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Hyakutake, Hiroto
Faculty of Mathematics, Kyushu University

Kawasaki, Hidefumi
Faculty of Mathematics, Kyushu University

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NOTES ON OPTIMAL ALLOCATION FOR FIXED SIZE CONFIDENCE REGIONS OF THE DIFFERENCE OF TWO MULTINORMAL MEANS

By

Hiroto Hyakutake* and **Hidefumi Kawasaki†**

Abstract

We consider the problem of constructing a fixed-size confidence region of the difference of two multinormal means when the covariance matrices have intraclass correlation structure. When the covariance matrices are known, we derive an optimal allocation. A two-stage procedure is given for the problem with unknown covariance matrices.

Key Words and Phrases: fixed-size confidence interval, intraclass correlation, semi-infinite programming problem, two-stage procedure.

1. Introduction

Let $\boldsymbol{x}_{i1}, \boldsymbol{x}_{i2}, \cdots$ be independent and identically distributed (i.i.d.) random vectors having p-variate normal distribution with mean $\boldsymbol{\mu}_i$ and covariance matrix Σ_i, $N_p(\boldsymbol{\mu}_i, \Sigma_i)$, $(i = 1, 2)$. We assume that the covariance matrices have the structure

$$\Sigma_i = \sigma_i^2\{(1-\rho_i)I_p + \rho_i \mathbf{1}_p \mathbf{1}_p'\}, \quad (i = 1, 2), \tag{1}$$

where $\sigma_i > 0$, $1 > \rho_i > -1/(p-1)$, I_p is the $p \times p$ identity matrix, and $\mathbf{1}_p : p \times 1 = (1, \cdots, 1)'$. The eigen values of Σ_i are $\tau_{i1} = \sigma_i^2\{1 + (p-1)\rho_i\}$ and $\tau_{i2} = \sigma_i^2(1-\rho_i)$. Here ρ_i is called the intraclass correlation coefficient. This structure, which is called an intraclass correlation model or equi-variance and equi-correlation model, is applied to MANOVA for repeated measurements, see e.g. Vonesh and Chinchilli (1997). Let $\boldsymbol{y}_n = \bar{\boldsymbol{x}}_{1,n_1} - \bar{\boldsymbol{x}}_{2,n_2}$ and $\boldsymbol{\mu} = \boldsymbol{\mu}_1 - \boldsymbol{\mu}_2$, where $\bar{\boldsymbol{x}}_{i,n_i}$ is the usual sample mean based on n_i observations $(i = 1, 2)$.

The problem is to determine the sample sizes satisfying

$$P\{|\boldsymbol{a}'(\boldsymbol{y}_n - \boldsymbol{\mu})| \le d, \text{ for all } \boldsymbol{a} \text{ such that } \boldsymbol{a}'\boldsymbol{a} = 1\} \ge 1 - \alpha, \tag{2}$$

where $d > 0$ and α $(0 < \alpha < 1)$ are given. For one sample problem, Hyakutake, Takada and Aoshima (1995) solved the problem by a two-stage procedure and a purely sequential procedure. Aoshima (1997) and Hyakutake (1998) considered the problem

* Faculty of Mathematics, Kyushu University, Ropponmatsu, Fukuoka 810-8560, Japan. hyakutak@math.kyushu-u.ac.jp

† Faculty of Mathematics, Kyushu University 33, Hakozaki, Fukuoka 812-8581, Japan. kawasaki@math.kyushu-u.ac.jp

of constructing the fixed-size spherical confidence region of the difference of two multinormal means by a two-stage procedure. However their procedures may not be optimal as stated in Hyakutake (1998), when the covariance matrices are known. For example, when $\sigma_1^2 = 1.0$, $\rho_1 = 0$, $\sigma_2^2 = 2.5$, $\rho_2 = 0.6$, $d = 1.0$, and $\alpha = 0.05$, the required sample sizes are $n_1 = 17.97$ and $n_2 = 35.95$ by Hyakutake (1998), which improves Aoshima (1997). Based on these sample sizes, the coverage probability is 0.971. This suggests that the procedure would be improved. We determine a pair of the sample sizes n_1^* and n_2^* that minimizes $n_1 + n_2$ under the constraint (2).

