Package ‘MuMIn’

February 24, 2022

Type Package
Title Multi-Model Inference
Version 1.46.0
Date 2022-02-23
Encoding UTF-8
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Description Tools for performing model selection and model averaging. Automated model selection through subsetting the maximum model, with optional constraints for model inclusion. Model parameter and prediction averaging based on model weights derived from information criteria (AICc and alike) or custom model weighting schemes.
License GPL-2
Depends R (>= 3.5.0)
Imports graphics, methods, Matrix, stats, stats4, nlme
Suggests lme4 (>= 1.1.0), mgcv (>= 1.7.5), gamm4, MASS, nnet, survival (>= 3.1.0), geepack
Enhances aod, aods3, betareg, caper, coxme, cplm, gee, glmmML, logistf, MCMCgamm, ordinal, pscl, spdep, spatialreg, splm, unmarked (>= 0.12.2), geeM (>= 0.7.5), gamlss
LazyData yes
ByteCompile yes
Repository CRAN
Repository/R-Forge/Project mumin
Repository/R-Forge/Revision 488
Repository/R-Forge/DateTimeStamp 2022-02-24 09:44:44
Date/Publication 2022-02-24 11:30:02 UTC
NeedsCompilation no

1
R topics documented:

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Description

The package MuMIn contains functions to streamline the information-theoretic model selection and carry out model averaging based on information criteria.

Details

The collection of functions includes:

- **dredge** performs an automated model selection with subsets of the supplied ‘global’ model and optional choices of other model properties (such as different link functions). The set of models can be generated with ‘all possible’ combinations or tailored according to the conditions specified.
- **model.sel** creates a model selection table from selected models.
- **model.avg** calculates model-averaged parameters, along with standard errors and confidence intervals. Furthermore, the **predict** method produces model-averaged predictions.
- **AICc** calculates the second-order Akaike information criterion. Some other criteria are provided, see below.
- **stdize**, **stdizeFit**, **std.coef**, **partial.sd** can be used to standardise data and model coefficients by Standard Deviation or Partial Standard Deviation.

For a complete list of functions, use `library(help = "MuMIn")`.

By default, AICc is used to rank the models and obtain model weights, although any other information criteria can be used. At least the following ones are currently implemented in R: AIC and BIC in package **stats**, and QAIC, QAICc, ICOMP, CAICF, and Mallows’ Cp in MuMIn. There is also a DIC extractor for MCMC models, and a QIC for GEE.

Most of common modelling functions in R are supported. For a full listing, see the list of supported models.

In addition to the “regular” information criteria, model averaging can be performed using various types of model weighting algorithms: Bates-Granger, bootstrapped, cos-squared, jackknife, stacking, or ARM. These weighting functions are mainly applicable to g1ms.

Author(s)

Kamil Bartoń

References


See Also

AIC, step or stepAIC for stepwise model selection by AIC.
Examples

```r
options(na.action = "na.fail") # change the default "na.omit" to prevent models # from being fitted to different datasets in # case of missing values.
fm1 <- lm(y ~ ., data = Cement)
ms1 <- dredge(fm1)

# Visualize the model selection table:
par(mar = c(3,5,6,4))
plot(ms1, labAsExpr = TRUE)
model.avg(ms1, subset = delta < 4)
confset.95p <- get.models(ms1, cumsum(weight) <= .95)
avgmod.95p <- model.avg(confset.95p)
summary(avgmod.95p)
confint(avgmod.95p)
```

---

**AICc**

*Second-order Akaike Information Criterion*

**Description**

Calculate Second-order Akaike Information Criterion for one or several fitted model objects (AICc, AIC for small samples).

**Usage**

```r
AICc(object, ..., k = 2, REML = NULL)
```

**Arguments**

- `object`: a fitted model object for which there exists a `logLik` method, or a "logLik" object.
- `...`: optionally more fitted model objects.
- `k`: the ‘penalty’ per parameter to be used; the default k = 2 is the classical AIC.
- `REML`: optional logical value, passed to the `logLik` method indicating whether the restricted log-likelihood or log-likelihood should be used. The default is to use the method used for model estimation.

**Value**

If just one object is provided, returns a numeric value with the corresponding AICc; if more than one object are provided, returns a `data.frame` with rows corresponding to the objects and columns representing the number of parameters in the model (df) and AICc.
**AICc**

**Note**

AICc should be used instead AIC when sample size is small in comparison to the number of estimated parameters (Burnham & Anderson 2002 recommend its use when $n/K < 40$).

**Author(s)**

Kamil Bartoń

**References**


**See Also**

Akaike’s An Information Criterion: AIC

Other implementations: AICc in package AICcmodavg, AICc in package bbmle and aicc in package glmulti

**Examples**

```r
# Model-averaging mixed models
options(na.action = "na.fail")
data(Orthodont, package = "nlme")

# Fit model by REML
fm2 <- lme(distance ~ Sex*age, data = Orthodont,
    random = ~ 1|Subject / Sex, method = "REML")

# Model selection: ranking by AICc using ML
ms2 <- dredge(fm2, trace = TRUE, rank = "AICc", REML = FALSE)

(attr(ms2, "rank.call"))

# Get the models (fitted by REML, as in the global model)
fmList <- get.models(ms2, 1:4)

# Because the models originate from 'dredge(..., rank = AICc, REML = FALSE)',
# the default weights in 'model.avg' are ML based:
summary(model.avg(fmList))

## Not run:
# the same result:
model.avg(fmList, rank = "AICc", rank.args = list(REML = FALSE))

## End(Not run)
```
Description

Combine all-subsets GLMs using the ARM algorithm. Calculate ARM weights for a set of models.

Usage

arm.glm(object, R = 250, weight.by = c("aic", "loglik"), trace = FALSE)

armWeights(object, ..., data, weight.by = c("aic", "loglik"), R = 1000)

Arguments

object for arm.glm, a fitted “global” glm object. For armWeights, a fitted glm object,
or a list of such, or an “averaging” object.

... more fitted model objects.

R number of permutations.

weight.by indicates whether model weights should be calculated with AIC or log-likelihood.

trace if TRUE, information is printed during the running of arm.glm.

data a data frame in which to look for variables for use with prediction. If omitted,
the fitted linear predictors are used.

Details

For each of all-subsets of the “global” model, parameters are estimated using randomly sampled half
of the data. Log-likelihood given the remaining half of the data is used to calculate AIC weights.
This is repeated R times and mean of the weights is used to average all-subsets parameters estimated
using complete data.

Value

arm.glm returns an object of class "averaging" containing only “full” averaged coefficients. See
model.avg for object description.

armWeights returns a numeric vector of model weights.

Note

Number of parameters is limited to floor(nobs(object) / 2) – 1. All-subsets respect marginality
constraints.

Author(s)

Kamil Bartoń
Beetle

References


See Also

`model.avg, par.avg`

Weights for assigning new model weights to an “averaging” object.

Other implementation of ARM algorithm: `arms` in (archived) package `MMIX`.

Other kinds of model weights: `BGWeights, bootWeights, cos2Weights, jackknifeWeights, stackingWeights`.

Examples

```r
fm <- glm(y ~ X1 + X2 + X3 + X4, data = Cement)

summary(am1 <- arm.glm(fm, R = 15))

mst <- dredge(fm)

am2 <- model.avg(mst, fit = TRUE)

Weights(am2) <- armWeights(am2, data = Cement, R = 15)

# differences are due to small R:
coef(am1, full = TRUE)
coef(am2, full = TRUE)
```

---

**Beetle**  
*Flour beetle mortality data*

**Description**

Mortality of flour beetles (*Tribolium confusum*) due to exposure to gaseous carbon disulfide CS$_2$, from Bliss (1935).

**Usage**

Beetle
**Format**

Beetle is a data frame with 5 elements.

- **Prop** a matrix with two columns named *nkilled* and *nsurvived*
- **mortality** observed mortality rate
- **dose** the dose of CS$_2$ in mg/L
- **n.tested** number of beetles tested
- **n.killed** number of beetles killed.

**Source**


**References**


**Examples**

```r
# "Logistic regression example"
# from Burnham & Anderson (2002) chapter 4.11
# Fit a global model with all the considered variables

globmod <- glm(Prop ~ dose + I(dose^2) + log(dose) + I(log(dose)^2),
                data = Beetle, family = binomial, na.action = na.fail)

# A logical expression defining the subset of models to use:
# * either log(dose) or dose
# * the quadratic terms can appear only together with linear terms
msubset <- expression(xor(dose, log(dose)) &
                       dc(dose, I(dose^2)) &
                       dc(log(dose), I(log(dose)^2)))

# Table 4.6
# Use 'varying' argument to fit models with different link functions
# Note the use of 'alist' rather than 'list' in order to keep the
# 'family' objects unevaluated
varying.link <- list(family = alist(
    logit = binomial("logit"),
    probit = binomial("probit"),
    cloglog = binomial("cloglog")
))

(ms12 <- dredge(globmod, subset = msubset, varying = varying.link,
                 rank = AIC))

# Table 4.7 "models justifiable a priori"
(ms3 <- subset(ms12, has(dose, !I(dose^2)')))```
# The same result, but would fit the models again:
# ms3 <- update(ms12, update(globmod, . ~ dose), subset =,
#  fixed = ~dose)
mod3 <- get.models(ms3, 1:3)
# Table 4.8. Predicted mortality probability at dose 40.
# calculate confidence intervals on logit scale
logit.ci <- function(p, se, quantile = 2) {
  C. <- exp(quantile * se / (p * (1 - p))
  p /(p + (1 - p) * c(C., 1/C.))
}
mavg3 <- model.avg(mod3, revised.var = FALSE)
# get predictions both from component and averaged models
pred <- lapply(c(component = mod3, list(averaged = mavg3)), predict,
newdata = list(dose = 40), type = "response", se.fit = TRUE)
# reshape predicted values
pred <- t(sapply(pred, function(x) unlist(x)[1:2]))
colnames(pred) <- c("fit", "se.fit")
# build the table
tab <- cbind(
  c(Weights(ms3), NA),
  pred,
  matrix(logit.ci(pred,"fit"), pred,"se.fit"),
  quantile = c(rep(1.96, 3), 2, ncol = 2)
)
colnames(tab) <- c("Akaike weight", "Predicted(40)", "SE", "Lower CI",
  "Upper CI")
rownames(tab) <- c(as.character(ms3$family), "model-averaged")
print(tab, digits = 3, na.print = "")
# Figure 4.3
newdata <- list(dose = seq(min(Beetle$dose), max(Beetle$dose), length.out = 25))
# add model-averaged prediction with CI, using the same method as above
avpred <- predict(mavg3, newdata, se.fit = TRUE, type = "response")
avci <- matrix(logit.ci(avpred$fit, avpred$se.fit, quantile = 2), ncol = 2)
matplot(newdata$dose, sapply(mod3, predict, newdata, type = "response",
  type = "1", xlab = quote(list("Dose of" ~ CS[2],(mg/L))),
  ylab = "Mortality", col = 2:4, lty = 3, lwd = 1)
matplot(newdata$dose, cbind(avpred$fit, avci), type = "l", add = TRUE,
  lwd = 1, lty = c(1, 2, 2), col = 1)
legend("topleft", NULL, c(as.character(ms3$family), expression(`averaged`
  %+-% CI)), lty = c(3, 3, 3, 1), col = c(2:4, 1))
**Description**

Computes empirical weights based on out of sample forecast variances, following Bates and Granger (1969).

**Usage**

`BGWeights(object, ..., data, force.update = FALSE)`

**Arguments**

- `object, ...` two or more fitted `glm` objects, or a list of such, or an "averaging" object.
- `data` a data frame containing the variables in the model.
- `force.update` if TRUE, the much less efficient method of updating `glm` function will be used rather than directly via `glm.fit`. This only applies to `glms`, in case of other model types `update` is always used.

**Details**

Bates-Granger model weights are calculated using prediction covariance. To get the estimate of prediction covariance, the models are fitted to randomly selected half of data and prediction is done on the remaining half. These predictions are then used to compute the variance-covariance between models, Σ. Model weights are then calculated as $w_{BG} = (1' \Sigma^{-1} 1)^{-1} \Sigma^{-1}$, where 1 a vector of 1-s.

Bates-Granger model weights may be outside of the [0, 1] range, which may cause the averaged variances to be negative. Apparently this method works best when data is large.

**Value**

A numeric vector of model weights.

**Note**

For matrix inversion, `MASS::ginv()` is more stable near singularities than `solve`. It will be used as a fallback if `solve` fails and `MASS` is available.

**Author(s)**

Carsten Dormann, Kamil Bartoń

**References**


**bootWeights**

**Description**

Computes model weights using bootstrap.

**Usage**

```r
bootWeights(object, ..., R, rank = c("AICc", "AIC", "BIC"))
```

**Arguments**

- `object, ...` two or more fitted `glm` objects, or a list of such, or an "averaging" object.
- `R` the number of replicates.
- `rank` a character string, specifying the information criterion to use for model ranking. Defaults to `AICc`.

**Details**

The models are fitted repeatedly to a resampled data set and ranked using AIC-type criterion. The model weights represent the proportion of replicates when a model has the lowest IC value.

**Value**

A numeric vector of model weights.
Author(s)

Kamil Bartoń, Carsten Dormann

References


See Also

Weights, model.avg
Other model weights: BGWeights(), cos2Weights(), jackknifeWeights(), stackingWeights()

Examples

```r
# To speed up the bootstrap, use `x = TRUE` so that model matrix is included
# in the returned object
fm <- glm(Prop ~ mortality + dose, family = binomial, data = Beetle,
  na.action = na.fail, x = TRUE)

fml <- lapply(dredge(fm, eval = FALSE), eval)
am <- model.avg(fml)

