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DEFICIENCIES IN LINEAR NORMAL EXPERIMENTS.

by

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Summary

Let X_1, \dots, X_n be independent and normally distributed variables, such that $0 < \text{var } X_i = \sigma^2$, $i=1, \dots, n$ and $E(X_1, \dots, X_n)' = A'\beta$ where A is an $k \times n$ matrix with known coefficients and $\beta = (\beta_1, \dots, \beta_n)'$ is an unknown column matrix. σ^2 may be known or unknown. Denote the experiment obtained by observing X_1, \dots, X_n by \mathcal{E}_A . Let A and B be matrices of dimension $n_A \times k$ and $n_B \times k$.

The deficiency $\delta(\mathcal{E}_A, \mathcal{E}_B)$ is computed when σ^2 is known, and for some cases, including the case $BB' - AA'$ positive semidefinite and AA' nonsingular, also when σ^2 is unknown.

2. Introduction and basic facts.

Definition. An experiment is a pair $\mathcal{E} = ((X, \mathcal{A}); (P_\theta, \theta \in \Theta))$ where (X, \mathcal{A}) is a measurable space and $(P_\theta, \theta \in \Theta)$ is a family of probability measures over (X, \mathcal{A}) .

For two experiments \mathcal{E} and \mathcal{F} indexed by the same parameter set Θ Le Cam defined in [2] the deficiency $\delta(\mathcal{E}, \mathcal{F})$ of \mathcal{E} relative to \mathcal{F} . The Δ -distance between \mathcal{E} and \mathcal{F} is the number $\Delta(\mathcal{E}, \mathcal{F}) = \max(\delta(\mathcal{E}, \mathcal{F}), \delta(\mathcal{F}, \mathcal{E}))$.

If $\delta(\mathcal{E}, \mathcal{F}) = 0$, we say that \mathcal{E} is more informative than \mathcal{F} and write this $\mathcal{E} \geq \mathcal{F}$. If also $\delta(\mathcal{F}, \mathcal{E}) = 0$, we say that \mathcal{E} and \mathcal{F} are equivalent and write this $\mathcal{E} \sim \mathcal{F}$.

For $\mathcal{E}, \mathcal{F}, \mathcal{G}$ experiments with the same parameter set Θ the following relations hold

$$0 \leq \delta(\mathcal{E}, \mathcal{F}) \leq 2 \quad \delta(\mathcal{E}, \mathcal{E}) = 0$$

$$\delta(\mathcal{E}, \mathcal{F}) \leq \delta(\mathcal{E}, \mathcal{G}) + \delta(\mathcal{G}, \mathcal{F})$$

In particular Δ is a pseudometric.

Let $\mathcal{E} = ((X, \mathcal{A}), (P_\theta, \theta \in \Theta))$ and $\mathcal{F} = ((Y, \mathcal{B}), (Q_\theta, \theta \in \Theta))$ be two experiments such that $(P_\theta, \theta \in \Theta)$ is dominated, Y is a Borel subset of a complete separable metric space and \mathcal{B} is the class of Borel subsets of Y . Then Le Cam [2] has shown that $\delta(\mathcal{E}, \mathcal{F}) = \inf_{M \in \mathcal{M}} \sup_{\theta \in \Theta} \|P_\theta M - Q_\theta\|$ where \mathcal{M} is the set of all Markov kernels from (X, \mathcal{A}) to (Y, \mathcal{B}) .

In this paper we will exploit certain symmetric properties of the experiments \mathcal{E} and \mathcal{F} to be able to substitute the class \mathcal{M} in the above expression with a smaller class consisting of "invariant" Markov kernels.

Let G be a group of transformations acting on Θ, X, Y such that $x \rightarrow g(x), y \rightarrow g(y)$ are measurable $g \in G$ and

$P_\theta g^{-1} = P_\theta g_\theta, Q_\theta g^{-1} = Q_\theta g_\theta, g \in G, \theta \in \Theta$. A Markov kernel is called invariant if $M(g(B)|g(x)) = M(B|x) g \in G, B \in \mathcal{B}, x \in X - N$ where $P_\theta(N) = 0, \theta \in \Theta$. Let \mathcal{M}_G be the set of invariant Markov kernels from (X, \mathcal{A}) to (Y, \mathcal{B}) . It then follows from [5] that the following conditions are sufficient for $\delta(\mathcal{E}, \mathcal{F}) =$

$$\inf_{M \in \mathcal{M}_G} \sup_{\theta} \|P_\theta M - Q_\theta\|$$

- (i) $(P_\theta, \theta \in \Theta)$ is dominated, Y is a Borel subset of a complete-separable metric space and \mathcal{B} is the class of Borel subsets of Y .
- (ii) The families $(P_\theta, \theta \in \Theta)$ and $(Q_\theta, \theta \in \Theta)$ are invariant
- (iii) There exists a σ -algebra \mathcal{G} in G such that the maps $(x, g) \rightarrow g(x), (y, g) \rightarrow g(y)$ are respectively $\mathcal{A} \times \mathcal{G}$ and $\mathcal{B} \times \mathcal{G}$ measurable.
- (iv) There exists a σ -finite measure τ on (G, \mathcal{G}) such that $\tau(B) = 0$ implies $\tau(Bg) = 0, B \in \mathcal{B}, g \in G$.
- (v) The group G has an invariant mean. If in addition:
- (vi) There exists one $M \in \mathcal{M}_G$ so that $M(g(B)|g(x)) = M(B|x) B \in \mathcal{B}, g \in G, x \in X, \mathcal{M}_G$ may be substituted with $\mathcal{M}_{G_0} = \{M \in \mathcal{M} | M(g(B)|g(x)) = M(B|x) B \in \mathcal{B}, g \in \mathcal{G}, x \in X\}$ i.e. we can restrict attention to invariant Markov kernels with \emptyset as exceptional set.

A sufficient condition for (v) to hold is that \mathcal{G} is solvable.

Suppose $\mathcal{G}_P = ((X, \mathcal{A}), (P_\theta, \theta \in \Theta))$ where $\Theta = X$ is a second countable locally compact topological group which is Hausdorff, \mathcal{A} is the Borel subsets of X , and the P_θ 's are given by $P_\theta(A) = P(A\theta^{-1}) A \in \mathcal{A}, \theta \in X$ where P is a probability

measure. Then \mathcal{E}_P is called a translation experiment. If $\mathcal{E}_Q = ((X, \mathcal{A}), (Q_\theta, \theta \in \Theta))$ is another translation experiment, let $g \in G$ be of the form $(x, g) \rightarrow x\theta^{-1}$ where $\theta \in \Theta$. Then the conditions (ii), (iii) and (vi) are satisfied, and X is a complete separable metric space. If we let τ be the Haar measure on (X, \mathcal{A}) , also (v) is seen to be satisfied. Hence $\delta(\mathcal{E}_P, \mathcal{E}_Q) = \inf_{M \in \mathcal{M}_{G\Theta}} \sup_{\theta} \|P_\theta M - Q_\theta\|$ provided $(P_\theta, \theta \in \Theta)$ is dominated and X is solvable. Torgersen [5] has shown that in this case every invariant Markov kernel with \emptyset as the exceptional set may be written $M(B|x) = N(Bx^{-1})$ where N is a probability measure over (X, \mathcal{A}) and that $\delta(\mathcal{E}_P, \mathcal{E}_Q) = \inf \|N * P - Q\|$ where $N * P(A) = \int N(x_1, x_2) dx_1 dx_2$ ($x_1, x_2 \in A$).

The following result, also from [5] and valid under the same conditions, gives a direct method to determine δ for translation experiments. If N_0 is a least favourable distribution for all level $\alpha \in [0, 1]$ for testing $H: P_\theta, \theta \in \Theta$ against Q where $P_\theta(A) = P(\theta^{-1}A)$, $\theta \in \Theta$, $A \in \mathcal{A}$, then $\delta(\mathcal{E}_P, \mathcal{E}_Q) = \|N_0 * P - Q\|$.

The purpose of this paper is to use the above results to compute the deficiencies between linear normal experiments. These experiments may be described as follows: Let A be a known $k \times n_A$ matrix and \mathcal{E}_A the experiment given by the independent normally distributed variables X_1, \dots, X_{n_A} with $\text{var } X_i = \sigma^2$, $i = 1, \dots, n_A$ and $E(X_1, \dots, X_{n_A})' = A'\beta$ where $\beta = (\beta_1, \dots, \beta_k)' \in \mathbb{R}^k$. To avoid trivialities we shall assume $n_A \geq k \geq 1$.

