Introduction to Structural Equation Modeling using lavaan
Model Selection

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AIC in R
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IC weights
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GORICA in R
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Previously: Model Comparisons: AIC / BIC

Suitable for comparing
- both nested and non-nested models.
- more than two models.

Choose the model with the lowest AIC and/or BIC.

To be discussed in the Model Selection lecture
- Quantify relative support via IC weights.

```
library(devtools) # Make sure you have Rtools
install_github("rebeccakuiper/ICweights")
library(ICweights)
?IC.weights
```

- Extension AIC for order-restricted hypotheses (GORIC and GORICA).

```
library(restriktor)
library(goric)
```

Outline of this lecture

IC

AIC in R

IC weights

GORICA in R

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Why information criteria?

Why do we need information criteria?

- to compare **non-nested** models.
- to compare **more than two** models at the time.
- because there are **different ideas** about what poses a good model.

Model selection using information criteria

Describe data as good as possible (fit)
with least amount of parameters (simplicity / non-complexity).

General form of information criteria:

model misfit + model complexity

Model with the **smallest value** is considered the best model.

AIC

IC = **model misfit** + **model complexity**

AIC: minimize the **Kullback-Leibler distance**

$$\textbf{AIC} = -2 \log f(y|\hat{\theta}_y) + 2p$$

where $\hat{\theta}_y$ is the maximum likelihood estimate.

Intermezzo: Kullback-Leibler (K-L) distance

The K-L distance quantifies the distance between

- the **truth**: $p(\cdot)$
- the **model under consideration**: $f(\cdot|\theta)$

Extra:

$$\text{K-L} = \mathrm{E}_{p(y)}\Big[\log p(y) - \log f(y|\theta)\Big]$$

Alternative to AIC: BIC

$$IC = \textbf{model misfit} + \textbf{model complexity}$$

BIC: maximize the **marginal model probability** (cf. Bayes Factor)

$$\textbf{BIC} = -2\log f(y|\hat{\theta}_y) + \log(n)p$$

where $\hat{\theta}_y$ is the maximum likelihood estimate.

Note:

Difference in penalty AIC vs BIC: $2p$ vs $\log(n)p$.
(due to different derivation)

Order-restricted generalization of AIC: GORIC

$$IC = \textbf{model misfit} + \textbf{model complexity}$$

GORIC: minimize the **K-L distance**

$$\textbf{GORIC} = -2\log f(y|\tilde{\theta}_y) + 2PT$$

where $\tilde{\theta}_y$ is the order-restricted maximum likelihood estimate and PT can be seen as the expected number of distinct parameters.

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.

Intermezzo: Idea penalty (PT)

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 (not parsimonious).

GORIC Approximation: GORICA

IC = **model misfit** + **model complexity**

GORICA: Approximate GORIC, thus minimize the **K-L distance**

$$\textbf{GORICA} = -2\log f(\hat{\theta}, \hat{\Sigma}_\theta | \tilde{\theta}) + 2PT$$

where

- $\hat{\theta}$ are the parameters of the unconstrained model,
- $\hat{\Sigma}_\theta$ is the variance matrix of $\hat{\theta}$,
- $\tilde{\theta}$ is the order-restricted maximum likelihood estimate, and
- PT can be seen as the expected number of distinct parameters.

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.

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GORICA vs GORIC

Similarities with GORIC:

- Form: -2 *fit* $+\, 2$ *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 models.
  Disadvantage: might work less well in case of small samples.
- Does not need data set, but mle's and their covariance matrix.
- Can leave out nuisance parameters (i.e., not part of hypotheses).
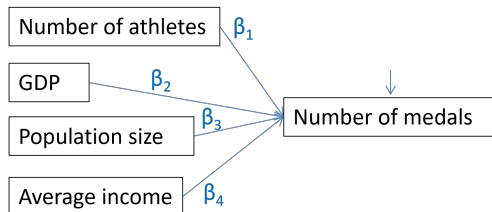
Note:
In case of normal linear models and/or not too small samples:
GORICA weights = GORIC weights.