If the covariance matrices are known, it is easy to see that

$$\begin{aligned} 1-\alpha &= P[(\boldsymbol{y}_n - \boldsymbol{\mu})'(\Sigma_1/n_1 + \Sigma_2/n_2)^{-1}(\boldsymbol{y}_n - \boldsymbol{\mu}) \leq \chi_p^2(\alpha)] \\ &= P[\max_{\boldsymbol{b}\neq\boldsymbol{0}} \frac{\{\boldsymbol{b}'(\boldsymbol{y}_n - \boldsymbol{\mu})\}^2}{\boldsymbol{b}'(\Sigma_1/n_1 + \Sigma_2/n_2)\boldsymbol{b}} \leq \chi_p^2(\alpha)] \\ &= P[\boldsymbol{b}'\boldsymbol{\mu} \in \boldsymbol{b}'\boldsymbol{y}_n \pm \sqrt{\chi_p^2(\alpha)\boldsymbol{b}'(\Sigma_1/n_1 + \Sigma_2/n_2)\boldsymbol{b}}, \text{ for all } \boldsymbol{b} \neq \boldsymbol{0}], \end{aligned}$$

where $\chi_p^2(\alpha)$ is the upper $100(1-\alpha)\%$ point of χ_p^2, which is a chi-square distribution with p degrees of freedom. Hence the confidence intervals of $\boldsymbol{b}'\boldsymbol{\mu}$ for all $\boldsymbol{b} \neq \boldsymbol{0}$ are

$$\boldsymbol{b}'\boldsymbol{y}_n \pm \sqrt{\chi_p^2(\alpha)\boldsymbol{b}'(\Sigma_1/n_1 + \Sigma_2/n_2)\boldsymbol{b}},$$

which are equivalent to

$$\boldsymbol{a}'\boldsymbol{y}_n \pm \sqrt{\chi_p^2(\alpha)\boldsymbol{a}'(\Sigma_1/n_1 + \Sigma_2/n_2)\boldsymbol{a}}, \tag{3}$$

for all $\boldsymbol{a}$ such that $\boldsymbol{a}'\boldsymbol{a} = 1$. It is not easy to derive the optimal sample sizes directly by (2). We consider the confidence intervals (3), say the problem is to determine n_1^* and n_2^* such that

$$\sqrt{\chi_p^2(\alpha)\boldsymbol{a}'(\Sigma_1/n_1 + \Sigma_2/n_2)\boldsymbol{a}} \leq d, \quad \text{for all } \boldsymbol{a}\ (\boldsymbol{a}'\boldsymbol{a} = 1). \tag{4}$$

In Section 2, we give the optimal sample sizes, when σ_i and ρ_i are known. When σ_i and ρ_i are unknown, (4) is changed to

$$\sqrt{c_m\boldsymbol{a}'(\hat{\Sigma}_1/n_1 + \hat{\Sigma}_2/n_2)\boldsymbol{a}} \leq d, \quad \text{for all } \boldsymbol{a}\ (\boldsymbol{a}'\boldsymbol{a} = 1), \tag{5}$$

where $\hat{\Sigma}_i$ is an estimator of Σ_i and c_m is a $100(1-\alpha)\%$ point of a distribution which is discussed in Section 3. We propose a two-stage procedure satisfying (5) and investigate its property in Section 3.

2. Optimal sample sizes

In this section, we asuume that the covariance matrices are known, that is, σ_i and ρ_i are known. The following lemma gives the optimal sample sizes n_i^* $(i = 1, 2)$ that minimize $n_1 + n_2$ under the constraint (4).

LEMMA 2.1. *A sample size (n_1^*, n_2^*) is a minimum if and only if there exists a unit eigen vector $\boldsymbol{a}_1 (\in R^p)$ of $\Sigma_1/n_1^* + \Sigma_2/n_2^*$ such that*

$$\chi_p^2(\alpha)\boldsymbol{a}_1'(\Sigma_1/n_1^* + \Sigma_2/n_2^*)\boldsymbol{a}_1 = d^2 \tag{6}$$

and

$$n_i^* = \frac{\chi_p^2(\alpha)}{d^2}\xi_i(\xi_1 + \xi_2), \quad (i = 1, 2) \tag{7}$$

where $\xi_i^2 = \boldsymbol{a}_1 \Sigma_i \boldsymbol{a}_1$. Furthermore, when $\boldsymbol{a}_1' \mathbf{1}_p \neq 0$, the corresponding eigen value equals $\tau_{11}/n_1^* + \tau_{21}/n_2^*$. When $\boldsymbol{a}_1'\mathbf{1}_p = 0$, it holds that $\xi_i^2 = \tau_{i2}$ $(i = 1, 2)$.