Weights(am) <- bootWeights(am, data = Beetle, R = 25)

summary(am)
```

Cement

*Cement hardening data*

Description

Cement hardening data from Woods et al (1932).

Usage

Cement

Format

Cement is a data frame with 5 variables. $x_1$-$x_4$ are four predictor variables expressed as a percentage of weight.

$y$ calories of heat evolved per gram of cement after 180 days of hardening

$X_1$ calcium aluminate

$X_2$ tricalcium silicate

$X_3$ tetracalcium alumino ferrite

$X_4$ dicalcium silicate.
Source

References

---

**coefplot**

*Plot model coefficients*

**Description**

Produce dot-and-whisker plot of the model(-averaged) coefficients, with confidence intervals

**Usage**

```r
c coefplot(
x, lci, uci, labels = NULL, width = 0.15, shift = 0, horizontal = TRUE, main = NULL, xlab = NULL, ylab = NULL, xlim = NULL, ylim = NULL, labAsExpr = TRUE, mar.adj = TRUE, lab.line = 0.5, lty = par("lty"), lwd = par("lwd"), pch = 21, col = par("col"), bg = par("bg"), dotcex = par("cex"), dotcol = col, staplelty = lty, staplelwd = lwd, staplecol = col, zerolty = "dotted", zerolwd = lwd, zerocol = "gray",
```

```r
```
\begin{verbatim}
las = 2,
ann = TRUE,
axes = TRUE,
add = FALSE,
type = "p",
...)

## S3 method for class 'averaging'
plot(
  x,
  full = TRUE,
  level = 0.95,
  intercept = TRUE,
  parm = NULL,
  labels = NULL,
  width = 0.1,
  shift = max(0.2, width * 2.1 + 0.05),
  horizontal = TRUE,
  xlim = NULL,
  ylim = NULL,
  main = "Model-averaged coefficients",
  xlab = NULL,
  ylab = NULL,
  add = FALSE,
  ...
)

Arguments

x either a (possibly named) vector of coefficients (for coefplot), or an “averaging” object.
lci, uci vectors of lower and upper confidence intervals. Alternatively a two-column matrix with columns containing confidence intervals, in which case uci is ignored.
labels optional vector of coefficient names. By default, names of x are used for labels.
width width of the staples (= end of whisker).
shift the amount of perpendicular shift for the dots and whiskers. Useful when adding to an existing plot.
horizontal logical indicating if the plots should be horizontal; defaults to TRUE.
main an overall title for the plot: see title.
xlab, ylab x- and y-axis annotation. Can be suppressed by ann=FALSE.
xlim, ylim optional, the x and y limits of the plot.
labAsExpr logical indicating whether the coefficient names should be transformed to expressions to create prettier labels (see plotmath)
\end{verbatim}
mar.adj logical indicating whether the (left or lower) margin should be expanded to fit the labels
lab.line margin line for the labels
lty, lwd, pch, col, bg
default line type, line width, point character, foreground colour for all elements, and background colour for open symbols.
dotcex, dotcol dots point size expansion and color.
staplelty, staplelwd, staplecol
staple line type, width, and colour.
zerolty, zerolwd, zerocol
zero-line type, line width, colour. Setting zerolty to NA suppresses the line.
las the style of labels for coefficient names. See par.
ann logical indicating if axes should be annotated (by xlab and ylab).
axes a logical value indicating whether both axes should be drawn on the plot.
add logical, if true add to current plot.
type if "n", the plot region is left empty, any other value causes the plot being drawn.
... additional arguments passed to coefplot or more graphical parameters.
full a logical value specifying whether the "full" model-averaged coefficients are plotted. If FALSE, the "subset"-averaged coefficients are plotted, and both types if NA. See model.avg.
level the confidence level required.
intercept logical indicating if intercept should be included in the plot
parm a specification of which parameters are to be plotted, either a vector of numbers or a vector of names. If missing, all parameters are considered.

Details
Plot model(-averaged) coefficients with confidence intervals.

Value
An invisible matrix containing coordinates of points and whiskers, or, a two-element list of such, one for each coefficient type in plot.averaging when full is NA.

Author(s)
Kamil Bartoń

Examples
fm <- glm(Prop ~ dose + I(dose^2) + log(dose) + I(log(dose)^2),
data = Beetle, family = binomial, na.action = na.fail)
ma <- model.avg(dredge(fm))

# default coefficient plot:
plot(ma, full = NA, intercept = FALSE)
# Add colours per coefficient type
# Replicate each colour n (= number of coefficients) times
clr <- c("black", "red2")
i <- rep(1:2, each = length(coef(ma)) - 1)
plot(ma, full = NA, intercept = FALSE,
     pch = 22, dotcex = 1.5,
     col = clr[i], bg = clr[i],
     lwd = 6, lend = 1, width = 0, horizontal = 0)

# Use `type = "n"` and `add` argument to e.g. add grid beneath the figure
plot(ma, full = NA, intercept = FALSE,
     width = 0, horizontal = FALSE, zerolty = NA, type = "n")
grid()
plot(ma, full = NA, intercept = FALSE,
     pch = 22, dotcex = 1.5,
     col = clr[i], bg = clr[i],
     lwd = 6, lend = 1, width = 0, horizontal = FALSE, add = TRUE)

---

**cos2Weights**  
*Cos-squared model weights*

### Description
Calculates cos-squared model weights, following the algorithm outlined in the appendix of Garthwaite & Mubwandarikwa (2010).

### Usage
```r
cos2Weights(object, ..., data, eps = 1e-06, maxit = 100, predict.args = list())
```

### Arguments
- **object, ...** two or more fitted `glm` objects, or a list of such, or an "averaging" object. Currently only `lm` and `glm` objects are accepted.
- **data** a test data frame in which to look for variables for use with `prediction`. If omitted, the fitted linear predictors are used.
- **eps** tolerance for determining convergence.
- **maxit** maximum number of iterations.
- **predict.args** optionally, a list of additional arguments to be passed to `predict`.

### Value
A numeric vector of model weights.

### Author(s)
Carsten Dormann, adapted by Kamil Bartoń
dredge

Automated model selection

Description

Generate a model selection table of models with combinations (subsets) of fixed effect terms in the global model, with optional model inclusion rules.

Usage

dredge(global.model, beta = c("none", "sd", "partial.sd"), evaluate = TRUE, rank = "AICc", fixed = NULL, m.lim = NULL, m.min, m.max, subset, trace = FALSE, varying, extra, ct.args = NULL, deps = attr(allTerms0, "deps"), cluster = NULL, ...)

## S3 method for class 'model.selection'
print(x, abbrev.names = TRUE, warnings = getOption("warn") != -1L, ...)

References


See Also

Weights, model.avg

Other model weights: BGWeights(), bootWeights(), jackknifeWeights(), stackingWeights()

Examples

```r
fm <- lm(y ~ X1 + X2 + X3 + X4, Cement, na.action = na.fail)
# most efficient way to produce a list of all-subsets models
models <- lapply(dredge(fm, evaluate = FALSE), eval)
ma <- model.avg(models)

test.data <- Cement
Weights(ma) <- cos2Weights(models, data = test.data)
predict(ma, data = test.data)
```
Arguments

global.model a fitted ‘global’ model object. See ‘Details’ for a list of supported types.

beta indicates whether and how the coefficients are standardized, and must be one of "none", "sd" or "partial.sd". You can specify just the initial letter. "none" corresponds to unstandardized coefficients, "sd" and "partial.sd" to coefficients standardized by SD and Partial SD, respectively. For backwards compatibility, logical value is also accepted, TRUE is equivalent to "sd" and FALSE to "none". See std.coef.

evaluate whether to evaluate and rank the models. If FALSE, a list of unevaluated calls is returned.

rank optionally, the rank function returning a sort of an information criterion, to be used instead AICc, e.g. AIC, QAIC or BIC. See ‘Details’.

fixed optional, either a single-sided formula or a character vector giving names of terms to be included in all models. See ‘Subsetting’.

m.lim, m.max, m.min optionally, the limits c(lower,upper) for the number of terms in a single model (excluding the intercept). An NA means no limit. See ‘Subsetting’. Specifying limits as m.min and m.max is allowed for backward compatibility.

subset logical expression describing models to keep in the resulting set. See ‘Subsetting’.

trace if TRUE or 1, all calls to the fitting function are printed before actual fitting takes place. If trace > 1, a progress bar is displayed.

varying optionally, a named list describing the additional arguments to vary between the generated models. Item names correspond to the arguments, and each item provides a list of choices (i.e. list(arg1 = list(choice1,choice2,...),...)). Complex elements in the choice list (such as family objects) should be either named (uniquely) or quoted (unevaluated, e.g. using alist, see quote), otherwise the result may be visually unpleasant. See example in Beetle.

extra optional additional statistics to include in the result, provided as functions, function names or a list of such (best if named or quoted). Similarly as in rank argument, each function must accept fitted model object as an argument and return (a value coercible to) a numeric vector. These can be e.g. additional information criteria or goodness-of-fit statistics. The character strings "R^2" and "adjR^2" are treated in a special way, and will add a likelihood-ratio based $R^2$ and modified-$R^2$ respectively to the result (this is more efficient than using r.squaredLR directly).

x a model.selection object, returned by dredge.

abbrev.names should printed term names be abbreviated? (useful with complex models).

warnings if TRUE, errors and warnings issued during the model fitting are printed below the table (only with pdredge). To permanently remove the warnings, set the object’s attribute "warnings" to NULL.

c.t.args optional list of arguments to be passed to coefTable (e.g. dispersion parameter for glm affecting standard errors used in subsequent model averaging).
dredge

deps a “dependency matrix” as returned by getAllTerms, attribute "deps". Can be used to fine-tune marginality exceptions.

cluster if a valid "cluster" object is provided it is used for parallel execution of the fitting function. If NULL or omitted single threaded execution is performed.
With parallel calculation, an extra argument check is accepted.
See pdredge for details and examples.

... optional arguments for the rank function. Any can be an unevaluated expression, in which case any x within it will be substituted with the current model.

Details
Models are fitted through repeated evaluation of modified call extracted from the global.model (in a similar fashion as with update). This approach, while robust in that it can be applied to most model types through the usual formula interface, may have considerable computational overhead.

Note that the number of combinations grows exponentially with the number of predictors (2^N, less when interactions are present, see below).

The fitted model objects are not stored in the result. To get (a subset of) the models, use get.models on the object returned by dredge. Another way to get all the models is to run lapply(dredge(..., evaluate = FALSE), eval), which avoids fitting models twice.

For a list of model types that can be used as a global.model see the list of supported models. Modelling functions that do not store a call in their result should be evaluated via a wrapper function created by updateable.

Information criterion: rank is found by a call to match.fun and may be specified as a function, a symbol, or as a character string specifying a function to be searched for from the environment of the call to dredge. It can be also a one-element named list, where the first element is taken as the rank function. The function rank must accept a model object as its first argument and always return a scalar.

Interactions: By default, marginality constraints are respected, so “all possible combinations” include only those containing interactions with their respective main effects and all lower-order terms. However, if global.model makes an exception to this principle (e.g. due to a nested design such as a / (b + d)), this will be reflected in the subset models.

Subsetting: There are three ways to constrain the resulting set of models: setting limits to the number of terms in a model with m.lim, binding term(s) to all models using fixed, and the subset argument can be used for more complex rules. For a model to be included in the selection table, its formulation must satisfy all these conditions.

subset may be an expression or a matrix. The latter should be a lower triangular matrix with logical values, where the columns and rows correspond to global.model terms. Value subset["a","b"] == FALSE will exclude any model containing both a and b terms.

demo(dredge.subset) has examples of using the subset matrix in conjunction with correlation matrices to exclude models containing collinear predictors.

In the form of expression, the argument subset acts in a similar fashion to that in the function subset for data.frames: model terms can be referred to by name as variables in the expression, with the difference being that are interpreted as logical values (i.e. equal to TRUE if the term exists in the model).
The expression can contain any of the `global.model` term names, as well as names of the varying list items. `global.model` term names take precedence when identical to names of varying, so to avoid ambiguity varying variables in subset expression should be enclosed in `V()` (e.g. `V(family) == "Gamma"`) assuming that varying is something like `list(family = c("Gamma",...))`.

If item names in varying are missing, the items themselves are coerced to names. Call and symbol elements are represented as character values (`via deparse`), and anything other than numeric, logical, character and NULL values is replaced by item numbers (e.g. `varying = list(family = list(gaussian,Gamma))` should be referred to as `subset = V(family) == 2`. This can quickly become confusing, so it is recommended to use named lists. Examples can be found in `demo(dredge.varying)`.

Term names appearing in fixed and subset must be given exactly as they are returned by `getAllTerms(global.model)`, which may differ from the original term names (e.g. the interaction term components are ordered alphabetically).

The `with(x)` and `with(+x)` notation indicates, respectively, any and all interactions including the main effect term `x`. This is only effective with marginality exceptions. The extended form `with(x, order)` allows to specify the order of interaction of terms of which `x` is a part. For instance, `with(b,2:3)` selects models with at least one second- or third-order interaction of variable `b`. The second (positional) argument is coerced to an integer vector. The “dot” notation `.x` is an alias for `with`.

The special variable `\`*nvar*`\` (backtick-quoted), in the subset expression is equal to the number of terms in the model (not the number of estimated parameters).

To make the inclusion of a model term conditional on the presence of another one, the function `dc` ("dependency chain") can be used in the subset expression. `dc` takes any number of term names as arguments, and allows a term to be included only if all preceding ones are also present (e.g. `subset = dc(a,b,c)` allows for models `a`, `a+b` and `a+b+c` but not `b`, `c`, `b+c` or `a+c`).

Subset expression can have a form of an unevaluated call, expression object, or a one-sided formula. See 'Examples'.

Compound model terms (such as interactions, ‘as-is’ expressions within `I()` or smooths in `gam`) should be enclosed within curly brackets (e.g. `{s(x,k=2)}`), or backticks (like non-syntactic names, e.g. `\`s(x,k = 2)`\`), except when they are arguments to `with` or `dc`. Backticks-quoted names must match exactly (including whitespace) the term names as returned by `getAllTerms`.

Subset expression syntax summary:

- `a & b` indicates that model terms `a` and `b` must be present (see Logical Operators)
- `{log(x,2)}` or `'log(x, 2)'` represent a complex model term `log(x,2)`
- `V(x)` represents a varying item `x`  
- `with(x)` indicates that at least one term containing the main effect term `x` must be present
- `with(+x)` indicates that all the terms containing the main effect term `x` must be present
- `with(x, n:m)` indicates that at least one term containing an `n`-th to `m`-th order interaction term of `x` must be present
- `dc(a, b, c,...)` 'dependency chain': `b` is allowed only if `a` is present, and `c` only if both `a` and `b` are present, etc.
- `\`*nvar*`\` the number of terms in the model.

To simply keep certain terms in all models, use of argument `fixed` is much more efficient. The fixed formula is interpreted in the same manner as model formula and so the terms must not be quoted.
**Missing values:** Use of `na.action = "na.omit"` (R’s default) or "na.exclude" in `global.model` must be avoided, as it results with sub-models fitted to different data sets if there are missing values. An error is thrown if it is detected.

It is a common mistake to give `na.action` as an argument in the call to `dredge` (typically resulting in an error from the `rank` function to which the argument is passed through `. . . ’), while the correct way is either to pass `na.action` in the call to the global model or to set it as a [global option](https://www.r-project.org/doc/contrib/Vignettes/RSEIS.html).

**Intercept:**
If present in the `global.model`, the intercept will be included in all sub-models.

**Methods:** There are `subset` and `plot` methods, the latter creates a graphical representation of model weights and per-model term sum of weights. Coefficients can be extracted with `coef` or `coefTable`.

**Value**
An object of class c("model.selection","data.frame"). being a data.frame, where each row represents one model. See `model.selection.object` for its structure.

**Note**
Users should keep in mind the hazards that a “thoughtless approach” of evaluating all possible models poses. Although this procedure is in certain cases useful and justified, it may result in selecting a spurious “best” model, due to the model selection bias.

“Let the computer find out” is a poor strategy and usually reflects the fact that the researcher did not bother to think clearly about the problem of interest and its scientific setting (Burnham and Anderson, 2002).

**Author(s)**
Kamil Bartoń

**See Also**
- `pdredge` is a parallelized version of this function (uses a cluster).
- `get.models`, `model.avg`, `model.sel` for manual model selection tables.
- Possible alternatives: `glmulti` in package [glmulti](https://cran.r-project.org/package=glmulti) and [bestglm](https://cran.r-project.org/package=bestglm). `regsubsets` in package `leaps` also performs all-subsets regression.
- Variable selection through regularization provided by various packages, e.g. `glmnet`, `lars` or `glmLasso`.

**Examples**