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Why GORIC and GORICA?

Most researchers have a-priori "order-restricted" / "informative" / "theory-based" hypotheses, e.g.:

$H_1 : \mu_1 > \mu_2 > \mu_3$ (in an ANOVA model) or
$H_1 : \beta_1 > \beta_2 > \beta_3 > \beta_4$ (in a regression/SEM model).

Note on comparable estimates

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 including "unconstrained" hypothesis

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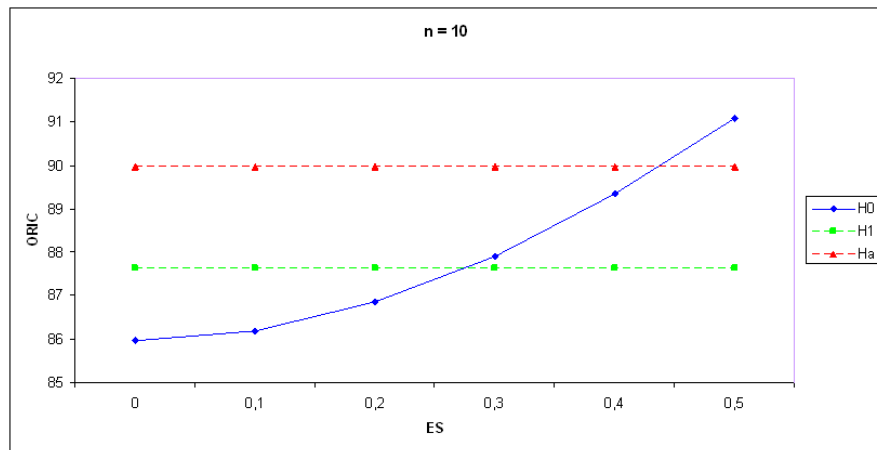Select the best of set of weak hypotheses.

Prevent choosing a weak hypothesis
by including unconstrained hypothesis H_u (or H_a):

$$H_0 : \qquad \mu_1 = \mu_2 = \mu_3,$$
$$H_1 : \qquad \mu_1 > \mu_2 > \mu_3,$$
$$H_u : \qquad \mu_1, \mu_2, \mu_3,$$
$$\qquad\qquad (\text{i.e., } no\ restrictions).$$

H_u highest fit but also most complex, thus failsafe.

Note: GORIC for H_0 and H_u equals AIC value.

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

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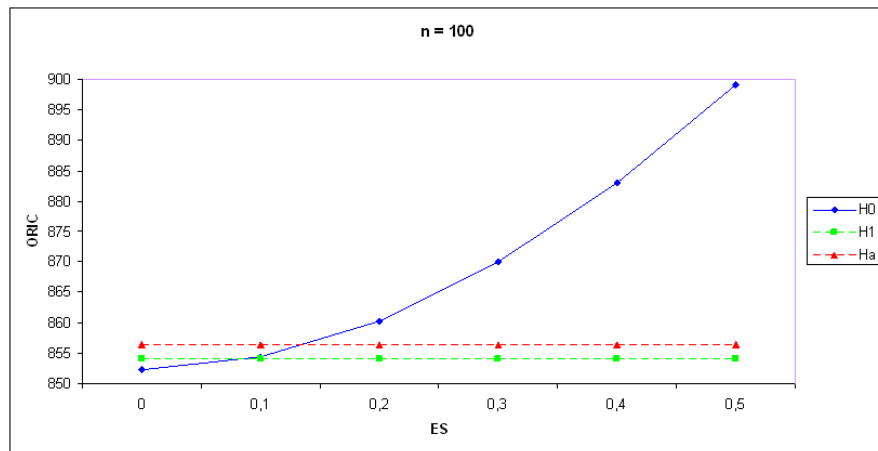
Note on hypotheses

1. Only include hypotheses with sound theoretical and/or empirical basis.
   Note: Often a null hypothesis is not of interest.