The parameter set is $]-\infty, \infty[^k$ if σ^2 is known, and

$]-\infty, \infty[$ $^k \times]0, \infty[$ if σ^2 is unknown.

From theorem 3.1 in [1] it follows that if A and B are matrices of dimension $k \times n_A$ and $k \times n_B$, then $\mathcal{G}_A \geq \mathcal{G}_B$ if and only if $AA' - BB'$ is positive semidefinite when σ^2 is known, and $\mathcal{G}_A \geq \mathcal{G}_B$ if and only if $AA' - BB'$ is positive semidefinite and $n_A \geq n_B + \text{rank}(AA' - BB')$ when σ^2 is unknown. Then $\mathcal{G}_A \sim \mathcal{G}_B$ if and only if $AA' = BB'$ if σ^2 is known, and $\mathcal{G}_A \sim \mathcal{G}_B$ if and only if $AA' = BB'$ and $n_A = n_B$ if σ^2 is unknown.

In the computation of $\delta(\mathcal{G}_A, \mathcal{G}_B)$ we may therefore choose the experiments within the equivalence classes determined by AA', BB' when σ^2 is known, and $(AA', n_A), (BB', n_B)$ when σ^2 is unknown.

3. The case of known variance σ^2

Proposition 3.1 Suppose $AA' = I$, $BB' = \Delta$ where Δ is a $k \times k$ diagonal matrix with diagonal elements $\Delta_1, \dots, \Delta_k \geq 0$. Then $\delta(\mathcal{G}_A, \mathcal{G}_B) = E \left| \prod_{i=1}^k \sqrt{\Delta_i} \exp \left(\frac{1}{2}(\Delta_i - 1) Y_i^2 \right) \right|$ where Y_1, \dots, Y_k are independent and identically $N(0,1)$ distributed.

Proof

We may choose $A = \begin{pmatrix} 1 \dots 0 & 0 \dots 0 \\ \vdots & \vdots \\ 0 \dots 1 & 0 \dots 0 \end{pmatrix}$ where the last

$n_A - k$ columns consist of only zeros, and

$B = \begin{pmatrix} \sqrt{\Delta_1} \dots 0 & 0 \dots 0 \\ \vdots & \vdots \\ 0 & \sqrt{\Delta_k} & 0 \dots 0 \end{pmatrix}$ where the last

$n_B - k$ columns consist of only zeros. Without loss of

generality we may assume that $\Delta_1, \dots, \Delta_l > 0$ and $\Delta_{l+1} = \dots =$

$\Delta_k = 0$ $0 \leq l \leq k$. This means that \mathcal{G}_A is given by the

independent, normally distributed variables X_1, \dots, X_{n_A} where

$$E X_i = \begin{cases} \beta_i & i = 1, \dots, k \\ 0 & i = k + 1, \dots, n_A \end{cases} \quad \text{var } X_i = \sigma^2 \quad i = 1, \dots, n_A$$

Similarly \mathcal{G}_B is given by the independent, normally distributed

variables Y_1, \dots, Y_{n_B} where

$$E Y_i = \begin{cases} \sqrt{\Delta_i} \beta_i & i = 1, \dots, l \\ 0 & i = l + 1, \dots, n_B \end{cases} \quad \text{var } Y_i = \sigma^2 \quad i = 1, \dots, n_B$$

By sufficiency X_{k+1}, \dots, X_{n_A} may be deleted from \mathcal{G}_A and

Y_{1+1}, \dots, Y_{n_B} may be deleted from \mathcal{G}_B . Furthermore, in the same way as in the proof of proposition 2.1 in [1], it may be shown that X_{1+1}, \dots, X_{n_A} may be deleted in \mathcal{G}_A . Finally we may replace Y_1, \dots, Y_l with Z_1, \dots, Z_l where $Z_i = \frac{Y_i}{\sqrt{\Delta_i}}$ $i = 1, \dots, l$.

Now \mathcal{G}_A and \mathcal{G}_B are translation experiments for addition in \mathbb{R}^1 . Since addition in \mathbb{R}^1 is commutative and \mathcal{G}_A and \mathcal{G}_B are both dominated, we may use the method indicated in section 2 to find $\delta(\mathcal{G}_A, \mathcal{G}_B)$. Let $P_\beta, \beta \in \mathbb{R}^1$ be the measure defined by X_1, \dots, X_l independent and normally distributed with $EX_i = \beta_i, \text{var}X_i = \sigma^2, i = 1, \dots, l$ and Q be the measure defined by Y_1, \dots, Y_l independent and normally distributed with $EY_i = 0, \text{var}Y_i = \frac{\sigma^2}{\Delta_i}, i = 1, \dots, l$. Then the least favourably distribution N_0 for testing $H: P_\beta, \beta \in \mathbb{R}^1$ against the alternative $K: Q$ is given by the independent variables U_1, \dots, U_l where $U_i = 0$ with probability 1 if $\Delta_i \geq 1$ and U_i is $N(0, \sigma \sqrt{\frac{1}{\Delta_i} - 1})$ distributed if $\Delta_i < 1$. Hence $\delta(\mathcal{G}_A, \mathcal{G}_B) = \|N_0 * P_0 - Q\|$. But $N_0 * P_0$ has density $\prod_{\Delta_i < 1} \frac{\sqrt{\Delta_i}}{\sigma} \varphi(\frac{\sqrt{\Delta_i} X_i}{\sigma}) \prod_{\Delta_i \geq 1} \frac{1}{\sigma} \varphi(\frac{X_i}{\sigma})$ with respect to the Lebesgues measure in \mathbb{R}^1 . □

Proposition 3.2 If rank $A' = k$, then $\delta(\mathcal{G}_A, \mathcal{G}_B) = E |1 - \prod_{\Delta_i > 1} \exp(-\frac{1}{2} (\Delta_i - 1) Y_i^2)|$ where $\Delta_1, \dots, \Delta_k$ are the solution of $\det[BB' - \lambda AA'] = 0$, and Y_1, \dots, Y_k are independent $N(0, 1)$ distributed.

Proof Since BB' is positive semidefinit, there exists a $k \times k$ nonsingular matrix F such that $F'AA'F = I$ and

$F'BB'F = \Delta$ where $\Delta_1, \dots, \Delta_k \geq 0$ and $\Delta_1, \dots, \Delta_k$ are the solutions of $\det(BB' - \lambda AA') = 0$.

Let $\tilde{A} = F'A$, $\tilde{B} = F'B$. If P_β and Q_β are, respectively, the probability measures inn \mathcal{G}_A and \mathcal{G}_B corresponding to the parameter value β , then since $A'F\beta = \tilde{A}'\beta$, $\delta(\mathcal{G}_A, \mathcal{G}_B) = \inf_M \sup_\beta \|P_\beta M - Q_\beta\| = \inf_M \sup_{F\beta} \|P_{F\beta} M - Q_{F\beta}\| = \delta(\mathcal{G}_{\tilde{A}}, \mathcal{G}_{\tilde{B}}) =$

$$E \left| 1 - \prod_{\Delta_i > 1} \sqrt{\Delta_i} \exp\left(-\frac{1}{2}(\Delta_i - 1) Y_i^2\right) \right|$$

Proposition 3.3 If $\text{row}[B'] \not\subset \text{row}[A']$, then $\delta(\mathcal{G}_A, \mathcal{G}_B) = 2$.

Proof $\text{row}[B'] \not\subset \text{row}[A']$ implies $(\text{row}[B'])^\perp \not\subset (\text{row}[A'])^\perp$.