```r
# Example from Burnham and Anderson (2002), page 100:
# prevent fitting sub-models to different datasets
options(na.action = "na.fail")
```
fm1 <- lm(y ~ ., data = Cement)
dd <- dredge(fm1)
subset(dd, delta < 4)

# Visualize the model selection table:

par(mar = c(3,5,6,4))
plot(dd, labAsExpr = TRUE)

# Model average models with delta AICc < 4
model.avg(dd, subset = delta < 4)

#or as a 95% confidence set:
model.avg(dd, subset = cumsum(weight) <= .95) # get averaged coefficients

#'Best' model
summary(get.models(dd, 1)[[1]])

## Not run:
# Examples of using 'subset':
# keep only models containing X3
dredge(fm1, subset = ~ X3) # subset as a formula
dredge(fm1, subset = expression(X3)) # subset as expression object
# the same, but more effective:
dredge(fm1, fixed = "X3")
# exclude models containing both X1 and X2 at the same time
dredge(fm1, subset = !(X1 && X2))
# Fit only models containing either X3 or X4 (but not both);
# include X3 only if X2 is present, and X2 only if X1 is present.
dredge(fm1, subset = dc(X1, X2, X3) && xor(X3, X4))
# the same as above, without "dc"
dredge(fm1, subset = (X1 | !X2) && (X2 | !X3) && xor(X3, X4))

# Include only models with up to 2 terms (and intercept)
dredge(fm1, m.lim = c(0, 2))

## End(Not run)

# Add R^2 and F-statistics, use the 'extra' argument
dredge(fm1, m.lim = c(NA, 1), extra = c("R^2", F = function(x)
  summary(x)$fstatistic[[1]]))

# with summary statistics:
dredge(fm1, m.lim = c(NA, 1), extra = list(
  "R^2", "*" = function(x) {
    s <- summary(x)
    c(Rsq = s$r.squared, adjRsq = s$adj.r.squared,
      F = s$fstatistic[[1]])
  }))

# Add other information criteria (but rank with AICc):
exprApply

dredge(fm1, m.lim = c(NA, 1), extra = alist(AIC, BIC, ICOMP, Cp))

---

Apply a function to calls inside an expression

Description

Apply function FUN to each occurrence of a call to what() (or a symbol what) in an unevaluated expression. It can be used for advanced manipulation of expressions. Intended primarily for internal use.

Usage

exprApply(expr, what, FUN, ..., symbols = FALSE)

Arguments

expr an unevaluated expression.
what character string giving the name of a function. Each call to what inside expr will be passed to FUN. what can be also a character representation of an operator or parenthesis (including curly and square brackets) as these are primitive functions in R. Set what to NA to match all names.
FUN a function to be applied.
symbols logical value controlling whether FUN should be applied to symbols as well as calls.
... optional arguments to FUN.

Details

FUN is found by a call to match.fun and can be either a function or a symbol (e.g., a backquoted name) or a character string specifying a function to be searched for from the environment of the call to exprApply.

Value

A (modified) expression.

Note

If expr has a source reference information ("srcref" attribute), modifications done by exprApply will not be visible when printed unless srcref is removed. However, exprApply does remove source reference from any function expression inside expr.

Author(s)

Kamil Bartoń
See Also

Expression-related functions: substitute, expression, quote and bquote.

Similar function walkCode exists in package codetools.

Functions useful inside FUN: as.name, as.call, call, match.call etc.

Examples

### simple usage:
# print all Y(...) terms in a formula (note that symbol "Y" is omitted):
exprApply(~ X(1) + Y(2 + Y(4)) + N(Y + Y(3)), "Y", print)

# replace X() with log(X, base = n)
exprApply(expression(A()) + B() + C()), c("A", "B", "C"), function(expr, base) {
  expr[[2]] <- expr[[1]]
  expr[[1]] <- as.name("log")
  expr$base <- base
  expr
}, base = 10)

###
# TASK: fit lm with two poly terms, varying the degree from 1 to 3 in each.
# lm(y ~ poly(X1, degree = a) + poly(X2, degree = b), data = Cement)
# for a = {1,2,3} and b = {1,2,3}

# First we create a wrapper function for lm. Within it, use "exprApply" to add
# "degree" argument to all occurrences of "poly()" having "X1" or "X2" as the
# first argument. Values for "degree" are taken from arguments "d1" and "d2"

lmpolywrap <- function(formula, d1 = NA, d2 = NA, ...) {
  cl <- origCall <- match.call()
  cl[[1]] <- as.name("lm")
  cl$formula <- exprApply(formula, "poly", function(e, degree, x) {
    i <- which(e[[2]] == x)[1]
    if(!is.na(i) && !is.na(degree[i])) e$degree <- degree[i]
    e
  }, degree = c(d1, d2), x = c("X1", "X2"))
  cl$d1 <- cl$d2 <- NULL
  fit <- eval(cl, parent.frame())
  fit$call <- origCall # replace the stored call
  fit
}

# global model:
fm <- lmpolywrap(y ~ poly(X1) + poly(X2), data = Cement)

# Use "dredge" with argument "varying" to generate calls of all combinations of
# degrees for poly(X1) and poly(X2). Use "fixed = TRUE" to keep all global model
# terms in all models.
# Since "dredge" expects that global model has all the coefficients the
# submodels can have, which is not the case here, we first generate model calls,
# evaluate them and feed to "model.sel"
modCalls <- dredge(fm,  
  varying = list(d1 = 1:3, d2 = 1:3),  
  fixed = TRUE,  
  evaluate = FALSE  
)  

model.sel(models <- lapply(modCalls, eval))  

# Note: to fit *all* submodels replace "fixed = TRUE" with:
# "subset = (d1==1 || (poly(X1))) && (d2==1 || (poly(X2)))"
# This is to avoid fitting 3 identical models when the matching "poly()" term is
# absent.

---

**Formula manipulation**  
*Manipulate model formulas*

**Description**

`simplify.formula` rewrites a formula using shorthand notation. Currently only the factor crossing operator `*` is applied, so that expanded expression such as `a*b+a:b` becomes `a*b`.

`expand.formula` does the opposite, additionally expanding other expressions, i.e. all nesting (`/`), grouping and `^`.

**Usage**

`simplify.formula(x)`  
`expand.formula(x)`

**Arguments**

- `x` a formula or an object from which it can be extracted (such as a fitted model object).

**Author(s)**

Kamil Bartoń

**See Also**

`formula`,  
`delete.response`,  
`drop.terms`,  
and  
`reformulate`

**Examples**

```r
simplify.formula(y ~ a + b + a:b + (c + b)^2)
simplify.formula(y ~ a + b + a:b + 0)
exand.formula(- a * b)
```
get.models

Retrieve models from selection table

Description

Generate or extract a list of fitted model objects from a "model.selection" table, optionally using parallel computation in a cluster.

Usage

get.models(object, subset, cluster = NA, ...)

Arguments

object
object returned by dredge.

subset
subset of models, an expression evaluated within the model selection table (see 'Details').

cluster
optionally, a "cluster" object. If it is a valid cluster, models are evaluated using parallel computation.

...
additional arguments to update the models. For example, in lme one may want to use method = "REML" while using "ML" for model selection.

Details

The argument subset must be explicitly provided. This is to assure that a potentially long list of models is not fitted unintentionally. To evaluate all models, set subset to NA or TRUE.

If subset is a character vector, it is interpreted as names of rows to be selected.

Value

list of fitted model objects.

Note

Alternatively, getCall and eval can be used to compute a model out of the "model.selection" table (e.g. eval(getCall(<model.selection>,i)), where i is the model index or name).

Using get.models following dredge is not efficient as the requested models have to be fitted again. If the number of generated models is reasonable, consider using lapply(dredge(...,evaluate = FALSE), eval), which generates a list of all model calls and evaluates them into a list of model objects. This avoids fitting the models twice.

pget.models is still available, but is deprecated.

Author(s)

Kamil Bartoń
See Also
dredge and pdredge, model.avg
makeCluster in packages parallel and snow

Examples

# Mixed models:

fm2 <- lme(distance ~ age + Sex, data = Orthodont,
    random = ~ 1 | Subject, method = "ML")
ms2 <- dredge(fm2)

# Get top-most models, but fitted by REML:
(confset.d4 <- get.models(ms2, subset = delta < 4, method = "REML"))

## Not run:
# Get the top model:
get.models(ms2, subset = 1)[[1]]

## End(Not run)

GPA

Grade Point Average data

Description

First-year college Grade Point Average (GPA) from Graybill and Iyer (1994).

Usage

GPA

Format

GPA is a data frame with 5 variables. y is the first-year college Grade Point Average (GPA) and x1-x4 are four predictor variables from standardized tests (SAT) administered before matriculation.

y GPA
x1 math score on the SAT
x2 verbal score on the SAT
x3 high school math
x4 high school English
Information criteria

Source


References


Description

Calculate Mallows’ *Cp* and Bozdogan’s ICOMP and CAIFC information criteria.

Extract or calculate Deviance Information Criterion from *MCMCglmm* and *merMod* object.

Usage

\[
\begin{align*}
\text{Cp}(\text{object, ...}, \text{dispersion} = \text{NULL}) \\
\text{ICOMP}(\text{object, ...}, \text{REML} = \text{NULL}) \\
\text{CAICF}(\text{object, ...}, \text{REML} = \text{NULL}) \\
\text{DIC}(\text{object, ...})
\end{align*}
\]

Arguments

- **object**: a fitted model object (in case of ICOMP and CAICF, `logLik` and `vcov` methods must exist for the object). For DIC, an object of class "MCMCglmm" or "merMod".
- **...**: optionally more fitted model objects.
- **dispersion**: the dispersion parameter. If `NULL`, it is inferred from object.
- **REML**: optional logical value, passed to the `logLik` method indicating whether the restricted log-likelihood or log-likelihood should be used. The default is to use the method used for model estimation.

Details

Mallows’ *Cp* statistic is the residual deviance plus twice the estimate of $\sigma^2$ times the residual degrees of freedom. It is closely related to AIC (and a multiple of it if the dispersion is known).

ICOMP (I for informational and COMP for complexity) penalizes the covariance complexity of the model, rather than the number of parameters directly.

CAICF (C is for ‘consistent’ and F denotes the use of the Fisher information matrix) includes with penalty the natural logarithm of the determinant of the estimated Fisher information matrix.
**jackknifeWeights**

### Value

If just one object is provided, the functions return a numeric value with the corresponding IC; otherwise a data.frame with rows corresponding to the objects is returned.

### References


### See Also

[AIC](https://CRAN.R-project.org/package=stats) and [BIC](https://CRAN.R-project.org/package=stats) in package stats, [AICC](https://CRAN.R-project.org/package=arm), [QIC](https://CRAN.R-project.org/package=arm) for GEE model selection. [extractDIC](https://CRAN.R-project.org/package=arm) in package arm, on which the (non-visible) method `extractDIC.merMod` used by DIC is based.

### jackknifeWeights

**Jackknifed model weights**

### Description

Computes model weights optimized for jackknifed model fits.

### Usage