2. Keep the number of hypotheses included as small as possible.

3. This is indeed a subjective endeavor, aim for inter-peer / inter-subjective agreement.

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Example: Multigroup regression

Regression example from lab meeting 'Intro and regression' and 'Multigroup analysis' lecture:

- Outcome: sw
- Predictors: overt and covert
- Group: gender (males and females)

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Example: Multigroup regression - data

```
# Data
data_regr <- read.table("popular_regr.txt", header = T)

data_regr[sapply(data_regr, function(x)
          as.character(x) %in% c("-99", "-999") )] <- NA

data_regr$gender <- factor(data_regr$gender,
                           labels = c("male", "female"))
```

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Example: Multigroup regression - model specification

```
# Model specification

# Model 1
model.MGregr <- '
  sw ~ overt + covert # regression
  sw ~~ sw            # residual variance
  sw ~ 1              # intercept
'

# Model 2
model.MGregr_equal <- '
  # model with labeled parameters
  sw ~ c(b1,b1)*overt + c(b2,b2)*covert
  sw ~~ sw
  sw ~ 1
'
```

Example: Multigroup regression - fitting model

```
# Fit model

# Model 1
fit_MGregr <- lavaan(model = model.MGregr,
                     data = data_regr,
                     group = "gender") # multigroup

# Model 2
fit_MGregr_equal <- lavaan(model = model.MGregr_equal,
                     data = data_regr,
                     group = "gender") # multigroup
```

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Example: Multigroup regression - Alternative specification

```
model.MGregr_unequal <- '
  # model with labeled parameters
  sw ~ c(b1_m,b1_f)*overt + c(b2_m,b2_f)*covert
  sw ~~ sw
  sw ~ 1
'

# Model 1
fit_MGregr <- lavaan(model = model.MGregr_unequal,
                     data = data_regr,
                     group = "gender") # multigroup

# Model 2
fit_MGregr_equal <- lavaan(model = model.MGregr_unequal,
                     data = data_regr,
                     group = "gender", # multigroup
                     constraints = c("b1_m == b1_f;
                                      b2_m == b2_f"))
```

Example: Multigroup regression - model comparison

```
# Compare models,
# i.e., evaluate equality of regression coefficients,
# using AIC

#anova(fit_MGregr, fit_MGregr_equal)[1:2]
# or
AIC(fit_MGregr, fit_MGregr_equal)

##                   df      AIC
## fit_MGregr         8 2319.833
## fit_MGregr_equal   6 2316.868
```

Model with equality constraints has lowest AIC, so is preferred.
But how much?

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Example: Multigroup regression - model comparison

AIC for n = 100 vs n = 1491:

```
round(AIC_n, 3)

##                      AIC_n100 AIC_n1491
## fit_MGregr            125.170   2319.833
## fit_MGregr_equal      124.309   2316.868
## abs. diff.              0.861      2.965
```

AIC increases with sample size.
Absolute difference in AIC values also increases.

Model with equality constraints has lowest AIC, so is preferred.
But how much?

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IC vs IC weights

IC values:
Cannot be interpreted, only compared: smallest is best.

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

Extra:
$w_m = \frac{exp(-0.5 \ IC_m)}{\sum_{m'=1}^{M} exp(-0.5 \ IC_{m'})}$.

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.

IC weights: Another interpretation

Say, $w_m/w_{m'} = 5$.

Possible interpretation in terms of betting odds:

- If I'm in favor of H_m and I'm correct,
  you give me 1 Euro.
- If I'm in favor of H_m and I'm wrong (i.e., $H_{m'}$ is correct),
  I give you 5 Euros.

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GORIC weights vs BF and PMPs

For those familiar with or interested in Bayesian model selection:

$w_m/w_{m'}$ = relative weight $\sim$ Bayes factor ($BF_{mm'}$).

$w_m \sim$ posterior model probability (PMP).