Let $\beta_0 \in (\text{row}[A'])^\perp$. $\beta_0 \notin (\text{row}[B'])^\perp$. Then $A'\beta_0 = 0, B'\beta_0 \neq 0$

and $\delta(\mathcal{G}_A, \mathcal{G}_B) = \inf_M \sup_\beta \|P_\beta M - Q_\beta\| \geq \inf_M \sup_{t \in \mathbb{R}} \|P_{t\beta_0} M - Q_{t\beta_0}\|$

$\|P_{t\beta_0} M - Q_{t\beta_0}\| = \inf_M \sup_t \|P_{\beta_0} M - Q_{t\beta_0}\|$. But $\|P_{\beta_0} M - Q_{t\beta_0}\| \rightarrow 2$ as $t \rightarrow \infty$

for all Markov kernels M , so that $\delta(\mathcal{G}_A, \mathcal{G}_B) = 2$. \square

Suppose $BB' - AA'$ is positive semidefinite and $\text{rank } A' = k$.

If F has the same meaning as in the foregoing proof, then

$$Y'(\Delta - I) = Y'F'F'^{-1}(\Delta - I)F^{-1}FY = Z'(BB' - AA')Z \text{ where}$$

$Z = FY$. Furthermore $EZZ' = EFYY'F' = FF' = (AA')^{-1}$ and

$$\frac{\det(BB')}{\det(AA')} = \frac{\det(F'BB'F)}{\det(F'AA'F)} = \Delta_1 \dots \Delta_k \text{ so that we may write}$$

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = E \left| \frac{\det(BB')}{\det(AA')} \exp\left[-\frac{1}{2} Z'(BB' - AA')Z\right] - 1 \right| \text{ where}$$

Z is multivariate normal with mean zero and covariance matrix $(AA')^{-1}$. This is the result given by Le Cam in [3]

Suppose next that $\text{row}[B'] \subset \text{row}[A']$ and let V_1', \dots, V_r' be a basis for $\text{row}[A']$, $0 \leq r \leq k$. Then as in the proof of theorem 3.1 in [1], we may write $A = VS$ where $V = (V_1', \dots, V_r')$ is a $k \times r$ matrix and S is a $r \times n_A$ matrix of rank r .

Similarly $B = VT$ with T a $r \times n_B$ matrix. By writing $\alpha = V'\beta$ so that $A'\beta = S'V\beta = S'\alpha$ and $B'\beta = T'\alpha$, it follows that $\delta(\mathcal{G}_A, \mathcal{G}_B) = \inf_M \sup_{\beta} \|P_{\beta}M - Q_{\beta}\| = \inf_M \sup_{\alpha} \|P'_{\alpha}M - Q'_{\alpha}\| = \delta(\mathcal{G}_S, \mathcal{G}_T)$ where P'_{α} and Q'_{α} are, respectively, the measures in \mathcal{G}_S and \mathcal{G}_T , corresponding to the parameter value α . The following result is then an immediate consequence of proposition 3.2

Proposition 3.4 If $\text{row } [B'] \subset \text{row } [A']$,

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = E \left| 1 - \prod_{\Delta_i > 1} \sqrt{\Delta_i} \exp(-\frac{1}{2}(\Delta_i - 1) Y_i^2) \right|$$

where $\Delta_1, \dots, \Delta_r$ are the solution of $\det(TT' - \lambda SS') = 0$ and $A = VS$, $B = VT$, $\text{rank } S = r$, $V = (V_1', \dots, V_r')$ with V_1', \dots, V_r' a basis for $\text{row } [A']$.

If $\text{row } [A'] \not\subset \text{row } [B']$ then either $\text{row } [A'] \not\subset \text{row } [B']$ or $\text{row } [B'] \not\subset \text{row } [A']$ so that $\delta(\mathcal{G}_B, \mathcal{G}_A) = 2$ or $\delta(\mathcal{G}_A, \mathcal{G}_B) = 2$. Consequently $\Delta(\mathcal{G}_A, \mathcal{G}_B) = 2$.

Suppose next that $\text{row } [A'] = \text{row } [B']$, and let V, S, T have the same meaning as in proposition 3.4. If then λ is a solution of $\det(TT' - \lambda SS') = 0$, λ^{-1} is a solution of $\det(SS' - \lambda TT') = 0$. Nothing that $E \left| 1 - \prod_{\Delta_i < 1} \sqrt{\Delta_i} \exp(-\frac{1}{2}(\Delta_i^{-1} - 1) Y_i^2) \right| = E \left| 1 - \prod_{\Delta_i < 1} \sqrt{\Delta_i} \exp(-\frac{1}{2}(\Delta_i - 1) Y_i^2) \right|$, this gives together with proposition 3.4:

Theorem 3.1 If $\text{row } [A'] = \text{row } [B']$, then $\Delta(\mathcal{G}_A, \mathcal{G}_B) = 2$

If $\text{row } A' = \text{row } B'$ and $A = VS$, $B = VT$ where $V = (V_1', \dots, V_r')$ and V_1', \dots, V_r' is a basis for $\text{row } [A']$, then $\Delta(\mathcal{G}_A, \mathcal{G}_B) = \max(E \left| 1 - \prod_{\Delta_i > 1} \sqrt{\Delta_i} \exp(-\frac{1}{2}(\Delta_i - 1) Y_i^2) \right|, E \left| 1 - \prod_{\Delta_i < 1} \sqrt{\Delta_i} \exp(-\frac{1}{2}(\Delta_i - 1) Y_i^2) \right|)$ where $\Delta_1, \dots, \Delta_r$ are the solutions of $\det(TT' - \lambda SS') = 0$ and Y_1, \dots, Y_r are independent and identically $N(0, 1)$ distributed.

Consider now linear normal experiments where σ^2 is unknown. By fixing the parameter σ^2 , we obtain experiments for which δ can be found by the methods of this section. This means that a δ computed for known σ^2 always gives a lower bound for the corresponding δ with σ^2 unknown.

From theorem 2.1 it then follows that the Δ -distance is 2 between the experiments given by X_1, \dots, X_n independent and normally distributed with $\text{var } X_i = \sigma^2$, $E X_i = \alpha + \beta t_i$ $i = 1, \dots, n$, and Y_1, \dots, Y_n independent and normally distributed with $\text{var } Y_i = \sigma^2$, $E Y_i = \alpha + \beta t_i + \gamma t_i^2$ $i = 1, \dots, n$ whether σ^2 is known or not. The Δ -distance is thus of no help if we want to determine the amount of information obtained by observing Y_1, \dots, Y_n instead of X_1, \dots, X_n .

4. The case of unknown variance σ^2

Some of the notations which will be used in this section are:

If (X, τ) is a topological space, let $\mathcal{B}(X) = \sigma(\{B \mid B \in \tau\})$ be the Borel sets in X .

$P_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}, Q_{1, n_2, \beta_1, \dots, \beta_1, \sigma^2}$ are the probability measures over $(\mathbb{R}^1 \times \mathbb{R}^+, \mathcal{B}(\mathbb{R}^1 \times \mathbb{R}^+))$ given by X_1, \dots, X_l, S independent $X_i \sim N(\beta_i, \sigma)$ $i=1, \dots, l$, $S/\sigma^2 \sim \chi^2_{n_1}$ and by Y_1, \dots, Y_l, T independent $Y_i \sim N(\beta_i, \frac{\sigma}{\sqrt{\Delta_i}})$, $i=1, \dots, l$, $T/\sigma^2 \sim \chi^2_{n_2}$ where $\Delta_1, \dots, \Delta_l > 0$ are known.

$P'_{1, \beta_1, \dots, \beta_1, \sigma^2}, Q'_{1, \beta_1, \dots, \beta_1, \sigma^2}$ are the probability measures over $(\mathbb{R}^1, \mathcal{B}(\mathbb{R}^1))$ given by X_1, \dots, X_l independent $X_i \sim N(\beta_i, \sigma)$ $i = 1, \dots, l$ and by Y_1, \dots, Y_l independent $Y_i \sim N(\beta_i, \frac{\sigma}{\sqrt{\Delta_i}})$ $i = 1, \dots, l$

$$\varphi(x) = (2\pi)^{-\frac{1}{2}} \exp\left(-\frac{x^2}{2}\right), \quad \Phi(x) = \int_{-\infty}^x \varphi(u) du$$

$$\gamma_{n; t}(x) = (\Gamma(\frac{n}{2}) 2^{n/2})^{-1} x^{n/2-1} \exp\left(-\frac{x}{2t}\right) t^{-n/2}$$

$$x > 0 \quad t > 0 \quad \Gamma_{n, t}(x) = \int_0^x \gamma_{n, t}(u) du$$

(S) is the number of elements in S if S is finite.

