

Package ‘metafor’

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Title Meta-Analysis Package for R

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rmarkdown

Description A comprehensive collection of functions for conducting meta-analyses in R. The package includes functions to calculate various effect sizes or outcome measures, fit fixed-, random-, and mixed-effects models to such data, carry out moderator and meta-regression analyses, and create various types of meta-analytical plots (e.g., forest, funnel, radial, L'Abbe, Baujat, GOSH plots). For meta-analyses of binomial and person-time data, the package also provides functions that implement specialized methods, including the Mantel-Haenszel method, Peto's method, and a variety of suitable generalized linear (mixed-effects) models (i.e., mixed-effects logistic and Poisson regression models). Finally, the package provides functionality for fitting meta-analytic multivariate/multilevel models that account for non-independent sampling errors and/or true effects (e.g., due to the inclusion of multiple treatment studies, multiple endpoints, or other forms of clustering). Network meta-analyses and meta-analyses accounting for known correlation structures (e.g., due to phylogenetic relatedness) can also be conducted.

License GPL (>= 2)

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URL <http://www.metafor-project.org> <https://github.com/wwiechtb/metafor>
<https://wwiechtb.github.io/metafor/> <http://www.wvbauer.com>

BugReports <https://github.com/wwiechtb/metafor/issues>

NeedsCompilation no

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R topics documented:

metafor-package	4
addpoly	10
addpoly.default	11
addpoly.rma	13
anova.rma	15
baujat	19
bldiag	21
blup	22
coef.permutest.rma.uni	24
coef.rma	25
confint.rma	26
contrmat	31
cumul	33
dat.bangertdrowns2004	35
dat.begg1989	37
dat.berkey1998	38
dat.bonett2010	40
dat.bourassa1996	41
dat.colditz1994	43
dat.collins1985a	45
dat.collins1985b	46
dat.curtis1998	48
dat.debruin2009	50
dat.egger2001	51
dat.fine1993	53
dat.gibson2002	56
dat.graves2010	58
dat.hackshaw1998	59
dat.hart1999	60
dat.hasselblad1998	61
dat.hine1989	64
dat.ishak2007	65
dat.konstantopoulos2011	67
dat.laopaiboon2015	69
dat.lee2004	70
dat.li2007	71
dat.linde2005	72
dat.mcdaniel1994	74
dat.molloy2014	75

dat.nielweise2007	77
dat.nielweise2008	78
dat.normand1999	80
dat.pagliaro1992	81
dat.pignon2000	82
dat.pritz1997	84
dat.raudenbush1985	85
dat.riley2003	87
dat.senn2013	89
dat.yusuf1985	92
escalc	93
fitstats	109
fitted.rma	111
forest	112
forest.cumul.rma	113
forest.default	116
forest.rma	120
formula.rma	127
fsn	128
funnel	130
gosh	135
hc	138
influence.rma.mv	140
influence.rma.uni	142
labbe	145
leave1out	148
llplot	150
metafor.news	152
model.matrix.rma	153
permutest	154
plot.cumul.rma	158
plot.gosh.rma	160
plot.infl.rma.uni	162
plot.rma	164
predict.rma	165
print.anova.rma	169
print.confint.rma	171
print.escalc	172
print.fsn	174
print.gosh.rma	175
print.hc.rma.uni	176
print.list.rma	177
print.permutest.rma.uni	177
print.ranktest.rma	179
print.regtest.rma	180
print.rma	181
print.robust.rma	184
profile.rma.uni	186

qqnorm.rma.uni	189
radial	192
ranef	194
ranktest	197
regtest	198
replmiss	202
reporter	203
residuals.rma	205
rma.glmm	209
rma.mh	217
rma.mv	221
rma.peto	233
rma.uni	236
robust	247
simulate.rma	250
to.long	251
to.table	254
to.wide	257
transf	259
trimfill	261
update.rma	264
vcov.rma	265
vif	267
weights.rma.uni	269