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IC weights: Illustration in R

```r
library(devtools) # Make sure you have Rtools
install_github("rebeccakuiper/ICweights")
#
library(ICweights)
#?IC.weights
```

```r
# AIC weights
AICvalues <- AIC(fit_MGregr, fit_MGregr_equal)$AIC
Hypo.names <- c("Unc", "Equal")
#summary(IC.weights(AICvalues, Hypo.names))
IC.weights(AICvalues, Hypo.names)

##
## Per hypothesis/model, the information criterion value (IC), its weight (IC.w
##
##         IC   IC.weights ratio.IC.weights.vs.Unc ratio.IC.weights.vs.Equal
## Unc   2320  0.185       1.0                      0.227
## Equal 2317  0.815       4.4                      1.000
```

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IC weights: Illustration in R Ctd.

```
# AIC weights
IC.weights(AICvalues, Hypo.names)$IC.weights

##       Unc      Equal
## 0.1850568 0.8149432

IC.weights(AICvalues, Hypo.names)$ratio.IC.weights

##          vs Unc   vs Equal
## Unc    1.000000  0.2270794
## Equal  4.403746  1.0000000
```

H_{Equal} is $.815/.185 \approx 4.4 > 1$ times more supported than H_{Unc}.
Thus, there is quite some evidence that H_{Equal} is the best of this set.

Repition: Note on comparable estimates

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.

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Note on comparable estimates in lavaan

Default lavaan (and Mplus)

Unstandardized estimates.

Standardized estimates

Can obtain them, e.g.: summary(fit, standardized = TRUE)
but cannot do tests or model selection on them.

Solutions

− Standardize your data first.
− Use GORICA weights.

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GORICA in R

```
# Option 1 - used in this course
if (!require("restriktor")) install.packages("restriktor")
library(restriktor)
#
#goric(fitted.lavaan.model, H_1, H_2, ..., H_M,
#       standardized = TRUE)
#
#type = "gorica" # default in case of fitted lavaan model
#comparison = "complement" # will be discussed later

# Option 2
if (!require("gorica")) install.packages("gorica")
library(gorica)
#?gorica
```

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Example: Multigroup regression - model

```
# Model specification: Unconstrained model
model.MGregr_unequal <- '
  # model with labeled parameters
  sw ~ c(b1_m,b1_f)*overt + c(b2_m,b2_f)*covert
  sw ~~ sw
  sw ~ 1
'

# Fit model: Unconstrained model
fit_MGregr <- lavaan(model = model.MGregr_unequal,
                     data = data_regr,
                     group = "gender") # multigroup
```

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Extra: GORICA as AIC proxy

```
H_AIC <- "abs(b1_m) = abs(b1_f);  abs(b2_m) = abs(b2_f)"


#On unstandardized estimates, as done by default in lavaan:
set.seed(100)
results_MGregr_AIC_Unstand <- goric(fit_MGregr, H_AIC)
results_MGregr_AIC_Unstand$result$gorica.weights

## [1] 0.8149104 0.1850896

# Same as for AIC obtained via lavaan


#On standardized estimates
set.seed(100)
results_MGregr_AIC_Stand <- goric(fit_MGregr, H_AIC,
                                  standardized = T)
results_MGregr_AIC_Stand$result$gorica.weights

## [1] 0.8102574 0.1897426
```

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Example: Multigroup regression - hypothesis

```
H1 <- "abs(b1_m) > abs(b1_f);  abs(b2_m) < abs(b2_f)"
```

Remark: I assume we want to compare the absolute strength.

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Example: Multigroup regression - model comparison

```
set.seed(100)
results_MGregr <- goric(fit_MGregr, H1, standardized = T)
#summary(results_MGregr)
results_MGregr$result

##              model    loglik  penalty    gorica gorica.weights
## 1              H1 10.26185 3.195804 -14.13209      0.6908713
## 2 unconstrained 10.26185 4.000000 -12.52370      0.3091287

results_MGregr$ratio.gw

##                    vs. H1 vs. unconstrained
## H1            1.0000000          2.234899
## unconstrained 0.4474475          1.000000
```

H_1 is $.691/.309 \approx 2.235 > 1$ times more supported than H_{Unc}.
Thus, there is some evidence that H_1 is the best of this set.
Note that H_{Unc} includes the true hypothesis...