```
jackknifeWeights(
  object, ...
  data, type = c("loglik", "rmse"),
  family = NULL,
  weights = NULL,
  optim.method = "BFGS",
  maxit = 1000,
  optim.args = list(),
  start = NULL,
  force.update = FALSE,
  py.matrix = FALSE
)
```
Arguments

object, ... two or more fitted glm objects, or a list of such, or an "averaging" object.
data a data frame containing the variables in the model. It is optional if all models are glm.
type a character string specifying the function to minimize. Either "rmse" or "loglik".
family used only if type = "loglik", a family object to be used for likelihood calculation. Not needed if all models share the same family and link function.
weights an optional vector of 'prior weights' to be used in the model fitting process. Should be NULL or a numeric vector.
optim.method optional, optimisation method, passed to optim.
maxit optional, the maximum number of iterations, passed to optim.
optim.args optional list of other arguments passed to optim.
start starting values for model weights. Numeric of length equal the number of models.
force.update for glm, the glm.fit function is used for fitting models to the train data, which is much more efficient. Set to TRUE to use update instead.
py.matrix either a boolean value, then if TRUE a jackknifed prediction matrix is returned and if FALSE a vector of jackknifed model weights, or a \( N \times M \) matrix (number of cases \( \times \) number of models) that is interpreted as a jackknifed prediction matrix and it is used for optimisation (i.e. the jackknife procedure is skipped).

Details

Model weights are chosen (using optim) to minimise RMSE or log-likelihood of the prediction for data point \( i \), of a model fitted omitting that data point \( i \). The jackknife procedure is therefore run for all provided models and for all data points.

Value

The function returns a numeric vector of model weights.

Note

This procedure can give variable results depending on the optimisation method and starting values. It is therefore advisable to make several replicates using different optim.methods. See optim for possible values for this argument.

Author(s)

Kamil Bartoń. Carsten Dormann

References


See Also

Weights, model.avg

Other model weights: BGWeights(), bootWeights(), cos2Weights(), stackingWeights()

Examples

fm <- glm(Prop ~ mortality * dose, binomial(), Beetle, na.action = na.fail)
fits <- lapply(dredge(fm, eval = FALSE), eval)
amJk <- amAICc <- model.avg(fits)
set.seed(666)
Weights(amJk) <- jackknifeWeights(fits, data = Beetle)

coef(amJk)
coef(amAICc)

Description

Leave-one-out cross-validation

Usage

loo(object, type = c("loglik", "rmse"), ...)

Arguments

object a fitted object model, currently only lm/glm is accepted.
type the criterion to use, given as a character string, either "rmse" for Root-Mean-Square Error or "loglik" for log-likelihood.
... other arguments are currently ignored.

Details

Leave-one-out cross validation is a $K$-fold cross validation, with $K$ equal to the number of data points in the set $N$. For all $i$ from 1 to $N$, the model is fitted to all the data except for $i$-th row and a prediction is made for that value. The average error is computed and used to evaluate the model.

Value

A single numeric value of RMSE or mean log-likelihood.
merge.model.selection

Combine model selection tables

Description

Combine two or more model selection tables.

Usage

```r
## S3 method for class 'model.selection'
merge(x, y, suffixes = c(".x", ".y"), ...)
```

```r
## S3 method for class 'model.selection'
rbind(..., deparse.level = 1, make.row.names = TRUE)
```

Arguments

- `x, y, ...`: `model.selection` objects to be combined. (...ignored in `merge`)
- `suffixes`: a character vector with two elements that are appended respectively to row names of the combined tables.
- `make.row.names`: logical indicating if unique and valid `row.names` should be constructed from the arguments.
- `deparse.level`: ignored.

Examples

```r
fm <- lm(y ~ X1 + X2 + X3 + X4, Cement)
loo(fm, type = "l")
loo(fm, type = "r")

## Compare LOO_RMSE and AIC/c
options(na.action = na.fail)
dd <- dredge(fm, rank = loo, extra = list(AIC, AICc), type = "rmse")
plot(loo ~ AIC, dd, ylab = expression(LOO[RMSE]), xlab = "AIC/c")
points(loo ~ AICc, data = dd, pch = 19)
legend("topleft", legend = c("AIC", "AICc"), pch = c(1, 19))
```

References


Author(s)

Kamil Bartoń, based on code by Carsten Dormann
Value

A "model.selection" object containing models (rows) from all provided tables.

Note

Both $\Delta IC$ values and Akaike weights are recalculated in the resulting tables.
Models in the combined model selection tables must be comparable, i.e. fitted to the same data, however only very basic checking is done to verify that. The models must also be ranked by the same information criterion.
Unlike the merge method for data.frame, this method appends second table to the first (similarly to rbind).

Author(s)

Kamil Bartoń

See Also

dredge, model.sel, merge, rbind.

Examples

```r
## Not run:
require(mgcv)
ms1 <- dredge(glm(Prop ~ dose + I(dose^2) + log(dose) + I(log(dose)^2),
data = Beetle, family = binomial, na.action = na.fail))
fm2 <- gam(Prop ~ s(dose, k = 3), data = Beetle, family = binomial)
merge(ms1, model.sel(fm2))
## End(Not run)
```

Description

These functions extract or calculate various values from provided fitted model objects(s). They are mainly meant for internal use.
coeffs extracts model coefficients;
getAllTerms extracts independent variable names from a model object;
coefTable extracts a table of coefficients, standard errors and associated degrees of freedom when possible;
get.response extracts response variable from fitted model object;
model.names generates shorthand (alpha)numeric names for one or several fitted models.
**Usage**

```r
coeffs(model)
getAllTerms(x, ...)
## S3 method for class 'terms'
ggetAllTerms(x, intercept = FALSE, offset = TRUE, ...)

coefTable(model, ...)
## S3 method for class 'averaging'
coefTable(model, full = FALSE, adjust.se = TRUE, ...)
## S3 method for class 'lme'
coefTable(model, adjustSigma, ...)
## S3 method for class 'gee'
coefTable(model, ..., type = c("naive", "robust"))

g.get.response(x, data = NULL, ...)

model.names(object, ..., labels = NULL, use.letters = FALSE)
```

**Arguments**

- `model` a fitted model object.
- `object` a fitted model object or a list of such objects.
- `x` a fitted model object or a formula.
- `offset` should ‘offset’ terms be included?
- `intercept` should terms names include the intercept?
- `full, adjust.se` logical, apply to “averaging” objects. If full is TRUE, the full model-averaged coefficients are returned, and subset-averaged ones otherwise. If adjust.se is TRUE, inflated standard errors are returned. See ‘Details’ in `par.avg`.
- `adjustSigma` See `summary.lme`.
- `type` for GEE models, the type of covariance estimator to calculate returned standard errors on. Either "naive" or "robust" (‘sandwich’).
- `labels` optionally, a character vector with names of all the terms, e.g. from a global model. `model.names` enumerates the model terms in order of their appearance in the list and in the models. Therefore changing the order of the models leads to different names. Providing labels prevents that.
- `...` in `model.names`, more fitted model objects. In `coefTable` arguments that are passed to appropriate `vcov` or summary method (e.g. dispersion parameter for glm may be used here). In `get.response`, if data is given, arguments to be passed to `model.frame`. In other functions may be silently ignored.
- `data` a data.frame, list or environment (or object coercible to a data.frame), containing the variables in x. Required only if x is a formula, otherwise it can be used to get the response variable for a different data set.
- `use.letters` logical, whether letters should be used instead of numeric codes.
Details

The functions `coeffs`, `getAllTerms` and `coefTable` provide interface between the model object and `model.avg` (and `dredge`). Custom methods can be written to provide support for additional classes of models.

Note

coeffs's value is in most cases identical to that returned by `coef`, the only difference being it returns fixed effects' coefficients for mixed models, and the value is always a named numeric vector.

Use of `tTable` is deprecated in favour of `coefTable`.

Author(s)

Kamil Bartoń

---

model.avg  

Model averaging

Description

Model averaging based on an information criterion.

Usage

```r
model.avg(object, ..., revised.var = TRUE)
## Default S3 method:
model.avg(object, ..., beta = c("none", "sd", "partial.sd"),
  rank = NULL, rank.args = NULL, revised.var = TRUE,
  dispersion = NULL, ct.args = NULL)
## S3 method for class 'model.selection'
model.avg(object, subset, fit = FALSE, ..., revised.var = TRUE)
```

Arguments

- **object**
  - a fitted model object or a list of such objects, or a "model.selection" object. See ‘Details’.
- **...**
  - for default method, more fitted model objects. Otherwise, arguments that are passed to the default method.
- **beta**
  - indicates whether and how the component models’ coefficients should be standardized. See the argument’s description in `dredge`. 
model.avg may be used either with a list of models or directly with a model.selection object (e.g. returned by dredge). In the latter case, the models from the model selection table are not evaluated unless the argument fit is set to TRUE or some additional arguments are present (such as rank or dispersion). This results in a much faster calculation, but has certain drawbacks, because the fitted component model objects are not stored, and some methods (e.g. predict, fitted, model.matrix or vcov) would not be available with the returned object. Otherwise, get.models is called prior to averaging, and ... are passed to it.

For a list of model types that are accepted see list of supported models.

rank is found by a call to match.fun and typically is specified as a function or a symbol or a character string specifying a function to be searched for from the environment of the call to lapply. rank must be a function able to accept model as a first argument and must always return a numeric scalar.

Several standard methods for fitted model objects exist for class averaging, including summary, predict, coef, confint, formula, and vcov.

coef, vcov, confint and coefTable accept argument full that if set to TRUE, the full model-averaged coefficients are returned, rather than subset-averaged ones (when full = FALSE, being the default).

logLik returns a list of logLik objects for the component models.

Value
An object of class "averaging" is a list with components:

msTable a data.frame with log-likelihood, IC, ΔIC, and ‘Akaike weights’ for the component models. Its attribute "term.codes" is a named vector with numerical representation of the terms in the row names of msTable.

coefficients a matrix of model-averaged coefficients. “full” coefficients in the first row, “subset” coefficients in the second row. See ‘Note’

coefArray a 3-dimensional array of component models’ coefficients, their standard errors and degrees of freedom.
model.avg

sw

object of class sw containing per-model term sum of model weights over all of the models in which the term appears.

formula

a formula corresponding to the one that would be used in a single model. The formula contains only the averaged (fixed) coefficients.

call

the matched call.

The object has the following attributes:

rank

the rank function used.

modelList

optionally, a list of all component model objects. Only if the object was created with model objects (and not model selection table).

beta

Corresponds to the function argument.

nobs

number of observations.

revised.var

Corresponds to the function argument.

Note

The ‘subset’ (or ‘conditional’) average only averages over the models where the parameter appears. An alternative, the ‘full’ average assumes that a variable is included in every model, but in some models the corresponding coefficient (and its respective variance) is set to zero. Unlike the ‘subset average’, it does not have a tendency of biasing the value away from zero. The ‘full’ average is a type of shrinkage estimator, and for variables with a weak relationship to the response it is smaller than ‘subset’ estimators.

Averaging models with different contrasts for the same factor would yield nonsense results. Currently, no checking for contrast consistency is done.

print method provides a concise output (similarly as for lm). To print more details use summary function, and confint to get confidence intervals.

Author(s)

Kamil Bartoń

References


See Also

See par.avg for more details of model-averaged parameter calculation.

dredge, get.models

AICc has examples of averaging models fitted by REML.

modavg in package AICcmodavg, and coef.glmulti in package glmulti also perform model averaging.
Examples

# Example from Burnham and Anderson (2002), page 100:
fm1 <- lm(y ~ ., data = Cement, na.action = na.fail)
(ms1 <- dredge(fm1))

#models with delta.aicc < 4
summary(model.avg(ms1, subset = delta < 4))

#or as a 95% confidence set:
avgmod.95p <- model.avg(ms1, cumsum(weight) <= .95)
confint(avgmod.95p)

## Not run:
# The same result, but re-fitting the models via 'get.models'
confset.95p <- get.models(ms1, cumsum(weight) <= .95)
model.avg(confset.95p)

# Force re-fitting the component models
model.avg(ms1, cumsum(weight) <= .95, fit = TRUE)
# Models are also fitted if additional arguments are given
model.avg(ms1, cumsum(weight) <= .95, rank = "AIC")

## End(Not run)

## Not run:
# using BIC (Schwarz's Bayesian criterion) to rank the models
BIC <- function(x) AIC(x, k = log(length(residuals(x))))
model.avg(confset.95p, rank = BIC)
# 'x' in a quoted 'rank' argument is substituted with a model object
# (in this case it does not make much sense as the number of observations is
# common to all models)
model.avg(confset.95p, rank = AIC, rank.args = alist(k = log(length(residuals(x)))))

## End(Not run)

---

model.sel  
model selection table

Description

Build a model selection table.

Usage

model.sel(object, ...)

## Default S3 method:
model.sel(object, ..., rank = NULL, rank.args = NULL,
  beta = c("none", "sd", "partial.sd"), extra)

## S3 method for class 'model.selection'
model.sel(object, rank = NULL, rank.args = NULL, fit = NA,
  ..., beta = c("none", "sd", "partial.sd"), extra)

**Arguments**

object  
a fitted model object, a list of such objects, or a "model.selection" object.

...  
more fitted model objects.

rank  
optional, custom rank function (returning an information criterion) to use instead
of the default AICc, e.g. QAIC or BIC, may be omitted if object is a model list
returned by get.models.

rank.args  
optional list of arguments for the rank function. If one is an expression, an x
within it is substituted with a current model.

fit  
logical, stating whether the model objects should be re-fitted if they are not
stored in the "model.selection" object. Set to NA to re-fit the models only if
this is needed. See 'Details'.

beta  
indicates whether and how the component models’ coefficients should be stan-
dardized. See the argument’s description in dredge.

extra  
optional additional statistics to include in the result, provided as functions, func-
tion names or a list of such (best if named or quoted). See dredge for details.

**Details**

model.sel used with "model.selection" object will re-fit model objects, unless they are stored
in object (in attribute "modelList"), if argument extra is provided, or the requested beta is
different than object’s "beta" attribute, or the new rank function cannot be applied directly to
logLik objects, or new rank.args are given (unless argument fit = FALSE).

**Value**

An object of class c("model.selection","data.frame"), being a data.frame, where each row
represents one model and columns contain useful information about each model: the coefficients,
df, log-likelihood, the value of the information criterion used, \( \Delta IC \) and ‘Akaike weight’. If any
arguments differ between the modelling function calls, the result will include additional columns
showing them (except for formulas and some other arguments).

See model.selection.object for its structure.

**Author(s)**

Kamil Bartoń

**See Also**

dredge, AICc, list of supported models.

Possible alternatives: ICItab (in package bbmle), or aictab (AICcmodavg).
Examples

Cement$X1 <- cut(Cement$X1, 3)
Cement$X2 <- cut(Cement$X2, 2)

fm1 <- glm(formula = y ~ X1 + X2 * X3, data = Cement)
fm2 <- update(fm1, . ~ . - X1 - X2)
fm3 <- update(fm1, . ~ . - X2 - X3)

## ranked with AICc by default
(msAICc <- model.sel(fm1, fm2, fm3))

## ranked with BIC
model.sel(fm1, fm2, fm3, rank = AIC, rank.args = alist(k = log(nobs(x))))
# or
# model.sel(msAICc, rank = AIC, rank.args = alist(k = log(nobs(x))))
# or
# update(msAICc, rank = AIC, rank.args = alist(k = log(nobs(x))))

model.selection.object

Description of Model Selection Objects

Description

An object of class "model.selection" holds a table of model coefficients and ranking statistics. It is produced by dredge or model.sel.

Value

The object is a data.frame with additional attributes. Each row represents one model. The models are ordered by the information criterion value specified by rank (lowest on top).

Data frame columns:

model terms For numeric covariates these columns hold coefficient value, for factors their presence in the model. If the term is not present in a model, value is NA.
‘varying’ arguments optional. If any arguments differ between the modelling function calls (except for formulas and some other arguments), these will be held in additional columns (of class "factor").
"df" Number of model parameters
"logLik" Log-likelihood (or quasi-likelihood for GEE)
rank Information criterion value
"delta" $\Delta IC$
Attributes:

- **model.calls**: A list containing model calls (arranged in the same order as in the table). A model call can be retrieved with `getCall(*,i)` where `i` is a vector of model index or name (if given as character string).
- **global**: The `global.model` object
- **global.call**: Call to the `global.model`
- **terms**: A character string holding all term names. Attribute "interceptLabel" gives the name of the intercept term.
- **rank**: The rank function used
- **beta**: A character string, representing the coefficient standardizing method used. Either "none", "sd" or "partial.sd"
- **coefTables**: List of matrices of class "coefTable" containing each model’s coefficients with std. errors and associated dfs
- **nobs**: Number of observations
- **warnings**: optional (pdredge only). A list of errors and warnings issued by the modelling function during the fitting, with a model number appended to each.

Most attributes does not need (and should not) be accessed directly, use of extractor functions is preferred. These functions include `getCall` for retrieving model calls, `coefTable` and `coef` for coefficients, and `nobs`. `logLik` extracts list of model log-likelihoods (as "logLik" objects), and `Weights` extracts ‘Akaike weights’.

The object has class c("model.selection","data.frame").

See Also

dredge, model.sel.

---

**MuMIn-models**

**List of supported models**

**Description**

List of model classes accepted by `model.avg`, `model.sel`, and `dredge`.

**Details**

Fitted model objects that can be used with model selection and model averaging functions include those produced by:

- `lm, glm` (package `stats`);
- `rlm, glm.nb` and `polr` (`MASS`);
- `multinom` (`nnet`);
• **lme, gls** (nlme);
• **lmer, glmer** (lme4);
• **cplm, cplm** (cplm);
• **gam, gamm** (mgcv);
• **gamm4** (gamm4);
• **gamlss** (gamlss);
• **gllmm (gllmm)**;
• **gllmmTMB (gllmmTMB)**;
• **MCMGglmm** (MCMCglmm);
• **lme** (non-free commercial package asreml; allows only for REML comparisons);
• **hurdle, zeroinfl** (pscl);
• **negbin, betabin** (class "glimML"), package aod);
• **aodml, aodql** (aods3);
• **betareg** (betareg);
• **brglm** (brglm);
• *sarlm models, spautolm (spatialreg);
• **spml** (if fitted by ML, splm);
• **coxph, survreg** (survival);
• **coxme, lmekin** (coxme);
• **rqt** (quantreg);
• **clm and clmm** (ordinal);
• **logistf** (logistf);
• **brglm, pgls** (caper);
• **maxlike** (maxlike);
• functions from package unmarked (within the class "unmarkedFit");
• **mark** and related functions (class mark from package RMark). Currently dredge can only manipulate formula element of the argument model.parameters, keeping its other elements intact.

Generalized Estimation Equation model implementations: **geeglm** from package geepack, **gee** from gee, **geem** from geem, **wgee** from wgeesel, and yags from yags (on R-Forge) can be used with QIC as the selection criterion.

Other classes are also likely to be supported, in particular if they inherit from one of the above classes. In general, the models averaged with model.avg may belong to different types (e.g. glm and gam), provided they use the same data and response, and if it is valid to do so. This applies also to constructing model selection tables with model.sel.

**Note**

* In order to use gamm, gamm4, spml (> 1.0.0), crunch or MCMCglmm with dredge, an updateable wrapper for these functions should be created.
See Also

*model.avg*, *model.sel* and *dredge*.

---

**Description**

Find models that are ‘nested’ within each model in the model selection table.

**Usage**