Index	271
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metafor-package

metafor: A Meta-Analysis Package for R

Description

The **metafor** package provides a comprehensive collection of functions for conducting meta-analyses in R. The package includes functions for calculating various effect size or outcome measures frequently used in meta-analyses (e.g., risk differences, risk ratios, odds ratios, standardized mean differences, Fisher’s *r*-to-*z*-transformed correlation coefficients) and then allows the user to fit fixed-, random-, and mixed-effects models to these data. By including study-level covariates (‘moderators’) in these models, so-called ‘meta-regression’ analyses can be carried out. For meta-analyses of 2×2 tables, proportions, incidence rates, and incidence rate ratios, the package also provides functions that implement specialized methods, including the Mantel-Haenszel method, Peto’s method, and a variety of suitable generalized linear (mixed-effects) models (i.e., mixed-effects (conditional) logistic and Poisson regression models). For non-independent effect sizes or outcomes (e.g., due to correlated sampling errors, correlated true effects or outcomes, or other forms of clustering), the package also provides a function for fitting multilevel/multivariate meta-analytic models.

Various methods are available to assess model fit, to identify outliers and/or influential studies, and for conducting sensitivity analyses (e.g., standardized residuals, Cook’s distances, leave-one-out analyses). Advanced techniques for hypothesis tests and obtaining confidence intervals (e.g., for

the average effect size or for the model coefficients in a meta-regression model) have also been implemented (e.g., the Knapp and Hartung method, permutation tests).

The package also provides functions for creating forest, funnel, radial (Galbraith), normal quantile-quantile, L'Abbé, Baujat, and GOSH plots. The presence of funnel plot asymmetry (which may be indicative of publication bias) and its potential impact on the results can be examined via the rank correlation and Egger's regression test and by applying the trim and fill method.

The `escalc` Function

`escalc` Before a meta-analysis can be conducted, the relevant results from each study must be quantified in such a way that the resulting values can be further aggregated and compared. The `escalc` function can be used to compute a wide variety of effect size or outcome measures (and the corresponding sampling variances) that are often used in meta-analyses (e.g., risk ratios, odds ratios, risk differences, mean differences, standardized mean differences, ratios of means, correlation coefficients). Measures for quantifying some outcome for individual groups (e.g., proportions and incidence rates and transformations thereof), measures of change (e.g., raw and standardized mean changes), and measures of variability (e.g., standard deviations and coefficients of variation) are also available.

The `rma.uni` Function

`rma.uni` The various meta-analytic models that are typically used in practice are special cases of the general linear (mixed-effects) model. The `rma.uni` function (with alias `rma`) provides a general framework for fitting such models. The function can be used in conjunction with any of the usual effect size or outcome measures used in meta-analyses (e.g., as computed using the `escalc` function). The notation and models underlying the `rma.uni` function are explained below.

For a set of $i = 1, \dots, k$ independent studies, let y_i denote the observed value of the effect size or outcome measure in the i th study. Let θ_i denote the corresponding (unknown) true effect or outcome, such that

$$y_i | \theta_i \sim N(\theta_i, v_i).$$

In other words, the observed effects or outcomes are assumed to be unbiased and normally distributed estimates of the corresponding true effects or outcomes with sampling variances equal to v_i . The v_i values are assumed to be known. Depending on the outcome measure used, a bias correction, normalizing, and/or variance stabilizing transformation may be necessary to ensure that these assumptions are (approximately) true (e.g., the log transformation for odds ratios, the bias correction for standardized mean differences, Fisher's r-to-z transformation for correlations; see `escalc` for more details).

The **fixed-effects model** conditions on the true effects/outcomes and therefore provides a *conditional inference* about the set of k studies included in the meta-analysis. When using weighted estimation, this implies that the fitted model provides an estimate of

$$\bar{\theta}_w = \sum_{i=1}^k w_i \theta_i / \sum_{i=1}^k w_i,$$

that is, the *weighted average* of the true effects/outcomes in the set of k studies, with weights equal to $w_i = 1/v_i$ (this is what is often described as the 'inverse-variance' method in the meta-analytic

literature). One can also employ an unweighted estimation method, which provides an estimate of the *unweighted average* of the true effects/outcomes in the set of k studies, that is, an estimate of

$$\bar{\theta}_u = \sum_{i=1}^k \theta_i / k.$$

For weighted estimation, one could also choose to estimate $\bar{\theta}_w$, where the w_i values are user-defined weights (inverse-variance weights or unity weights as in unweighted estimation are just special cases). It is up to the user to decide to what extent $\bar{\theta}_w$ is a meaningful parameter to estimate (regardless of the weights used).

