## Profile Analysis

Martin Singull

Department of Mathematics
Linköping University, Sweden

## Example 1

The same example again but now twelve subjects are asked to estimate the price of the bar.

For six of the subjects, the packages
$P_{1}$ : plain wrapped, unboxed,
$P_{2}$ : plain wrapped, boxed,
$P_{3}$ : foil wrapped, unboxed, and
$P_{4}$ : foil wrapped, boxed.
have been labeled with a well-known brand name. For the remaining six subjects, no label is used.

Srivastava, M. S., \& Carter, E. M. (1983). An introduction to applied multivariate statistics. North-holland.

|  | Packaging |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Subject | $P_{1}$ | $P_{2}$ | $P_{3}$ | $P_{4}$ |
| 1 | 0.30 | 0.40 | 0.55 | 0.65 |
| 2 | 0.20 | 0.65 | 0.30 | 0.80 |
| labeled 3 | 0.30 | 0.50 | 0.50 | 0.70 |
| 4 | 0.25 | 0.35 | 0.45 | 0.65 |
| 5 | 0.35 | 0.35 | 0.55 | 0.55 |
| 6 | 0.50 | 0.50 | 0.50 | 0.50 |
| mean | 0.317 | 0.458 | 0.475 | 0.642 |
| 1 | 0.40 | 0.40 | 0.60 | 0.60 |
| 2 | 0.45 | 0.50 | 0.55 | 0.85 |
| unlabeled 3 | 0.90 | 0.95 | 1.10 | 1.10 |
| 4 | 0.60 | 0.70 | 0.85 | 0.95 |
| 5 | 0.55 | 0.75 | 1.00 | 1.20 |
| 6 | 0.70 | 0.70 | 1.00 | 1.10 |
| mean | 0.600 | 0.667 | 0.850 | 0.967 |



## Example 2, $p=4$ and $k=4$ (Srivastava, 1987)

We wish to compare the performance of students from four different schools in four different subjects such as Mathematics $\left(S_{1}\right)$, Science $\left(S_{2}\right)$, English $\left(S_{3}\right)$ and History $\left(S_{4}\right)$.

Assume that we have $n_{i}$ students from school $i=1,2,3,4$.

Students were required to solve problems in each subject. All the problem were planned to be of the same difficulty and the time to solve each problem was recorded. From the data (fictitious) we obtain

$$
\begin{aligned}
& \bar{x}_{1}=\left(\begin{array}{llll}
38.41 & 47.81 & 67.49 & 54.30
\end{array}\right)^{\prime}, n_{1}=10 \\
& \bar{x}_{2}=\left(\begin{array}{llll}
21.06 & 28.26 & 49.10 & 37.05
\end{array}\right)^{\prime}, n_{2}=15 \\
& \bar{x}_{3}=\left(\begin{array}{llll}
30.50 & 38.05 & 58.33 & 46.41
\end{array}\right)^{\prime}, n_{3}=14 \\
& \bar{x}_{4}=\left(\begin{array}{llll}
18.53 & 25.27 & 46.99 & 34.35
\end{array}\right)^{\prime}, n_{4}=12
\end{aligned}
$$



Martin Singull

## Profile analysis of several groups

Considered the following three hypotheses:

1. $H_{1}: \boldsymbol{\mu}_{i}-\boldsymbol{\mu}_{k}=\gamma_{i} \mathbf{1}_{p}, i=1, \ldots, k-1 \quad$ vs. $\quad A_{1} \neq H_{1}$ (parallelism - no interaction)
2. $H_{2} \mid H_{1}: \gamma_{i}=0, i=1, \ldots k-1, \quad$ vs. $\quad A_{2} \neq H_{2} \mid H_{1}$ (same level)
3. $H_{3} \mid H_{1}: \mu_{\bullet}=\gamma_{k} \mathbf{1}_{p} \quad$ vs. $\quad A_{3} \neq H_{3} \mid H_{1}$ (flatness - no row effect)

Here $\boldsymbol{\mu}_{\bullet}=\boldsymbol{N}^{-1} \sum_{i=1}^{k} n_{i} \boldsymbol{\mu}_{i} \quad$ and the scalars $\gamma_{i}$ are unknown.

Srivastava, M. S. (1987). Profile analysis of several groups.
Communications in Statistics - Theory and Methods, 16(3):909-926.

