

Informative hypotheses evaluation

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Table of Contents

Example Null hypothesis (H_0) vs Informative hypothesis (H_m)

GORIC weights

Examples with R code

GORICA

GORIC(A) in JASP

End & Extra

ANOVA Example: Comparisons of 3 Means

Palmer and Gough (2007) examined the difference in the attribution of importance of defective education as an explanation for criminal behavior between three types of “offenders”:

(1) non-offenders, (2) property offenders, and (3) person offenders.

ANOVA

$$y_j = \mu_1 d_{1j} + \mu_2 d_{2j} + \mu_3 d_{3j} + \epsilon_j,$$

where μ_i ($i = 1, 2, 3$) is the mean in group i ,
 d_{ij} is a dummy variable denoting group membership,
 ϵ_j is an error term and $\epsilon_j \sim N(0, \sigma^2)$.

$(n_i = 20, 20, 31)$

Hypotheses of interest

Palmer and Gough (2007) expect that

- non-offenders (1) attribute more importance to defective education for explaining crime than the other two offenders;
i.e., $\mu_1 > \mu_2$ and $\mu_1 > \mu_3$,
- property offenders (2) attribute more importance to defective education than person offenders (3);
i.e., $\mu_2 > \mu_3$.

$$H_1 : \quad \mu_1 > \mu_2 > \mu_3.$$

Note that ‘<’ denotes “smaller than” and ‘>’ denotes “larger than”.

Testing the null hypothesis

Test H_0 with ANOVA F test.

$$H_0 : \mu_1 = \mu_2 = \mu_3,$$

$$H_a : \text{not } H_0.$$

Then, reject or accept H_0 .

But, often not interested in H_0 !

Cannot say anything about $H_1 : \mu_1 > \mu_2 > \mu_3$.

Conclusions w.r.t. hypothesis of interest $H_1 : \mu_1 > \mu_2 > \mu_3$

With post-hoc test (e.g., Bonferroni) and on basis of the sample means, we could say a bit more.

But, what if

- $\mu_1 \neq \mu_2, \mu_1 \neq \mu_3, \mu_2 = \mu_3,$
- $\bar{y}_1 > \bar{y}_2,$

which implies $\mu_1 > \mu_2 = \mu_3$.

But also not interested in this.

Furthermore, inconsistent results are possible (like in this data example):

$\mu_1 \neq \mu_3, \mu_1 = \mu_2,$ and $\mu_2 = \mu_3,$

which is logically impossible, since latter two imply $\mu_1 = \mu_3$.

Using planned contrasts would overcome this, but still = restrictions then.

NHST on Palmer & Gough (2007) Data

```
PandG_data <- read.table("Data_PalmerAndGough.txt",  
                          header=TRUE)  
PandG_data$group <- factor(PandG_data$group)  
pairwise.t.test(PandG_data$Importance, PandG_data$group,  
                p.adj = 'bonferroni')  
  
##  
## Pairwise comparisons using t tests with pooled SD  
##  
## data: PandG_data$Importance and PandG_data$group  
##  
##      1      2  
## 2 0.191 -  
## 3 0.011 1.000  
##  
## P value adjustment method: bonferroni
```

Exploration and Confirmation

Exploration (like in post hoc tests and possibly AIC)

Test all possible pairs/subsets of means whether significant different (“,”) or not (“=”).

For example, when $k = 3$:

$$H_{0E} : \mu_1 = \mu_2 = \mu_3$$

$$H_{1E} : \mu_1 = \mu_2, \mu_3$$

$$H_{2E} : \mu_1, \mu_2 = \mu_3$$

$$H_{3E} : \mu_1 = \mu_3, \mu_2$$

$$H_a : \mu_1, \mu_2, \mu_3$$

When $k = 5$, there are even 52 hypotheses.

Confirmation

Limited set: Compare only prespecified hypotheses including order restrictions ($<$, $>$, but also $=$).

Confirmatory methods

Most researchers are able to specify “order-restricted” / “informative” / “theory-based” hypotheses, like $H_1 : \mu_1 > \mu_2 > \mu_3$.
Use prior knowledge and/or expertise in hypothesis.

Methods to evaluate theory-based hypotheses

- Hypothesis testing: F_{bar} (\bar{F}) test
(renders p-value and can test only one theory-based hypothesis)
- Confirmatory model selection using information criteria:
GORIC and GORICA
- (Confirmatory) Bayesian model selection (BMS)

Note: ‘model’ refers to hypothesis.