Moderators can be included in the fixed-effects model, yielding a **fixed-effects with moderators model**. Again, since the model conditions on the set of k studies included in the meta-analysis, the regression coefficients from the fitted model estimate the weighted relationship (in the least squares sense) between the true effects/outcomes and the moderator variables within the set of k studies included in the meta-analysis (again using weights equal to $w_i = 1/v_i$). The unweighted relationship between the true effects/outcomes and the moderator variables can be estimated when using the unweighted estimation method. Again, user-defined weights could also be used.

The **random-effects model** does not condition on the true effects/outcomes. Instead, the k studies included in the meta-analysis are assumed to be a random selection from a larger population of studies. In rare cases, the studies included in a meta-analysis are actually sampled from a larger collection of studies. More typically, the population of studies is a hypothetical population of an essentially infinite set of studies comprising all of the studies that have been conducted, that could have been conducted, or that may be conducted in the future. We assume that $\theta_i \sim N(\mu, \tau^2)$, that is, the true effects/outcomes in the population of studies are normally distributed with μ denoting the average true effect/outcome and τ^2 denoting the variance of the true effects/outcomes in the population (τ^2 is therefore often referred to as the ‘amount of heterogeneity’ in the true effects/outcomes). The random-effects model can therefore also be written as

$$y_i = \mu + u_i + e_i,$$

where $u_i \sim N(0, \tau^2)$ and $e_i \sim N(0, v_i)$. The fitted model provides an estimate of μ and τ^2 . Consequently, the random-effects model provides an *unconditional inference* about the average true effect/outcome in the population of studies (from which the k studies included in the meta-analysis are assumed to be a random selection).

When including moderator variables in the random-effects model, we obtain what is typically called a **mixed-effects model** in the meta-analytic literature. Such a meta-regression model can also be written as

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + u_i + e_i,$$

where $u_i \sim N(0, \tau^2)$ and $e_i \sim N(0, v_i)$ as before, x_{i1} denotes the value of the first moderator variable for the i th study, x_{i2} denotes the value of the second moderator variable for the i th study, and so on (letting p denote the total number of coefficients in the model, including the model intercept if it is included). Therefore, β_1 denotes how the average true effect/outcome changes for a one unit increase in x_{i1} , β_2 denotes how the average true effect/outcome changes for a one unit increase in x_{i2} , and so on, and the model intercept β_0 denotes the average true effect/outcome when the values of all moderator variables are equal to zero. The coefficients from the fitted model therefore estimate the relationship between the average true effect/outcome in the population of studies and the moderator variables included in the model. The value of τ^2 in the mixed-effects

model denotes the ‘amount of residual heterogeneity’ in the true effects/outcomes (i.e., the amount of variability in the true effects/outcomes that is not accounted for by the moderators included in the model).

When using weighted estimation in the context of a random-effects model, the model is fitted with weights equal to $w_i = 1/(\tau^2 + v_i)$, with τ^2 replaced by its estimate (again, this is the standard ‘inverse-variance’ method for random-effects models). One can also choose unweighted estimation in the context of the random-effects model and even any user-defined weights, although the parameter that is estimated (i.e., μ) remains the same regardless of the estimation method and weights used (as opposed to the fixed-effect model case, where the parameter estimated is different for weighted versus unweighted estimation or when using different weights than the standard inverse-variance weights). Since weighted estimation with inverse-variance weights is most efficient, it is usually to be preferred for random-effects models (while in the fixed-effect model case, we must carefully consider whether $\bar{\theta}_w$ or $\bar{\theta}_u$ is the more meaningful parameter to estimate). The same principle applies to mixed-effects (versus fixed-effects with moderators) models.

Contrary to what is often stated in the literature, it is important to realize that the fixed-effects model does *not* assume that the true effects/outcomes are homogeneous (i.e., that θ_i is equal to some common value θ in all k studies). In other words, fixed-effects models provide perfectly valid inferences under heterogeneity, as long as one is restricting these inferences to the set of studies included in the meta-analysis and one realizes that the model does not provide an estimate of θ , but of $\bar{\theta}_w$ or $\bar{\theta}_u$.

