sum_{j=1}^p a_{ij} x_j, \quad i=1, 2, \dots, m; \quad 2 \leq m \leq p.$$

In order to determine the coefficients  $a_{ij}$ 's we consider the generalization of  $\eta^2$  given by Hayashi [2]. This generalization is  $\lambda = 1 - \sigma_w^2 / \sigma^2$ , where now  $\sigma^2$  is the observed generalized variance of  $y' = (y_1, y_2, \dots, y_m)$  and  $\sigma_w^2$  is the observed generalized variance of  $y$  within groups. We now define certain sample characteristics of  $y$  which are obtained from the sample characteristics of  $x$ . It is assumed that  $s$  samples one for each group of sizes  $N_1, N_2, \dots, N_s$  are available on the  $p$  component vector  $x' = (x_1, x_2, \dots, x_p)$ .

*The sample characteristics of  $y$*

- $\mu_i(\nu)$ : the mean of  $y_i$  within the  $\nu$ th group,
- $\sigma_{ii}(\nu)$ : the variance of  $y_i$  within  $\nu$ th group,
- $\sigma_{ij}(\nu)$ : the covariance of  $y_i$  and  $y_j$  within  $\nu$ th group,

$$\begin{aligned}
\mu_i &: \text{ the overall mean of } y_i \\
\sigma_{ii} &: \text{ the overall variance of } y_i \\
\sigma_{ij} &: \text{ the overall covariance of } y_i \text{ and } y_j, \\
\pi_\nu &: \text{ the relative size of the } \nu\text{th group, } \sum_{\nu=1}^s \pi_\nu = 1, \\
\mu(\nu) &= (\mu_1(\nu), \mu_2(\nu), \dots, \mu_m(\nu)), \quad \mu = (\mu_1, \mu_2, \dots, \mu_m), \\
\Sigma &= (\sigma_{ij}), \quad \Sigma_\nu = (\sigma_{ij}(\nu)), \quad \Sigma_b = \left( \sum_{\nu=1}^s \pi_\nu [\mu_i(\nu) - \mu_i] [\mu_j(\nu) - \mu_j] \right), \\
\Sigma_w &= \pi_1 \Sigma_1 + \pi_2 \Sigma_2 + \dots + \pi_s \Sigma_s = \left[ \sum_{\nu=1}^s \pi_\nu \sigma_{ij}(\nu) \right] \\
\sigma^2 &= |\Sigma|, \quad \sigma_w^2 = |\Sigma_w|.
\end{aligned}$$

Thus we have that

$$(2) \quad \lambda = 1 - |\Sigma_w| / |\Sigma|,$$

and we may also consider the function

$$(3) \quad \lambda^* = |\Sigma_b| / |\Sigma|,$$

as a function to be maximized with respect to  $a_{ij}$ 's.

*The sample characteristics of  $x$*

$$\begin{aligned}
m_i(\nu) &: \text{ the mean of } x_i \text{ within } \nu\text{th group,} \\
\lambda_{ii}(\nu) &: \text{ the variance of } x_i \text{ within the } \nu\text{th group,} \\
\lambda_{ij}(\nu) &: \text{ the covariance of } x_i \text{ and } x_j \text{ in } \nu\text{th group,} \\
m_i &: \text{ the overall mean of } x_i, \\
\lambda_{ii} &: \text{ the overall variance of } x_i, \\
\lambda_{ij} &: \text{ the overall covariance of } x_i \text{ and } x_j, \\
m(\nu) &= (m_1(\nu), m_2(\nu), \dots, m_p(\nu)), \quad m = (m_1, m_2, \dots, m_p), \\
A &= (\lambda_{ij}), \quad A_\nu = (\lambda_{ij}(\nu)), \quad A_w = \sum_{\nu=1}^s \pi_\nu A_\nu \\
a'_i &= (a_{i1}, a_{i2}, \dots, a_{ip}), \quad A = (a_{ij}).
\end{aligned}$$

It follows that  $\mu(\nu) = m(\nu)A'$ ,  $\mu = mA'$ ,  $\Sigma_\nu = AA_\nu A'$ ,  $\Sigma = AAA'$ ,  $\Sigma_w = AA_w A'$ , and  $\Sigma_b = ADD'A'$ , where

$$(4) \quad D = \sum_{\nu=1}^s \sqrt{\pi_\nu} (m'(\nu) - m').$$

Thus we have to determine  $A$  which will maximize

$$(5) \quad \lambda = 1 - |AA_w A'| / |AAA'|,$$

or that  $A$  which will maximize

$$(6) \quad \lambda^* = |ADD'A'| / |AAA'|.$$

We shall find an  $m \times p$  matrix  $A$  that will maximize  $\lambda^*$ , the matrix  $A$

that maximizes  $\lambda$  may be found on similar lines. The solution for the particular case  $m=2$  is given by Uematu [6] by a very complicated procedure. We give the solution for the general case by using the following result.