PROOF. It follows from the necessary optimality condition for a semi-infinite programming problem that there exist a number $1 \leq \ell \leq 2$ (2 is the number of the variables n_1 and n_2), multipliers $\lambda_j \geq 0$, and vectors $\boldsymbol{a}_j \in R^p$ $(1 \leq j \leq \ell)$ such that

$$\frac{\partial L}{\partial n_i}(n_1^*, n_2^*) = 0, \quad (i = 1, 2) \tag{8}$$

and

$$\chi_p^2(\alpha)\boldsymbol{a}_j'\Big(\frac{\Sigma_1}{n_1^*} + \frac{\Sigma_2}{n_2^*}\Big)\boldsymbol{a}_j = d^2, \quad (1 \leq j \leq \ell), \tag{9}$$

where L is the Lagrange function

$$L(n_1, n_2) := n_1 + n_2 + \sum_{j=1}^{\ell} \lambda_j \Big\{\chi_p^2(\alpha)\boldsymbol{a}_j'\Big(\frac{\Sigma_1}{n_1^*} + \frac{\Sigma_2}{n_2^*}\Big)\boldsymbol{a}_j - d^2\Big\}, \tag{10}$$

see, e.g., Theorem 3.2 in Ben-Tal et al (1979) or Theorem 10.13.1 in Kawasaki (2004).

It is not hard to show that either n_1^* or n_2^* is negative when $\ell = 2$, so $\ell = 1$. Then (8) and (9) reduce to

$$\lambda_1 \chi_p^2(\alpha)\xi_i^2/n_i^{*2} = 1 \;\; (i = 1, 2) \tag{11}$$

and

$$\chi_p^2(\alpha)(\xi_1^2/n_1^* + \xi_2^2/n_2^*) = d^2, \tag{12}$$

respectively. Solving (11) and (12) with respect to $(n_1^*, n_2^*, \lambda_1)$, we get (7). On the other hand, $\boldsymbol{a}_1$ is a maximum of $\chi_p^2(\alpha)\boldsymbol{a}'(\Sigma_1/n_1 + \Sigma_2/n_2)\boldsymbol{a}$ subject to $\boldsymbol{a}'\boldsymbol{a} = 1$. Hence there exists a Lagrange multiplier $\eta \geq 0$ such that $\partial M/\partial \boldsymbol{a} = \mathbf{0}$, where

$$M(\boldsymbol{a}) = \chi_p^2(\alpha)\boldsymbol{a}'(\Sigma_1/n_1 + \Sigma_2/n_2)\boldsymbol{a} - \eta(\boldsymbol{a}'\boldsymbol{a} - 1),$$

that is,

$$\chi_p^2(\alpha)(\Sigma_1/n_1^* + \Sigma_2/n_2^*)\boldsymbol{a}_1 - \eta \boldsymbol{a}_1 = \mathbf{0}. \tag{13}$$

Hence $\boldsymbol{a}_1$ is an eigen vector of $\Sigma_1/n_1^* + \Sigma_2/n_2^*$ and its eigen value is equal to $\eta/\chi_p^2(\alpha)$. Multiplying (13) by $\boldsymbol{a}_1$, we see that the eigen value equals

$$\xi_1^2/n_1^* + \xi_2^2/n_2^*. \tag{14}$$

Multiplying (13) by $\mathbf{1}_p$, we have

$$\chi_p^2(\alpha)(\mathbf{1}_p'\Sigma_1\boldsymbol{a}_1/n_1^* + \mathbf{1}_p'\Sigma_2\boldsymbol{a}_1/n_2^*) - \eta\mathbf{1}_p'\boldsymbol{a}_1 = 0. \tag{15}$$

Since $\mathbf{1}_p'\Sigma_i = \tau_{i1}\mathbf{1}_p'$, we get

$$\{\chi_p^2(\alpha)(\tau_{11}/n_1^* + \tau_{21}/n_2^*) - \eta\}\mathbf{1}_p'\boldsymbol{a}_1 = 0. \tag{16}$$

Hence, when $\mathbf{1}_p'\boldsymbol{a}_1 \neq 0$, the eigen value equals $\tau_{11}/n_1^* + \tau_{21}/n_2^*$. When $\mathbf{1}_p'\boldsymbol{a}_1 = 0$, we get $\xi_i^2 = \tau_{i2}$ $(i = 1, 2)$ from the form of (1).

On the other hand, since the present semi-infinite programming problem is a convex programming problem, the necessary optimility condition turns out to be a sufficient condition for a miniimum.