GORIC on Palmer & Gough (2007) Data

$$H_0 : \mu_1 = \mu_2 = \mu_3,$$

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

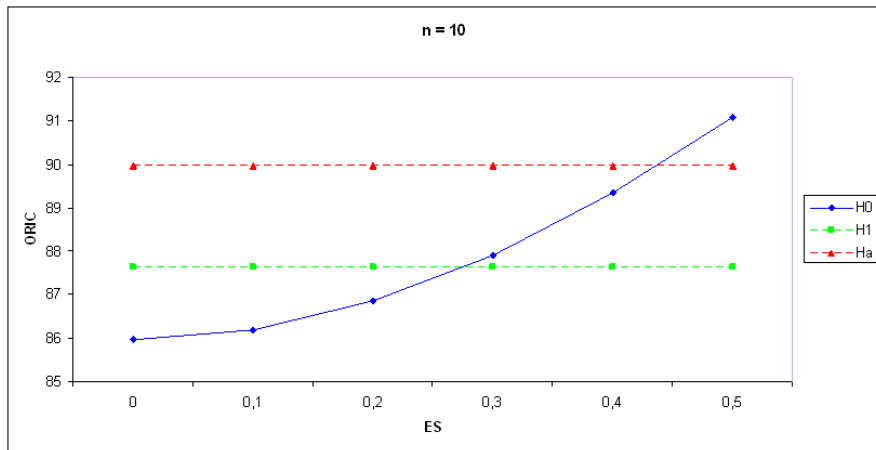
$$H_u : \mu_1, \mu_2, \mu_3.$$

GORIC

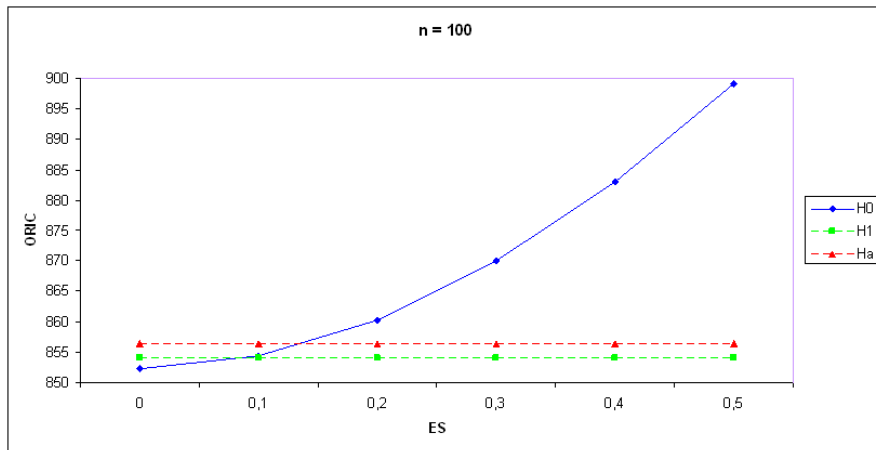
Model	Fit	Complexity	GORIC	GORIC weights
H_0	-196.36	2.00	396.71	0.02
H_1	-191.89	2.81	389.41	0.75
H_u	-191.89	4.00	391.79	0.23

Confirmatory methods have more “power” than their exploratory counterparts (cf. one-sided testing).

Confirmation more power: 1 data set. GORIC values for 3 groups, effect size ES , and $n = 10$ observations per group



Confirmation more power: 1 data set. GORIC values for 3 groups, effect size ES , and $n = 100$ observations per group



Confirmatory methods - some of my references

- Kuiper, R. M., and Hoijtink, H. (2010). Comparisons of Means Using Exploratory and Confirmatory Approaches. *Psychological Methods*, 15(1), 69–86.
- Kuiper, R. M., Klugkist, I., and Hoijtink, H. (2010). A Fortran 90 Program for Confirmatory Analysis of Variance. *Journal of Statistical Software*, 34(8), 1–31.
- Kuiper, R.M., Hoijtink, H. and Silvapulle, M.J. (2011). An Akaike type information criterion for model selection under inequality constraints. *Biometrika*, 98, 495-501. (GORIC)
- Kuiper, R.M., Nederhof, T., and Klugkist, I. (2015). Properties of hypothesis testing techniques and (Bayesian) model selection for exploration-based and theory-based (order-restricted) hypotheses. *British Journal of Mathematical and Statistical Psychology*, 68(2), 220 – 245.
- Altınışık, Y., Van Lissa, C. J., Hoijtink, H., Oldehinkel, A. J., and Kuiper, R. M. (2021). Evaluation of inequality constrained hypotheses using a generalization of the AIC. *Psychological Methods*, 26(5), 599–621.
<https://doi.org/10.1037/met0000406> (GORICA)

If you have your own data

- What is your research question?
- What is your theory / expectation?
- What is your statistical hypothesis?
- Is there a competing statistical hypothesis?

Notably, think outside of the H_0 -box...

Table of Contents

Example Null hypothesis (H_0) vs Informative hypothesis (H_m)

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GORIC weights

Examples with R code

Failsafe/Safeguard hypotheses: Unconstrained & Complement

GORICA

GORIC(A) in JASP

End & Extra

Generalized Order-Restricted Information Criterion

GORIC

'IC' = $-2 \text{ fit} + 2 \text{ complexity}$

Fit = Maximized order-restricted log likelihood

Maximized log likelihood based on parameters in agreement with H_m .

Complexity = Penalty

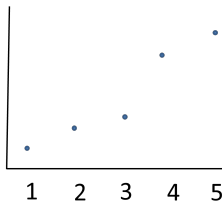
Represents: Expected number of distinct parameters.

Here, expected number of distinct mean values plus 1 (because of the unknown variance term).

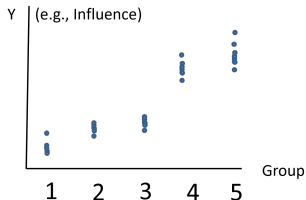
Details: Function of level probabilities.

Intermezzo: Balance Fit and Complexity

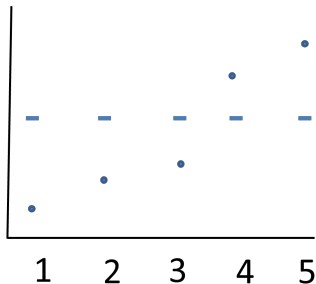
Data for 5 groups – Oversimplified representation



Data for 5 groups – Better representation (scatter of data points)



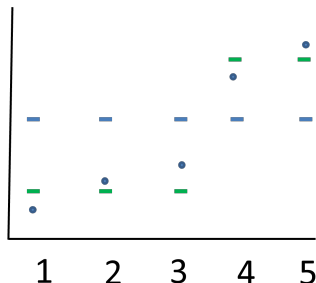
Intermezzo: Balance Fit and Complexity



$$\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu$$

parameters: 1 mean parameter (i.e., μ)
Fit: Bad fit

Intermezzo: Balance Fit and Complexity



$$\mu_1 = \mu_2 = \mu_3 = \mu_{\text{low}}$$

$$\mu_4 = \mu_5 = \mu_{\text{high}}$$

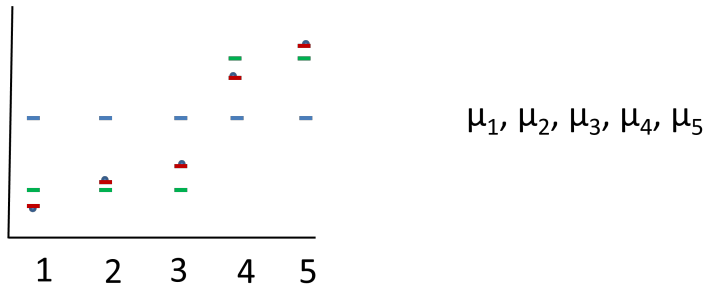
parameters:

2 mean parameters (i.e., μ_{low} and μ_{high})

Fit:

Better than with one parameter, even good fit.

Intermezzo: Balance Fit and Complexity



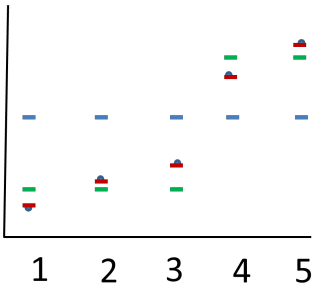
parameters: 5 mean parameter (complex)

Fit: Better than with two parameters, even best possible fit.

Thus: Best fit (= highest likelihood), but also most complex (= highest penalty).

In this example: Two means may be best trade-off between fit & complexity.

Intermezzo: Balance Fit and Complexity



Now, we also incorporate order-restrictions (e.g., $\mu_1 < \mu_2$).