Suppose first that $AA' = I$, $BB' = \Delta$ where Δ is a diagonal matrix with diagonal elements $\Delta_1, \dots, \Delta_k \geq 0$. Without loss of generality we may assume that $\Delta_1, \dots, \Delta_{l-m} \geq 1$, $0 < \Delta_{l-m+1}, \dots, \Delta_l < 1$ and $\Delta_{l+1} = \dots = \Delta_k = 0$ where $k \geq l \geq 0$. In the same manner as in section 3 we may consider a situation

where

$$\mathcal{G}_A = ((\mathbb{R}^1 \times \mathbb{R}^+, \quad \mathbb{R}^1 \times \mathbb{R}^+), (P_{1, n_A - k, \beta_1, \dots, \beta_1, \sigma^2},$$

$$(\beta_1, \dots, \beta_1, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+)) \quad \text{if } n_A > k$$

$$\mathcal{G}_A = ((\mathbb{R}^1, \quad \mathbb{R}^1), (P'_{1, \beta_1, \dots, \beta_1, \sigma^2}, (\beta_1, \dots, \beta_1, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+))$$

$$\text{if } n_A = k$$

$$\mathcal{G}_B = ((\mathbb{R}^1 \times \mathbb{R}^+, \quad \mathbb{R}^1 \times \mathbb{R}^+), (Q_{1, n_B - 1, \beta_1, \dots, \beta_1, \sigma^2},$$

$$(\beta_1, \dots, \beta_1, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+)) \quad \text{if } n_B > 1$$

$$\mathcal{G}_B = ((\mathbb{R}^1, \quad \mathbb{R}^1), (Q'_{1, \beta_1, \dots, \beta_1, \sigma^2}, (\beta_1, \dots, \beta_1, \sigma^2) \in (\mathbb{R}^1 \times \mathbb{R}^+))$$

$$\text{if } n_B = 1$$

The reduction is quite analogous with what was done in section 3 except that sufficiency now gives that X_{k+1}, \dots, X_{n_A}

must be replaced with $S = \sum_{i=k+1}^{n_A} X_i^2$ when $n_A > k$ and that Y_{1+1}, \dots, Y_{n_B} must be replaced with $T = \sum_{i=1+1}^{n_B} Y_i^2$ when $n_B > 1$.

Consider now the group $\mathbb{R}^1 \times \mathbb{R}^+$ with group operation $xy = (y_1 + \sqrt{y^1} x_1, \dots, y_1 + \sqrt{y^1} x_1, x^1 y^1)$ if $x = (x_1, \dots, x_1, x^1)$, $y = (y_1, \dots, y_1, y^1) \in \mathbb{R} \times \mathbb{R}^+$ It may be shown that this group is solvable and consequently has an invariant mean. With the standard topology for $\mathbb{R}^1 \times \mathbb{R}^+$ the group operation is continuous. Hence $\mathbb{R}^1 \times \mathbb{R}^+$ is a topological group.

Proposition 4.1 If $n_A = k$ and $n_B = 1$, $\delta(\mathcal{G}_A, \mathcal{G}_B) = 2$

Proof Let the group G be given by

$$g(x_1, \dots, x_1) = (\sqrt{g^1} x_1 + g_1, \dots, \sqrt{g^1} x_1 + g_1)$$

$$g(y_1, \dots, y_l, t) = (\sqrt{g^1} y_1 + g_1, \dots, \sqrt{g^1} y_l + g_l, g^1 t)$$

$$g(\beta_1, \dots, \beta_l, \sigma^2) = (\sqrt{g^1} \beta_1 + g_1, \dots, \sqrt{g^1} \beta_l + g_l, g^1 \sigma^2)$$

where $(g_1, \dots, g_l, g^1) \in \mathbb{R}^l + \mathbb{R}^+$. It may be verified that the assumptions (i) - (v) given in section 2 are satisfied so that we may restrict attention to the set of invariant Markov kernels \mathcal{M}_G . It is furthermore not difficult to show that every $M \in \mathcal{M}_G$ must have ϕ as exceptional set i.e. $\mathcal{M}_G = \mathcal{M}_{G_0}$

Assume $\delta(\mathcal{G}_A, \mathcal{G}_B) = \delta < 2$ and let $\epsilon > 0$ so that $\delta + \epsilon < 2$. Then there exists $M \in \mathcal{M}_{G_0}$ so that

$$\| P'_{1, \beta_1, \dots, \beta_l, \sigma^2} - Q'_{1, n_B-1, \beta_1, \dots, \beta_l, \sigma^2} \| < \epsilon + \delta$$

$$(\beta_1, \dots, \beta_l, \sigma^2) \in \mathbb{R}^l \times \mathbb{R}^+$$

Suppose $B_1 \times \dots \times B_l \times B \subset K$ where K is compact and $B_i \in \mathcal{B}(\mathbb{R})$ $i=1, \dots, l$, $B \in \mathcal{B}(\mathbb{R}^+)$. Then

$$M(B_1 \times \dots \times B_l \times B | x_1, \dots, x_l) = M(\sqrt{g^1} B_1 + g_1 x_1 \dots \times \sqrt{g^1} B_l + g_l x_l | \sqrt{g^1} x_1 + g_1, \dots, \sqrt{g^1} x_l + g_l)$$

Now let $g^1 \rightarrow 0$. Then $\sqrt{g^1} B_1 + g_1 x_1 \dots \times \sqrt{g^1} B_l + g_l x_l \rightarrow \emptyset$ so that $M(B_1 \times \dots \times B_l \times B | x_1, \dots, x_l) = 0$ which is a contradiction since $\mathbb{R}^l \times \mathbb{R}^+$ is σ -compact and probability measures on metric spaces are regular. \square

Proposition 4.2 If $n_A = k$, $n_B = l$,

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = \| P'_{1, 0, \dots, 0, 1} - Q'_{1, 0, \dots, 0, 1} \|$$

Proof The proof is analogous to a part of the proof of proposition 2.1 i [1].

Let G be the group given by

$$g(x_1, \dots, x_l) = (\sqrt{g^1} x_1 + g_1, \dots, \sqrt{g^1} x_l + g_l)$$

$$g(y_1, \dots, y_l) = (\sqrt{g^T} y_1 + g_1, \dots, \sqrt{g^T} y_l + g_l)$$

$$g(\beta_1, \dots, \beta_l, \epsilon^2) = (\sqrt{g^T} \beta_1 + g_1, \dots, \sqrt{g^T} \beta_l + g_l, g^1 \sigma^2)$$

$$(g_1, \dots, g_l, g^1) \in \mathbb{R}^l \times \mathbb{R}^+$$

It is easily verified that

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = \inf_{M \in \mathcal{M}_G} \sup_{(\beta_1, \dots, \beta_l, \sigma^2)} \|P'_{1, \beta_1, \dots, \beta_l, \sigma^2} - Q'_{1, \beta_1, \dots, \beta_l, \sigma^2}\|$$

$$\sigma^2 \|\cdot\| = \inf_{M \in \mathcal{M}_G} \|P'_{1, 0, \dots, 0, 1} - Q'_{1, 0, \dots, 0, 1}\|$$

Suppose $M \in \mathcal{M}_G$. Since $M(\cdot | x_1, \dots, x_l)$ is a probability measure over a complete separable metric space, $M(\cdot | x_1, \dots, x_l)$ is regular. Thus, for $\epsilon > 0$ there exists K compact so that $M(K | x_1, \dots, x_l) > 1 - \epsilon$. Let $\{x_1, \dots, x_l\} \cup K \subset \prod_{i=1}^l [a_i, b_i]$.

Then

$$M\left(\prod_{i=1}^l [a_i, b_i] | x_1, \dots, x_l\right) = M\left(\prod_{i=1}^l \sqrt{g^T} [a_i, b_i] + g_i | \sqrt{g^T} x_1 + g_1, \dots, \sqrt{g^T} x_l + g_l\right)$$

$$= M\left(\prod_{i=1}^l \sqrt{g^T} ([a_i, b_i] + x_i) | x_1, \dots, x_l\right) > 1 - \epsilon \text{ by inserting } g_i = x_i - \sqrt{g^T} x_i$$

$i = 1, \dots, l$. Now let $g^1 \rightarrow 0$. Then $M(\{x_1, \dots, x_l\} | x_1, \dots, x_l) > 1 - \epsilon$, so that $M(B | x_1, \dots, x_l) = I_B(x_1, \dots, x_l) \in \mathcal{B}(\mathbb{R}^l)$. \square

Let us now consider the case where $n_A > k$. First we need a lemma.