In Lemma 2.1, it is easy to see that $\min(\tau_{i1}, \tau_{i2}) \leq \xi_i^2 \leq \max(\tau_{i1}, \tau_{i2})$ by $\boldsymbol{a}_1'\boldsymbol{a}_1 = 1$. The vector $\boldsymbol{a}_1$ would depend on the parameters σ_i and ρ_i, so we write $\boldsymbol{a}_1 = \boldsymbol{a}_1(\sigma_1, \sigma_2, \rho_1, \rho_2)$, $(i = 1, 2)$, which implies that $\boldsymbol{a}_1$ is a function of τ_{ij}.

3. Two-stage procedure

When σ_i and ρ_i are unknown, there is no fixed sample size procedure. We give a two-stage procedure satisfying (5). Let the first low of a $p \times p$ orthogonal matrix Q defined by $(1/\sqrt{p}, \cdots, 1/\sqrt{p})$, and define $\boldsymbol{z}_{ir} = (z_{ir,1}, \cdots, z_{ir,p})' = Q(\boldsymbol{x}_{ir} - \boldsymbol{\mu}_i)$, $r = 1, 2, \cdots$ and $i = 1, 2$. Then $\boldsymbol{z}_{ir}$'s are i.i.d. according to $N_p(\mathbf{0}, D)$, where $D_i = \mathrm{diag}(\tau_{i1}, \tau_{i2}, \cdots, \tau_{i2})$.

First take the initial sample size $m(> p)$ from each population and compute

$$\hat{\tau}_{i1} = \frac{1}{m-1}\sum_{r=1}^{m}(z_{ir,1} - \bar{z}_{i,1})^2 \quad \text{and} \quad \hat{\tau}_{i2} = \frac{1}{(p-1)(m-1)}\sum_{j=2}^{p}\sum_{r=1}^{m}(z_{ir,j} - \bar{z}_{i,j})^2, \tag{17}$$

where $(\bar{z}_{i,1}, \cdots, \bar{z}_{i,p})' = \sum_{r=1}^{m}\boldsymbol{z}_{ir}/m$. Then $\hat{\tau}_{i1}$ and $\hat{\tau}_{i2}$ are independent and are unbiased estimators of τ_{i1} and τ_{i2}, respectively, see e.g., Hyakutake, Takada and Aoshima (1995). The estimator of Σ_i is $S_i = Q'\hat{D}_iQ$, where $\hat{D}_i = \mathrm{diag}(\hat{\tau}_{i1}, \hat{\tau}_{i2}, \cdots, \hat{\tau}_{i2})$, say S_i is used in $\hat{\Sigma}_i$ of (5). Hence $\hat{\xi}_i^2 = \hat{\boldsymbol{a}}_1 S_i \hat{\boldsymbol{a}}_1$ is an estimator of ξ_i^2, where $\hat{\boldsymbol{a}}_1 = \boldsymbol{a}_1(\hat{\sigma}_1, \hat{\sigma}_2, \hat{\rho}_1, \hat{\rho}_2)$, which is expressed by $\hat{\tau}_{i1} = \hat{\sigma}_i^2\{1 + (p-1)\hat{\rho}_i\}$ and $\hat{\tau}_{i2} = \hat{\sigma}_i^2(1 - \hat{\rho}_i)$. It would hold that $\min(\hat{\tau}_{i1}, \hat{\tau}_{i2}) \leq \hat{\xi}_i^2 \leq \max(\hat{\tau}_{i1}, \hat{\tau}_{i2})$ as in Section 2.

The total sample sizes are defined by

$$N_i = \max\left\{m,\ \left[c_m\frac{\hat{\xi}_i(\hat{\xi}_1 + \hat{\xi}_2)}{d^2}\right] + 1\right\}, \quad (i = 1, 2), \tag{18}$$

where $[q]$ denotes the greatest integer less than q and c_m is a solution of an equation $H(c_m) = 1 - \alpha$. $H(c_m)$ is a cummulative distribution function (c.d.f.) of

$$\nu_1 v_{01}/\min(v_{11}, v_{21}) + \nu_2 v_{02}/\min(v_{12}, v_{22}), \tag{19}$$

where v_{1i} and v_{2i} are independently distributed as $\chi^2_{\nu_i}$ with $\nu_1 = m-1$ and $\nu_2 = (p-1)\nu_1$, and the conditonal distributions of v_{01} and v_{02} given $\hat{\xi}_1, \hat{\xi}_2$ are χ^2_1 and χ^2_{p-1}, respectively.

Next we take $N_i - m$ additional observations from each population and compute the sample mean $\bar{\boldsymbol{x}}_{i,N_i}$ $(i = 1, 2)$. Then we have the following theorem.