Then, helpful to look at likelihood (not scatter plot).

In presentation, I will use contour plots (in case of two means, not five).

H0 vs Hm
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○○○○○○

GORIC
○○○
○○○○○●○
○○○
○○○○○

Weights
○○○

Example R
○○○○○
○○○○○
○○○○○

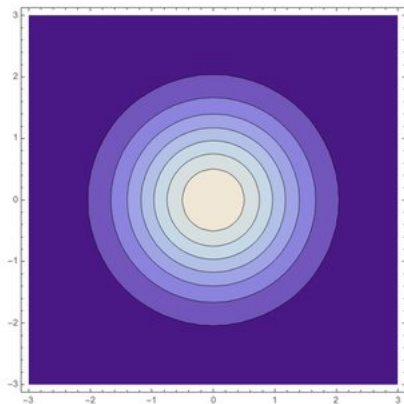
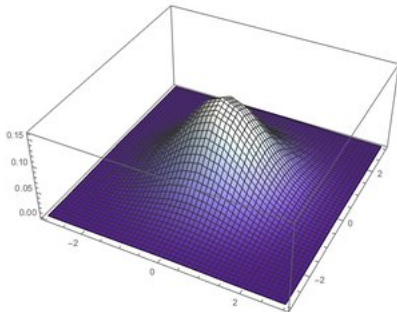
Failsafe
○○○○○
○○○○○
○○○○○

GORICA
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JASP
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○○

End & Extra
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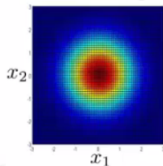
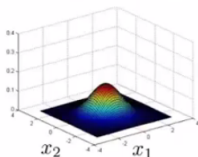
Intermezzo: Contour plot



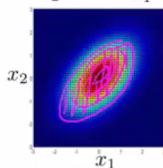
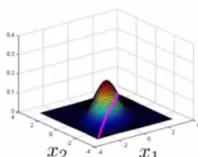
Intermezzo: Contour plot ctd.

Multivariate Gaussian (Normal) examples

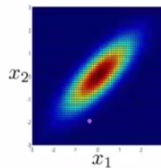
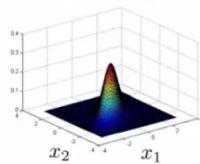
$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$



$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$



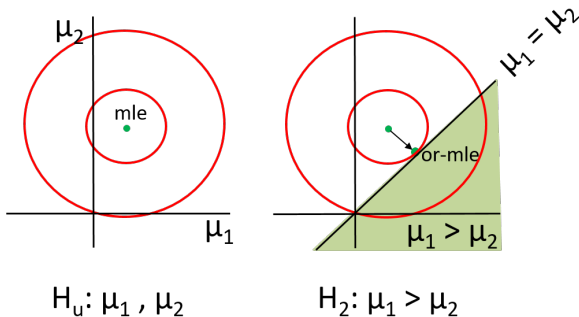
$$\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Sigma = \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix}$$



Andreas

Idea fit

order-restricted maximum likelihood (or-ml)



mle not in H_2 : Find highest likelihood in allowable (= green) space.
The resulting estimated mean $\hat{\mu} = (\hat{\mu}_1, \hat{\mu}_2)$ is referred to as or-ml.

Idea fit

GORIC on Palmer & Gough (2007) Data

$$H_0 : \mu_1 = \mu_2 = \mu_3,$$

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_2 : \mu_1 > \mu_2 < \mu_3,$$

$$H_3 : \mu_1 < \mu_2 < \mu_3,$$

$$H_u : \mu_1, \mu_2, \mu_3.$$

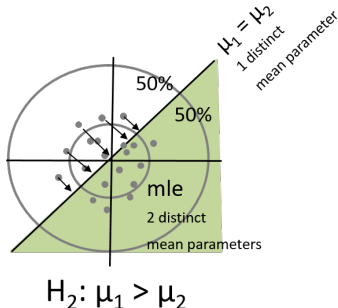
```
## group1 group2 group3
## 11.95  9.75  8.77
```

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-196.36	2.00	396.71	0.01
H_1	-191.89	2.81	389.41	0.56
H_2	-192.34	3.19	391.05	0.25
H_3	-196.36	2.81	398.34	0.01
H_u	-191.89	4.00	391.79	0.17

Idea complexity

penalty (PT)



Note: sampling from null distribution: $H_0: \mu_1 = \mu_2 = 0$.
 complexity $H_2 = PT_2 = 1 + 0.5 \times 1 + 0.5 \times 2 = 2.5$.
 PT = number of expected distinct parameters (under H_0).

Idea complexity

loose interpretation

$$H_1 : \mu_1 > \mu_2 > \mu_3$$

contains 1 ordering of three means, 1-2-3.

Thus, not complex (i.e., parsimonious).

$$H_2 : \mu_1 > \mu_2, \mu_3$$

contains 2 orderings of three means: 1-2-3 and 1-3-2.

Thus, more complex (less parsimonious).

$$H_u : \mu_1, \mu_2, \mu_3$$

contains all six possible orderings of three means.

Thus, is most complex one (least parsimonious).

Idea complexity

GORIC on Palmer & Gough (2007) Data

$$H_0 : \mu_1 = \mu_2 = \mu_3,$$

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_2 : \mu_1 > \mu_2 < \mu_3,$$

$$H_3 : \mu_1 < \mu_2 < \mu_3,$$

$$H_u : \mu_1, \mu_2, \mu_3.$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-196.36	2.00	396.71	0.01
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H_2	-192.34	3.19	391.05	0.25
H_3	-196.36	2.81	398.34	0.01
H_u	-191.89	4.00	391.79	0.17

GORIC

$$IC_m = -2 \text{ fit}_m + 2 \text{ complexity}_m$$

Broad type of restrictions

More or less: any linear restriction.

e.g., the interaction $H_1 : \mu_1 - \mu_2 < \mu_3 - \mu_4$.

Note

If no inequalities ($<$ and/or $>$), then (G)ORIC = AIC.

Reference:

Kuiper, R.M., Hoijtink, H. and Silvapulle, M.J. (2011). An Akaike type information criterion for model selection under inequality constraints. *Biometrika*, 98, 495-501.

GORIC on Palmer & Gough (2007) Data

$$H_0 : \mu_1 = \mu_2 = \mu_3,$$

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_u : \mu_1, \mu_2, \mu_3.$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-196.36	2.00	396.71	0.02
H_1	-191.89	2.81	389.41	0.75
H_u	-191.89	4.00	391.79	0.23

Hands-on/Demo (1a): GORIC

Let's practice.

