Package 'gorica'

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Type Package

Title Evaluation of Inequality Constrained Hypotheses Using GORICA

Version 0.1.5

Description Implements the generalized order-restricted information criterion
approximation (GORICA), an AIC-like information criterion that can be
utilized to evaluate informative hypotheses specifying directional
relationships between model parameters in terms of (in)equality
constraints (see Altinisik, Van Lissa, Hoijtink, Oldehinkel, & Kuiper,
2021), <doi:10.31234/osf.io/t3c8g>. The GORICA is applicable not only to
normal linear models, but also to generalized linear models (GLMs),
generalized linear mixed models (GLMMs), structural equation models
(SEMs), and contingency tables. For contingency tables, restrictions on cell
probabilities can be non-linear.

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Suggests testthat, FRACTION, matrixcalc

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Contents

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academic_awards   *Academic awards data*

Description

Simulated dataset based on the UCLA Statistical Consulting Group's website.

Usage

```
data(academic_awards)
```

Format

A data frame with 200 rows and 4 variables.

Details

num_awards	integer	Outcome variable; indicates the number of awards earned by students at a high school in a year
math	integer	Continuous predictor variable; represents students' scores on their math final exam
prog	factor	Categorical predictor variable with three levels, indicating the type of program in which the studen

References

Introduction to SAS. UCLA: Statistical Consulting Group. from https://stats.oarc.ucla.edu/sas/modules/introduction-to-the-features-of-sas/ (accessed August 22, 2021).

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gorica   *Evaluate informative hypotheses using the GORICA*

Description

GORICA is an acronym for "generalized order-restricted information criterion approximation". It can be utilized to evaluate informative hypotheses, which specify directional relationships between model parameters in terms of (in)equality constraints.

Usage

```
gorica(x, hypothesis, comparison = "unconstrained", iterations = 1e+05, ...)

## S3 method for class 'lavaan'
gorica(
  x,
  hypothesis,
  comparison = "unconstrained",
  iterations = 1e+05,
  ...,
  standardize = FALSE
)

## S3 method for class 'table'
gorica(x, hypothesis, comparison = "unconstrained", ...)
```

Arguments

x   An R object containing the outcome of a statistical analysis. Currently, the following objects can be processed:

- `lm()` objects (anova, ancova, multiple regression).
- `t_test()` objects.
- `lavaan` objects.
- `lmerMod` objects.
- A named vector containing the estimates resulting from a statistical analysis, when the argument `Sigma` is also specified. Note that, named means that each estimate has to be labeled such that it can be referred to in `hypotheses`.

hypothesis   A character string containing the informative hypotheses to evaluate (see Details).

comparison   A character string indicating what the `hypothesis` should be compared to. Defaults to `comparison = "unconstrained"`; options include `c("unconstrained", "complement", "none")`.

iterations   Integer. Number of samples to draw from the parameter space when computing the `gorica` penalty.

...   Additional arguments passed to the internal function `compare_hypotheses`.

standardize   Logical. For `lavaan` objects, whether or not to extract the standardized model coefficients. Defaults to `FALSE`.

Details

The GORICA is applicable to not only normal linear models, but also applicable to generalized linear models (GLMs) (McCullagh & Nelder, 1989), generalized linear mixed models (GLMMs) (McCullogh & Searle, 2001), and structural equation models (SEMs) (Bollen, 1989). In addition, the GORICA can be utilized in the context of contingency tables for which (in)equality constrained hypotheses do not necessarily contain linear restrictions on cell probabilities, but instead often contain non-linear restrictions on cell probabilities.

`hypotheses` is a character string that specifies which informative hypotheses have to be evaluated. A simple example is `hypotheses <- "a > b > c; a = b = c;"` which specifies two hypotheses using three estimates with names "a", "b", and "c", respectively.

The hypotheses specified have to adhere to the following rules:

1. Parameters are referred to using the names specified in `names()`.
2. Linear combinations of parameters must be specified adhering to the following rules:
   (a) Each parameter name is used at most once.
   (b) Each parameter name may or may not be pre-multiplied with a number.
   (c) A constant may be added or subtracted from each parameter name.
   (d) A linear combination can also be a single number.