```r
nested(x, indices = c("none", "numeric", "rownames"), rank = NULL)
```

**Arguments**

- `x`: a "model.selection" object (result of *dredge* or *model.sel*).
- `indices`: if omitted or "none" then the function checks if, for each model, there are any higher ranked models nested within it. If "numeric" or "rownames", indices or names of all nested models are returned. See “Value”.
- `rank`: the name of the column with the ranking values (defaults to the one before "delta"). Only used if indices is "none".

**Details**

In model comparison, a model is said to be “nested” within another model if it contains a subset of parameters of the latter model, but does not include other parameters (e.g. model ‘A+B’ is nested within ‘A+B+C’ but not ‘A+C+D’).

This function can be useful in a model selection approach suggested by Richards (2008), in which more complex variants of any model with a lower IC value are excluded from the candidate set.

**Value**

A vector of length equal to the number of models (table rows).

If `indices = "none"` (the default), it is a vector of logical values where `i`-th element is TRUE if any model(s) higher up in the table are nested within it (i.e. if simpler models have lower IC pointed by `rank`).

For `indices` other than "none", the function returns a list of vectors of numeric indices or names of models nested within each `i`-th model.

**Note**

This function determines nesting based only on fixed model terms, within groups of models sharing the same ‘varying’ parameters (see *dredge* and example in *Beetle*).
par.avg

Parameter averaging

Description

Average a coefficient with standard errors based on provided weights. This function is intended chiefly for internal use.

Usage

par.avg(x, se, weight, df = NULL, level = 1 - alpha, alpha = 0.05,
  revised.var = TRUE, adjusted = TRUE)
Arguments

x     vector of parameters.
se    vector of standard errors.
weight vector of weights.
df    optional vector of degrees of freedom.
alpha, level  significance level for calculating confidence intervals.
revised.var  logical, should the revised formula for standard errors be used? See ‘Details’.
adjusted logical, should the inflated standard errors be calculated? See ‘Details’.

Details

Unconditional standard errors are square root of the variance estimator, calculated either according to the original equation in Burnham and Anderson (2002, equation 4.7), or a newer, revised formula from Burnham and Anderson (2004, equation 4) (if revised.var = TRUE, this is the default). If adjusted = TRUE (the default) and degrees of freedom are given, the adjusted standard error estimator and confidence intervals with improved coverage are returned (see Burnham and Anderson 2002, section 4.3.3).

Value

par.avg returns a vector with named elements:

Coefficient  model coefficients
SE            unconditional standard error
Adjusted SE   adjusted standard error
Lower CI, Upper CI  unconditional confidence intervals.

Author(s)

Kamil Barto

References


See Also

model.avg for model averaging.
Automated model selection using parallel computation

Description

Parallelized version of dredge.

Usage

pdredge(global.model, cluster = NULL,
        beta = c("none", "sd", "partial.sd"), evaluate = TRUE, rank = "AICc",
        fixed = NULL, m.lim = NULL, m.min, m.max, subset, trace = FALSE,
        varying, extra, ct.args = NULL, deps = attr(allTerms0, "deps"),
        check = FALSE, ...)

Arguments

  global.model, beta, rank, fixed, m.lim, m.max, m.min, subset, varying, extra, ct.args, deps, ...

  see dredge.

  evaluate     whether to evaluate and rank the models. If FALSE, a list of unevaluated calls
               is returned and cluster is not used.

  trace        displays the generated calls, but may not work as expected since the models are
               evaluated in batches rather than one by one.

  cluster      either a valid "cluster" object, or NULL for a single threaded execution.

  check        either integer or logical value controlling how much checking for existence and
               correctness of dependencies is done on the cluster nodes. See ‘Details’.

Details

All the dependencies for fitting the global.model, including the data and any objects the modelling
function will use must be exported into the cluster worker nodes (e.g. via clusterExport). The re-
quired packages must be also loaded thereinto (e.g. via clusterEvalQ(...,library(package))
before the cluster is used by pdredge.

If check is TRUE or positive, pdredge tries to check whether all the variables and functions used in
the call to global.model are present in the cluster nodes’.GlobalEnv before proceeding further.
This causes false errors if some arguments of the model call (other than subset) would be evaluated
in data environment. In that case using check = FALSE (the default) is desirable.

If check is TRUE or greater than one, pdredge will compare the global.model updated at the cluster
nodes with the one given as argument.

Value

  See dredge.
Note

As of version 1.45.0, using pdredge directly is deprecated. Use dredge instead and provide cluster argument.

Author(s)

Kamil Bartoń

See Also

makeCluster and other cluster related functions in packages parallel or snow.

Examples

# One of these packages is required:
## Not run: require(parallel) || require(snow)

# From example(Beetle)
Beetle100 <- Beetle[sample(nrow(Beetle), 100, replace = TRUE),]

fm1 <- glm(Prop ~ dose + I(dose^2) + log(dose) + I(log(dose)^2),
  data = Beetle100, family = binomial, na.action = na.fail)

msubset <- expression(xor(dose, `log(dose)` & (dose | !`I(dose^2)`)
  & (`log(dose)` | !`I(log(dose)^2)`))

varying.link <- list(family = alist(logit = binomial("logit"),
  probit = binomial("probit"), cloglog = binomial("cloglog")))

# Set up the cluster
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"
clust <- try(makeCluster(getOption("cl.cores", 2), type = clusterType))

clusterExport(clust, "Beetle100")

# noticeable gain only when data has about 3000 rows (Windows 2-core machine)
print(system.time(dredge(fm1, subset = msubset, varying = varying.link)))
print(system.time(dredge(fm1, cluster = FALSE, subset = msubset, varying = varying.link)))
print(system.time(pdd <- dredge(fm1, cluster = clust, subset = msubset, varying = varying.link)))

print(pdd)

## Not run:
# Time consuming example with 'unmarked' model, based on example(pcount).
# Having enough patience you can run this with 'demo(pdredge.pcount)'.
library(unmarked)
data(mallard)
mallardUMF <- unmarkedFramePCount(mallard.y, siteCovs = mallard.site, 
obsCovs = mallard.obs)
(ufm.mallard <- pcount(~ ivel + date + I(date^2) ~ length + elev + forest, 
mallardUMF, K = 30))
clusterEvalQ(clust, library(unmarked))
clusterExport(clust, "mallardUMF")

# 'stats4' is needed for AIC to work with unmarkedFit objects but is not
# loaded automatically with 'unmarked'.
require(stats4)
invisible(clusterCall(clust, "library", "stats4", character.only = TRUE))

#system.time(print(pdd1 <- dredge(ufm.mallard, 
# subset = 'p(date)' | '!p(I(date^2))', rank = AIC))

system.time(print(pdd2 <- dredge(ufm.mallard, cluster = clust, 
subset = 'p(date)' | '!p(I(date^2))', rank = AIC, extra = "adjR^2")))

# best models and null model
subset(pdd2, delta < 2 | df == min(df))

# Compare with the model selection table from unmarked
# the statistics should be identical:
models <- get.models(pdd2, delta < 2 | df == min(df), cluster = clust)
modSel(fitList(fits = structure(models, names = model.names(models, 
labels = getAllTerms(ufm.mallard)))), nullmod = "(Null)"

## End(Not run)

stopCluster(clust)

plot.model.selection  Visualize model selection table

Description
produces a graphical representation of model weights per model term.

Usage
## S3 method for class 'model.selection'
plot(x, ylab = NULL, xlab = NULL, labels = attr(x, "terms"), 
labAsExpr = TRUE, mar.adj = TRUE, 
col = c("SlateGray", "SlateGray2"), col2 = "white", border = par("col"), 
par.lab = NULL, par.vlab = NULL, 
axes = TRUE, ann = TRUE, ...)
predict.averaging

Arguments

- `x`: a "model.selection" object.
- `xlab`, `ylab`: labels for the x and y axes.
- `labels`: optional, a character vector or an expression containing model term labels (to appear on top side of the plot). Its length must be equal to number of model terms in the table. Defaults to the model term names.
- `labAsExpr`: a logical indicating whether the character labels should be interpreted (parsed) as R expressions.
- `mar.adj`: logical indicating whether the upper margin should be expanded to fit the labels
- `col`, `col2`: vector of colors for columns (if more than one `col` is given, columns will be filled with alternating colors). If `col2` is specified cells will be filled with gradient from `col` to `col2`. `col2 = NA` produces no gradient.
- `border`: border color for cells and axes.
- `par.lab`, `par.vlab`: optional lists of graphical parameters for the term labels (top axis) and model names (right axis), respectively.
- `axes`, `ann`: logical values indicating whether the axis and annotation should appear on the plot.
- ... further graphical parameters to be set for the plot.

Value

A numeric vector of model weights.

Author(s)

Kamil Bartoń

See Also

- `plot.default.par`

Examples

# For examples, see \sQuote{MuMIn-package}

predict.averaging  

Description

Model-averaged predictions, optionally with standard errors.
predict.averaging

Usage

## S3 method for class 'averaging'
predict(object, newdata = NULL, se.fit = FALSE, 
    interval = NULL, type = NA, backtransform = FALSE, full = TRUE, ...)

Arguments

object an object returned by model.avg.
newdata optional data.frame in which to look for variables with which to predict. If omitted, the fitted values are used.
se.fit logical, indicates if standard errors should be returned. This has any effect only if the predict methods for each of the component models support it.
interval currently not used.
type the type of predictions to return (see documentation for predict appropriate for the class of used component models). If omitted, the default type is used. See ‘Details’.
backtransform if TRUE, the averaged predictions are back-transformed from link scale to response scale. This makes sense provided that all component models use the same family, and the prediction from each of the component models is calculated on the link scale (as specified by type). For glm, use type = "link"). See ‘Details’.
full if TRUE, the full model-averaged coefficients are used (only if se.fit = FALSE and the component objects are a result of lm).
... arguments to be passed to respective predict method (e.g. level for lme model).

Details

predicting is possible only with averaging objects with "modelList" attribute, i.e. those created via model.avg from a model list, or from model.selection object with argument fit = TRUE (which will recreate the model objects, see model.avg).

If all the component models are ordinary linear models, the prediction can be made either with the full averaged coefficients (the argument full = TRUE this is the default) or subset-averaged coefficients. Otherwise the prediction is obtained by calling predict on each component model and weighted averaging the results, which corresponds to the assumption that all predictors are present in all models, but those not estimated are equal zero (see ‘Note’ in model.avg). Predictions from component models with standard errors are passed to par.avg and averaged in the same way as the coefficients are.

Predictions on the response scale from generalized models can be calculated by averaging predictions of each model on the link scale, followed by inverse transformation (this is achieved with type = "link" and backtransform = TRUE). This is only possible if all component models use the same family and link function. Alternatively, predictions from each model on response scale may be averaged (with type = "response" and backtransform = FALSE). Note that this leads to results differing from those calculated with the former method. See also predict.glm.
Value

If `se.fit = FALSE`, a vector of predictions, otherwise a list with components: `fit` containing the predictions, and `se.fit` with the estimated standard errors.

Note

This method relies on availability of the `predict` methods for the component model classes (except when all component models are of class `lm`).

The package `MuMIn` includes `predict` methods for `lme`, and `gls` that calculate standard errors of the predictions (with `se.fit = TRUE`). They enhance the original `predict` methods from package `nlme`, and with `se.fit = FALSE` they return identical result. `MuMIn`'s versions are always used in averaged model predictions (so it is possible to predict with standard errors), but from within global environment they will be found only if `MuMIn` is before `nlme` on the search list (or directly extracted from namespace as `MuMIn:::predict.lme`).

Author(s)

Kamil Bartoń

See Also

`model.avg`, and `par.avg` for details of model-averaged parameter calculation.

`predict.lme`, `predict.gls`

Examples