- Go to <https://github.com/rebeccakuiper/Tutorials>:
 1. Click on green button called Code.
 2. Download zip (last option in list).
 3. Unzip it on your machine (that folder is now your working directory).
- Start Rstudio. Optional: make project.
- Open 'Tutorial_GORIC_restriktor_ANOVA.html', 'PalmerAndGough_and_Lucas.R', and 'Hands-on_1_GORIC_Unc_ANOVA_restriktor.R' (in 'Hands-on files').
- Install packages and load them.
- Read and inspect data. Use Data_PalmerAndGough.txt (in 'data').
- Run model (`lm()`).
- Specify hypotheses (make up your own).
Note: Use names used in the model.
- Run `goric()`.
- Inspect and interpret output.
Note: 'GORIC weights' will be explained next.

Table of Contents

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Examples with R code

Failsafe/Safeguard hypotheses: Unconstrained & Complement

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Interpretation: GORIC weights

GORIC values

GORIC values cannot be interpreted, only compared:
Smallest is best.

GORIC weights (w_m) and ratios ($w_m/w_{m'}$)

w_m quantifies how much H_m is more supported than others in set.
 $w_m/w_{m'}$ quantifies relative support of H_m vs $H_{m'}$.
The bigger, the better.

Reference:

Kuiper, R.M., Hoijtink, H. and Silvapulle, M.J. (2012). Generalization of the order restricted information criterion for multivariate normal linear models. *Journal of Statistical Planning and Inference*, 142, 2454-2463.

Illustration of the GORIC weights (w_m)

$$H_0 : \mu_1 = \mu_2 = \mu_3,$$

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_u : \mu_1, \mu_2, \mu_3.$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-196.36	2.00	396.71	0.02
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R code: Data and fit object

Palmer & Gough

```
# Data
PandG_data <- read.table("Data_PalmerAndGough.txt",
                          header=TRUE)
PandG_data$group <- factor(PandG_data$group)

# fit object (needed as input for gorica function)
fit.PandG <- lm(Importance ~ group - 1, data = PandG_data)
```

R code: Hypotheses

Palmer & Gough

$$H_0 : \mu_1 = \mu_2 = \mu_3$$

$$H_1 : \mu_1 = \mu_2 > \mu_3$$

$$H_u : \quad \mu_1, \mu_2, \mu_3$$

Hypotheses

```
H0 <- 'group1 = group2 = group3'
```

```
H1 <- 'group1 > group2 > group3'
```

R code: GORIC

Palmer & Gough

$$H_0 : \mu_1 = \mu_2 = \mu_3$$

$$H_1 : \mu_1 = \mu_2 > \mu_3$$

$$H_u : \mu_1, \mu_2, \mu_3$$

```
# GORIC (using goric function in restriktor package)
library(restriktor)
set.seed(123) # Set seed value
goric.PandG <- goric(fit.PandG,
                     hypotheses = list(H0, H1))
```


GORIC on Palmer & Gough Data

$$H_0 : \mu_1 = \mu_2 = \mu_3$$

$$H_1 : \mu_1 = \mu_2 > \mu_3$$

$$H_u : \mu_1, \mu_2, \mu_3$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-196.36	2.00	396.71	0.02
H_1	-191.89	2.81	389.41	0.75
H_u	-191.89	4.00	391.79	0.23

Another illustration: one-way ANOVA

Lucas: 5 groups

Lucas (2003) investigated difference between female and male leadership w.r.t. influence of the leader.

Five experimental groups:

1. a randomly selected male leader
2. a randomly selected female leader
3. male leader selected via task
4. female leader selected via task
5. female leader selected via task + institutionalized female leadership via movie

(Two informative) hypotheses of interest

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (include only when of interest),

$H_1 : \mu_5 = \mu_3 > \{\mu_1, \mu_4\} > \mu_2$,

$H_2 : \mu_3 > \mu_1 > \mu_4 = \mu_5 > \mu_2$,

$H_u : \mu_1, \mu_2, \mu_3, \mu_4, \mu_5$ (included as failsafe).

Descriptive statistics of Lucas' Data

Group	Mean Influence	SD	n
1 (male, random)	2.33	1.86	30
2 (female, random)	1.33	1.15	30
3 (male, selected)	3.20	1.79	30
4 (female, selected)	2.23	1.45	30
5 (female, selected+)	3.23	1.50	30

R code: Data and fit object

Lucas

```
# Data
lucas_data <- read.table("Data_Lucas.txt", header=TRUE)
lucas_data$group <- factor(lucas_data$group)

# fit object (needed as input for goric function)
fit.lucas <- lm(Influence ~ group - 1, data = lucas_data)
```

R code: Hypotheses

Lucas

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5,$$

$$H_1 : \mu_5 = \mu_3 > \{\mu_1, \mu_4\} > \mu_2$$

$$H_2 : \mu_3 > \mu_1 > \mu_4 = \mu_5 > \mu_2,$$

$$H_u : \mu_1, \mu_2, \mu_3, \mu_4, \mu_5.$$

Hypotheses

```
H0 <- 'group1 = group2 = group3 = group4 = group5'
```

```
H1 <- 'group5 = group3 > group1 > group2;  
      group3 > group4 > group2'
```

```
H2 <- 'group3 > group1 > group4 = group5 > group2'
```

R code: GORIC

Lucas

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5,$$

$$H_1 : \mu_5 = \mu_3 > \{\mu_1, \mu_4\} > \mu_2$$

$$H_2 : \mu_3 > \mu_1 > \mu_4 = \mu_5 > \mu_2,$$

$$H_u : \mu_1, \mu_2, \mu_3, \mu_4, \mu_5.$$

```
# GORIC (using goric function in restriktor package)
library(restriktor)
set.seed(123) # Set seed value
goric.lucas <- goric(fit.lucas,
                     hypotheses = list(H0, H1, H2))
```

GORIC on Lucas' Data

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5,$$

$$H_1 : \mu_5 = \mu_3 > \{\mu_1, \mu_4\} > \mu_2$$

$$H_2 : \mu_3 > \mu_1 > \mu_4 = \mu_5 > \mu_2,$$

$$H_u : \mu_1, \mu_2, \mu_3, \mu_4, \mu_5.$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-292.27	2.00	588.54	0.00
H_1	-278.05	3.20	562.49	0.92
H_2	-281.76	3.14	569.79	0.02
H_u	-278.05	6.00	568.10	0.06

GORIC on Lucas' Data: GORIC weights (w_m)

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-292.27	2.00	588.54	0.00
H_1	-278.05	3.20	562.49	0.92
H_2	-281.76	3.14	569.79	0.02
H_u	-278.05	6.00	568.10	0.06

H_1 is $.921/.024 \approx 38.6$ (∞) times more supported than H_2 (H_0 , resp.). Thus, there is quite some evidence that H_1 is the best of this set.

