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Wei-Hsiung Shen and Bimal K. Sinha*

Center for Multivariate Analysis
University of Pittsburgh
Pittsburgh PA 15260
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ADMISSIBLE BAYES TESTS FOR STRUCTURAL RELATIONSHIP

BY WEI-HSIUNG SHEN

University of Maryland Baltimore County

AND

BIMAL K. SINHA*

University of Maryland Baltimore County

and

Center for Multivariate Analysis, University of Pittsburgh

Abstract

It is an open problem to construct a test for structural relationship among the mean vectors of several multivariate normal populations with known but unequal covariance matrices. In this paper, a class of admissible Bayes tests for the above problem is derived. As a byproduct, in the special case of known and equal covariance matrices, the likelihood ratio test of Rao(1973) is shown to be admissible Bayes.

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1. Introduction. Fisher (1939) pointed out the importance of tests for structural relationship among the mean vectors of several multivariate normal populations. To be specific, consider $k$ independent $p$-variate multivariate normal populations, $N_p(\mu_i, \Sigma_i), i = 1, \ldots, k$ and the problem of testing

\begin{equation}
H_0 : H_0 : H\mu = \xi, i = 1, \ldots, k \quad \text{versus} \quad H_1 : \mu_1, \ldots, \mu_k \text{ arbitrary}
\end{equation}

where $H : s \times p$ is an unknown matrix of known rank $s < p$ and $\xi$ is an unknown $s$-vector. The hypothesis $H_0$, if true, implies that the $k$ mean vectors $\mu_1, \ldots, \mu_k$ lie in a $(p - s)$-dimensional subspace of the Euclidean $p$-space $E^p$ rather than in $E^p$ itself, and provides a structural relationship among the mean vectors. As Fisher (1939) and Rao (1973) rightly emphasized, it is essential that in dealing with several multinormal populations a hypothesis of the form (1.1) be tested prior to using the models for prediction etc.

It is an open problem in the literature to construct a suitable test for the hypotheses in (1.1) based on independent samples from the $k$ populations when $\Sigma_1, \ldots, \Sigma_k$ are unequal. In the case when $\Sigma_1, \ldots, \Sigma_k$ are equal (and $= \Sigma$, say), Rao (1973) derived the likelihood ratio test (LRT) of $H_0$ against $H_1$. 


which rejects the null hypothesis for large values of \( T = \sum_{i=1}^{p} \lambda_i (B \Sigma^{-1}) \). Here \( B \) is the matrix of the sums of squares and products due to the hypotheses (between groups), \( \lambda_1 < \lambda_2 < \cdots < \lambda_p \) are the ordered roots of \( B \Sigma^{-1} \), and the matrix \( \Sigma \) is assumed known. If \( \Sigma \) is unknown, one replaces \( \Sigma \) in the definition of \( T \) by \( W \), the within matrix sum of squares and products due to error (within groups). That the resultant test is the LRT is proved in Fujikoshi(1974) and also in Rao(1985).

It is the object of this paper to provide a simple solution to the above open problem when \( \Sigma_1, \ldots, \Sigma_k \) are assumed known. We have derived in Section 2 a class of admissible Bayes tests for the hypothesis \( H_0 \) versus \( H_1 \). Interestingly enough, inspite of the somewhat complicated structures of the model and the problem, the derived tests are of extremely simple form. In the special case of equal and known covariance matrices, the LRT of Rao(1973) is shown to be admissible Bayes.

We may recall that a Bayes critical region (for 0-1 loss function) is of the form

\[
\{ x : \int f(x; \theta) \pi_1(d\theta) \int f(x; \theta) \pi_i(d\theta) - r \}
\]

for some positive constant \( c \), where \( f(x; \theta) \) is the underlying joint density.
θ is the vector of parameters, π₁ and π₀ are the prior probability measures over the alternative parameter space Θ₁ and the null parameter space Θ₀ respectively, and f is over the respective parameter spaces (Kiefer and Schwartz, 1965). Assuming that we have available a random sample of size nᵢ from the ith population, denoted as \( x_{i1}, \ldots, x_{inᵢ}, \ i = 1, \ldots, k \), we can write