Lemma 4.1 Let $\mathcal{G}_i = (\mathcal{X}_i, \mathcal{A}_i), (P_{\theta_1, \theta_3}(\theta_1, \theta_3) \in \Theta_i \times \Theta_3)$ $i=1, 2$

$\mathcal{F}_j = (\mathcal{Y}_j, \mathcal{B}_j), (Q_{\theta_j, \theta_3}(\theta_j, \theta_3) \in \Theta_j \times \Theta_3)$ $j=1, 2$ be four experiments such that $(Q_{\theta_j, \theta_3}(\theta_j, \theta_3) \in \Theta_j \times \Theta_3)$ $j=1, 2$ are dominated and

\mathcal{Y}_j $j=1, 2$ are Borel subsets of complete separable metric spaces and \mathcal{B}_j $j=1, 2$ are the classes of Borel subsets of

\mathcal{Y}_j $j=1, 2$.

Let $\mathcal{G} = ((X_1 \times X_2, \mathcal{A}_1 \times \mathcal{A}_2), (P_{\theta_1, \theta_3} \times P_{\theta_1, \theta_3} \\ (\theta_1, \theta_2, \theta_3) \in \Theta_1 \times \Theta_2 \times \Theta_3))$

$\mathcal{F} = ((Y_1 \times Y_2, \mathcal{B}_1 \times \mathcal{B}_2), Q_{\theta_1, \theta_3} \times Q_{\theta_2, \theta_3} \\ (\theta_1, \theta_2, \theta_3) \in \Theta_1 \times \Theta_2 \times \Theta_3))$

Then if $\mathcal{G}_2 \geq \mathcal{F}_2$, $\delta(\mathcal{G}, \mathcal{F}) \leq \delta(\mathcal{G}, \mathcal{F})$.

Proof From the assumptions it follows that there exists a Markov kernel M_2 from (X_2, \mathcal{B}_2) to (Y_2, \mathcal{A}_2) such that

$P_{\theta_2, \theta_3} M_2 = Q_{\theta_2, \theta_3}$ $(\theta_2, \theta_3) \in \Theta_2 \times \Theta_3$. If M_1 is a Markov kernel from (X_1, \mathcal{A}_1) to (Y_1, \mathcal{B}_1) , Then $M_1 \times M_2$ is a Markov kernel from $(X_1 \times X_2, \mathcal{A}_1 \times \mathcal{A}_2)$ to

$(Y_1 \times Y_2, \mathcal{B}_1 \times \mathcal{B}_2)$ and $\| P_{\theta_1, \theta_2} \times P_{\theta_2, \theta_3} M_1 \times M_2 -$

$$Q_{\theta_1, \theta_2} \times Q_{\theta_2, \theta_3} \| = \| P_{\theta_1, \theta_3} M_1 - Q_{\theta_1, \theta_3} \|$$

Proposition 4.3 If $n_A - k \geq n_B - 1 + m \geq 0$, then

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = \| P^{1-m, 0, \dots, 0, 1} - Q^{1-m, 0, \dots, 0, 1} \| \quad \square$$

Remark If $n_A - k = n_B - 1 = m = 0$ proposition 4.2 and 4.3 give the same result.

Proof Let $n_1 = n_A - k$, $n_B - 1 = n_2$. The proof will be carried out only for $n_1, n_2 > 0$, the proofs of the cases $n_1 = 0, n_2 > 0$ and $n_1 > 0, n_2 = 0$ are quite analogous.

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = \inf_M \sup_{(\beta_1, \dots, \beta_1, \sigma^2)} \|P_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}^{M-Q_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}}\| \geq$$

$$\inf_M \sup_{(\beta_1, \dots, \beta_1, \sigma^2)} \|P_{1, n_1, \beta_1, \dots, \beta_{1-m}, 0, \dots, 0, 1}^{M-Q_{1, n_2, \beta_1, \dots, \beta_{1-m}, 0, \dots, 0, 1}}\|$$

$$= \delta(\mathcal{G}'_A, \mathcal{G}'_B) \quad \text{where}$$

\mathcal{G}'_A is given by X_1, \dots, X_1, S independent, $X_i \sim N(\beta_i, 1) \quad i=1, \dots, 1$
 $S \sim \chi^2_{n_1}$ and \mathcal{G}'_B is given by Y_1, \dots, Y_1, T independent
 $Y_i \sim N(\beta_i, \sqrt{\Delta_i}) \quad i=1, \dots, 1 \quad T \sim \chi^2_{n_2}$. By sufficiency S may be deleted

in \mathcal{G}'_A and T in \mathcal{G}'_B . Then proposition 3.1 gives

$$\delta(\mathcal{G}_A, \mathcal{G}_B) \geq \delta(\mathcal{G}'_A, \mathcal{G}'_B) = \|P'_{1-m, 0, \dots, 0, 1}^{-Q'_{1-m, 0, \dots, 0, 1}}\|.$$

But by lemma 4.1 the other equality also must hold since we may write $\mathcal{G}_A = \mathcal{G}_1, \mathcal{G}_B = \mathcal{G}_2$ with \mathcal{G}_1 given by $X_1, \dots, X_{1-m}, \mathcal{G}_2$ given by $X_{1-m+1}, \dots, X_1, S, \mathcal{F}_1$ given by Y_1, \dots, Y_{1-m} and \mathcal{F}_2 given by Y_{1-m+1}, \dots, Y_1, T . Then the assumptions of the lemma are satisfied. In particular $\mathcal{G}_2 \geq \mathcal{G}_2$ follows from proposition 2.1 in [1]. \square

Suppose now that $n_A > k$ and $n_B > 1$. With the group operation defined in the beginning of this section and with the standard topology $\mathbb{R}^1 \times \mathbb{R}^+$ becomes a locally topological group which is Hausdorff and satisfies the second axiom of countability.

Let X_1, \dots, X_1, S be independent $X_i \sim N(0, 1) \quad i=1, \dots, 1, S \sim \chi^2_{n_A-k}$
 Then $(X_1, \dots, X_1, S)(\beta_1, \dots, \beta_1, \sigma^2) = (\sigma X_1 + \beta_1, \dots, \sigma X_1 + \beta_1, \sigma^2 S)$ and
 $P_{1, n_A-k, \beta_1, \dots, \beta_1, \sigma^2}(B) = P_{1, n_A-k, 0, \dots, 0, 1}((X_1, \dots, X_1, S)(\beta_1, \dots, \beta_1, \sigma^2) \in B) =$
 $P_{1, n_A-k, 0, \dots, 0, 1}(B(\beta_1, \dots, \beta_1, \sigma^2)^{-1}) \quad B \in (\mathbb{R}^1 \times \mathbb{R}^+)$. Similarly
 $Q_{1, n_B-1, \beta_1, \dots, \beta_1, \sigma^2}(B) = Q_{1, n_B-1, 0, \dots, 0, 1}(B(\beta_1, \dots, \beta_1)^{-1}) \quad B \in (\mathbb{R}^1 \times \mathbb{R}^+)$
 so that \mathcal{G}_A and \mathcal{G}_B are translation experiments.

Since $\{P_{1, n_A-k, \beta_1, \dots, \beta_1, \sigma^2} | (\beta_1, \dots, \beta_1, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+\}$ and

$\{Q_{1, n_B-1, \beta_1, \dots, \beta_1, \sigma^2} | (\beta_1, \dots, \beta_1, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+\}$ are

dominated and $\mathbb{R}^1 \times \mathbb{R}^+$ is solvable, the method described in section 2, may be applied.