## Model

Let $\boldsymbol{x}_{i j}$ be $p$-dimensional random vectors independent distributed as $\boldsymbol{x}_{i j} \sim N_{p}\left(\boldsymbol{\mu}_{i}, \boldsymbol{\Sigma}\right)$, where $\boldsymbol{\mu}_{i}=\left(\mu_{i 1}, \ldots, \mu_{i p}\right)^{\prime}, \boldsymbol{\Sigma}>0$, $j=1, \ldots, n_{i}, i=1, \ldots, k$ and $N=n_{1}+\cdots+n_{k}$.

This model can be written as (observe that it is transposed to the usual observation matrix)

$$
\boldsymbol{X} \sim N_{N, p}\left(\mathbf{A} M, I_{N}, \boldsymbol{\Sigma}\right)
$$

where

$$
\begin{aligned}
\boldsymbol{X} & =\left(\boldsymbol{X}_{1}, \ldots, \boldsymbol{X}_{k}\right)^{\prime}, \\
\boldsymbol{X}_{i} & =\left(\boldsymbol{x}_{i 1}, \ldots, \boldsymbol{x}_{i n_{i}}\right), \\
\boldsymbol{M} & =\left(\boldsymbol{\mu}_{1}, \ldots, \boldsymbol{\mu}_{k}\right)^{\prime}
\end{aligned}
$$

and

$$
\boldsymbol{A}=\operatorname{diag}\left(\mathbf{1}_{n_{1}}, \ldots, \mathbf{1}_{n_{k}}\right)
$$

## The likelihood function

The likelihood function is now given by

$$
c|\boldsymbol{\Sigma}|^{-\frac{N}{2}} \operatorname{etr}\left\{-\frac{1}{2} \boldsymbol{\Sigma}^{-1}\left[\boldsymbol{V}+(\boldsymbol{Y}-\boldsymbol{\eta}) \Xi^{-1}()^{\prime}+N\left(\overline{\boldsymbol{x}}-\boldsymbol{\mu}_{\bullet}\right)()^{\prime}\right]\right\}
$$

where $c$ is a constant,

$$
\begin{aligned}
& \boldsymbol{V}=\boldsymbol{X}^{\prime}\left(\boldsymbol{I}-\boldsymbol{A}\left(\boldsymbol{A}^{\prime} \boldsymbol{A}\right)^{-1} \boldsymbol{A}^{\prime}\right) \boldsymbol{X}: p \times p \\
& \quad(\boldsymbol{V} \text { is the within sum of squares }), \\
& \boldsymbol{Y}=\left(\overline{\boldsymbol{x}}_{1}-\overline{\boldsymbol{x}}_{k}, \ldots, \overline{\boldsymbol{x}}_{k-1}-\overline{\boldsymbol{x}}_{k}\right): p \times(k-1), \\
& \boldsymbol{\eta}=\left(\boldsymbol{\mu}_{1}-\boldsymbol{\mu}_{k}, \ldots, \boldsymbol{\mu}_{k-1}-\boldsymbol{\mu}_{k}\right): p \times(k-1), \\
& \overline{\boldsymbol{x}}_{i}=\frac{1}{n_{i}} \boldsymbol{X}_{i} \mathbf{1}_{n_{i}}: p \times 1, \\
& \overline{\boldsymbol{x}}=\frac{1}{N} \boldsymbol{X}^{\prime} \mathbf{1}_{N}: p \times 1 \quad \text { and }
\end{aligned}
$$

the matrix

$$
\equiv=\operatorname{diag}\left(\frac{1}{n_{1}}, \ldots, \frac{1}{n_{k-1}}\right)+\frac{1}{n_{k}} \mathbf{1}_{k-1} \mathbf{1}_{k-1}^{\prime}
$$

with

$$
\mathbf{\Xi}^{-1}=\operatorname{diag}\left(n_{1}, \ldots, n_{k-1}\right)-\frac{1}{n} \boldsymbol{n}_{k-1} \boldsymbol{n}_{k-1}^{\prime}
$$

where $\boldsymbol{n}_{k-1}=\left(n_{1}, \ldots, n_{k-1}\right)^{\prime}$. This matrix can be used for the between sum of squares

$$
\boldsymbol{H}=\boldsymbol{Y} \Xi^{-1} \boldsymbol{Y}^{\prime}=\boldsymbol{Z} \boldsymbol{Z}^{\prime}
$$

where $\boldsymbol{Z}=\boldsymbol{Y} \mathbf{\Xi}^{-1 / 2}$.