\[
(1.3) \quad f(x; \theta) = (2\pi)^{-np/2} \prod_{i=1}^{k} |\Sigma_i|^{-nᵢ/2} e^{tr}\left\{ -1/2 \sum_{i=1}^{k} nᵢ \Sigma_i^{-1}(xᵢ - \muᵢ) (xᵢ - \muᵢ)' \right\} \]

where \( xᵢ = \frac{1}{nᵢ} \sum_{j=1}^{nᵢ} x_{ij}, \ Sᵢ = \sum_{j=1}^{nᵢ} (x_{ij} - xᵢ)(x_{ij} - xᵢ)', \ i = 1, \ldots, k. \)

\( n = \sum_{i=1}^{k} nᵢ, \ \theta = (\mu₁, \ldots, \muₖ), \ \Theta = \{(\mu₁, \ldots, \muₖ) : \muᵢ \in Eᵢ, \ i = 1, \ldots, k\}. \)

\( \Theta₀ = \{(\mu₁, \ldots, \muₖ) : Hμᵢ = \xi, \ i = 1, \ldots, k. \ H : s < p \ unknown, \)

\( \text{rank}(H) = s < p, \ s \ known, \xi : s \cdot 1 \in Eᵢ unknown\}, \ \Theta₁ = \Theta - \Theta₀. \)

In what follows the factor \( (2\pi)^{-np/2} \prod_{i=1}^{k} |\Sigma_i|^{-nᵢ/2} e^{tr}\left\{ -1/2 \sum_{i=1}^{k} \Sigma_i^{-1}Sᵢ \right\} \) appearing in \( f(x; \theta) \) is ignored because it is independent of \( \theta \) and has no influence on Bayes tests of the form (1.2). Thus one can write (1.2) in the form

\[
(1.4) \quad \{x : \int f'(x; \theta) π₁(dθ), \int f'(x; \theta) π₀(dθ) \cdot c\} \]
where

\[ f^*(x; \theta) = etr \{ -1/2 \sum_{i=1}^{k} n_i \Sigma_i^{-1} (\bar{x}_i - \mu_i)(\bar{x}_i - \mu_i)' \}. \]

Appropriate choices of \( \pi_1 \) and \( \pi_n \) are made in Section 2 and the resultant Bayes tests are derived.

2. Admissible Bayes tests of (1.1). Under the alternative \( H_1 \), we choose \( \pi_1 \) as the absolutely continuous measure on the space \( \mathbb{R}^k \) of the \( \mu_i \)'s given by

\[ d\pi_1(\mu_1, \ldots, \mu_k), d\mu_1 \cdots d\mu_k = \]

\[ (2\pi)^{kp/2} \prod_{i=1}^{k} |A_i|^{-1/2} (\prod_{i=1}^{k} n_i)^{p/2} etr \{ -1/2 \sum_{i=1}^{k} n_i A_i^{-1} (\mu_i - \zeta_i)(\mu_i - \zeta_i)' \} \]

where \( A_i : p \times p \), p.d. matrix, and \( \zeta_i : p \times 1 \) vector, \( i = 1, \ldots, k \). Clearly \( \pi_1 \) corresponds to choosing independent normal priors for each \( \mu_i \). The matrices \( A_i \) and the vectors \( \zeta_i, i = 1, \ldots, k \), will be chosen later. This immediately results in the numerator of the expression in (1.4) as

\[ \int f^*(x; \theta) \pi_1(d\theta) = \]

\[ (2\pi)^{-pk/2} (\prod_{i=1}^{k} n_i)^{-p/2} (\prod_{i=1}^{k} |A_i|)^{-1/2} etr \{ -1/2 \sum_{i=1}^{k} n_i \Sigma_i^{-1} x_i x_i' \} \]

\[ \cdot etr \{-1/2 \sum_{i=1}^{k} n_i A_i^{-1} \zeta_i \zeta_i' \} \]
\[ \cdot \text{etr}\left\{ \frac{1}{2} \sum_{i=1}^{k} n_i (\Sigma_i^{-1} x_i + A_i^{-1} z_i)(\Sigma_i^{-1} x_i + A_i^{-1} z_i)'(\Sigma_i^{-1} + A_i^{-1})^{-1} \right\} \]