If $B \in \mathcal{B}(\mathbb{R}^1 \times \mathbb{R}^+)$, then $P_{1, n_A-k, \beta_1, \dots, \beta_1, \sigma^2}^{n_A-k, \beta_1, \dots, \beta_1, \sigma^2}(B) =$
 $P_{1, n_A-k; 0, \dots, 0, 1}((\beta_1, \dots, \beta_1, \sigma^2)^{-1}B) = P_{1, n_A-k, 0, \dots, 0, 1}((X_1, \dots, X_1, S)$
 $\in (\beta_1, \dots, \beta_1, \sigma^2)^{-1}B) = P_{1, n_A-k, 0, \dots, 0, 1}((\beta_1, \dots, \beta_1, \sigma^2)(X_1, \dots, X_1, S) \in B) =$
 $P_{1, n_A-k; 0, \dots, 0, 1}((X_1 + \beta_1 \sqrt{S}, \dots, X_1 + \beta_1 \sqrt{S}, S \sigma^2) \in B) =$
 $\int I_B(x_1 + \beta_1 \sqrt{s}, \dots, x_1 + \beta_1 \sqrt{s}, s \sigma^2) \prod_{i=1}^1 \varphi(x_i) \gamma_{n_A-k, 1}(s) dx_1 \dots dx_1, ds =$
 $\int \prod_{i=1}^1 (x_i - \beta_1 \sqrt{\frac{s}{\sigma^2}}) \frac{1}{\sigma^2} \gamma_{n_A-k, 1}(\frac{s}{\sigma^2}) dx_1 \dots dx_1, ds.$ Thus

$P_{1, n_A-k, \beta_1, \dots, \beta_1, \sigma^2}^{n_A-k, \beta_1, \dots, \beta_1, \sigma^2}$ has density $\prod_{i=1}^1 \varphi(x_i - \beta_1 \sqrt{\frac{s}{\sigma^2}}) \frac{1}{\sigma^2} \gamma_{n_A-k, 1}(\frac{s}{\sigma^2})$
 with respect to the Lebesgues measure.

Similarly $Q_{1, n_A=1, 0, \dots, 0, 1}$ has density $\prod_{i=1}^1 \sqrt{\Delta_i} \varphi(x_i \sqrt{\Delta_i}) \gamma_{n_B-1}(s)$
 with respect to the Lebesgues measure.

Proposition 4.4 If $m=0$ i.e. $\Delta_1, \dots, \Delta_1 \geq 1$ and

$n_B-1 > n_A-k \geq 1$, then $\delta(\mathcal{G}_A, \mathcal{G}_B) = \|P_{1, n_A-k, 0, \dots, 0, \frac{n_B-1}{n_A-k}}^{n_A-k, 0, \dots, 0, \frac{n_B-1}{n_A-k}} -$
 $Q_{1, n_B-1, 0, \dots, 0, 1}\| =$
 $\int \left| \prod_{i=1}^1 (x_i) \gamma_{n_A-k, \frac{n_B-1}{n_A-k}}(s) - \prod_{i=1}^1 \sqrt{\Delta_i} \varphi(x_i \sqrt{\Delta_i}) \gamma_{n_B-1, 1}(s) \right| dx_1 \dots dx_1, ds$

Proof Let $n_A-k=n_1, n_B-1=n_2$ and let $\delta_x(B) = I_B(x)$ We must show
 that $N_0 = \delta_0 \times \dots \times \delta_0 \times \delta_{\frac{n_2}{n_1}}$ is a least favourable distribution for
 testing.

$H = \{P_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}^{n_1, \beta_1, \dots, \beta_1, \sigma^2} : (\beta_1, \dots, \beta_1, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+\}$ against Q
 at all levels α . Then the proposition will follow from the

results given in section 2.

The strongest α -level test for H_{No} against Q is given by:

$$\delta_{N_0}(x_1, \dots, x_1, s) = 1 \Leftrightarrow \prod_{i=1}^1 \sqrt{\Delta_i} \varphi(x_i \sqrt{\Delta_i}) \gamma_{n_2, 1}(s) > C \prod_{i=1}^1 \varphi(x_i)$$

$$\gamma_{n_1, 1}\left(s \frac{n_1}{n_2}\right) \frac{n_1}{n_2} \Leftrightarrow \exp\left(-\frac{1}{2} \sum_{i=1}^1 (\Delta_i - 1) x_i^2\right) s^{\frac{1}{2}(n_2 - n_1)} \exp$$

$$\left(-s/2(1 - n_1/n_2)\right) > C' \Leftrightarrow (x_1, \dots, x_1, s) \in K \text{ where}$$

(i) $\alpha = P_{1, n_1, 0, \dots, 0, n_2/n_1}(K)$

(ii) $K_s = \{(x_1, \dots, x_1) \mid (x_1, \dots, x_1, s) \in K\} =$

$$\{(x_1, \dots, x_1) \mid \frac{1}{2} \sum_{i=1}^1 (\Delta_i - 1) x_i^2 < -\log C' + \log\left[s \frac{n_2 - n_1}{2}\right]$$

$\exp\left(-\frac{s}{2}(1 - n_1/n_2)\right)\}$ is an ellipse which may be degenerate since $\Delta_i = 1$ is possible.

$$\text{Let } k_3 = \max_s \log s \frac{n_2 - n_1}{2} \exp\left(-s/2(1 - n_1/n_2)\right)$$

(iii) $K_{x_1, \dots, x_1} = \{s \mid (x_1, \dots, x_1, s) \in K\} = \langle k_1(x_1, \dots, x_1),$

$$k_2(x_1, \dots, x_1) \rangle \text{ where}$$

$$k_1(x_1, \dots, x_1) = \frac{n_2 - n_1}{2} \exp\left(-\frac{1}{2} k_1(x_1, \dots, x_1) \left(1 - \frac{n_1}{n_2}\right)\right) =$$

$$k_2(x_1, \dots, x_1) = \frac{n_2 - n_1}{2} \exp\left(-\frac{1}{2} k_2(x_1, \dots, x_1) \left(1 - \frac{n_1}{n_2}\right)\right)$$

Then $P_{1, n_1, 0, \dots, 0, \frac{n_2}{n_1}}(K) =$

$$\int \prod_{i=1}^1 \varphi(x_i) \frac{n_1}{n_2} \gamma_{n_1, 1}\left(\frac{sn_1}{n_2}\right) ds dx_1, \dots, dx_1$$

$$-\frac{1}{2} \sum (\Delta_i - 1) x_i^2 < \log C' + k_3 \quad k_1(x_1, \dots, x_1)$$

Let $E_{\beta_1, \dots, \beta_1, \sigma^2}$ be the expectation taken relative to

$P''_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}$. Then $P''_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}(K) =$

$$E_{\beta_1, \dots, \beta_1, \sigma^2} [I_K(x_1, \dots, x_1, s)] =$$

$E_{\beta_1, \dots, \beta_1, \sigma^2} E_{\beta_1, \dots, \beta_1, \sigma^2} [I_K(X_1, \dots, X_1, S) | S]$. But
 $E_{\beta_1, \dots, \beta_1, \sigma^2} (I_K(X_1, \dots, X_1, S) | S)$ is a function of (X_1, \dots, X_1, S)
 only through S . Thus the distribution is independent of
 $(\beta_1, \dots, \beta_1)$. Consequently $P_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}^n(K) =$
 $E_{0, \dots, 0, \sigma^2} E_{\beta_1, \dots, \beta_1, \sigma^2} [I_K(X_1, \dots, X_1, S) | S]$. Furthermore
 $E_{\beta_1, \dots, \beta_1, \sigma^2} [I_K(X_1, \dots, X_1, S) | S] \leq E_{0, \dots, 0, \sigma^2} [I_K(X_1, \dots, X_1, S) | S]$
 since K_S is an ellipse with center in $(0, \dots, 0) \in \mathbb{R}^1$,
 and the probability for $(X_1, \dots, X_1) \in K_S$ where (X_1, \dots, X_1)
 are independent $X_i \sim N(\beta_i \sqrt{\frac{S}{\sigma^2}}, 1)$ $i=1, \dots, 1$, is maximized
 when the center in the ellipse and the distribution coincide.

Thus $P_{1, n_1, \beta_1, \dots, \beta_1, \sigma^2}^n(K) \leq$

$P_{1, n_1, 0, \dots, 0, \sigma^2}^n(K), (\beta_1, \dots, \beta_1, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+$.

Finally if we show that $P_{1, n_1, 0, \dots, 0, \sigma^2}^n(K) \leq$

$P_{1, n_1, 0, \dots, 0, \frac{n_2}{n_1}}^n(K) = \alpha, \sigma^2 > 0$, theorem 3.7 in [4] will
 give that N_0 is the least favourable distribution.