   Examples are: `3 * a + 5; a + 2 * b + 3 * c - 2; a - b;` and `5`.
3. (Linear combinations of) parameters can be constrained using `<`, `>`, and `=`. For example, `a > 0` or `a > b = 0` or `2 * a < b + c > 5`.
4. The ampersand `&` can be used to combine different parts of a hypothesis. For example, `a > b & b > c` which is equivalent to `a > b > c` or `a > 0 & b > 0 & c > 0`.
5. Sets of (linear combinations of) parameters subjected to the same constraints can be specified using (). For example, `a > (b,c)` which is equivalent to `a > b & a > c`.
6. The specification of a hypothesis is completed by typing `;` For example, `hypotheses <- "a > b > c; a = b = c;"`, specifies two hypotheses.
7. Hypotheses have to be compatible, non-redundant and possible. What these terms mean will be elaborated below.

The set of hypotheses has to be compatible. For the statistical background of this requirement see Gu, Mulder, Hoijtink (2018). Usually the sets of hypotheses specified by researchers are compatible, and if not, `gorica` will return an error message. The following steps can be used to determine if a set of hypotheses is compatible:

1. Replace a range constraint, e.g., `1 < a1 < 3`, by an equality constraint in which the parameter involved is equated to the midpoint of the range, that is, `a1 = 2`.
2. Replace in each hypothesis the `<` and `>` by `=`. For example, `a1 = a2 > a3 > a4` becomes `a1 = a2 = a3 = a4`.
3. The hypotheses are compatible if there is at least one solution to the resulting set of equations. For the two hypotheses considered under 1. and 2., the solution is `a1 = a2 = a3 = a4 = 2`. An example of two non-compatible hypotheses is `hypotheses <- "a = 0; a > 2;"` because there is no solution to the equations `a=0` and `a=2`.

Each hypothesis in a set of hypotheses has to be non-redundant. A hypothesis is redundant if it can also be specified with fewer constraints. For example, a = b & a > 0 & b > 0 is redundant because it can also be specified as a = b & a > 0. gorica will work correctly if hypotheses specified using only < and > are redundant. gorica will return an error message if hypotheses specified using at least one = are redundant.

Each hypothesis in a set of hypotheses has to be possible. An hypothesis is impossible if estimates in agreement with the hypothesis do not exist. For example: values for a in agreement with a = 0 & a > 2 do not exist. It is the responsibility of the user to ensure that the hypotheses specified are possible. If not, gorica will either return an error message or render an output table containing Inf's.

Value

An object of class gorica, containing the following elements:

- fit A data.frame containing the loglikelihood, penalty (for complexity), the GORICA value, and the GORICA weights. The GORICA weights are calculated by taking into account the misfits and complexities of the hypotheses under evaluation. These weights are used to quantify the support in the data for each hypothesis under evaluation. By looking at the pairwise ratios between the GORICA weights, one can determine the relative importance of one hypothesis over another hypothesis.

- call The original function call.

- model The original model object (x).

- estimates The parameters extracted from the model.

- Sigma The asymptotic covariance matrix of the estimates.

- comparison Which alternative hypothesis was used.

- hypotheses The hypotheses evaluated in fit.

- relative_weights The relative weights of each hypothesis (rows) versus each other hypothesis in the set (cols). The diagonal is equal to one, as each hypothesis is equally likely as itself. A value of, e.g., 6, means that the hypothesis in the row is 6 times more likely than the hypothesis in the column.

Contingency tables

When specifying hypotheses about contingency tables, the asymptotic covariance matrix of the model estimates is derived by means of bootstrapping. This makes it possible for users to define derived parameters: For example, a ratio between cell probabilities. For this purpose, the bain syntax has been enhanced with the command :=. Thus, the syntax "a := x[1,1]/(x[1,1]+x[1,2])" defines a new parameter a by reference to specific cells of the table x. This new parameter can now be named in hypotheses.

Author(s)

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References

Altinisik, Y., Van Lissa, C. J., Hoijtink, H., Oldehinkel, A. J., & Kuiper, R. M. (2021). Evaluation of inequality constrained hypotheses using a generalization of the AIC. Psychological Methods, 26(5), 599–621. doi:10.31234/osf.io/t3c8g.