\[ \cdot \int \text{etr}\left\{ -\frac{1}{2} \sum_{i=1}^{k} n_i (\Sigma_i^{-1} + A_i^{-1})(\mu_i - (\Sigma_i^{-1} + A_i^{-1})^{-1} \cdot (\Sigma_i^{-1} x_i + A_i^{-1} z_i))' \right\} \]

\[ \cdot d\mu_1 \cdots d\mu_k \]

\[ = \prod_{i=1}^{k} |\Sigma_i^{-1} A_i + I_p|^{-1/2} \text{etr}\left\{ -\frac{1}{2} \sum_{i=1}^{k} n_i A_i^{-1} z_i z_i' \right\} \]

\[ \cdot \text{etr}\left\{ -\frac{1}{2} \sum_{i=1}^{k} n_i \Sigma_i^{-1} x_i x_i' \right\} \]

\[ \cdot \text{etr}\left\{ \frac{1}{2} \sum_{i=1}^{k} n_i (\Sigma_i^{-1} x_i + A_i^{-1} z_i)(\Sigma_i^{-1} x_i + A_i^{-1} z_i)'(\Sigma_i^{-1} + A_i^{-1})^{-1} \right\} \]

The crux of the problem now is to evaluate the denominator of the expression in (1.4), namely \( \int f^*(x; \theta) \pi_n(d\theta) \) for suitable \( \pi_n \)'s. Towards this end, first note that

\[ (2.3) \quad H \mu_i = \xi \iff \mu_i = H'(H H')^{-1} \xi + (I_p - H'(H H')^{-1} H) \eta_i \]

for arbitrary \( \eta_i \in E^p \)

so that \( \Theta_0 \) can be rewritten as

\[ (2.4) \quad \Theta_0 = \{ (\mu_1, \ldots, \mu_k) : \mu_i = H'(H H')^{-1} \xi + (I_p - H'(H H')^{-1} H) \eta_i, \]

\[ \eta_i \in E^p, i = 1, \ldots, k, \xi, \eta_1, \ldots, \eta_k \text{ all arbitrary} \].
\[ H : s \cdot p \text{ unknown}, \ rank(H) \neq s \cdot p, s \text{ known}. \]

Our choice of \( \pi_0 \) on \( \Theta_0 \) corresponds to choosing suitable priors for \( H \) in \( \{ H : s \cdot p \ \ rank(H) \neq s \cdot p, \ s \cdot p, s \text{ known} \}. \)

Throughout the following, as far as \( H \) is concerned, we assume that \( \pi_0 \) assigns all its measure to the subset \( \{ H : s \cdot p \ H \neq (I, : 0) \} \) of \( \mathcal{H} \). It remains to specify priors of \( \xi \) and \( \eta_1, \ldots, \eta_k \). This is done below.

Choose the conditional density of \((\eta_1, \ldots, \eta_k)\), given \( \xi \), as

\[
(2.5) \quad d\pi_0(\eta_1, \ldots, \eta_k, \xi) d\eta_1 \cdots d\eta_k = (2\pi)^{-k} Q^{\frac{1}{2}} e^{tr\{ \frac{1}{2} \sum_{i=1}^k n_i P_i^{-1}(\eta_i - (\eta_i - \Delta_i, \xi))(\eta_i - (\eta_i - \Delta_i, \xi))' \}}
\]

and the marginal density of \( \xi \) as

\[
(2.6) \quad d\pi_0(\xi) d\xi = (2\pi)^{-\frac{p^2}{2}} Q^{\frac{1}{2}} e^{tr\{ \frac{1}{2} 2Q^{-1}(\xi - \xi')(\xi - \xi')' \}}
\]

where \( \eta_0^0 : p \cdot 1, \xi_0^0 : s \cdot 1, \Delta_i : p \cdot s, P_i : p \cdot p, p.d., Q : s \cdot s, p.d. \) are to be suitably chosen. Let