Note:

H_1 is $.921/.056 \approx 16.5 > 1$ times more supported than H_ν .

Hence, H_1 not weak and thus comparable to the other informative hypotheses (as explained next).

Hands-on/Demo (1b): GORIC weights

Let's practice.

- If needed: Start Rstudio again (optional: make project) and then also load packages again.
- Read and inspect data.
Use Data_Lucas.txt and/or Data_PalmerAndGough.txt.
- Run model (`lm()`).
- Specify hypotheses (make up your own).
Note: Use names used in the model.
- Run `goric()`.
- Inspect and interpret output: Focus on GORIC weights.

H0 vs Hm
○○○○○○
○○○○○○○

GORIC
○○○
○○○○○○○
○○○
○○○○○

Weights
○○○

Example R
○○○○○
○○○○
○○○○

Failsafe
●○○○
○○○○○
○○○○

GORICA
○○○○○

JASP
○○○○○
○○

End & Extra
○○○
○○○○○
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Table of Contents

Example Null hypothesis (H_0) vs Informative hypothesis (H_m)

Generalized Order-Restricted Information Criterion (GORIC)

GORIC weights

Examples with R code

Failsafe/Safeguard hypotheses: Unconstrained & Complement

GORICA

GORIC(A) in JASP

End & Extra

Include “unconstrained” hypothesis

If set of hypotheses does not contain a reasonable/good one:
Select the best of set of weak hypotheses.

E.g.: $w_0 = .2$ and $w_1 = .8$.

Prevent choosing a weak hypothesis

Include unconstrained hypothesis H_u (or H_a):

$$H_0 : \quad \mu_1 = \mu_2 = \mu_3,$$

$$H_1 : \quad \mu_1 > \mu_2 > \mu_3,$$

$$H_u : \quad \mu_1, \mu_2, \mu_3, \\ \text{(i.e., no restrictions).}$$

H_u highest fit but also most complex, thus failsafe/safeguard.

E.g.: $w_0 = .02$, $w_1 = .08$, and $w_u = .90$.

What if another hypothesis is true?

What if another informative hypothesis is true?

The failsafe hypothesis will be preferred over the informative hypotheses in the set, if the sample size is large enough.

E.g.: $w_0 = .02$, $w_1 = .08$, and $w_\mu = .90$.

Use of H_u : Palmer & Gough (2007) Data

$$H_0 : \mu_1 = \mu_2 = \mu_3,$$

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_u : \mu_1, \mu_2, \mu_3.$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_0	-196.36	2.00	396.71	0.02
H_1	-191.89	2.81	389.41	0.75
H_u	-191.89	4.00	391.79	0.23

If at least one informative hypothesis not weak ($w_1 > w_u$ or $w_1/w_u > 1$), then compare informative hypotheses.

Hence: H_u is only a failsafe not another hypothesis of interest.

H_1 vs H_u : Palmer & Gough (2007) Data

What if only one informative hypothesis:

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_u : \mu_1, \mu_2, \mu_3.$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H_1	-191.89	2.81	389.41	.77
H_u	-191.89	4.00	391.79	.23

H_1 is $.77/.23 \approx 3.3$ times more supported than H_u .

BUT: H_u includes H_1 .

So, support for H_u contains support for H_1 .

H_1 vs H_u : Upper bound

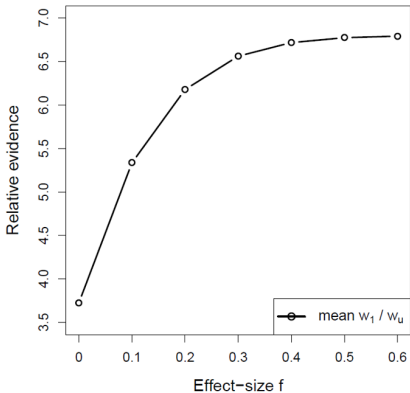


Figure: IC weights can have an upper bound, when informative hypothesis has maximum fit (i.e., is fully in agreement with the data).

Alternative failsafe: Complement of H_m

Alternatively (in case of one hypothesis of interest)

Evaluate hypothesis of interest against its complement;
that is, all other possible hypotheses.

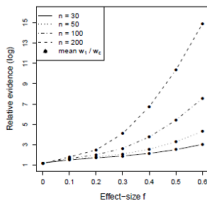
More powerful than against the unconstrained
if H_m has maximum fit.

Reference:

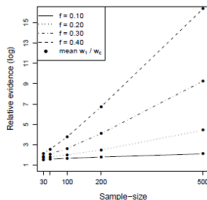
Vanbrabant, L., Van Loey, N., and Kuiper, R. M. (2020). Evaluating a Theory-Based Hypothesis Against Its Complement Using an AIC-Type Information Criterion With an Application to Facial Burn Injury. *Psychological Methods*, 25(2), 129-142.
<https://doi.org/10.1037/met0000238>

Alternative failsafe: Complement of H_m using GORIC

vs complement

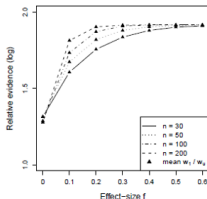


(a)

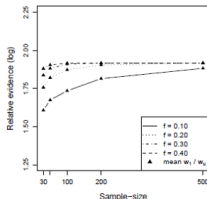


(b)

vs unconstrained



(c)



(d)

R code: complement

Palmer & Gough

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_c : \text{not } H_1.$$

GORIC

```
H1 <- 'group1 > group2 > group3'  
# GORIC (using goric function in restriktor package)  
library(restriktor)  
set.seed(123) # Set seed value  
goric.lucas_C <- goric(fit.PandG,  
                        hypotheses = list(H1),  
                        comparison = 'complement')
```

Palmer & Gough (2007): H_1 vs H_c

$$H_1 : \quad \mu_1 > \mu_2 > \mu_3,$$

$$H_c : \quad \text{not } H_1.$$

GORIC

Model	Fit	Complexity	GORIC	GORIC weights
H1	-191.89	2.81	389.41	0.79
complement	-192.34	3.69	392.05	0.21

H_1 is $.79/.21 \approx 3.8$ times more supported than its complement, that is, any other hypothesis.

Hands-on/Demo (2): GORIC - H_m vs complement

Let's practice.