## MLEs under $A_{1}$ and $H_{1}$

The MLEs under $A_{1}$, i.e., no mean structure, are given by

$$
\widehat{\boldsymbol{\mu}}_{\bullet}=\overline{\boldsymbol{x}}, \quad \widehat{\boldsymbol{\eta}}=\boldsymbol{Y} \quad \text { and } \quad N \widehat{\boldsymbol{\Sigma}}=\boldsymbol{V}
$$

The first hypothesis is given by

$$
H_{1}: \boldsymbol{\mu}_{i}-\boldsymbol{\mu}_{k}=\gamma_{i} \mathbf{1}_{p}, i=1, \ldots, k-1 \quad \Leftrightarrow \quad H_{1}: \boldsymbol{\eta}=\mathbf{1}_{p} \gamma^{\prime}
$$

where $\gamma=\left(\gamma_{1}, \ldots, \gamma_{k-1}\right)^{\prime}$. The MLEs under $H_{1}$ are

$$
\begin{aligned}
\widehat{\boldsymbol{\mu}}_{\bullet} & =\overline{\boldsymbol{x}}, \quad \widehat{\gamma}^{\prime}=\left(\mathbf{1}^{\prime} \boldsymbol{V}^{-1} \mathbf{1}\right)^{-1} \mathbf{1}^{\prime} \boldsymbol{V}^{-1} \boldsymbol{Y} \quad \text { and } \\
N \stackrel{\widehat{\boldsymbol{\Sigma}}}{ } & =\boldsymbol{V}+\left(\boldsymbol{Y}-\mathbf{1} \widehat{\boldsymbol{\gamma}}^{\prime}\right) \bar{\Xi}^{-1}()^{\prime}=\ldots= \\
& =\boldsymbol{V}+\left(\boldsymbol{I}-\left(\mathbf{1}^{\prime} \boldsymbol{V}^{-1} \mathbf{1}\right)^{-1} \mathbf{1 1}^{\prime} \boldsymbol{V}^{-1}\right) \boldsymbol{H}()^{\prime} .
\end{aligned}
$$

The LRT, for the parallel hypothesis $H_{1}: \boldsymbol{\eta}=\mathbf{1}_{p} \gamma^{\prime}$ is given by

$$
\begin{aligned}
\Lambda_{H_{1}} & =\frac{\left|N \widehat{\boldsymbol{\Sigma}}_{A_{1}}\right|}{\left|N \widehat{\boldsymbol{\Sigma}}_{H_{1}}\right|}=\ldots= \\
& =\left|\boldsymbol{I}+\boldsymbol{Z}^{\prime}\left(\boldsymbol{V}^{-1}-\boldsymbol{V}^{-1} \mathbf{1}\left(\mathbf{1}^{\prime} \boldsymbol{V}^{-1} \mathbf{1}\right)^{-1} \mathbf{1}^{\prime} \boldsymbol{V}^{-1}\right) \boldsymbol{Z}\right|^{-1}
\end{aligned}
$$

and we reject $H_{1}$ for small values of $\Lambda_{H_{1}}$.

## Lemma

Let $\boldsymbol{C}$ be a $(p-1) \times p$ matrix of rank $p-1$ such that $\mathbf{C 1}=\mathbf{0}$. Let $\boldsymbol{V}$ be a $p \times p$ positive definite matrix. Then

$$
C^{\prime}\left(C V C^{\prime}\right)^{-1}=V^{-1}-V^{-1} \mathbf{1}\left(\mathbf{1}^{\prime} V^{-1} \mathbf{1}\right)^{-1} \mathbf{1}^{\prime} V^{-1}
$$

Using the lemma, the LRT can be rewritten as

$$
\Lambda_{H_{1}}=\left|\boldsymbol{I}_{p-1}+\left(\boldsymbol{C H} \boldsymbol{C}^{\prime}\right)\left(\boldsymbol{C V} \boldsymbol{C}^{\prime}\right)^{-1}\right|^{-1}=\frac{\left|\boldsymbol{C V} \boldsymbol{C}^{\prime}\right|}{\left|\boldsymbol{C V} \boldsymbol{C}^{\prime}+\boldsymbol{C H} \boldsymbol{C}^{\prime}\right|}
$$