```r
# Example from Burnham and Anderson (2002), page 100:
fm1 <- lm(y ~ X1 + X2 + X3 + X4, data = Cement)

ms1 <- dredge(fm1)
confset.95p <- get.models(ms1, subset = cumsum(weight) <= .95)
avgm <- model.avg(confset.95p)

nseq <- function(x, len = length(x)) seq(min(x, na.rm = TRUE),
    max(x, na.rm=TRUE), length = len)

# New predictors: X1 along the range of original data, other
# variables held constant at their means
newdata <- as.data.frame(lapply(lapply(Cement[, -1], mean), rep, 25))
newdata$X1 <- nseq(Cement$X1, nrow(newdata))

n <- length(confset.95p)

# Predictions from each of the models in a set, and with averaged coefficients
pred <- data.frame(
    model = sapply(confset.95p, predict, newdata = newdata),
    averaged.subset = predict(avgm, newdata, full = FALSE),
)```
averagefull = predict(avgm, newdata, full = TRUE)
)
opal <- palette(c(topo.colors(n), "black", "red", "orange"))
matplot(newdata$X1, pred, type = "l",
lwd = c(rep(2,n),3,3), lty = 1,
xlab = "X1", ylab = "y", col=1:7)

# For comparison, prediction obtained by averaging predictions of the component models
pred.se <- predict(avgm, newdata, se.fit = TRUE)
y <- pred.se$fit
ci <- pred.se$se.fit * 2
matplot(newdata$X1, cbind(y, y - ci, y + ci), add = TRUE, type="l",
lty = 2, col = n + 3, lwd = 3)

legend("topleft",
legend=c(lapply(confset.95p, formula),
paste(c("subset", "full"), "averaged"), "averaged predictions + CI"),
lty = 1, lwd = c(rep(2,n),3,3,3), cex = .75, col=1:8)
palette(opal)

---

**QAIC**

### Quasi AIC or AICc

**Description**

Calculate a modification of Akaike's Information Criterion for overdispersed count data (or its version corrected for small sample, "quasi-AICc"), for one or several fitted model objects.

**Usage**

QAIC(object, ..., chat, k = 2, REML = NULL)
QAICc(object, ..., chat, k = 2, REML = NULL)

**Arguments**

- `object` a fitted model object.
- `...` optionally, more fitted model objects.
- `chat` \( \hat{\epsilon} \), the variance inflation factor.
- `k` the 'penalty' per parameter.
- `REML` optional logical value, passed to the `logLik` method indicating whether the restricted log-likelihood or log-likelihood should be used. The default is to use the method used for model estimation.
Value

If only one object is provided, returns a numeric value with the corresponding QAIC or QAICc; otherwise returns a data.frame with rows corresponding to the objects.

Note

\( \hat{c} \) is the dispersion parameter estimated from the global model, and can be calculated by dividing model’s deviance by the number of residual degrees of freedom.

In calculation of QAIC, the number of model parameters is increased by 1 to account for estimating the overdispersion parameter. Without overdispersion, \( \hat{c} = 1 \) and QAIC is equal to AIC.

Note that glm does not compute maximum-likelihood estimates in models within the quasi-family. In case it is justified, it can be worked around by ‘borrowing’ the aic element from the corresponding ‘non-quasi’ family (see ‘Example’).

Consider using negative binomial family with overdispersed count data.

Author(s)

Kamil Bartoń

See Also

AICc, quasi family used for models with over-dispersion.

Tests for overdispersion in GLM[M]: check_overdispersion.

Examples

```r
options(na.action = "na.fail")

# Based on "example(predict.glm)", with one number changed to create
# overdispersion
budworm <- data.frame(
  ldose = rep(0:5, 2), sex = factor(rep(c("M", "F"), c(6, 6))),
  numdead = c(10, 4, 9, 12, 18, 20, 8, 2, 6, 10, 12, 16))
budworm$SF = cbind(numdead = budworm$numdead,
  numalive = 20 - budworm$numdead)

budworm.lg <- glm(SF ~ sex*ldose, data = budworm, family = binomial)
(chat <- deviance(budworm.lg) / df.residual(budworm.lg))

dredge(budworm.lg, rank = "QAIC", chat = chat)
dredge(budworm.lg, rank = "AIC")

## Not run:
# A 'hacked' constructor for quasibinomial family object that allows for
# ML estimation
hacked.quasibinomial <- function(...) {
  res <- quasibinomial(...)
```
QIC and quasi-Likelihood for GEE

Description

Calculate quasi-likelihood under the independence model criterion (QIC) for Generalized Estimating Equations.

Usage

```r
QIC(object, ..., typeR = FALSE)
QICu(object, ..., typeR = FALSE)
quasiLik(object, ...)
```

Arguments

- `object`: a fitted model object of class "gee", "geepack", "geem", "wgee", or "yags".
- `...`: for QIC and QICu, optionally more fitted model objects.
- `typeR`: logical, whether to calculate QIC(R). QIC(R) is based on quasi-likelihood of a working correlation $R$ model. Defaults to FALSE, and QIC(I) based on independence model is returned.

Value

If just one object is provided, returns a numeric value with the corresponding QIC; if more than one object are provided, returns a `data.frame` with rows corresponding to the objects and one column representing QIC or QICu.

Note

This implementation is based partly on (revised) code from packages `yags` (R-Forge) and `ape`.

Author(s)

Kamil Bartoń

References


See Also

Methods exist for **gee** (package **gee**), **geeglm** (geepack), **geem** (geeM), **wgee** (wgeesel, the package's QIC.gee function is used), and **yags** (**yags** on R-Forge). There is also a QIC function in packages **MESS** and **geepack**, returning some extra information (such as CIC and QICc). **yags** and **compar.gee** from package **ape** both provide QIC values.

Examples

```r
data(ohio)
f1 <- geeglm(resp ~ age * smoke, id = id, data = ohio,
    family = binomial, corstr = "exchangeable", scale.fix = TRUE)
f2 <- update(f1, corstr = "ar1")
f3 <- update(f1, corstr = "unstructured")
# QIC function is also defined in 'geepack' but is returns a vector[6], so
# cannot be used as 'rank'. Either use 'MuMIn::QIC' syntax or make a wrapper
# around 'geepack::QIC'
QIC <- MuMIn::QIC
## Not run:
QIC <- function(x) geepack::QIC(x)[1]
## End(Not run)
model.sel(f1, f2, f3, rank = QIC)
```

####
```r
library(geepack)
library(MuMIn)
## Not run:
# same result:
# same result:
dredge(f1, m.lim = c(3, NA), rank = QIC, varying = list(
    corstr = list("exchangeable", "unstructured", "ar1")
))
## End(Not run)
```

---

### `r.squaredGLMM`

**Pseudo-R-squared for Generalized Mixed-Effect models**

**Description**

Calculate conditional and marginal coefficient of determination for Generalized mixed-effect models ($R^2_{GLMM}$).
r.squaredGLMM

Usage

r.squaredGLMM(object, null, ...)  
## S3 method for class 'merMod'  
r.squaredGLMM(object, null, envir = parent.frame(), pj2014 = FALSE, ...)

Arguments

object a fitted linear model object.
null optionally, a null model, including only random effects. See ‘Details’.
envir optionally, the environment in which the null model is to be evaluated. Defaults
to the current frame. See eval.
pj2014 logical, if TRUE and object is of poisson family, the result will include $\hat{R}^2_{\text{GLMM}}$
using original formulation of Johnson (2014). This requires fitting object with
an observation-level random effect term added.
... additional arguments, ignored.

Details

For mixed-effects models, $R^2_{\text{GLMM}}$ comes in two types: marginal and conditional.  

Marginal $R^2_{\text{GLMM}}$ represents the variance explained by the fixed effects, and is defined as:

$$R^2_{\text{GLMM}(m)} = \frac{\sigma_f^2}{\sigma_f^2 + \sigma_\alpha^2 + \sigma_\varepsilon^2}$$

Conditional $R^2_{\text{GLMM}}$ is interpreted as a variance explained by the entire model, including both
fixed and random effects, and is calculated according to the equation:

$$R^2_{\text{GLMM}(c)} = \frac{\sigma_f^2 + \sigma_\alpha^2}{\sigma_f^2 + \sigma_\alpha^2 + \sigma_\varepsilon^2}$$

where $\sigma_f^2$ is the variance of the fixed effect components, $\sigma_\alpha$ is the variance of the random effects,
and $\sigma_\varepsilon^2$ is the “observation-level” variance.

Three different methods are available for deriving the observation-level variance $\sigma_\varepsilon$: the delta
method, lognormal approximation and using the trigamma function.

The delta method can be used with for all distributions and link functions, while lognormal approxi-
mation and trigamma function are limited to distributions with logarithmic link. Trigamma-estimate
is recommended whenever available. Additionally, for binomial distributions, theoretical variances
exist specific for each link function distribution.

Null model. Calculation of the observation-level variance involves in some cases fitting a null model
containing no fixed effects other than intercept, otherwise identical to the original model (including
all the random effects). When using r.squaredGLMM for several models differing only in their fixed
effects, in order to avoid redundant calculations, the null model object can be passed as the argument
null. Otherwise, a null model will be fitted via updating the original model. This assumes that all
the variables used in the original model call have the same values as when the model was fitted. The
function warns about this when fitting the null model is required. This warnings can be disabled by
setting options(MuMIn.noUpdateWarning = TRUE).
Value

`r.squaredGLMM` returns a two-column numeric matrix, each (possibly named) row holding values for marginal and conditional $R^2_{GLMM}$ calculated with different methods, such as “delta”, “log-normal”, “trigamma”, or “theoretical” for models of binomial family.

Note

**Important**: as of `MuMIn` version 1.41.0, `r.squaredGLMM` returns a revised statistics based on Nakagawa et al. (2017) paper. The returned value’s format also has changed (it is a matrix rather than a numeric vector as before). Pre-1.41.0 version of the function calculated the “theoretical” $R^2_{GLMM}$ for binomial models.

$R^2_{GLMM}$ can be calculated also for fixed-effect models. In the simplest case of OLS it reduces to $\frac{\text{var(fitted)}}{\text{var(fitted)} + \text{deviance} / 2}$. Unlike likelihood-ratio based $R^2$ for OLS, value of this statistic differs from that of the classical $R^2$.

Currently methods exist for classes: merMod, lme, glmmTMB, glmmADMB, glmmPQL, cpglm and (g)lm. See note in `r.squaredLR` help page for comment on using $R^2$ in model selection.

Author(s)

Kamil Bartoń. This implementation is based on `R` code from ‘Supporting Information’ for Nakagawa et al. (2014), (the extension for random-slopes) Johnson (2014), and includes developments from Nakagawa et al. (2017).