\[
\begin{align*}
    d_i &= \Sigma_i^{-1} x_i, \quad i = 1, \ldots, k, \\
    \beta &= \sum_{i=1}^k n_i \Sigma_i^{-1} x_i = \sum_{i=1}^k n_i \beta_i, \\
    \Psi_1 &= (I, : 0) : s \cdot p.
\end{align*}
\]
\[
(2.7) \quad \Psi_2 = \begin{pmatrix} 0 & 0 \\ 0 & I_{p-r} \end{pmatrix} : p \cdot p
\]

\[
\Psi_3 = \Psi_1(\sum_{i=1}^{k} n_i \sum_i^{-1})\Psi_2 : s \cdot s.
\]

\[
\Psi_{4i} = \Psi_2 \sum_{i=1}^{-1}\Psi_2 : p \cdot p, \quad i = 1, \ldots, k.
\]

\[
\Psi_{5i} = \Psi_2 \sum_{i=1}^{-1}\Psi_1 : p \cdot s, \quad i = 1, \ldots, k.
\]

Then the denominator of the expression in (1.4) can be simplified as

\[
(2.8) \quad \int f^* (x; \theta) \pi_0 (d\theta) =
\]

\[
(2\pi)^{-p/2 \sum_{i=1}^{k} n_i} p^{2 \sum_{i=1}^{k} |P_i|^{-2} (2\pi)^{-2} Q^{-1}^{1/2}
\]

\[
\cdot \operatorname{etr} \{-1 \cdot 2 \sum_{i=1}^{k} n_i \sum_i^{-1} x_i x_i' \} \operatorname{etr} \{-1 \cdot 2 Q^{-1} \xi', \xi''
\]

\[
\cdot \operatorname{etr} \{-1 \cdot 2 \sum_{i=1}^{k} n_i P_i^{-1} \eta_i \eta_i''
\]

\[
\cdot \int \operatorname{etr} \{-1 \cdot 2 (\Psi_3 + Q^{-1}) \xi', - 1 \cdot 2 (\Psi_3 + Q^{-1}) \xi''
\]

\[
+ 1 \cdot 2 \xi (\Psi_3 + Q^{-1}) \xi'''
\]

\[
\cdot \operatorname{etr} \{-1 / 2 \sum_{i=1}^{k} n_i ([\Psi_4i + P_i^{-1}] \eta_i \eta_i') - (\Psi_2 \beta_i \cdot \Psi_5i \xi
\]

\[
P_i^{-1}(\eta_i + \Delta_i \xi)) \eta_i' - \eta_i(\Psi_2 \beta_i \cdot \Psi_5i \xi + P_i^{-1}(\eta_i + \Delta_i \xi)''
\]

\[
\cdot \operatorname{etr} \{-1 / 2 \sum_{i=1}^{k} n_i P_i^{-1}(\eta_i \xi, \Delta_i') \Delta_i \xi \eta_i'' - \Delta_i \xi \eta_i''
\]