Let $\alpha(\sigma^2) = P_{1, n_1, 0, \dots, 0, \sigma^2}^n(K) =$

$$\int \prod_{i=1}^1 \varphi(x_i) [\Gamma_{n_1, \sigma^2}(k_2(x_1, \dots, x_1)) - \Gamma_{n_1, \sigma^2}(k_1(x_1, \dots, x_1))] dx, \dots, dx_1$$

$$\frac{1}{2} \sum_{i=1}^1 (\Delta_i - 1) x_i^2 < k_3$$

$$= \int \prod_{i=1}^1 \varphi(x_i) [\Gamma_{n_1, 1}(\frac{1}{\sigma^2} k_2(x_1, \dots, x_1)) -$$

$$\frac{1}{2} \sum (\Delta_i - 1) x_i^2 < k_3$$

$$\Gamma_{n_1, 1}(\frac{1}{\sigma^2} k_1(x_1, \dots, x_1))] dx_1, \dots, dx_1$$

Now $\{P_{1, n_1, 0, \dots, 0, \sigma^2} : \sigma^2 \in \mathbb{R}^+\}$ is an exponential family of distributions and $\alpha(\sigma^2) = \int I_K(\mathbf{x}_1, \dots, \mathbf{x}_1, \mathbf{s})$

$P_{1, n_1, 0, \dots, 0, \sigma^2}(dx_1 \dots d\mathbf{x})$ Hence, by theorem 2.9 in [4] derivation with respect to σ^2 under the integration sign is permitted.

$$\alpha'(\sigma^2) = \int \prod_{i=1}^n \varphi(\mathbf{x}_i) \left(\frac{1}{\sigma^2}\right)^2 [k_1(\mathbf{x}_1, \dots, \mathbf{x}_1) - \frac{1}{2} \sum (\Delta_i - 1) \mathbf{x}_i^2 < k_3]$$

$$\Gamma_{n_1, 1} \left(\frac{1}{\sigma^2} k_1(\mathbf{x}_1, \dots, \mathbf{x}_1) - k_2(\mathbf{x}_1, \dots, \mathbf{x}_1) \right) \Gamma_{n_1, 1} \left(\frac{1}{\sigma^2} k_2(\mathbf{x}_1, \dots, \mathbf{x}_1)\right) dx_1, \dots, dx_1 .$$

By (iii) above $\alpha' \left(\frac{n_2}{n_1}\right) = 0$, so that α has an extremal point in $\frac{n_2}{n_1}$.

Consider $f(t) = \Gamma_{n_1, 1} \left(\frac{k_2}{t}\right) - \Gamma_{n_1, 1} \left(\frac{k_1}{t}\right)$ $k_2 > k_1 > 0, t > 0$.

$f(t)$ can have only one extremal point, t_0 . Since $f > 0$ and $\lim_{t \rightarrow 0} f(t) = \lim_{t \rightarrow \infty} f(t) = 0$, this must be a maximum point and

$f'(t) < 0 \quad t > t_0, f'(t) > 0 \quad t < t_0$. These results applied to the integrand in the expression for $\alpha'(\sigma^2)$, give that $\frac{n_2}{n_1}$ must be a maximum point □

It still remains to consider the case

$1 \leq n_A - k < n_B - 1 + m$ and $m > 0$. $\delta(\mathcal{G}_A, \mathcal{G}_B)$ is not known then.

Suppose now that $0 \leq \text{rank } A = r \leq k$. By the remark at the end of section 3 $\delta(\mathcal{G}_A, \mathcal{G}_B) = 2$ if $\text{row } [B'] \not\subset \text{row } [A']$

If $\text{row } [B'] \subset \text{row } [A']$ we may write, in the same way as in section 3, $A = VS, B = VT$. Then $\delta(\mathcal{G}_A, \mathcal{G}_B) = \delta(\mathcal{G}_S, \mathcal{G}_T)$

If $F'SS'F = I, F'TT'F = \Delta$ with F a nonsingular $r \times r$ matrix, $\text{rank}(B') = \text{rank}(T') = \#\{i \mid \Delta_i > 0\}$. Let $\tilde{S} = F'S, \tilde{T} = F'T$. Then $\delta(\mathcal{G}_A, \mathcal{G}_B) = \delta(\mathcal{G}_S, \mathcal{G}_T) = \delta(\mathcal{G}_{\tilde{S}}, \mathcal{G}_{\tilde{T}})$, and the results above may be summarized in the following theorem.

Theorem 4.1

If $\text{row}[B'] \not\subset \text{row}[A']$, $\delta(\mathcal{G}_A, \mathcal{G}_B) = 2$

If $\text{row}[B'] \subset \text{row}[A']$, let $A = VS, B = VT$ where

$V = (V_1', \dots, V_r')$ and V_1', \dots, V_r' are a basis for $\text{row}[A']$,

and let $\Delta_1, \dots, \Delta_{\text{rank}(A')}$ be the solutions of $\det(TT' - \Delta SS') = 0$.

Then

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = \begin{cases} 2 & \text{if } \text{rank}(A') = n_A \quad \text{rank}(B') < n_B \\ E \left| 1 - \prod_{\Delta_i > 0} \exp(-\frac{1}{2}(\Delta_i - 1) Y_i^2) \right| & \text{if } n_A = \text{rank}(A'), \\ & n_B = \text{rank}(B') \\ E \left| 1 - \prod_{\Delta_i > 1} \sqrt{\Delta_i} \exp(-\frac{1}{2}(\Delta_i - 1) Y_i^2) \right| & \text{if } n_A \geq n_B + \\ & \#\{i \mid 0 \leq \Delta_i < 1\} \\ E \left| 1 - \frac{n_B - \text{rank}(B')}{n_A - \text{rank}(A')} \prod_{n_B - \text{rank}(B'), 1}^S \right. & \\ & \left. \frac{n_A - \text{rank}(A')}{n_B - \text{rank}(B')} \prod_{n_A - \text{rank}(A'), 1}^S \right| \\ & \prod_{\Delta_i > 1} \sqrt{\Delta_i} \exp[-\frac{1}{2}(\Delta_i - 1) Y_i^2] \\ & \text{if } \#\{i \mid 0 < \Delta_i < 1\} = 0 \text{ and } n_B - \text{rank}(B') \geq \\ & n_A - \text{rank}(A') \geq 1 \end{cases}$$

$Y_1, \dots, Y_{\text{rank}(A')}, S$ are independent $Y_i \sim N(0, 1), \frac{n_A - \text{rank}(A')}{n_B - \text{rank}(B')} S \sim$

$\chi^2_{n_A - \text{rank}(A')}$

Proof

$n_A - \text{rank}(A') \geq n_B - \text{rank}(B') + \#\{i \mid 0 < \Delta_i < 1\}$ is equivalent with $n_A \geq n_B + \text{rank}(A') - \text{rank}(B') + \#\{i \mid 0 < \Delta_i < 1\} = n_B + \#\{i \mid 0 \leq \Delta_i < 1\}$, so that the third expression for $\delta(\mathcal{G}_A, \mathcal{G}_B)$ in the second half of the theorem follows from proposition 4.3.

Consider now the situation treated by Le Cam for σ^2 known.

Corollary

If AA' is nonsingular and $BB' - AA'$ is positive semi-definit

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = \begin{cases} 2 & \text{if } n_A = \text{rank}(A') < n_B \\ E \left| \left(\frac{n_B - \text{rank}(A')}{n_A - \text{rank}(A')} \right)^{\frac{n_A - \text{rank}(A')}{2}} \frac{\Gamma\left(\frac{n_A - \text{rank}(A')}{2}\right)}{\Gamma\left(\frac{n_B - \text{rank}(A')}{2}\right)} \right. \\ \frac{\det(BB')}{\det(AA')} \left(\frac{S}{2} \right)^{\frac{n_B - n_A}{2}} \exp\left(-\frac{1}{2}S \frac{n_B - n_A}{n_B - \text{rank}(A')}\right) \exp\left(-\frac{1}{2}Z'(BB' - AA')Z\right) - 1 & \text{if } \text{rank}(A') < n_A < n_B \\ E \left| \frac{\det(BB')}{\det(AA')} \exp\left(-\frac{1}{2}Z'(BB' - AA')Z\right) - 1 \right| & \\ n_A \geq n_B \geq \text{rank}(A') & \end{cases}$$

where Z is multilinear normal with expectation 0 and covariance matrix $(AA')^{-1}$, and $\frac{n_A - \text{rank}(A')}{n_B - \text{rank}(A')} S$ is

χ^2 -distributed with $n_A - \text{rank}(A')$ degrees of freedom and is independent of Z .