THEOREM 3.1. *If N_1 and N_2 are determined by (17), then (5) is satisfied.*

PROOF. If it is shown that

$$P[(\boldsymbol{y}_N - \boldsymbol{\mu})'(S_1/n_1 + S_2/n_2)^{-1}(\boldsymbol{y}_N - \boldsymbol{\mu}) \le c_m] \ge 1 - \alpha, \tag{20}$$

where $\boldsymbol{y}_N = \bar{\boldsymbol{x}}_{1,N_1} - \bar{\boldsymbol{x}}_{2,N_2}$ and $\hat{\Sigma}_i = \hat{\sigma}_i^2\{(1-\hat{\rho}_i)I_p + \hat{\rho}_i \mathbf{1}_p\mathbf{1}_p'\}$, then (5) is satisfied by Lemma 1.

Since $\boldsymbol{u} = (u_1, \boldsymbol{u}_2')' = Q(\boldsymbol{y}_N - \boldsymbol{\mu})$ is distributed as $N(\mathbf{0}, D_1/N_1 + D_2/N_2)$ given (N_1, N_2), the conditional distributions of $v_{01} = u_1^2/(\tau_{11}/N_1 + \tau_{21}/N_2)$ and $v_{02} = \boldsymbol{u}_2'\boldsymbol{u}_2/(\tau_{12}/N_1 + \tau_{22}/N_2)$ are χ^2_1 and χ^2_{p-1}, respectively. Hence we have

$$\begin{aligned}
& P\{(\boldsymbol{y}_N - \boldsymbol{\mu})'(S_1/N_1 + S_2/N_2)^{-1}(\boldsymbol{y}_N - \boldsymbol{\mu}) \le c_m\} \\
= \; & P\Big\{\frac{u_1^2}{\tau_{11}/N_1 + \tau_{21}/N_2}\,\frac{\tau_{11}/N_1 + \tau_{21}/N_2}{\hat{\tau}_{11}/N_1 + \hat{\tau}_{21}/N_2} + \frac{\boldsymbol{u}_2'\boldsymbol{u}_2'}{\tau_{12}/N_1 + \tau_{22}/N_2}\,\frac{\tau_{12}/N_1 + \tau_{22}/N_2}{\hat{\tau}_{12}/N_1 + \hat{\tau}_{22}/N_2} \le c_m\Big\} \\
= \; & P\Big\{\frac{v_{01}}{q_1\hat{\tau}_{11}/\tau_{11} + (1-q_1)\hat{\tau}_{21}/\tau_{21}} + \frac{v_{02}}{q_2\hat{\tau}_{12}/\tau_{12} + (1-q_2)\hat{\tau}_{22}/\tau_{22}} \le c_m\Big\} \\
= \; & P\{\nu_1 v_{01}/(q_1 v_{11} + (1-q_1)v_{21}) + \nu_2 v_{02}/(q_2 v_{12} + (1-q_2)v_{22}) \le c_m\},
\end{aligned}$$

where $q_j = (\tau_{1j}/N_1)(\tau_{1j}/N_1 + \tau_{2j}/N_2)$ $(j = 1, 2)$. Since $q_j v_{1j} + (1-q_1)v_{2j} \ge \min(v_{1j}, v_{2j})$, we have

$$\begin{aligned}
& P\{\nu_1 v_{01}/(q_1 v_{11} + (1-q_1)v_{21}) + \nu_2 v_{02}/(q_2 v_{12} + (1-q_2)v_{22}) \le c_m\} \\
\ge \; & P\{\nu_1 v_{01}/\min(v_{11}, v_{21}) + \nu_2 v_{02}/\min(v_{12}, v_{22}) \le c_m\} \\
= \; & 1 - \alpha,
\end{aligned}$$

which completes the proof.

Next we discuss an asymptotic property of the procedure. It is easy to see that $v_{ij}/\nu_j \to 1$ $(i, j = 1, 2)$ almost surely as $m \to \infty$ by $\hat{\tau}_{ij} \to \tau_{ij}$ almost surely as $m \to \infty$, see e.g., Hyakutake, Takada and Aoshima (1995). Then the limiting distribution of (19) is χ^2_p, say $c_m \to \chi^2_p(\alpha)$ as $m \to \infty$. Under the assumption that $m \to \infty$ and $d^2 m \to 0$ as $d \to 0$, we have

$$\lim_{d \to 0} \frac{E(N_1 + N_2)}{n_1^* + n_2^*} = 1,$$

that is the two-stage procedure based on (18) is asymptotic efficient. This can be shown by the same method as in Takada (1988), so the proof is omitted.

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