In the special case that the true effects/outcomes are actually homogeneous (the equal-effects case), the distinction between fixed- and random-effects models disappears, since homogeneity implies that $\mu = \bar{\theta}_w = \bar{\theta}_u \equiv \theta$. However, since there is no infallible method to test whether the true effects/outcomes are really homogeneous or not, a researcher should decide on the type of inference desired before examining the data and choose the model accordingly. In fact, there is nothing wrong with fitting both fixed- and random/mixed-effects models to the same data, since these models address different questions. For more details on the distinction between equal-, fixed-, and random-effects models, see Laird and Mosteller (1990) and Hedges and Vevea (1998).

The `rma.mh` Function

`rma.mh` The Mantel-Haenszel method provides an alternative approach for fitting fixed-effects models when dealing with studies providing data in the form of 2×2 tables or in the form of event counts (i.e., person-time data) for two groups (Mantel & Haenszel, 1959). The method is particularly advantageous when aggregating a large number of studies with small sample sizes (the so-called sparse data or increasing strata case). The Mantel-Haenszel method is implemented in the `rma.mh` function. It can be used in combination with risk ratios, odds ratios, risk differences, incidence rate ratios, and incidence rate differences. The Mantel-Haenszel method is always based on a weighted estimation approach.

The `rma.peto` Function

`rma.peto` Yet another method that can be used in the context of a meta-analysis of 2×2 table data is Peto’s method (see Yusuf et al., 1985), implemented in the `rma.peto` function. The method provides a weighted estimate of the (log) odds ratio under a fixed-effects model. The method is particularly advantageous when the event of interest is rare, but see the documentation of the function for some caveats.

The `rma.glmm` Function

`rma.glmm` Dichotomous outcomes and event counts (based on which one can calculate effect size or outcome measures such as odds ratios, incidence rate ratios, proportions, and incidence rates) are often assumed to arise from binomial and Poisson distributed data. Meta-analytic models that are directly based on such distributions are implemented in the `rma.glmm` function. These models are essentially special cases of generalized linear (mixed-effects) models (i.e., mixed-effects logistic and Poisson regression models). For 2×2 table data, a mixed-effects conditional logistic model (based on the non-central hypergeometric distribution) is also available. Random/mixed-effects models with dichotomous data are often referred to as ‘binomial-normal’ models in the meta-analytic literature. Analogously, for event count data, such models could be referred to as ‘Poisson-normal’ models.

The `rma.mv` Function

`rma.mv` Standard meta-analytic models assume independence between the observed effects or outcomes obtained from a set of studies. This assumption is often violated in practice. Dependencies can arise for a variety of reasons. For example, the sampling errors and/or true effects/outcomes may be correlated in multiple treatment studies (e.g., when multiple treatment groups are compared with a common control/reference group, such that the data from the control/reference group is used multiple times to compute the effect sizes or outcomes) or in multiple endpoint studies (e.g., when more than one effect size estimate or outcome is calculated based on the same sample of subjects due to the use of multiple endpoints or response variables) (Gleser & Olkin, 2009). Correlations in the true effects/outcomes can also arise due to other forms of clustering (e.g., effects/outcomes derived from the same paper, lab, research group, or species may be more similar to each other than effects/outcomes derived from different papers, labs, research groups, or species). In ecology and related fields, shared phylogenetic history among the organisms studied (e.g., plants, fungi, animals) can also induce correlations among the effects/outcomes. The `rma.mv` function can be used to fit suitable meta-analytic multivariate/multilevel models to such data, so that the non-independence in the observed/true effects or outcomes is accounted for. Network meta-analyses (also called multiple/mixed treatment comparison meta-analyses) can also be carried out with this function.

Future Plans and Updates

The **metafor** package is a work in progress and is updated on a regular basis with new functions and options. With `metafor.news()`, you can read the ‘NEWS’ file of the package after installation. Comments, feedback, and suggestions for improvements are very welcome.

Citing the Package

To cite the package, please use the following reference:

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

Getting Started with the Package

The paper mentioned above is a good starting place for those interested in using the **metafor** package. The purpose of the article is to provide a general overview of the package and its capabilities (as of version 1.4-0). Not all of the functions and options are described in the paper, but it should provide a useful introduction to the package. The paper can be freely downloaded from the URL given above or can be directly loaded with the command `vignette("metafor")`.