## Canonical reduction

One can use a canonical reduction to find the distribution of the LRT. Let $\boldsymbol{Q}: p \times p$ be an orthogonal matrix such that

$$
\boldsymbol{Q}=\left(\begin{array}{ll}
p^{-1 / 2} \mathbf{1}_{p} & \boldsymbol{Q}_{1}
\end{array}\right)
$$

Consider the transformation

$$
\boldsymbol{Z}^{*}=\boldsymbol{Q}^{\prime} \boldsymbol{Z}=\begin{gathered}
1 \\
p-1
\end{gathered}\binom{\boldsymbol{Z}_{1}^{* \prime}}{\boldsymbol{Z}_{2}^{*}}
$$

and

$$
\boldsymbol{V}^{*}=\boldsymbol{Q}^{\prime} \boldsymbol{V} \boldsymbol{Q}=\begin{gathered}
1 \\
p-1
\end{gathered}\left(\begin{array}{cc}
\boldsymbol{v}_{11}^{*} & \boldsymbol{v}_{12}^{* \prime} \\
\boldsymbol{v}_{12}^{*} & \boldsymbol{V}_{22}^{*}
\end{array}\right) .
$$

## Parallelism: $H_{1}: \boldsymbol{\eta}=\mathbf{1}_{p} \boldsymbol{\gamma}^{\prime}$

Theorem

The $L R T \Lambda_{H_{1}}$ can be written as

$$
\Lambda_{H_{1}}=\frac{\left|\boldsymbol{V}_{22}^{*}\right|}{\left|\boldsymbol{V}_{22}^{*}+\boldsymbol{Z}_{2}^{*} \boldsymbol{Z}_{2}^{* \prime}\right|}
$$

Under $H_{1}, \boldsymbol{Z}_{2}^{*}$ and $\boldsymbol{V}_{22}^{*}$ are independently distributed as

$$
\boldsymbol{Z}_{2}^{*} \sim N_{p-1, k-1}\left(\mathbf{0}, \boldsymbol{\Sigma}_{22}^{*}, \boldsymbol{I}_{k-1}\right)
$$

and

$$
\boldsymbol{V}_{22}^{*} \sim W_{p-1}\left(\boldsymbol{\Sigma}_{22}^{*}, N-k\right) .
$$

## The null distribution

## Theorem

The distribution of $\Lambda_{H_{1}}$ is the same as the distribution of the product of $p-1$ independent beta random variables with parameters $\frac{1}{2}(N-k+1-i)$ and $\frac{1}{2}(k-1)$, where $i=1, \ldots, p-1$.

For large $N$, the asymptotic null distribution of $\Lambda_{H_{1}}$ is given by

$$
-\left(N-\frac{1}{2}(k+p+1)\right) \ln \Lambda_{H_{1}} \sim \chi_{(p-1)(k-1)}^{2}
$$

## Level hypothesis: $H_{2} \mid H_{1}: \gamma=\mathbf{0}$

The estimator for the covariance matrix under the level hypothesis: $H_{2} \mid H_{1}: \gamma=\mathbf{0}$ is given by

$$
N \widehat{\boldsymbol{\Sigma}}_{H_{2} \mid H_{1}}=\boldsymbol{V}+\boldsymbol{Y} \Xi^{-1} \boldsymbol{Y}^{\prime}=\boldsymbol{V}+\boldsymbol{H}
$$

Hence, the LRT is given by

$$
\Lambda_{H_{2} \mid H_{1}}=\frac{\left|N \widehat{\boldsymbol{\Sigma}}_{H_{1}}\right|}{\left|N \widehat{\boldsymbol{\Sigma}}_{H_{2}\left|H_{1}\right|}\right|}=\frac{\left|\boldsymbol{C V} \boldsymbol{C}^{\prime}+\boldsymbol{C H} \boldsymbol{C}^{\prime}\right|}{\left|\boldsymbol{C V} \boldsymbol{C}^{\prime}\right|} \frac{|\boldsymbol{V}|}{|\boldsymbol{V}+\boldsymbol{H}|}
$$