References


See Also

`summary.lm, r.squaredLR`

Examples

data(Orthodont, package = "nlme")

fm1 <- lme(distance ~ Sex * age, ~ 1 | Subject, data = Orthodont)

fmnull <- lme(distance ~ 1, ~ 1 | Subject, data = Orthodont)
r.squaredGLMM(fm1)
r.squaredGLMM(fm1, fmnull)
r.squaredGLMM(update(fm1, . ~ Sex), fmnull)

r.squaredLR(fm1)
r.squaredLR(fm1, null.RE = TRUE)
r.squaredLR(fm1, fmnull) # same result

## Not run:
if(require(MASS)) {
  fm <- glmmPQL(y ~ trt + I(week > 2), random = ~ 1 | ID,
                 family = binomial, data = bacteria, verbose = FALSE)
  fmnull <- update(fm, . ~ 1)
  r.squaredGLMM(fm)

  # Include R2GLMM (delta method estimates) in a model selection table:
  # Note the use of a common null model
  dredge(fm, extra = list(R2 = function(x) r.squaredGLMM(x, fmnull)["delta", ]))
}

## End(Not run)

---

r.squaredLR

| Likelihood-ratio based pseudo-R-squared |

**Description**

Calculate a coefficient of determination based on the likelihood-ratio test ($R^2_{LR}$).

**Usage**

r.squaredLR(object, null = NULL, null.RE = FALSE, ...)

null.fit(object, evaluate = FALSE, RE.keep = FALSE, envir = NULL, ...)

**Arguments**

- **object**: a fitted model object.
- **null**: a fitted null model. If not provided, null.fit will be used to construct it. null.fit's capabilities are limited to only a few model classes, for others the null model has to be specified manually.
- **null.RE**: logical, should the null model contain random factors? Only used if no null model is given, otherwise omitted, with a warning.
- **evaluate**: if TRUE evaluate the fitted model object else return the call.
- **RE.keep**: if TRUE, the random effects of the original model are included.
the environment in which the null model is to be evaluated, defaults to the environment of the original model’s formula.

... further arguments, of which only x would be used, to maintain compatibility with older versions (x has been replaced with object).

Details

This statistic is is one of the several proposed pseudo-$R^2$’s for nonlinear regression models. It is based on an improvement from null (intercept only) model to the fitted model, and calculated as

$$R_{LR}^2 = 1 - \exp\left(-\frac{2}{n}(\log L(x) - \log L(0))\right)$$

where $\log L(x)$ and $\log L(0)$ are the log-likelihoods of the fitted and the null model respectively. ML estimates are used if models have been fitted by REstricted ML (by calling logLik with argument REML = FALSE). Note that the null model can include the random factors of the original model, in which case the statistic represents the ‘variance explained’ by fixed effects.

For OLS models the value is consistent with classical $R^2$. In some cases (e.g. in logistic regression), the maximum $R_{LR}^2$ is less than one. The modification proposed by Nagelkerke (1991) adjusts the $R_{LR}^2$ to achieve 1 at its maximum: $\bar{R}^2 = R_{LR}^2 / \max(R_{LR}^2)$ where $\max(R_{LR}^2) = 1 - \exp(\frac{2}{n} \log L(0))$.

null.fit tries to guess the null model call, given the provided fitted model object. This would be usually a glm. The function will give an error for an unrecognised class.

Value

r.squaredLR returns a value of $R_{LR}^2$, and the attribute "adj.r.squared" gives the Nagelkerke’s modified statistic. Note that this is not the same as nor equivalent to the classical ‘adjusted R squared’.

null.fit returns the fitted null model object (if evaluate = TRUE) or an unevaluated call to fit a null model.

Note

$R^2$ is a useful goodness-of-fit measure as it has the interpretation of the proportion of the variance ‘explained’, but it performs poorly in model selection, and is not suitable for use in the same way as the information criteria.

References


See Also

`summary.lm`, `r.squaredGLMM`
stackingWeights  

**Stacking model weights**

Description

Computes model weights based on a cross-validation-like procedure.

Usage

```
stackingWeights(object, ..., data, R, p = 0.5)
```

Arguments

- `object, ...`: Two or more fitted `glm` objects, or a list of such, or an "averaging" object.
- `data`: A data frame containing the variables in the model, used for fitting and prediction.
- `R`: The number of replicates.
- `p`: The proportion of the data to be used as training set. Defaults to 0.5.

Details

Each model in a set is fitted to the training data: a subset of \( p \times N \) observations in `data`. From these models a prediction is produced on the remaining part of `data` (the test or hold-out data). These hold-out predictions are fitted to the hold-out observations, by optimising the weights by which the models are combined. This process is repeated \( R \) times, yielding a distribution of weights for each model (which Smyth & Wolpert (1998) referred to as an ‘empirical Bayesian estimate of posterior model probability’). A mean or median of model weights for each model is taken and re-scaled to sum to one.

Value

A matrix with two rows, containing model weights calculated using mean and median.

Note

This approach requires a sample size of at least \( 2 \times \) the number of models.

Author(s)

Carsten Dormann, Kamil Bartoň
References


See Also

Weights, model.avg

Other model weights: BGWeights(), bootWeights(), cos2Weights(), jackknifeWeights()

Examples

```r
# simulated Cement dataset to increase sample size for the training data
fm0 <- glm(y ~ X1 + X2 + X3 + X4, data = Cement, na.action = na.fail)
dat <- as.data.frame(apply(Cement[, -1], 2, sample, 50, replace = TRUE))
dat$y <- rnorm(nrow(dat), predict(fm0), sigma(fm0))

# global model fitted to training data:
fm <- glm(y ~ X1 + X2 + X3 + X4, data = dat, na.action = na.fail)

# generate a list of some* subsets of the global model
models <- lapply(dredge(fm, evaluate = FALSE, fixed = "X1", m.lim = c(1, 3)), eval)
wts <- stackingWeights(models, data = dat, R = 10)
ma <- model.avg(models)
Weights(ma) <- wts["mean", ]
predict(ma)
```

---

### std.coef

#### Standardized model coefficients

**Description**

Standardize model coefficients by Standard Deviation or Partial Standard Deviation.

**Usage**

```r
std.coef(x, partial.sd, ...)
partial.sd(x)
```
# Deprecated:
beta.weights(model)

**Arguments**

- `x, model` a fitted model object.
- `partial.sd` logical, if set to `TRUE`, model coefficients are multiplied by partial SD, otherwise they are multiplied by the ratio of the standard deviations of the independent variable and dependent variable.
- `...` additional arguments passed to `coefTable`, e.g. dispersion.

**Details**

Standardizing model coefficients has the same effect as centring and scaling the input variables. “Classical” standardized coefficients are calculated as $\beta_i^* = \beta_i \cdot \frac{s_{X_i}}{s_y}$, where $\beta_i$ is the unstandardized coefficient, $s_{X_i}$ is the standard deviation of the associated dependent variable $X_i$ and $s_y$ is SD of the response variable.

If variables are intercorrelated, the standard deviation of $X_i$ used in computing the standardized coefficients $\beta_i^*$ should be replaced by the partial standard deviation of $X_i$ which is adjusted for the multiple correlation of $X_i$ with the other $X$ variables included in the regression equation. The partial standard deviation is calculated as $s_{X_i}^* = s_{X_i} \cdot \frac{\text{VIF}(X_i)^{-0.5} \cdot (\frac{n-1}{n-p})^{0.5}}{n}$, where VIF is the variance inflation factor, $n$ is the number of observations and $p$, the number of predictors in the model. The coefficient is then transformed as $\beta_i^* = \beta_i s_{X_i}^*$.

**Value**

A matrix with at least two columns for the standardized coefficient estimate and its standard error. Optionally, the third column holds degrees of freedom associated with the coefficients.

**Author(s)**

Kamil Bartoń. Variance inflation factors calculation is based on function `vif` from package `car` written by Henric Nilsson and John Fox.

**References**


**See Also**

`partial.sd` can be used with `stdize`.

`coef` or `coeffs` and `coefTable` for unstandardized coefficients.
stdize

Examples

# Fit model to original data:
f <- lm(y ~ x1 + x2 + x3 + x4, data = GPA)

# Partial SD for the default formula: y ~ x1 + x2 + x3 + x4
psd <- partial.sd(lm(data = GPA))[-1]  # remove first element for intercept

# Standardize data:
zGPA <- stdize(GPA, scale = c(NA, psd), center = TRUE)
# Note: first element of 'scale' is set to NA to ignore the first column 'y'

# Coefficients of a model fitted to standardized data:
#zapla(sm(coeffTable(stdizeFit(f, newdata = zGPA)))
# Standardized coefficients of a model fitted to original data:
#zapla(sm(std.coef(f, partial = TRUE))

# Standardizing nonlinear models:
fam <- Gamma("inverse")
fmg <- glm(log(y) ~ x1 + x2 + x3 + x4, data = GPA, family = fam)

psd <- partial.sd(fmg)
zGPA <- stdize(GPA, scale = c(NA, psd[-1]), center = FALSE)
fmgz <- glm(log(y) ~ z.x1 + z.x2 + z.x3 + z.x4, zGPA, family = fam)

# Coefficients using standardized data:
#coef(fmgz)  # (intercept is unchanged because the variables haven't been
# # centred)
# Standardized coefficients:
#coef(fmg) * psdg

stdize

**Standardize data**

Description

stdize standardizes variables by centring and scaling.

stdizeFit modifies a model call or existing model to use standardized variables.

Usage

```r
## Default S3 method:
stdize(x, center = TRUE, scale = TRUE, ...)

## S3 method for class 'logical'
stdize(x, binary = c("center", "scale", "binary", "half", "omit"),
       center = TRUE, scale = FALSE, ...)
```
## also for two-level factors

## S3 method for class 'data.frame'
stdize(x, binary = c("center", "scale", "binary", "half", "omit"),
      center = TRUE, scale = TRUE, omit.cols = NULL, source = NULL,
      prefix = TRUE, append = FALSE, ...)

## S3 method for class 'formula'
stdize(x, data = NULL, response = FALSE,
      binary = c("center", "scale", "binary", "half", "omit"),
      center = TRUE, scale = TRUE, omit.cols = NULL, prefix = TRUE,
      append = FALSE, ...)

stdizeFit(object, newdata, which = c("formula", "subset", "offset", "weights",
              "fixed", "random", "model"), evaluate = TRUE, quote = NA)

**Arguments**

- **x**: a numeric or logical vector, factor, numeric matrix, data.frame or a formula.
- **center, scale**: either a logical value or a logical or numeric vector of length equal to the number of columns of x (see ‘Details’). scale can be also a function to use for scaling.
- **binary**: specifies how binary variables (logical or two-level factors) are scaled. Default is to "center" by subtracting the mean assuming levels are equal to 0 and 1; use "scale" to both centre and scale by SD, "binary" to centre to 0/1, "half" to centre to -0.5 / 0.5, and "omit" to leave binary variables unmodified. This argument has precedence over center and scale, unless it is set to NA (in which case binary variables are treated like numeric variables).
- **source**: a reference data.frame, being a result of previous stdize, from which scale and center values are taken. Column names are matched. This can be used for scaling new data using statistics of another data.
- **omit.cols**: column names or numeric indices of columns that should be left unaltered.
- **prefix**: either a logical value specifying whether the names of transformed columns should be prefixed, or a two-element character vector giving the prefixes. The prefixes default to “z.” for scaled and “c.” for centred variables.
- **append**: logical, if TRUE, modified columns are appended to the original data frame.
- **response**: logical, stating whether the response should be standardized. By default, only variables on the right-hand side of the formula are standardized.
- **data**: an object coercible to data.frame, containing the variables in formula. Passed to, and used by model.frame.
- **newdata**: a data.frame returned by stdize, to be used by the modified model.
- **...**: for the formula method, additional arguments passed to model.frame. For other methods, it is silently ignored.
- **object**: a fitted model object or an expression being a call to the modelling function.
- **which**: a character string naming arguments which should be modified. This should be all arguments which are evaluated in the data environment. Can be also TRUE to
modify the expression as a whole. The data argument is additionally replaced with that passed to stdizeFit.

evaluate
if TRUE, the modified call is evaluated and the fitted model object is returned.

quote
if TRUE, avoids evaluating object. Equivalent to stdizeFit(quote(expr),...). Defaults to NA in which case object being a call to non-primitive function is quoted.

Details

stdize resembles scale, but uses special rules for factors, similarly to standardize in package arm.

stdize differs from standardize in that it is used on data rather than on the fitted model object. The scaled data should afterwards be passed to the modelling function, instead of the original data.

Unlike standardize, it applies special ‘binary’ scaling only to two-level factors and logical variables, rather than to any variable with two unique values.

Variables of only one unique value are unchanged.

By default, stdize scales by dividing by standard deviation rather than twice the SD as standardize does. Scaling by SD is used also on uncentred values, which is different from scale where root-mean-square is used.

If center or scale are logical scalars or vectors of length equal to the number of columns of x, the centring is done by subtracting the mean (if center corresponding to the column is TRUE), and scaling is done by dividing the (centred) value by standard deviation (if corresponding scale is TRUE). If center or scale are numeric vectors with length equal to the number of columns of x (or numeric scalars for vector methods), then these are used instead. Any NAs in the numeric vector result in no centring or scaling on the corresponding column.

Note that scale = 0 is equivalent to no scaling (i.e. scale = 1).

Binary variables, logical or factors with two levels, are converted to numeric variables and transformed according to the argument binary, unless center or scale are explicitly given.

Value

stdize returns a vector or object of the same dimensions as x, where the values are centred and/or scaled. Transformation is carried out column-wise in data.frames and matrices.

The returned value is compatible with that of scale in that the numeric centring and scalings used are stored in attributes "scaled:center" and "scaled:scale" (these can be NA if no centring or scaling has been done).

stdizeFit returns a modified, fitted model object that uses transformed variables from newdata, or, if evaluate is FALSE, an unevaluated call where the variable names are replaced to point the transformed variables.

Author(s)

Kamil Bartoń
References


See Also

Compare with `scale` and `standardize` or `rescale` (the latter two in package `arm`).