In addition to reading the paper, carefully read this page and then the help pages for the `escalc` and the `rma.uni` functions (or the `rma.mh`, `rma.peto`, `rma.glmm`, `rma.mv` functions if you intend to use these methods). The help pages for these functions provide links to many additional functions, which can be used after fitting a model. You can also read the entire documentation online at <https://wviechtb.github.io/metafor/reference/index.html> (where it is nicely formatted, equations are shown correctly, and the output from all examples is provided).

A (pdf) diagram showing the various functions in the metafor package (and how they are related to each other) can be opened with the command `vignette("diagram")`.

Finally, additional information about the package, several detailed analysis examples, examples of plots and figures provided by the package (with the corresponding code), some additional tips and notes, and a FAQ can be found on the package website at <http://www.metafor-project.org/>.

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Suggestions on how to obtain help with using the package can found on the package website at: <http://www.metafor-project.org/doku.php/help>

References

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addpoly

Add Polygons to Forest Plots

Description

The function `addpoly` is generic. It can be used to add polygons to a forest plot, for example, to indicate summary estimates for all or subgroups of studies and to indicate fitted/predicted values based on models involving moderators.

Usage

```
addpoly(x, ...)
```

Arguments

<code>x</code>	either an object of class "rma" or the values at which polygons should be drawn. See 'Details'.
<code>...</code>	other arguments.

Details

Currently, methods exist for two types of situations.

In the first case, object `x` is a fitted model coming from the `rma.uni`, `rma.mh`, `rma.peto`, or `rma.glm` functions. The model must either be a fixed- or random-effects model, that is, the model should not contain any moderators. The corresponding method is called `addpoly.rma`. It can be used to add a polygon to an existing forest plot (often at the bottom), showing the summary estimate with corresponding confidence interval based on the fitted model.

Alternatively, object `x` can be a vector with values at which one or more polygons should be drawn. The corresponding method is then `addpoly.default`.

Author(s)

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References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[addpoly.rma](#), [addpoly.default](#), [forest.rma](#), [forest.default](#)

addpoly.default *Add Polygons to Forest Plots (Default Method)*

Description

Function to add one or more polygons to a forest plot.

Usage

```
## Default S3 method:
addpoly(x, vi, sei, ci.lb, ci.ub, cr.lb, cr.ub,
        rows=-1, level=95, annotate=TRUE, digits=2, width, mlab,
        transf, atransf, targ, efac=1, col, border, fonts, cex, ...)
```

Arguments

<code>x</code>	vector with the values at which the polygons should be drawn.
<code>vi</code>	vector with the corresponding variances.
<code>sei</code>	vector with the corresponding standard errors note: only one of the two, <code>vi</code> or <code>sei</code> , needs to be specified).
<code>ci.lb</code>	vector with the corresponding lower confidence interval bounds. Not needed if <code>vi</code> or <code>sei</code> is specified. See ‘Details’.
<code>ci.ub</code>	vector with the corresponding upper confidence interval bounds. Not needed if <code>vi</code> or <code>sei</code> is specified. See ‘Details’.
<code>cr.lb</code>	optional vector with the corresponding lower credibility/prediction interval bounds.
<code>cr.ub</code>	optional vector with the corresponding upper credibility/prediction interval bounds.
<code>rows</code>	vector specifying the rows (or more generally, the horizontal positions) for plotting the polygons (defaults is <code>-1</code>). Can also be a single value specifying the row (horizontal position) of the first polygon (the remaining polygons are then plotted below this starting row).
<code>level</code>	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
<code>annotate</code>	logical specifying whether annotations should be added to the plot for the polygons that are drawn (the default is <code>TRUE</code>).
<code>digits</code>	integer specifying the number of decimal places to which the annotations should be rounded (the default is 2).
<code>width</code>	optional integer to manually adjust the width of the columns for the annotations.
<code>mlab</code>	optional character vector with the same length as <code>x</code> giving labels for the polygons that are drawn.
<code>transf</code>	optional argument specifying the name of a function that should be used to transform the <code>x</code> values and confidence interval bounds (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.