Using the canonical reduction, the LRT for the second hypothesis $H_{2} \mid H_{1}: \gamma=\mathbf{0}$ is

$$
\begin{aligned}
\Lambda_{H_{2} \mid H_{1}} & =\frac{\left|\boldsymbol{V}^{*}\right|\left|\boldsymbol{I}+\boldsymbol{Z}^{* \prime}\left(\boldsymbol{V}^{*-1}-\boldsymbol{V}^{*-1} \boldsymbol{e}\left(\boldsymbol{e}^{\prime} \boldsymbol{V}^{*-1} \boldsymbol{e}\right)^{-1} \boldsymbol{e}^{\prime} \boldsymbol{V}^{*-1}\right) \boldsymbol{Z}^{*}\right|}{\left|\boldsymbol{V}^{*}+\boldsymbol{Z}^{*} \boldsymbol{Z}^{* \prime}\right|} \\
& =\cdots=\frac{v_{1.2}^{*}}{v_{1.2}^{*}+\boldsymbol{y}_{2}^{* \prime} \boldsymbol{y}_{2}^{*}},
\end{aligned}
$$

where $\boldsymbol{e}=\left(\begin{array}{llll}1 & 0 & \ldots & 0\end{array}\right)^{\prime}: p \times 1$,

$$
\begin{aligned}
& v_{1.2}^{*}=v_{11}^{*}-\boldsymbol{v}_{12}^{* \prime} \boldsymbol{V}_{22}^{*-1} \boldsymbol{v}_{12}^{*}, \\
& \boldsymbol{y}_{2}^{* \prime}=\left(\boldsymbol{I}-\boldsymbol{Z}_{2}^{* \prime} \boldsymbol{V}_{22}^{*-1} \boldsymbol{Z}_{2}^{*}\right)^{-1 / 2}\left(\boldsymbol{z}_{1}^{*}-\boldsymbol{Z}_{2}^{*} \boldsymbol{V}_{22}^{*-1} \boldsymbol{v}_{12}^{*}\right) .
\end{aligned}
$$

$\boldsymbol{y}_{2}^{*}$ and $v_{1.2}^{*}$ are independently distributed as

$$
\boldsymbol{y}_{2}^{*} \sim N_{k-1}\left(\mathbf{0}, \sigma_{1.2}^{*} \boldsymbol{I}_{k-1}\right) \quad \text { and } \quad \frac{v_{1.2}^{*}}{\sigma_{1.2}^{*}} \sim \chi^{2}(N-k-p+1)
$$

## The null distribution

## Theorem

Rejecting the hypothesis $H_{2} \mid H_{1}$ for small values of $\Lambda_{H_{2} \mid H_{1}}$ is equal to reject the hypothesis for large values of

$$
F=\frac{1-\Lambda_{H_{2} \mid H_{1}}}{\Lambda_{H_{2} \mid H_{1}}}=\frac{\boldsymbol{y}_{2}^{* \prime} \boldsymbol{y}_{2}^{*}}{v_{1.2}^{*}},
$$

where

$$
\begin{aligned}
& v_{1.2}^{*}=v_{11}^{*}-\boldsymbol{v}_{12}^{* \prime} \boldsymbol{V}_{22}^{*-1} \boldsymbol{v}_{12}^{*}, \\
& \boldsymbol{y}_{2}^{* \prime}=\left(\boldsymbol{z}_{1}^{* \prime}-\boldsymbol{v}_{12}^{* \prime} \boldsymbol{V}_{22}^{*-1} \boldsymbol{Z}_{2}^{* \prime}\right)\left(\boldsymbol{I}-\boldsymbol{Z}_{2}^{* \prime} \boldsymbol{V}_{22}^{*-1} \boldsymbol{Z}_{2}^{*}\right)^{-1 / 2} .
\end{aligned}
$$

The null distribution of $F$ is given by

$$
\frac{N-k-p+1}{k-1} F \sim F_{k-1, N-k-p+1} .
$$

## Example 1, cont.

$P_{1}$ : plain wrapped, unboxed,
$P_{2}$ : plain wrapped, boxed,
$P_{3}$ : foil wrapped, unboxed, and
$P_{4}$ : foil wrapped, boxed.