\[
\cdot d\xi d\eta_1 \cdots d\eta_k
\]
\[ (2\pi)^{-n/2} \prod_{r=1}^{k} (P_{r})^{-1} \prod_{r=1}^{k} |P_{r}^{-1} - (2\pi)^{-1} |Q|^{-1/2} \]
\[ \cdot \text{etr} \{ - \cdot 2 \sum_{i=1}^{k} n_{r} \Sigma_{r}^{-1} x_{r} x_{r}^{*} \} \text{etr} \{ - \cdot 2Q^{-1} \xi^{(r)} \xi^{(r)*} \} \]
\[ \cdot \text{etr} \{ - \cdot 2 \sum_{i=1}^{k} n_{r} P_{r}^{-1} \eta_{r} \eta_{r}^{*} \} \]
\[ \cdot \text{etr} \{ 1 \sum_{i=1}^{k} n_{r}(\Psi_{2} \beta_{i} - P_{r}^{-1} \eta_{r}) \} \text{etr} \{ (\Psi_{2} + P_{r}^{-1})^{-1} \} \text{etr} \{ 1 \cdot 2Q^{-1} \Xi^{-1} \} \]
\[ \cdot \int \text{etr} \{ - \cdot 2 \sum_{i=1}^{k} n_{r}(\Psi_{3} \beta_{i} - P_{r}^{-1} \eta_{r}) \} (\eta_{r} - (\Psi_{4} + P_{r}^{-1})^{-1}(\Psi_{2} \beta_{i} - \Psi_{5} \xi - P_{r}^{-1} \eta_{r}) \}
\[ \cdot (\eta_{r}^{*} - \Delta_{r} \xi)) (\eta_{r} - (\Psi_{4} + P_{r}^{-1})^{-1}(\Psi_{2} \beta_{i} - \Psi_{5} \xi - P_{r}^{-1} \eta_{r} + \Delta_{r} \xi))^{*} \}
\[ \cdot \text{etr} \{ 1 \sum_{i=1}^{k} n_{r}(\Psi_{2} \beta_{i} - P_{r}^{-1} \eta_{r}) \} \text{etr} \{ 1 \cdot 2Q^{-1} \Xi^{-1} \} \}
\[ \cdot d\xi d\eta_{1} \ldots d\eta_{k} \]
\[ \cdot \prod_{r=1}^{k} |P_{r} \Psi_{4} - I_{p}|^{-1/2} |Q|^{-1/2} \Xi^{-1} \cdot 2 \text{etr} \{ - \cdot 2Q^{-1} \xi^{(r)} \xi^{(r)*} \} \]
\[ \cdot \text{etr} \{ 1 \sum_{i=1}^{k} n_{r}(\Psi_{2} \beta_{i} - P_{r}^{-1} \eta_{r}) \} \text{etr} \{ - \cdot 2 \sum_{i=1}^{k} n_{r} P_{r}^{-1} \eta_{r} \eta_{r}^{*} \} \text{etr} \{ 1 \cdot 2Q^{-1} \Xi^{-1} \} \]
\[ \cdot \text{etr} \{ 1 \sum_{i=1}^{k} n_{r}(\Psi_{2} \beta_{i} - P_{r}^{-1} \eta_{r}) \} \text{etr} \{ (\Psi_{2} + P_{r}^{-1})^{-1} \} \}

\text{where}

(2.9) \quad \Psi_{3} \cdot Q^{-1} \cdot \sum_{i=1}^{k} n_{r} \Delta_{r} P_{r}^{-1} \Delta_{r}^{-1}
\[ \cdot \sum_{i=1}^{k} n_{r}(P_{r}^{-1} \Delta_{i} - \Psi_{3})(\Psi_{4} - P_{r}^{-1})^{-1}(P_{r}^{-1} \Delta_{i} - \Psi_{3}) \]

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and

\[(2.10)\quad \tau = \Psi \beta + Q^{-1} \xi^0 - \sum_{i=1}^{k} n_i \Delta_i P_i^{-1} \eta_i^0 + \sum_{i=1}^{k} n_i (P_i^{-1} \Delta_i - \Psi \xi_i)'(\Psi_4 + P_i^{-1})^{-1}(\Psi_2 \beta_i + P_i^{-1} \eta_i^0).\]

In the above, \(\Delta_i\)'s, \(P_i\)'s, and \(Q\) are chosen so that \(\Xi\) is p.d.. Hence, combining (2.2) and (2.8), and taking the logarithm of the ratio of the expressions in (2.2) and (2.8), the Bayes test turns out to be of the form

\[(2.11)\quad tr\left\{\sum_{i=1}^{k} n_i (\Sigma_i^{-1} X_i + A_i^{-1} \xi_i)(\Sigma_i^{-1} X_i + A_i^{-1} \xi_i)'(\Sigma_i^{-1} + A_i^{-1})^{-1}\right\}
- tr\left\{\sum_{i=1}^{k} n_i (\Psi_2 \beta_i + P_i^{-1} \eta_i^o)'(\Psi_4 + P_i^{-1})^{-1}(\Psi_2 \beta_i + P_i^{-1} \eta_i^o)\right\}
- tr\{\tau' \Xi^{-1}\}
\geq c'.\]

We now choose \(P_i, Q, A_i, \Delta_i, \xi_i, \eta_i^o, \) and \(\xi_i\) suitably subject to \(\Xi\) being p.d. to reduce (2.11) to a nice form.