a <code>transf</code>	optional argument specifying the name of a function that should be used to transform the annotations (e.g., <code>a<code>transf</code>=exp</code> ; see also transf). If unspecified, no transformation is used.
<code>targs</code>	optional arguments needed by the function specified via <code>transf</code> or <code>a<code>transf</code></code> .
<code>efac</code>	vertical expansion factor for the polygons. The default value of 1 should usually work okay.
<code>col</code>	optional character string specifying the name of a color to use for the polygons. If unspecified, the function sets a default color.
<code>border</code>	optional character string specifying the name of a color to use for the border of the polygons. If unspecified, the function sets a default color.
<code>fonts</code>	optional character string specifying the font to use for the labels and annotations. If unspecified, the default font is used.
<code>cex</code>	optional symbol expansion factor. If unspecified, the function tries to set this to a sensible value.
<code>...</code>	other arguments.

Details

The function can be used to add one or more polygons to an existing forest plot created with the [forest](#) function. For example, summary estimates based on a model involving moderators can be added to the plot this way. See example below.

To use the function, one should specify the values at which the polygons should be drawn (via the `x` argument) together with the corresponding variances (via the `vi` argument) or with the corresponding standard errors (via the `sei` argument). Alternatively, one can specify the values at which the polygons should be drawn together with the corresponding confidence interval bounds (via the `ci.lb` and `ci.ub` arguments). Optionally, one can also specify the bounds of the corresponding credibility/prediction interval bounds via the `cr.lb` and `cr.ub` arguments.

The arguments `transf`, `atransf`, `efac`, and `cex` should always be set equal to the same values used to create the forest plot.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest.rma](#), [forest.default](#)

Examples

```

### meta-analysis of the log risk ratios using a mixed-
### effects model with absolute latitude as a moderator
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, mods = ~ ablat,
          slab=paste(author, year, sep=" ", data=dat.bcg))

### forest plot of the observed risk ratios
forest(res, addfit=FALSE, atransf=exp, xlim=c(-8,5), ylim=c(-4.5,16), cex=.8,
       order=order(dat.bcg$ablat), ilab=dat.bcg$ablat, ilab.xpos=-4,
       header="Author(s) and Year")

### predicted average log risk ratios for 10, 30, and 50 degrees absolute latitude
x <- predict(res, newmods=c(10, 30, 50))

### add predicted average risk ratios to forest plot
addpoly(x$pred, sei=x$se, atransf=exp, col="white", rows=-2,
       mlab=c("- at 10 Degrees", "- at 30 Degrees", "- at 50 Degrees"), cex=.8)
abline(h=0)
text(-8, -1, "Model-Based Estimates of RR:", pos=4, cex=.8)
text(-4, 15, "Latitude", cex=.8, font=2)

```

addpoly.rma

Add Polygons to Forest Plots (Method for 'rma' Objects)

Description

Function to add a polygon to a forest plot showing the summary estimate with corresponding confidence interval based on an object of class "rma".

Usage

```

## S3 method for class 'rma'
addpoly(x, row=-2, level=x$level, annotate=TRUE,
       addcred=FALSE, digits=2, width, mlab, transf, atransf, targs,
       efac=1, col, border, fonts, cex, ...)

```

Arguments

x	an object of class "rma".
row	value specifying the row (or more generally, the horizontal position) for plotting the polygon (the default is -2).
level	numerical value between 0 and 100 specifying the confidence interval level (the default is to take the value from the object).
annotate	logical specifying whether annotations for the summary estimate should be added to the plot (the default is TRUE).
addcred	logical specifying whether the bounds of the credibility/prediction interval should be added to the plot (the default is FALSE).

digits	integer specifying the number of decimal places to which the annotations should be rounded (the default is 2).
width	optional integer to manually adjust the width of the columns for the annotations.
mlab	optional character string giving a label for the summary estimate polygon. If unspecified, the function sets a default label.
transf	optional argument specifying the name of a function that should be used to transform the summary estimate and confidence interval bound (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.
atransf	optional argument specifying the name of a function that should be used to transform the annotations (e.g., <code>atransf=exp</code> ; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified via <code>transf</code> or <code>atransf</code> .
efac	vertical expansion factor for the polygon. The default value of 1 should usually work okay.
col	optional character string specifying the name of a color to use for the polygon. If unspecified, the function sets a default color.
border	optional character string specifying the name of a color to use for the border of the polygon. If unspecified, the function sets a default color.
fonts	optional character string specifying the font to use for the label and annotations. If unspecified, the default font is used.
cex	optional symbol expansion factor. If unspecified, the function tries to set this to a sensible value.
...	other arguments.