**2. A useful result**

We wish to prove that

$$(7) \quad \text{Min}_{y_1, \dots, y_k} \sum_{i=1}^k \frac{y_i' \Delta y_i}{y_i' y_i} = \text{Min}_Y \text{tr } Y \Delta Y' = \theta_{p-k+1} + \dots + \theta_p,$$

where  $\theta_1 > \theta_2 > \dots > \theta_p$  are roots of  $\Delta$ ,  $Y$  is  $k \times p$  and of rank  $k$ , such that  $Y Y' = I$ . The minimum is actually attained when  $y_i$  is proportional to a linear function of the eigenvectors of  $\Delta$ . The result (7) is established by repeated application of Rao's result ([5], p. 51, If. 2.5) that

$$(8) \quad \text{Min}_y y' \Delta y, \quad \text{subject to } y' y = 1, \text{ and } H y = 0 \text{ is } \theta_{p-k},$$

where  $H$  is  $k \times p$  and of rank  $k$  and the minimum is sought over all  $H$ . Thus from (8) we know that

$$(9) \quad \text{Min}_{y_1} \frac{y_1' \Delta y_1}{y_1' y_1}, \quad \text{subject to } y_1' y_1 = 1, y_1' y_2 = 0, \dots, y_1' y_k = 0 \text{ is } \theta_{p-k+1}.$$

Next we consider the  $\text{Min}(y_2' \Delta y_2 / y_2' y_2)$  subject to  $y_2' y_2 = 1$ , and  $y_2' y_3 = 0 \dots, y_2' y_k = 0$  and this minimum is  $\theta_{p-k+2}$  and so on, finally we consider  $\text{Min } y_k' \Delta y_k / y_k' y_k$  subject to  $y_k' y_k = 1$  which is  $\theta_p$ . Adding these minima we get (7). Thus from (7) we note that minimum is given by  $k$  last roots and hence the maximum must be given by first  $k$  roots, i.e.,

$$(10) \quad \text{Max}_Y \text{tr } Y \Delta Y', \quad \text{subject to } Y Y' = I \text{ is } \theta_1 + \theta_2 + \dots + \theta_k.$$

The minimum in (7) is obtained by setting  $y_i = P_{p-k+1}$ ,  $i=1, 2, \dots, k$  and maximum in (10) is given by  $y_i = P_i$ ,  $i=1, \dots, k$ , where  $P_i$  is the eigenvector of  $\Delta$  corresponding to  $\theta_i$ .

**3. Determination of the coefficients A**

By using (6) and setting  $B = A A^{1/2}$  where  $A^{1/2}$  is any positive definite symmetric square root of  $A$ , we find that

$$(11) \quad \lambda^* = |B A^{-1/2} D D' A^{-1/2} B' | / |B B'|.$$

Since the maximum of (11) is sought over all  $B$ , we take  $B B' = I$ , and thus from (10) we conclude that

$$(12) \quad \text{Max } \lambda^* = \alpha_1 \alpha_2 \cdots \alpha_m ,$$

where  $\alpha_1 > \alpha_2 > \cdots > \alpha_p$  are roots of  $DD'A^{-1}$ , and the maximum is attained when the row vectors of  $b'_1, b'_2, \dots, b'_m$  of  $B$  are such that  $b'_i = P_i$ ,  $i=1, \dots, m$ , where  $P_i$  is the eigenvector of  $DD'A^{-1}$  corresponding to  $\alpha_i$ . From  $B$  we determine  $A$ . By taking  $m=2$  in (12), we get Uematu's result.

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#### REFERENCES

- [1] Hayashi, C. (1952). On the prediction of phenomena from qualitative data and the quantification of qualitative data from the mathematics-statistical point of view, *Ann. Inst. Statist. Math.*, **3**, 69-98.
- [2] Hayashi, C. (1954). Multidimensional quantification with applications to analysis of social phenomena, *Ann. Inst. Statist. Math.*, **5**, 120-143.
- [3] Kendall, M. G. and Stuart, A. (1966). *Advanced Theory of Statistics*, **3**, Charles Griffin, London, England.
- [4] Radcliffe, J. (1966). Factorization of the residual likelihood criterion in discriminant analysis, *Proc. Camb. Phil. Soc.*, **62**, 743-751.
- [5] Rao, C. R. (1965). *Linear Statistical Inference and its Applications*, Wiley, New York.
- [6] Uematu, T. (1964). On a multidimensional linear discriminant function, *Ann. Inst. Statist. Math.*, **16**, 431-437.