- If needed: Start Rstudio again (optional: make project) and then also load packages again.
- Optional: Open 'Tutorial_GORIC_restriktor_ANOVA.html', 'PalmerAndGough_and_Lucas.R', and **'Hands-on_2_GORIC_Compl_ANOVA_restriktor.R'**.
- Read and inspect data.
Use Data_Lucas.txt and/or Data_PalmerAndGough.txt.
- Run model (lm()).
- Specify hypotheses (make up your own). E.g., for Lucas:

$$H_1 : \quad \mu_5 = \mu_3 > \{\mu_1, \mu_4\} > \mu_2$$

Note: Use names used in the model.

- Run `goric()`; now, add:
`comparison = "complement"`
- Inspect and interpret output.

Table of Contents

Generalized Order-Restricted Information Criterion (GORIC)

GORIC weights

Examples with R code

GORICA

GORIC(A) in JASP

End & Extra

◀ ◻ ▶ ◀ ◻ ▶ ◀ ≡ ▶ ◀ ≡ ▶ ≡ ↺ 🔍 ↻ 64/98

GORICA

Similarities with GORIC

- Form: $GORICA_m = -2 \text{ fit} + 2 \text{ complexity}$.
- Broad type of restrictions.

Differences compared to GORIC

- Uses asymptotic expression of the likelihood (is a normal):
can therefore be easily applied to all types of statistical models.
Disadvantage: might work less well in case of small samples.
- Does not need data set; mle's and their covariance matrix suffice.
- Can leave out nuisance parameters (i.e., not part of hypotheses).

Note

In case of normal linear models and/or not too small samples:
GORICA weights = GORIC weights.

R code: GORICA

Palmer & Gough

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_c : \text{not } H_1.$$

GORICA: type = "gorica"

```
H1 <- 'group1 > group2 > group3'  
# GORICA (using goric function in restriktor package)  
library(restriktor)  
set.seed(123) # Set seed value  
gorica.lucas_C <- goric(fit.PandG,  
                        hypotheses = list(H1),  
                        comparison = 'complement',  
                        type = "gorica")
```

GORICA on Palmer & Gough (2007) Data

$$H_1 : \mu_1 > \mu_2 > \mu_3,$$

$$H_c : \text{not } H_1.$$

GORIC

Model	Fit	Complexity	GORICA	GORICA weights
H1	-1.96	1.81	7.55	0.79
complement	-2.39	2.69	10.15	0.21

H_1 is $.79/.21 \approx 3.8$ times more supported than its complement, that is, any other hypothesis.

Note: GORIC weights are the same.

Hands-on/Demo (3): GORICA - H_m vs complement

Let's practice.

- If needed: Start Rstudio again (optional: make project) and then also load packages again.
- Optional: Open 'Tutorial_GORIC_restriktor_ANOVA.html', 'PalmerAndGough_and_Lucas.R', and **'Hands-on_3_GORICA_UncAndCompl_ANOVA_restriktor.R'**.
- Read and inspect data.
Use Data_Lucas.txt and/or Data_PalmerAndGough.txt.
- Run model (lm()).
- Specify hypotheses (make up your own). E.g., for Lucas:

$$H_1 : \quad \mu_5 = \mu_3 > \{\mu_1, \mu_4\} > \mu_2$$

Note: Use names used in the model (or overwrite those).

- Run goric(); now, add:
`type = "gorica"`
- Inspect and interpret output.

Table of Contents

Example Null hypothesis (H_0) vs Informative hypothesis (H_m)

Generalized Order-Restricted Information Criterion (GORIC)

GORIC weights

Examples with R code

Failsafe/Safeguard hypotheses: Unconstrained & Complement

GORICA

GORIC(A) in JASP

End & Extra

GORIC in JASP: Palmer & Gough

- Open JASP and 'Data_PalmerAndGough_JASP.txt'.
Check measurement levels.
- Go to ANOVA and denote variables of interest.
- Go to Order Restrictions tab.
- Specify hypotheses. For example,

$$H_1 : \quad \mu_1 > \mu_2 > \mu_3$$

$$\text{JASP} : \quad \text{group1} > \text{group2} > \text{group3}$$

- Press Ctrl+Enter. Inspect and interpret output.

More in (demo and) lab.

GORIC in JASP: Lucas

- Open JASP and 'Data_Lucas_JASP.txt'. Check measurement levels.
- Go to ANOVA and denote variables of interest.
- Go to Order Restricted Hypotheses tab.
- Specify hypotheses. For example,

$$H_1 : \quad \mu_5 = \mu_3 > \{\mu_1, \mu_4\} > \mu_2$$

$$\begin{aligned} \text{JASP :} \quad & \text{group5} = \text{group3} > \text{group1} > \text{group2} \\ & \text{group3} > \text{group4} > \text{group2} \end{aligned}$$

- Press Ctrl+Enter. Inspect and interpret output.

GORIC in JASP: Lucas

Descriptives

T-Tests

ANOVA

Mixed Models

Regression

Frequencies

Factor

Bain

SEM

R (Beta)

Order Restricted Hypotheses

Results

Enter each restriction of one hypothesis on a new line, e.g.,
factorLow == factorMid
factorMid < factorHigh
where 'factor' is the factor (or covariate) name and 'Low'/'Mid'/'High' are the factor level names.
Click on the 'plus' icon to add more hypotheses.
Click the information icon for more examples.

Syntax settings

Set for all models

Include intercept

Show available coefficients

Model summary

Marginal means

Informed hypothesis tests

Model 1

group5 = group3 > group1 > group2
group3 > group4 > group2

Ctrl + Enter to apply. Click on the blue button above for help on the restriction syntax

Summary for Model 1

Marginal means for Model 1

Informed hypothesis tests for Model 1

ANOVA

ANOVA - Influence

Cases	Sum of Squares	df	Mean Square	F	p
group	74.700	4	18.675	7.567	< .001
Residuals	357.835	145	2.468		

Note. Type III Sum of Squares

Order Restricted Hypotheses

Model Comparison

Model	Log-likelihood	Penalty	GORIC	Weight	Weights ratio
Model 1	-278.051	3.197	562.495	0.930	13.357
Complement	-278.048	5.791	567.680	0.070	1.000

Note. Weights ratios indicate the relative weight for each model against the "complement" model. GORIC = Generalized Order-Restricted Information Criterion (Kuiper, Hoijtink, & Silvapulle, 2011).

73/98

GORIC and GORICA in JASP

	GORIC R	GORIC JASP	GORICA R	GORICA JASP
ANOVA	✓	✓	✓	
RM-ANOVA			✓	✓
Regression	✓	Not yet	✓	
SEM		Future?	✓	Future?
Other model		Future?	✓	Future?