Bollen, K. (1989). Structural equations with latent variables. New York, NY: John Wiley and Sons.

Kuiper, R. M., Hoijtink, H., & Silvapulle, M. J. (2011). An Akaike-type information criterion for model selection under inequality constraints. Biometrika, 98, 495-501. doi:10.31219/osf.io/ekxsn

Kuiper, R. M., Hoijtink, H., & Silvapulle, M. J. (2012). Generalization of the order-restricted information criterion for multivariate normal linear models. Journal of statistical planning and inference, 142(8), 2454-2463. doi:10.1016/j.jspi.2012.03.007

Vanbrabant, L., Van Loey, N., and Kuiper, R.M. (2019). Evaluating a theory-based hypothesis against its complement using an AIC-type information criterion with an application to facial burn injury. Psychological Methods. doi:10.31234/osf.io/n6ydv

McCullagh, P. & Nelder, J. (1989). Generalized linear models (2nd ed.). Boca Raton, FL: Chapman & Hall / CRC.

McCulloch, C. E., & Searle, S. R. (2001). Generalized linear and mixed models. New York, NY: Wiley.

Examples

```
# EXAMPLE 1. One-sample t test
ttest1 <- t_test(iris$Sepal.Length,mu=5)
gorica(ttest1,"x<5.8")

# EXAMPLE 2. ANOVA
aov1 <- aov(yield ~ block-1 + N * P + K, npk)
gorica(aov1,hypothesis="block1=block5;
   K1<0")

# EXAMPLE 3. glm
counts <- c(18,17,15,20,10,20,25,13,12)
outcome <- gl(3,1,9)
treatment <- gl(3,3)
fit <- glm(counts ~ outcome-1 + treatment, family = poisson())
gorica(fit, "outcome1 > (outcome2, outcome3)")

# EXAMPLE 4. ANOVA
res <- lm(Sepal.Length ~ Species-1, iris)
est <- get_estimates(res)
est
gor <- gorica(res, "Speciessetosa < (Speciesversicolor, Speciesvirginica)",
comparison = "complement")
gor
```

hox_2010 *Sesame Street data based on Hox (2010)*

Description

Synthetic data based on Hox (2010, p. 16). In the study, the outcome variable popular represents the popularity score of pupils, ranging from 0 (very unpopular) to 10 (very popular), for pupils nested in 100 classes of varying size. The popularity scores are predicted by pupil level predictors gender (G) and pupil extroversion scores (PE) that range from 1 (introversion) to 10 (extroversion), a class-level predictor teacher experience (TE), and the cross-level interactions between G and TE as well as PE and TE. Since standardization is recommended when the model contains interactions, we standardize PS, PE and TE by means of grand mean centering. That is, we first subtract the overall means of the continuous variables PS, PE, and TE from each of their values, before dividing these values by their standard deviations.

Usage

```
data(hox_2010)
```

Format

A data frame with 2000 rows and 6 variables.

Details

ID	integer	Pupil ID
class	integer	Class ID
PE	numeric	Pupil extroversion, standardized
G	factor	Pupil sex
PS	numeric	Popularity scores, standardized
TE	integer	Teacher experience, standardized

References

Hox, J. J. (2010). Multilevel analysis: Techniques and applications (2nd ed.). New York, NY: Routledge.

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nederhof_2014   *Data based on Nederhof, Ormel, and Oldehinkel (2014)*

Description

Synthetic data, (N = 310) based on Nederhof, Ormel, and Oldehinkel (2014). The 11 years old participants are divided into three groups: Sustainers, Shifters, and Comparison group, based on their performance on a sustained-attention task and on a shifting-set task. The outcome depressive episode (D: no depressive episode, versus experienced an episode) is predicted by the categorical variable early life stress (ES: Low versus High), the standardized continuous variable recent stress, RS, and the interaction between both predictors. The continuous variable recent stress, RS, is standardized to improve the interpretation of main effects when interactions exist.

Usage

```
data(nederhof_2014)
```

Format

A data frame with 310 rows and 4 variables.