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Alternative safeguard: Complement of H_m

Until now

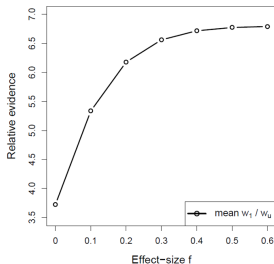Prevent choosing weak hypothesis, include unconstrained hypothesis (H_u).

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

Alternative safeguard: Complement of H_m

Alternatively (in case of one hypothesis of interest)

Evaluate hypothesis of interest against its complement.

More powerful than against the unconstrained
if H_m has maximum fit (which can lead to an upper bound for the
GORIC weights).

Reference:
Vanbrabant, L., Van Loey, N., & 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

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AIC in R
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IC weights
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GORICA in R
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Complement
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Extra
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The end
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Alternative safeguard: Complement of H_m
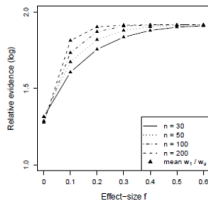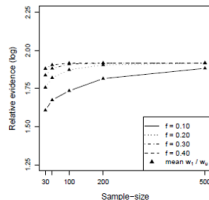
vs complement
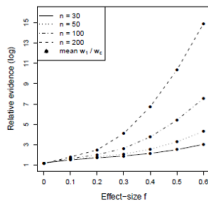
(a)
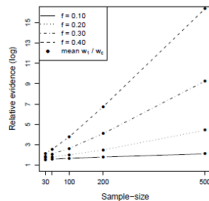
(b)

vs unconstrained

(c)

(d)

Note: 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_u, you choose H_m 'sooner' because of low penalty for H_m.

Example: Multigroup regression - model comparison

```
set.seed(100)
results_MGregr_compl <- goric(fit_MGregr, H1,
                              comparison = "complement",
                              standardized = T)
#summary(results_MGregr_compl)
results_MGregr_compl$result

##          model     loglik  penalty    gorica gorica.weights
## 1           H1  10.261849 3.195804 -14.13209      0.6219892
## 2 complement   9.872241 3.304196 -13.13609      0.3780108

results_MGregr_compl$ratio.gw[1,2]

## [1] 1.645427
```

H_1 is $.622/.378 \approx 1.645$ times more supported than its complement.
Thus, there is only little evidence that H_1 is the best of this set.
I would now explore for a competing hypothesis for next research...

Use of unconstrained and complement

In case of 1 hypothesis of interest:
Use the complement.
It acts as another competing (non-overlapping) hypothesis.

In case of 2 or more hypotheses of interest:
Use the complement of the set, but this is not yet possible in the software.
So, use the unconstrained as failsafe.
This is used to check whether at least one of the hypothesis is not weak.
Then, the non-weak hypotheses can be compared to all other.

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Contact

Websites

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

E-mail

r.m.kuiper@uu.nl

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)

Note on possibilities multiple studies

- Update hypotheses.
  First data set (or a part of it) generates one or more hypotheses.
  Then, other(s) used to determine evidence for that/those.

- Aggregate evidence for hypotheses.
  Aggregate the support for theories (diverse designs allowed).
  Note: Meta-analysis aggregates parameter estimates or effect sizes which need to be comparable.

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Summary

- IC
- AIC in R
- IC weights
- GORICA in R
- Complement

Exploratory vs confirmatory.

Thanks & How to proceed

Thanks for listening!

Are there any questions?

- Ask fellow participant on course platform.
- Ask teacher during Q&A (or via course platform).
- See if making the lab exercises help.
- Check a GORICA article or a GORICA tutorial: e.g., `https://github.com/rebeccakuiper/Tutorials`.

You can start working on the lab exercises.