GORIC and GORICA in JASP

GORIC or GORICA in the following statistical models (as part of that model)

The screenshot displays the JASP software interface with three statistical model windows open: ANOVA, ANCOVA, and Repeated Measures ANOVA. In each window, the 'Order Restricted Hypotheses' option is highlighted with a red circle. The ANOVA window shows the 'GORIC' label. The ANCOVA window shows the 'GORICA' label. The Repeated Measures ANOVA window shows the 'GORICA' label. The right-hand pane shows the 'ANCOVA' model configuration, including the list of variables and the 'Order Restricted Hypotheses' option, which is also highlighted with a red circle.

ANOVA

Order Restricted Hypotheses

GORIC

ANOVA

ANOVA

Cases Sum of Squares df Mean Square F p

Note: Type III Sum of Squares

ANCOVA

Order Restricted Hypotheses

GORICA

ANCOVA

ANCOVA

Cases Sum of Squares df Mean Square F p

Note: Type III Sum of Squares

Repeated Measures ANOVA

Order Restricted Hypotheses

GORICA

Repeated Measures ANOVA

Within Subjects Effects

Cases Sum of Squares df Mean Square F p

Note: Type III Sum of Squares

Between Subjects Effects

Cases Sum of Squares df Mean Square F p

Note: Type III Sum of Squares

ANCOVA

id site sex age viewcat sailing treat prebody prelat preform pronumb preclas postbody postlat postnum postclas postclas postclas

Dependent Variable

Fixed Factors

Covariates

WLS Weights

Display

☐ Descriptive statistics

☐ Estimates of effect size

☐ Partial η^2

☐ Work-Saline maximum p-ratio

Model

Assumption Checks

Contrasts

Order Restricted Hypotheses

Table of Contents

Generalized Order-Restricted Information Criterion (GORIC)

GORIC weights

Examples with R code

GORICA

GORIC(A) in JASP

End & Extra

Your hypothesis of interest

If you have your own data

Before:

- What is your research question?
- What is your theory / expectation?
- What is your statistical hypothesis?
- Is there a competing statistical hypothesis?

Additionally:

- Are you able to specify your statistical hypothesis/-es?
- How will you evaluate it/them?

The End
GORIC(A)

Thanks for listening!

Are there any questions?

Websites

<https://github.com/rebeccakuiper/Tutorials>
www.uu.nl/staff/RMKuiper/Software
www.uu.nl/staff/RMKuiper/Websites%20%2F%20Shiny%20apps
informative-hypotheses.sites.uu.nl/software/goric/

E-mail

r.m.kuiper@uu.nl

Notes

Note on comparable estimates

Until now: comparing means.

Continuous predictors

If compare relative strength/importance of parameters (e.g., $\beta_1 > \beta_2$), then make sure comparable:
e.g., standardize continuous predictors.

Multiple outcomes

If compare parameters across outcomes, then (also) standardize outcomes.

Note on using complement

Complement not always higher weight

In case H_m is almost true, but not true:

1. H_m does not have maximum fit (but much lower penalty).
2. Support for H_m is less when evaluating it against its complement (than H_u).

This is of course a good thing, since H_m is not true.

Explanation:

Penalty of H_c is smaller than that of H_u .

Against H_μ , you choose H_m 'sooner' because of low penalty for H_m .

Note on hypotheses

1. Only include hypotheses with sound theoretical and/or empirical basis.
Often a null hypothesis is not of interest.
2. Keep the number of hypotheses included as small as possible.
3. This is a subjective endeavor, aim for inter-peer / inter-subjective agreement.

Note on possibilities multiple studies

- Update GORIC(A) values & weights.
More data collected: (re-)calculate.
- Update hypotheses.
First data set (or a part of it) generates one or more hypotheses.
Other data set (or part) used to determine evidence / support.
Download 'Tutorial_GORIC_restriktor_UpdateHypo.html' and/or
'Hands-on_4_GORIC_UpdateHypo_restriktor.R' from
<https://github.com/rebeccakuiper/Tutorials>.
- Aggregate evidence for hypotheses.
Aggregate the support for theories (diverse designs allowed).
Bear in mind: Meta-analysis aggregates parameter estimates or
effect sizes which need to be comparable (often same designs
required).

Download 'Tutorial_GORIC_restriktor_evSyn.html' and/or
'Hands-on_4_GORIC_evSyn_restriktor.R' from

<https://github.com/rebeccakuiper/Tutorials>.

Extra material

- **Logistic Regression Modeling**
 - Article: <https://doi.org/10.1037/met0000406>
- **GORICA on SEM**
 - Article:
<https://www.tandfonline.com/doi/full/10.1080/10705511.2020.1836967>.
 - R scripts: https://github.com/rebeccakuiper/GORICA_in_SEM.
- **GORICA on cross-lagged panel model (CLPM)** – Article:
<https://doi.org/10.1111/bjep.12455>.
 - R scripts: https://github.com/rebeccakuiper/GORICA_in_SEM.
- **GORICA on Random-Intercept CLPM (RI-CLPM)**
 - Article: Sukpan, C. and Kuiper, R.M. (submitted 2023). How to evaluate causal dominance hypotheses in lagged effects models.
 - R scripts: <https://github.com/Chuenjai/Causal-dominance>.
- **GORICA on CTmeta**
 - Article: <https://doi.org/10.1080/10705511.2020.1823228>.
 - R scripts: https://github.com/rebeccakuiper/GORICA_on_CTmeta.
- **GORICA on Meta-analysis**
 - Article: <https://doi.org/10.3390/e24111525>.
 - R scripts: https://github.com/rebeccakuiper/GORICA_on_MetaAn.

Note: On github site, go to Code (green button) and download zip

Note on BF as an IC

The fit in GORICA refers to the maximum log likelihood.
The fit in BF refers to the maximum likelihood.

Notably, BF can be written as an IC (and vice versa):

$$\begin{aligned}
 -2 \log BF_{1u} &= -2 \log \frac{f_1}{c_1} \\
 &= -2 \log f_1 + 2 \log c_1 \\
 &= -2 \log \text{fit } H_1 + 2 \log \text{complexity } H_1.
 \end{aligned}$$

Note: complexity value in BF depends on prior.

Note on GORIC weights vs BF and PMPs

ratio GORIC weights ($w_m/w_{m'}$) \sim Bayes factor ($BF_{mm'}$).

GORIC weight (w_m) \sim posterior model probability (PMP).

1 - w_m = conditional error probability.

Like PMP, w_m depends on set of hypotheses.