Let \(\Sigma_i\) be partitioned as

\[(2.12)\quad \Sigma_i = \begin{pmatrix} \Sigma_{i(11)} & \Sigma_{i(12)} \\ \Sigma_{i(21)} & \Sigma_{i(22)} \end{pmatrix},\]

where \(\Sigma_{i(11)} : s \times s, \Sigma_{i(22)} : (p - s) \times (p - s)\), and let \(\Sigma_i^{-1}\) be similarly
partitioned into

\[(2.13) \quad \Sigma^{-1}_t = \begin{pmatrix} \Sigma_{11}^{-1} & \Sigma_{12}^{-1} \\ \Sigma_{21}^{-1} & \Sigma_{22}^{-1} \end{pmatrix} \]

where \( \Sigma_{11}^{-1} \), \( \Sigma_{12}^{-1} \), \( \Sigma_{21}^{-1} \), and \( \Sigma_{22}^{-1} \) are defined as follows:

\[ \Sigma_{11}^{-1} = \Sigma_{(11)}^{-1} \]
\[ \Sigma_{12}^{-1} = \Sigma_{(12)}^{-1} \]
\[ \Sigma_{21}^{-1} = \Sigma_{(21)}^{-1} \]
\[ \Sigma_{22}^{-1} = \Sigma_{(22)}^{-1} \]

and \( \Sigma_{11}^{-1} - \Sigma_{12}^{-1}, \Sigma_{12}^{-1} - \Sigma_{11}^{-1}, \Sigma_{21}^{-1} - \Sigma_{22}^{-1}, \Sigma_{22}^{-1} - \Sigma_{21}^{-1} \)

Choose

\[(i) \quad P_i = \begin{pmatrix} P_{i(1)} & 0 \\ 0 & \Sigma_{i(22)} \end{pmatrix}, \quad i = 1, \ldots, k, \]

where \( P_{i(1)} \) is any s. s. p.d. matrix.

\[(ii) \quad Q = (\sum_{i=1}^{k} \eta_i \Sigma_{i(11)}^{-1})^{-1}; \]

\[(iii) \quad A_i = \begin{pmatrix} \Sigma_{i(11)} & \Sigma_{i(21)} \\ \Sigma_{i(21)} & \Sigma_{i(22)} \end{pmatrix}, \quad i = 1, \ldots, k; \]

\[(iv) \quad \Delta_i = P_i \Psi_i, \quad i = 1, \ldots, k; \]

\[(v) \quad \xi_i'' = Q(\sum_{i=1}^{k} \eta_i \Psi_i, \eta''_i); \]

\[(vi) \quad \zeta_i = \Delta_i (\Sigma_i^{-1} - A_i^{-1}) \Psi_i (\Psi_i + P_i^{-1})^{-1} P_i^{-1} \eta''_i, \quad i = 1, \ldots, k; \]

and \( (vii) \quad \eta''_i, \quad i = 1, \ldots, k, \) arbitrary.
It may be noted that $\Xi$ simplifies to

\[(2.14) \quad \Xi = \Psi_3 + Q^{-1} + \sum_{i=1}^{k} n_i \Psi_i^t P_i \Psi_i\]

\[= \Psi_1 (\sum_{i=1}^{k} n_i \Sigma_i^{-1}) \Psi_1^t + \sum_{i=1}^{k} n_i (\Sigma_i^{-1} \Psi_i^t + \Psi_i^t \Sigma_i^{-1} \Psi_i)\]

\[= \Psi_1 (\sum_{i=1}^{k} n_i \Sigma_i^{-1}) \Psi_1^t + \sum_{i=1}^{k} n_i (\Sigma_i^{-1} + \Sigma_i^{-1} \Sigma_{(22)} \Sigma_i^{-1})\]

\[= \sum_{i=1}^{k} n_i (\Sigma_i^{11} + \Sigma_i^{-1} + \Sigma_i^{11} - \Sigma_i^{-1})\]

\[= 2 \sum_{i=1}^{k} n_i \Sigma_i^{11}\]

which is clearly p.d. and $P_{(11)}$ does not affect the calculation.