For typical standardizing, model coefficients transformation may be easier, see `std.coef`. `apply` and `sweep` for arbitrary transformations of columns in a `data.frame`.

Examples

```r
# compare "stdize" and "scale"
mmat <- matrix(runif(15, 0, 10), ncol = 3)

stdize(mmat)
scale(mmat)

rootmeansq <- function(v) {
  v <- v[!is.na(v)]
  sqrt(sum(v^2) / max(1, length(v) - 1L))
}

scale(mmat, center = FALSE)
stdize(mmat, center = FALSE, scale = rootmeansq)

if(require(lme4)) {
  # define scale function as twice the SD to reproduce "arm::standardize"
twosd <- function(v) 2 * sd(v, na.rm = TRUE)

  # standardize data (scaled variables are prefixed with "z.")
z.C02 <- stdize(uptake ~ conc + Plant, data = CO2, omit = "Plant", scale = twosd)
summary(z.C02)

  fmz <- stdizeFit(lmer(uptake ~ conc + I(conc^2) + (1 | Plant)), newdata = z.C02)
  # produces:
  # lmer(uptake ~ z.conc + I(z.conc^2) + (1 | Plant), data = z.C02)

  ## standardize using scale and center from "z.C02", keeping the original data:
  z.C02a <- stdize(CO2, source = z.C02, append = TRUE)
  # Here, the "subset" expression uses untransformed variable, so we modify only
  # "formula" argument, keeping "subset" as-is. For that reason we needed the
  # untransformed variables in "newdata".
  stdizeFit(lmer(uptake ~ conc + I(conc^2) + (1 | Plant),
               subset = conc > 100,
               ), newdata = z.C02a, which = "formula", evaluate = FALSE)

  # create new data as a sequence along "conc"
```
newdata <- data.frame(conc = seq(min(CO2$conc), max(CO2$conc), length = 10))

# scale new data using scale and center of the original scaled data:
z.newdata <- stdize(newdata, source = z.CO2)

# plot predictions against "conc" on real scale:
plot(newdata$conc, predict(fmz, z.newdata, re.form = NA))

# compare with "arm::standardize"
## Not run:
library(arm)
fms <- standardize(lmer(uptake ~ conc + I(conc^2) + (1 | Plant), data = CO2))
plot(newdata$conc, predict(fms, z.newdata, re.form = NA))
## End(Not run)

subset.model.selection

Subsetting model selection table

Description

Extract a subset of a model selection table.

Usage

## S3 method for class 'model.selection'
subset(x, subset, select, recalc.weights = TRUE, recalc.delta = FALSE, ...)
## S3 method for class 'model.selection'
x[i, j, recalc.weights = TRUE, recalc.delta = FALSE, ...]
## S3 method for class 'model.selection'
x[...], exact = TRUE]

Arguments

- **x**: a model.selection object to be subbedted.
- **subset, select**: logical expressions indicating columns and rows to keep. See `subset`.
- **i, j**: indices specifying elements to extract.
- **recolc.weights**: logical specifying whether Akaike weights should be normalized across the new set of models to sum to one.
- **recolc.delta**: logical specifying whether $\Delta IC$ should be calculated for the new set of models (not done by default).
- **exact**: logical, see `[.`.
- **...**: further arguments passed to `.data.frame (drop).
Details

Unlike the method for \texttt{data.frame}, single bracket extraction with only one index \texttt{x[i]} selects rows (models) rather than columns.

To select rows according to presence or absence of the variables (rather than their value), a pseudo-function \texttt{has} may be used with \texttt{subset}, e.g. \texttt{subset(x, has(a, !b))} will select rows with \texttt{a} \textbf{and} without \texttt{b} (this is equivalent to \texttt{!is.na(a) & !is.na(b)}). \texttt{has} can take any number of arguments.

Complex model terms need to be enclosed within curly brackets (e.g \{s(a,k=2)\}), except for within \texttt{has}. Backticks-quoting is also possible, but then the name must match exactly (including whitespace) the term name as returned by \texttt{getAllTerms}.

Enclosing in \texttt{I} prevents the name from being interpreted as a column name.

To select rows where one variable can be present conditional on the presence of other variables, the function \texttt{dc} (dependency chain) can be used. \texttt{dc} takes any number of variables as arguments, and allows a variable to be included only if all the preceding arguments are also included (e.g. \texttt{subset = dc(a,b,c)} allows for models of form \texttt{a}, \texttt{a+b} and \texttt{a+b+c} but not \texttt{b}, \texttt{c}, \texttt{b+c} or \texttt{a+c}).

Value

A \texttt{model.selection} object containing only the selected models (rows). If columns are selected (via argument \texttt{select} or the second index \texttt{x[,j]}) and not all essential columns (i.e. all except "varying" and "extra") are present in the result, a plain \texttt{data.frame} is returned. Similarly, modifying values in the essential columns with [<- or $<- produces a regular data frame.

Author(s)

Kamil Bartoń

See Also

dredge, subset and [.data.frame for subsetting and extracting from data.frames.

Examples

\begin{verbatim}
fm1 <- lm(formula = y ~ X1 + X2 + X3 + X4, data = Cement, na.action = na.fail)

# generate models where each variable is included only if the previous
# are included too, e.g. X2 only if X1 is there, and X3 only if X2 and X1
dredge(fm1, subset = dc(X1, X2, X3, X4))

# which is equivalent to
# dredge(fm1, subset = (!X2 | X1) & (!X3 | X2) & (!X4 | X3))

# alternatively, generate "all possible" combinations
ms0 <- dredge(fm1)

# ...and afterwards select the subset of models
subset(ms0, dc(X1, X2, X3, X4))

# which is equivalent to
# subset(ms0, (has(!X2) | has(X1)) & (has(!X3) | has(X2)) & (has(!X4) | has(X3)))

# Different ways of finding a confidence set of models:
\end{verbatim}
# delta(AIC) cutoff
subset(ms0, delta <= 4, recalc.weights = FALSE)

# cumulative sum of Akaike weights
subset(ms0, cumsum(weight) <= .95, recalc.weights = FALSE)

# relative likelihood
subset(ms0, (weight / weight[1]) > (1/8), recalc.weights = FALSE)

---

**sw**

*Per-variable sum of model weights*

---

**Description**
Sum of model weights over all models including each explanatory variable.

**Usage**

```
sw(x)
importance(x)
```

**Arguments**

*x*  
either a list of fitted model objects, or a "model.selection" or "averaging" object.

**Value**

a named numeric vector of so called relative importance values, for each predictor variable.

**Author(s)**

Kamil Bartoń

**See Also**

*Weights*

dredge, model.avg, model.sel

**Examples**

```
# Generate some models
fm1 <- lm(y ~ ., data = Cement, na.action = na.fail)
ms1 <- dredge(fm1)

# Sum of weights can be calculated/extracted from various objects:
sw(ms1)
## Not run:
sw(subset(model.sel(ms1), delta <= 4))
sw(model.avg(ms1, subset = delta <= 4))
```
## End(Not run)

# Re-evaluate SW according to BIC
# note that re-ranking involves fitting the models again

# 'nobs' is not used here for backwards compatibility
lognobs <- log(length(resid(fm1)))

sw(subset(model.sel(ms1, rank = AIC, rank.args = list(k = lognobs)),
         cumsum(weight) <= .95))

# This gives a different result than previous command, because 'subset' is
# applied to the original selection table that is ranked with 'AICc'
sw(model.avg(ms1, rank = AIC, rank.args = list(k = lognobs),
     subset = cumsum(weight) <= .95))

---

### updateable

**Make a function return updateable result**

#### Description

Creates a function wrapper that stores a call in the object returned by its argument FUN.

#### Usage

```r
updateable(FUN, eval.args = NULL, Class)
```

get_call(x)

#### Arguments

- **FUN**: function to be modified, found via `match.fun`.
- **eval.args**: optionally a character vector of function arguments’ names to be evaluated in the stored call. See ‘Details’.
- **Class**: optional character vector naming class(es) to be set onto the result of FUN (not possible with formal S4 objects).
- **x**: an object from which the call should be extracted.
- **formula, random, ...**: arguments to be passed to `gamm` or `gamm4`
- **lme4**: if TRUE, `gamm4` is called, `gamm` otherwise.
Details

Most model fitting functions in \texttt{R} return an object that can be updated or re-fitted via \texttt{update}. This is thanks to the call stored in the object, which can be used (possibly modified) later on. It is also utilised by \texttt{dredge} to generate sub-models. Some functions (such as \texttt{gamm} or \texttt{MCMCglmm}) do not provide their result with the call element. To work that around, \texttt{updateable} can be used on that function to store the call. The resulting “wrapper” should be used in exactly the same way as the original function.

\texttt{updateable} can also be used to repair an existing \texttt{call} element, e.g. if it contains dotted names that prevent re-evaluation of such a call.

Argument \texttt{eval.args} specifies names of function arguments that should be evaluated in the stored call. This is useful when, for example, the model object does not have \texttt{formula} element. The default \texttt{formula} method tries to retrieve formula from the stored call, which works unless the formula has been given as a variable and value of that variable changed since the model was fitted (the last ‘example’ demonstrates this).

Value

\texttt{updateable} returns a function with the same arguments as \texttt{FUN}, wrapping a call to \texttt{FUN} and adding an element named \texttt{call} to its result if possible, otherwise an attribute “\texttt{call}” (if the returned value is atomic or a formal S4 object).

Note

\texttt{get\_call} is similar to \texttt{getCall} (defined in package \texttt{stats}), but it can also extract the call when it is an \texttt{attribute} (and not an element of the object). Because the default \texttt{getCall} method cannot do that, the default \texttt{update} method will not work with atomic or S4 objects resulting from \texttt{updateable} wrappers.

\texttt{uGamm} sets also an appropriate class onto the result ("\texttt{gamm4}" and/or "\texttt{gamm}"), which is needed for some generics defined in \texttt{MuMIn} to work (note that unlike the functions created by \texttt{updateable} it has no formal arguments of the original function). As of version 1.9.2, \texttt{MuMIn::gamm} is no longer available.

Author(s)

Kamil Bartoń

See Also

\texttt{update, getCall, getElement, attributes}

\texttt{gamm, gamm4}

Examples

# Simple example with \texttt{cor.test}:

# From \texttt{example(cor.test)}

\texttt{x <- c(44.4, 45.9, 41.9, 53.3, 44.7, 44.1, 50.7, 45.2, 60.1)}
y <- c(2.6, 3.1, 2.5, 5.0, 3.6, 4.0, 5.2, 2.8, 3.8)

ct1 <- cor.test(x, y, method = "kendall", alternative = "greater")

uCor.test <- updateable(cor.test)

c2 <- uCor.test(x, y, method = "kendall", alternative = "greater")

getCall(ct1) # --> NULL
gCall(c2)

#update(ct1, method = "pearson") --> Error
update(c2, method = "pearson")
update(c2, alternative = "two.sided")

## predefined wrapper for 'gamm':

set.seed(0)
dat <- gamSim(6, n = 100, scale = 5, dist = "normal")

fmm1 <- uGamm(y ~ s(x0) + s(x3) + s(x2), family = gaussian, data = dat,
random = list(fac = ~1))

gCall(fmm1)
class(fmm1)

###

## Not run:
library(caper)
data(shorebird)
shorebird <- comparative.data(shorebird.tree, shorebird.data, Species)

fm1 <- crunch(Egg.Mass ~ F.Mass * M.Mass, data = shorebird)

uCrunch <- updateable(crunch)

fm2 <- uCrunch(Egg.Mass ~ F.Mass * M.Mass, data = shorebird)

gCall(fm1)
gCall(fm2)
update(fm2) # Error with 'fm1'
dredge(fm2)

## End(Not run)

###

## Not run:
# "lmekin" does not store "formula" element
library(coxme)
uLmekin <- updateable(lmekin, eval.args = "formula")
Weights

f <- effort ~ Type + (1|Subject)
fml <- lme(f, data = ergoStool)
f2 <- uLme(f, data = ergoStool)

f <- wrong ~ formula # reassigning "f"

getCall(fm1) # formula is "f"
getCall(fm2)

formula(fm1) # returns the current value of "f"
formula(fm2)

## End(Not run)

---

Weights

### Description

Calculate, extract or set normalized model likelihoods (‘Akaike weights’).

### Usage

Weights(x)
Weights(x) <- value

### Arguments

- **x**: a numeric vector of information criterion values such as AIC, or objects returned by functions like AIC. There are also methods for extracting ‘Akaike weights’ from "model.selection" or "averaging" objects.
- **value**: numeric, the new weights for the "averaging" object or NULL to reset the weights based on the original IC used.

### Details

The replacement function can assign new weights to an "averaging" object, affecting coefficient values and order of component models.

### Value

For the extractor, a numeric vector of normalized likelihoods.

### Note

On assigning new weights, the model order changes accordingly, so assigning the same weights again will cause incorrect re-calculation of averaged coefficients. To avoid that, either re-set model weights by assigning NULL, or use ordered weights.
Author(s)

Kamil Bartoń

See Also

sw, weighted.mean

can be used to produce model weights.
weights, which extracts fitting weights from model objects.

Examples

fm1 <- glm(Prop ~ dose, data = Beetle, family = binomial)
fm2 <- update(fm1, . ~ . + I(dose^2))
fm3 <- update(fm1, . ~ log(dose))
fm4 <- update(fm3, . ~ . + I(log(dose)^2))

round(Weights(AICc(fm1, fm2, fm3, fm4)), 3)

am <- model.avg(fm1, fm2, fm3, fm4)

# Assign equal weights to all models:
Weights(am) <- rep(1, 4) # assigned weights are rescaled to sum to 1
Weights(am)
coef(am)

# Assign dummy weights:
wts <- c(2,1,4,3)
Weights(am) <- wts
coef(am)
# Component models are now sorted according to the new weights.
# The same weights assigned again produce incorrect results!
Weights(am) <- wts
coef(am) # wrong!

# Reset to original model weights
Weights(am) <- NULL
Weights(am) <- wts
coef(am) # correct
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