Note on conditional error probability

using PMPs and GORIC(A) weights

What if we compare many hypotheses?

H_m	weights
H_1 : Sex Match	.013
H_2 : Gender Role Match	.270
H_3 : Sex Mismatch	.003
H_4 : Gender Role Mismatch	.000
H_5 : Lets try this one too	.180
...	...
H_{12} : Don't miss something	.040
H_u :	.047

The conditional error probability for H_2 becomes $1 - .27 = .77$ (was .19).

Namely, included additional hypotheses may obtain some support.
Hence, the conditional error probabilities becomes larger.

Properties of Methods: Simulation study

1. All methods (e.g., (G)ORIC and BMS) programmed in Fortran.
2. Generate data sets with know structure (conditions).
3. Apply methods to all data sets (within one condition).
4. Summarize results (per condition):
proportion of (correct) chosen hypotheses.

Reference:

Kuiper, R.M., Nederhof, T., and Klugkist, I. (2015). Properties of hypothesis testing techniques and (Bayesian) model selection for exploration-based and theory-based (order-restricted) hypotheses. *British Journal of Mathematical and Statistical Psychology*, 68(2), 220 – 245.

Results Confirmation ($k = 3$ and $n = 50$)

 $H_{30C} : \mu_1 = \mu_2 = \mu_3$
 $H_{31C} : \mu_1 < \mu_2 < \mu_3$
 $H_{32C} : \mu_1 = \mu_2 < \mu_3$
 $H_{33C} : \mu_1 < \mu_2 > \mu_3$
 $H_{34C} : \mu_1, \mu_2, \mu_3$

'ES'	Method	'Prior'	H_{30C}	H_{31C}	H_{32C}	H_{33C}	H_{34C}
0	ORIC		0.662	0.065	0.119	0.120	0.034
0	BMS	3	0.865	0.012	0.075	0.036	0.012
0	BMS	2	0.774	0.022	0.124	0.058	0.022
0	BMS	1	0.656	0.047	0.147	0.120	0.033
2	ORIC		0.148	0.506	0.311	0.029	0.006
2	BMS	3	0.299	0.299	0.371	0.031	0.001
2	BMS	2	0.252	0.328	0.381	0.040	0.000
2	BMS	1	0.125	0.494	0.321	0.063	0.000
5	ORIC		0.000	0.955	0.044	0.001	0.000
5	BMS	3	0.000	0.887	0.112	0.001	0.000
5	BMS	2	0.001	0.890	0.107	0.002	0.000
5	BMS	1	0.000	0.928	0.070	0.002	0.000

Results Confirmation ($k = 3$ and $n = 50$)

 $H_{30C} : \mu_1 = \mu_2 = \mu_3$
 $H_{31C} : \mu_1 < \mu_2 < \mu_3$
 $H_{32C} : \mu_1 = \mu_2 < \mu_3$
 $H_{33C} : \mu_1 < \mu_2 > \mu_3$
 $H_{34C} : \mu_1, \mu_2, \mu_3$

1 – **Type I error** (here):

not preferring the true null hypothesis,
given the set of hypotheses (!).

'ES'	Method	'Prior'	H_{30C}	H_{31C}	H_{32C}	H_{33C}	H_{34C}
0	ORIC		0.662	0.065	0.119	0.120	0.034
0	BMS	3	0.865	0.012	0.075	0.036	0.012
0	BMS	2	0.774	0.022	0.124	0.058	0.022
0	BMS	1	0.656	0.047	0.147	0.120	0.033
2	ORIC		0.148	0.506	0.311	0.029	0.006
2	BMS	3	0.299	0.299	0.371	0.031	0.001
2	BMS	2	0.252	0.328	0.381	0.040	0.000
2	BMS	1	0.125	0.494	0.321	0.063	0.000
5	ORIC		0.000	0.955	0.044	0.001	0.000
5	BMS	3	0.000	0.887	0.112	0.001	0.000
5	BMS	2	0.001	0.890	0.107	0.002	0.000
5	BMS	1	0.000	0.928	0.070	0.002	0.000

Results Confirmation ($k = 3$ and $n = 50$)

 $H_{30C} : \mu_1 = \mu_2 = \mu_3$
 $H_{31C} : \mu_1 < \mu_2 < \mu_3$
 $H_{32C} : \mu_1 = \mu_2 < \mu_3$
 $H_{33C} : \mu_1 < \mu_2 > \mu_3$
 $H_{34C} : \mu_1, \mu_2, \mu_3$

1 – **Type II error** (here):

not preferring the true hypothesis,
given the set of hypotheses (!).

'ES'	Method	'Prior'	H_{30C}	H_{31C}	H_{32C}	H_{33C}	H_{34C}
0	ORIC		0.662	0.065	0.119	0.120	0.034
0	BMS	3	0.865	0.012	0.075	0.036	0.012
0	BMS	2	0.774	0.022	0.124	0.058	0.022
0	BMS	1	0.656	0.047	0.147	0.120	0.033
2	ORIC		0.148	0.506	0.311	0.029	0.006
2	BMS	3	0.299	0.299	0.371	0.031	0.001
2	BMS	2	0.252	0.328	0.381	0.040	0.000
2	BMS	1	0.125	0.494	0.321	0.063	0.000
5	ORIC		0.000	0.955	0.044	0.001	0.000
5	BMS	3	0.000	0.887	0.112	0.001	0.000
5	BMS	2	0.001	0.890	0.107	0.002	0.000
5	BMS	1	0.000	0.928	0.070	0.002	0.000

Extra: Prior choice for BMS

Prior

$$P(\mu, \sigma^2) = P(\mu_1) \times \dots \times P(\mu_k) \times P(\sigma^2),$$

where $P(\mu_i) = P(\mu) \forall i = 1, \dots, k$.

$P(\mu)$ is a data-based normal distribution, with parameters β_0 and τ_0^2 , and $P(\sigma^2)$ an inverse chi-squared distribution (see Klugkist et al., 2005)

β_0 and τ_0^2 data-based hyperparameters

For each μ_i ($i = 1, \dots, k$) a credibility interval is computed:

estimated group mean \pm $PV \times$ *the group standard error*.

The credibility interval for μ_i is represented by " $[LB_i, UB_i]$ ".

Lowest lower bound: LB_{min} .

Highest upper bound: UB_{max} .

Then, $\beta_0 = \frac{LB_{min} + UB_{max}}{2}$ and $\tau_0^2 = \left[\frac{UB_{max} - LB_{min}}{2} \right]^2$.

Three types of prior vagueness: BMS PV 1, BMS PV 2 and BMS PV 3