The three terms appearing in the left hand side of (2.11) can now be evaluated. Combining the first term and the second term of (2.11) and using $(v')$, we have

\[(2.15) \quad tr\left(\sum_{i=1}^{k} n_i x_i x_i^t (\Sigma_i^{-1} + A_i^{-1})^{-1} - \Psi_2 (\Psi_4 + P_i^{-1})^{-1} \Psi_2 \Sigma_i^{-1}\right)\]

\[- \sum_{i=1}^{k} n_i x_i (\zeta_i A_i^{-1} (\Sigma_i^{-1} + A_i^{-1})^{-1} - \eta_i P_i^{-1} (\Psi_4 + P_i^{-1})^{-1} \Psi_2) \Sigma_i^{-1}\]

\[- \sum_{i=1}^{k} n_i \Sigma_i^{-1} ((\Sigma_i^{-1} + A_i^{-1})^{-1} A_i^{-1} \zeta_i - \Psi_2 (\Psi_4 + P_i^{-1})^{-1} P_i^{-1} \eta_i) x_i^t\]

\[- \sum_{i=1}^{k} n_i (\zeta_i A_i^{-1} (\Sigma_i^{-1} + A_i^{-1})^{-1} A_i^{-1} \zeta_i - \eta_i P_i^{-1} (\Psi_4 + P_i^{-1})^{-1} P_i^{-1} \eta_i)\}

\[= tr\left(\sum_{i=1}^{k} n_i x_i x_i^t (\Sigma_i^{-1} + A_i^{-1})^{-1} - \Psi_2 (\Psi_4 + P_i^{-1})^{-1} \Psi_2 \Sigma_i^{-1}\right)\]

\[= \]
\[ + \sum_{i=1}^{k} n_i (\Sigma_i^{-1} A_i^{-1} (\Sigma_i^{-1} + A_i^{-1})^{-1} A_i^{-1} - \eta_i^0 \eta_i^0 P_i^{-1} (\Psi_{4i} + P_i^{-1})^{-1} P_i^{-1}) \].

Since the second term of the last equation does not contain data, we may drop it. So (2.15) is now

\[ (2.16) \quad tr \left\{ \sum_{i=1}^{k} n_i (\Sigma_i^{-1} x_i)(\Sigma_i^{-1} x_i)' ((\Sigma_i^{-1} + A_i^{-1})^{-1} \Psi_2(\Psi_{4i} + P_i^{-1})^{-1} \Psi_2) \right\} \]

\[ = tr \left\{ 1/2 \sum_{i=1}^{k} n_i (\Sigma_i^{-1} x_i)(\Sigma_i^{-1} x_i)' \right\} \]

\[ = tr \left\{ 1/2 \sum_{i=1}^{k} \left( \begin{array}{c} \Sigma_i(11) 2 \text{ } 0 \\ 0 \text{ } \Sigma_i(22) 1 \end{array} \right) \right\} \]

Also, using (ii), (iv) and (v), the third term of (2.11) reduces to

\[ (2.17) \quad tr \left\{ r r' \Sigma^{-1} \right\} \]

\[ = tr \left\{ 1/2 (\Psi_{1\beta})(\Psi_{1\beta})' \left( \sum_{i=1}^{k} n_i \Sigma_i^{11} \right)^{-1} \right\} \]

\[ = tr \left\{ 1/2 \beta \beta' \left( \sum_{i=1}^{k} n_i \Sigma_i^{11} \right)^{-1} \right\} \]

\[ = tr \left\{ 1/2 \left( \sum_{i=1}^{k} n_i \Sigma_i^{-1} x_i \right) \left( \sum_{i=1}^{k} n_i \Sigma_i^{-1} x_i \right)' \left( \sum_{i=1}^{k} n_i \Sigma_i^{11} \right)^{-1} \right\} \]

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Clearly $P_{i(11)}$ does not affect the above calculations. Combining (2.16) and
(2.17), (2.11) is now of the form

\[
(2.18) \quad tr \left\{ \sum_{i=1}^{k} n_i (\Sigma_i^{-1} \bar{x}_i) (\Sigma_i^{-1} \bar{x}_i)' \left( \begin{array}{cc} \Sigma_{i(11)} & 0 \\ 0 & 0 \end{array} \right) \right\} 
- tr \left\{ \left( \sum_{i=1}^{k} n_i \Sigma_i^{-1} \bar{x}_i \right) \left( \sum_{i=1}^{k} n_i \Sigma_i^{-1} \bar{x}_i \right)' \left( \begin{array}{cc} (\Sigma_{i=1}^{k} n_i \Sigma_{i(11)}^{-1})^{-1} & 0 \\ 0 & 0 \end{array} \right) \right\}
\]

\[> c'' .\]

This immediately prove the following result.