Proof

Let F be a nonsingular matrix such that $F'AA'F = I$, $F'BB'F = \Delta$. Then, since $BB' - AA'$ is positive semidefinite and since $\Delta_1, \dots, \Delta_{\text{rank } A}$ are the solutions of $\det (BB' - \Delta AA') = 0$, $\Delta_1, \dots, \Delta_k \geq 1$. By noting that AA' nonsingular implies BB' nonsingular, the corollary now follows in the same way as the corresponding result in section 3. \square

5. Examples

Example 1

Let $A' = \begin{pmatrix} 1 & t_1 \\ \vdots & \vdots \\ 1 & t_{n_A} \end{pmatrix}$ $B' = \begin{pmatrix} 1 & S_1 \\ \vdots & \vdots \\ 1 & S_{n_B} \end{pmatrix}$

Then $AA' = \begin{pmatrix} n_A & n_A \bar{t} \\ n_A \bar{t} & \sum_{i=1}^{n_A} t_i^2 \end{pmatrix}$

Suppose $\text{rank } A' = 2$, i.e. not all t_1, \dots, t_{n_A} equal. If

$$M_A = \sum_{i=1}^{n_A} (t_i - \bar{t})^2, \quad M_B = \sum_{i=1}^{n_B} (S_i - \bar{S})^2, \quad \det(BB' - \Delta AA') = 0$$

has 2 zeroes Δ_1, Δ_2 given by

$$\frac{1}{2n_A M_A} \left[\frac{n_B}{n_A} M_A + n_A M_B + n_B n_A (\bar{S} - \bar{t}) \pm (n_B M_A + n_A M_B + n_A n_B (\bar{t} - \bar{S}) - 4n_B n_A M_A M_B)^{\frac{1}{2}} \right]$$

$\delta(\mathcal{G}_A, \mathcal{G}_B)$ may now be computed for σ^2 known, and for σ^2 unknown except when $0 < n_A - 2 < n_B - \text{rank} B + \{i | 0 < \Delta_i < 1\}$ and $\{i | 0 < \Delta_i < 1\} > 0$.

Note that if $\bar{t} = \bar{S}$, $\Delta_1 = \frac{n_B}{n_A}$, $\Delta_2 = \frac{M_B}{M_A}$.

Example 2 If \mathcal{M}_1 and \mathcal{M}_2 are the minimal informative and the maximal informative experiments respectively,

$\delta(\mathcal{G}_A, \mathcal{G}_i)$ and $\delta(\mathcal{G}_A, \mathcal{G}_A)$ give absolute measures of the information in the experiment \mathcal{G}_A . Unfortunately for translation experiments on the real line both of these deficiencies are equal to 2 as shown by Torgersen in [5]. Hence $\delta(\mathcal{G}_A, \mathcal{G}_i) =$

$\delta(M_a, \xi_A) = 2$ for the case when σ^2 is known and consequently also for σ^2 unknown.

However, if an experiment is given by the independent observations X_1, \dots, X_n , deficiencies may be used to compute the information contained in an additional observation.

In the experiments considered in this paper, the observations are not identically distributed, because the distribution of the additional observation is dependent of the choice of the regression coefficients. The question then naturally arises whether deficiencies may be of help to determine the regression coefficients so the additional observation contains as much information as possible.

$$\text{Let } A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{k1} & \dots & a_{kn} \end{pmatrix} \quad B = \begin{pmatrix} a_{11} & \dots & a_{1n} & t_1 \\ \vdots & & \vdots & \vdots \\ a_{k1} & \dots & a_{kn} & t_k \end{pmatrix}$$

Suppose $\text{rank } A = k$

Then $\det(BB' - \Delta AA') = \det(AA' + tt' - \Delta AA') = \det(tt' - (\Delta - 1)AA')$. Since $\text{rank } [tt'] = 1$, the solutions of $\det(tt' - \Delta AA') = 0$ are all equal to zero, except one.

The solution $\Delta = 0$ has multiplicity $k-1$. Hence

$$\det(tt' - \Delta AA') = 0 = \det(AA') \det((tt')(AA')^{-1} - \Delta I) = \det(AA')(-\Delta)^{k-1} (\Delta_0 - \Delta) = [(-1)^k \Delta^k + (-1)^{k-1} \Delta_0 \Delta^{k-1}] \det(AA')$$

where Δ_0 is the nonzero solution of $\det[(tt')(AA')^{-1} - \Delta I] = 0$

But $\det[(tt')(AA')^{-1} - \Delta I] = (-\Delta)^k + \text{tr}((tt')(AA')^{-1})(-\Delta)^{k-1} +$
factors of lower order in Δ . Hence $\Delta_0 = \text{tr}((tt')(AA')^{-1})$,

and $1 + \text{tr}(tt')(AA')^{-1}, 1, \dots, 1$ are the k solutions of $\det(BB' - \Delta AA') = 0$

Let $X \sim N(0, 1)$. Then, by noting that $\text{tr}(tt')(AA')^{-1} = t'(AA')^{-1}t$, $\delta(\mathcal{G}_A, \mathcal{G}_B) = E|1 - \sqrt{t'(AA')^{-1}t+1} \exp(-\frac{1}{2} t'(AA')^{-1}tX^2)| =$

$$4 \left[\Phi \left(\left[(1+t'(AA')^{-1}t) \frac{\log(1+t'(AA')^{-1}t)}{t'(AA')^{-1}t} \right]^{\frac{1}{2}} \right) - \Phi \left(\left(\frac{\log(1+t'(AA')^{-1}t)}{t'(AA')^{-1}t} \right)^{\frac{1}{2}} \right) \right]$$

for σ^2 known. In the above expression we have written the integrand f , and used that $\int |f| = 2 \int f^+$.

If Y, S are independent $Y \sim N(0, 1)$, $\frac{n-k}{n-k+1} S \sim \chi^2_{n-k}$,

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = \int |\varphi(x) \gamma_{n-k}, \frac{n-k+1}{n-k}(s) - (1+t'(AA')^{-1}t)^{\frac{1}{2}} \varphi(x(1+t'(AA')^{-1}t)^{\frac{1}{2}}) \gamma_{n-k+1}(s) | dx ds$$

$$= E|1 - \frac{(\frac{n-k+1}{n-k})^{(n-k)/2} \Gamma(\frac{n-k}{2})}{\Gamma(\frac{n-k+1}{2})} (1+t'(AA')^{-1}t) \sqrt{\frac{S}{2}} \exp(-\frac{1}{2} \frac{S}{n-k+1} - \frac{1}{2} t'(AA')^{-1}t Y^2)|$$

when σ^2 is unknown.

If σ^2 is known and $s'(AA')^{-1}s > t'(AA')t$ the experiment where the $n+1$ th observation has regression coefficients (s_1, \dots, s_k) is more informative than the experiment where the $n+1$ th observation has regression coefficients (t_1, \dots, t_k) Hence $\delta(\mathcal{G}_A, \mathcal{G}_B)$ is increasing in $t'(AA')^{-1}t$ for σ^2 known.

Consider again the situation in example 1. If we write $t' = (1, t_{n+1})'$, $t'(AA')^{-1}t = \frac{1}{M} (t_{n+1}^2 - 2\bar{t} t_{n+1} + \frac{1}{n} \sum_{i=1}^n t_i^2)$

$\bar{t} = \frac{1}{n} \sum_{i=1}^n t_i$, so that the minimal increase in $\delta(\mathcal{G}_A, \mathcal{G}_B)$

is obtained by letting $t_{n+1} = \bar{t}$, and in this case

$$\delta(\mathcal{G}_A, \mathcal{G}_B) = 4[\Phi\left(\left[(n+1) \log\left(1 + \frac{1}{n}\right)\right]^{\frac{1}{2}}\right) - \Phi\left(\left[n \log\left(1 + \frac{1}{n}\right)\right]^{\frac{1}{2}}\right)]$$

when σ^2 is known.

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