Details

Groups	factor	Group membership
RS	numeric	Recent stress
ES	Factor	Early life stress
D	Factor	Experienced a depressive episode

References

Nederhof, E., Ormel, J., & Oldehinkel, A. J. (2014). Mismatch or cumulative stress: The pathway to depression is conditional on attention style. Psychological Science, 25, 684-692. doi:10.1177/0956797613513473.

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reading_ach   *Reading achievement data*

Description

Dataset based on Finch, Bolin, and Kelley (2014, p.32).

Usage

```
data(reading_ach)
```

Format

A data frame with 10320 rows and 5 variables.

Details

school	integer	Clustering variable representing the school a given participant was enrolled in
gender	factor	Binary factor variable representing participants' assigned sex
age	integer	Participants' age in months
geread	numeric	Reading achievement
gevocab	numeric	Vocabulary

References

Finch, W. H., Bolin, J. E., & Kelley, K. (2014). Multilevel modeling using r. CRC Press 2014.

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school_admissions   *High School Admissions Data*

Description

This dataset, provided by the UCLA Statistical Consulting Group (2021), contains information on factors that influence whether or not a high school senior is admitted into a very competitive engineering school. The dataset includes the following variables:

Usage

```
data(school_admissions)
```

Format

A data frame with 30 rows and 3 variables.

Details

female	binary	Binary variable indicating the gender of the student.
apcalc	binary	Binary variable indicating whether or not the student took Advanced Placement calculus in high school.
admit	binary	Binary outcome variable indicating admission status, where 1 represents admission and 0 represents non-a

The dataset is used for exact logistic regression analysis due to the binary outcome variable. It aims to identify the factors that contribute to admission decisions in a highly competitive engineering school. Since the dataset has a small sample size, specialized procedures are required for accurate estimation.

References

Introduction to SAS. UCLA: Statistical Consulting Group. from https://stats.oarc.ucla.edu/sas/modules/introduction-to-the-features-of-sas/ (accessed August 22, 2021).

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stevens_1999	*Sesame Street data based on Stevens (1999)*

Description

Synthetic data based Stevens (1999, p. 596). This study evaluates the effects of the first year of the Sesame Street television series in a sample of 3-5 years old children in the USA (N = 240).

Usage

```
data(stevens_1999)
```

Format

A data frame with 240 rows and 14 variables.

Details

age	numeric	Age in months
prebody	numeric	Pretest on knowledge of body parts
prelet	numeric	Pretest on knowledge of letters
preform	numeric	Pretest on knowledge of forms
prenumb	numeric	Pretest on knowledge of numbers
prerelat	numeric	Pretest on knowledge of relational terms
preclas	numeric	Pretest on classification skills
postbody	numeric	Posttest on knowledge of body parts
postlet	numeric	Posttest on knowledge of letters
postform	numeric	Posttest on knowledge of forms
postnumb	numeric	Posttest on knowledge of numbers
postrelat	numeric	Posttest on knowledge of relational terms
postclas	numeric	Posttest on classification skills
peabody	numeric	Mental age score obtained from the Peabody Picture Vocabulary test

References

Stevens, J. (1999). Applied multivariate statistics for the social sciences. (3rd ed.). New Jersey, Lawrance Erlbaum Associates, Inc.

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wechsler *Wechsler intelligence test data*

Description

Dataset based on McArdle and Prescott (1992, p.90). This study evaluates intelligence and cognitive ability in a sample of individuals over 18 years of age (N = 1680) using the IQ test Wechsler Adult Intelligence Scale-Revised (WAIS-R) (Wechsler, 1981).

Usage

```
data(wechsler)
```

Format

A data frame with 1680 rows and 10 variables.

Details

age	integer	Participants' age (recoded)
edc	factor	Whether a participant graduated high school or not (1 = not graduated, 2 = graduated)
y1	integer	information; general knowledge of participants
y2	integer	comprehension; ability of abstract reasoning or judgment
y3	integer	similarities; unifying a theme
y4	integer	vocabulary; verbal definition
y5	integer	picture completion; perceiving visual images with missing features
y6	integer	block design; arranging blocks to match a design
y7	integer	picture arrangement; ordering cards with true story lines
y8	integer	object assembly; reassembling puzzles

References

McArdle, J. J., & Prescott, C. A. (1992). Age-based construct validation using structural equation modeling. Experimental Aging Research, 18, 87-115.

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