$$
\begin{aligned}
& H_{1}: \boldsymbol{\mu}_{1}-\boldsymbol{\mu}_{2}=\gamma \mathbf{1}_{4}, \quad \text { vs. } \quad A_{1} \neq H_{1} \\
& -\left(N-\frac{1}{2}(k+p+1)\right) \ln \Lambda_{H_{1}}=3.6169
\end{aligned}
$$

$$
\text { with } N=12, k=2, p=4 \text { and } c=\chi_{(p-1)(k-1), 0.95}^{2}=7.8147
$$

Since $k=2$ we could use an exact $F$-test instead (as before).
Hence, we can't reject $H_{1}$, i.e., the profiles are similar.

$$
H_{2} \mid H_{1}: \gamma=0, \quad \text { vs. } \quad A_{2} \neq H_{2} \mid H_{1}
$$

$\Lambda_{H_{2} \mid H_{1}}=0.4368$ and $\frac{N-k-p+1}{k-1} F=9.0243$
with $c=F_{k-1, N-k-p+1,0.95}=5.5914$.

Hence, reject $H_{2} \mid H_{1}$, i.e., the profiles are not on the same level.

## $H_{3} \mid H_{1}: \boldsymbol{\mu}_{\bullet}=\gamma_{k} \mathbf{1}_{p}$

We wish to test the hypothesis
$H_{3} \mid H_{1}: \boldsymbol{\mu}_{\bullet}=\gamma_{k} \mathbf{1}_{p} \quad$ vs. $\quad A_{3} \neq H_{3} \mid H_{1} \quad$ (flatness - no row effect), where $\boldsymbol{\mu}_{\boldsymbol{\bullet}}=\boldsymbol{N}^{-1} \sum_{i=1}^{k} n_{i} \boldsymbol{\mu}_{i}$ and the scalars $\gamma_{i}$ are unknown.

The MLE of $\boldsymbol{\Sigma}$ under $H_{1}$ is given above (page 10 ), and the MLE of $\boldsymbol{\Sigma}$ under $H_{3}$ is given by

$$
N \widehat{\boldsymbol{\Sigma}}_{H_{3} \mid H_{1}}=\boldsymbol{V}+\left(\boldsymbol{Y}-\mathbf{1} \widehat{\gamma}^{\prime}\right) \bar{\Xi}^{-1}()^{\prime}+N\left(\overline{\boldsymbol{x}}-\hat{\gamma}_{k} \mathbf{1}\right)()^{\prime}
$$

where $\hat{\gamma}_{k}=\frac{\overline{\boldsymbol{x}}^{\prime} \boldsymbol{V}^{-1} \mathbf{1}}{\mathbf{1}^{\prime} \boldsymbol{V}^{-1} \mathbf{1}}$.

Hence, the LRT rejects the hypothesis $H_{3} \mid H_{1}$ for small values of

$$
\begin{aligned}
\Lambda_{H_{3} \mid H_{1}} & =\frac{\left|\boldsymbol{V}+\left(\boldsymbol{Y}-\mathbf{1} \widehat{\gamma}^{\prime}\right) \Xi^{-1}()^{\prime}\right|}{\left|\boldsymbol{V}+\left(\boldsymbol{Y}-\mathbf{1} \widehat{\boldsymbol{\gamma}}^{\prime}\right) \Xi^{-1}()^{\prime}+N\left(\overline{\boldsymbol{x}}-\hat{\gamma}_{k} \mathbf{1}\right)()^{\prime}\right|}=\ldots= \\
& =\frac{1}{1+N \bar{x}^{\prime} \boldsymbol{C}^{\prime}\left(\boldsymbol{C V} \boldsymbol{C}^{\prime}+\boldsymbol{C H} \boldsymbol{C}^{\prime}\right)^{-1} \mathbf{C} \overline{\boldsymbol{x}}}
\end{aligned}
$$

for some matrix $\boldsymbol{C}$ such that $\mathbf{C 1}=\mathbf{0}$.

Hence, the hypothesis $H_{3} \mid H_{1}$ is rejected if
$N \overline{\boldsymbol{x}}^{\prime} \boldsymbol{C}^{\prime}\left(\boldsymbol{C V} \boldsymbol{C}^{\prime}+\boldsymbol{C H} \boldsymbol{C}^{\prime}\right)^{-1} \boldsymbol{C} \overline{\boldsymbol{x}} \geq \frac{p-1}{N-p+1} F_{1-\alpha}(p-1, N-p+1)$.

Linköping University - Research that makes a difference