**THEOREM 2.1.** An admissible Bayes test of (1.1) rejects $H_0$ for large values of the test statistic given by the left hand side of (2.18).

When $\Sigma_1, \ldots, \Sigma_k$ are equal (and = $\Sigma$, say), (2.18) reduces to

\[
(2.19) \quad tr \left\{ \left( \sum_{i=1}^{k} n_i \bar{x}_i \bar{x}_i' \right) - 1/n \left( \sum_{i=1}^{k} n_i \bar{x}_i \right) \left( \sum_{i=1}^{k} n_i \bar{x}_i' \right) \left( \begin{array}{cc} \Sigma^{-1} & 0 \\ 0 & 0 \end{array} \right) \right\}
\]

\[> c .\]

which is the same as

\[
(2.20) \quad tr \left\{ B \left( \Sigma^{-1} - \left( \begin{array}{cc} 0 & 0 \\ 0 & \Sigma_{22}^{-1} \end{array} \right) \right) \right\} > c ,
\]

where $B$ is defined earlier.
This leads to the following important result.

**Theorem 2.2.** An admissible Bayes test of (1.1) when \( \Sigma_k = \Sigma \) rejects \( H_0 \) for large values of the test statistic given by the left hand side of (2.19) or (2.20).

**Remark 2.1.** It is interesting to observe that the test statistic given by the left hand side of (2.19) can be interpreted as the sum of the first \( s \) roots of the matrix \( B\Sigma^{-1} \). This follows because one can always take \( \Sigma = I_p \) due to the nature of the hypotheses (1.1) and change \( B \) to \( \Sigma^{-1/2} B \Sigma^{-1/2} \).

**Remark 2.2.** It is clear from the preceding calculations that if, under \( H_0, \pi_0 \) is chosen as assigning all its measure to the subspace \( \Psi_{11} \) of the form \( \Psi_{11} = \{ H : s \cdot p \} \), \( 0 \cdots 1, 0 \cdots 1, \cdots, 0 \cdot 1 \) with \( 1 \) at the \( j \)-th position, \( \Psi_1, \Psi_2, \) and appropriate changes are made accordingly in the definitions of \( \Psi_1, \Psi_2, \) and also in the choice of \( P, Q, A, \) etc., in the above priors of \( \xi \) and \( \eta_1, \cdots, \eta_s \), then the Bayes test rejects \( H_0 \) for large values of the test statistic

\[
(2.21) \quad tr \left\{ \sum_{i=1}^{k} n_i (\Sigma_i^{-1} x_i)(\Sigma_i^{-1} x_i)^t \right\} \begin{pmatrix} 0 & 0 & 0 \\ \Sigma_i^{1/2} & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}
\]

* \( 1 \leq j \leq s, \) and \( l_{i,j} \) as the \( i,j \)-th column of \( H, \)
where $\Sigma_{i(1,2)}$ is the appropriate $s \times s$ proper submatrix of $\Sigma_i$ corresponding to the rows $(i_1, \ldots, i_s)$ and the columns $(i_1, \ldots, i_s)$. In the special case of the equality of $\Sigma_1, \ldots, \Sigma_k$, it therefore follows from (2.21) that a test which rejects $H_0$ for large values of the sum of any $s$ roots of $B\Sigma^{-1}$ is admissible Bayes. In particular, the likelihood ratio test of Rao (1973) for equal covariance matrices which rejects $H_0$ for large values of the sum of $s$ smallest roots of $B\Sigma^{-1}$ is admissible Bayes.
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DEPARTMENT OF MATHEMATICS
UNIVERSITY OF MARYLAND BALTIMORE COUNTY
CATONSVILLE, MARYLAND 21228

CENTER FOR MULTIVARIATE ANALYSIS
UNIVERSITY OF PITTSBURGH
PITTSBURGH, PENNSYLVANIA 15260