Details

The function can be used to add a polygon to an existing forest plot created with the [forest](#) function. The polygon shows the summary estimate based on a fixed- or random-effects model. Using this function, summary estimates based on different types of models can be shown in the same plot. Also, summary estimates based on a subgrouping of the studies can be added to the plot this way. See examples below.

The arguments `transf`, `atransf`, `efac`, and `cex` should always be set equal to the same values used to create the forest plot.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest.rma](#), [forest.default](#)

Examples

```

### meta-analysis of the log risk ratios using the Mantel-Haenszel method
res <- rma.mh(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
             slab=paste(author, year, sep=" "))

### forest plot of the observed risk ratios with summary estimate
forest(res, atransf=exp, xlim=c(-8,6), ylim=c(-2.5,16), header=TRUE)

### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### add summary estimate from the random-effects model to forest plot
addpoly(res, atransf=exp)

### forest plot with subgrouping of studies and summaries per subgroup
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
          slab=paste(author, year, sep=" "))
forest(res, xlim=c(-16, 6), at=log(c(.05, .25, 1, 4)), atransf=exp,
       ilab=cbind(dat.bcg$tpos, dat.bcg$tneg, dat.bcg$cpos, dat.bcg$cneg),
       ilab.xpos=c(-9.5,-8,-6,-4.5), cex=.75, ylim=c(-1, 27),
       order=order(dat.bcg$alloc), rows=c(3:4,9:15,20:23),
       mlab="RE Model for All Studies", header="Author(s) and Year")
op <- par(cex=.75, font=4)
text(-16, c(24,16,5), c("Systematic Allocation", "Random Allocation",
                       "Alternate Allocation"), pos=4)

par(font=2)
text(c(-9.5,-8,-6,-4.5), 26, c("TB+", "TB-", "TB+", "TB-"))
text(c(-8.75,-5.25), 27, c("Vaccinated", "Control"))
par(op)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
          subset=(alloc=="systematic"))
addpoly(res, row=18.5, cex=.75, atransf=exp, mlab="RE Model for Subgroup")
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
          subset=(alloc=="random"))
addpoly(res, row=7.5, cex=.75, atransf=exp, mlab="RE Model for Subgroup")
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
          subset=(alloc=="alternate"))
addpoly(res, row=1.5, cex=.75, atransf=exp, mlab="RE Model for Subgroup")

```

Description

For two (nested) models of class "rma.uni" or "rma.mv", the function provides a full versus reduced model comparison in terms of model fit statistics and a likelihood ratio test. When a single model is specified, a Wald-type test of one or more model coefficients or linear combinations thereof is carried out.

Usage

```
## S3 method for class 'rma'
anova(object, object2, btt, L, digits, ...)
```

Arguments

<code>object</code>	an object of class "rma.uni" or "rma.mv".
<code>object2</code>	an (optional) object of class "rma.uni" or "rma.mv". See 'Details'.
<code>btt</code>	optional vector of indices specifying which coefficients to include in the Wald-type test. Can also be a string to grep for. See 'Details'.
<code>L</code>	optional numeric vector or matrix specifying linear combinations of the coefficients in the model that should be tested to be zero. See 'Details'.
<code>digits</code>	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
<code>...</code>	other arguments.

Details

When a single model is specified, the function provides Wald-type tests of one or more model coefficients or linear combinations thereof.

In particular, for a fixed- or random-effects model (i.e., a model without moderators), this is just the test of the single coefficient of the model. For models including moderators, an omnibus test of all the model coefficients is conducted that excludes the intercept (the first coefficient) if it is included in the model. If no intercept is included in the model, then the omnibus test includes all of the coefficients in the model including the first.

Alternatively, one can manually specify the indices of the coefficients to test via the `btt` argument. For example, with `btt=c(3,4)`, only the third and fourth coefficient from the model would be included in the test (if an intercept is included in the model, then it corresponds to the first coefficient in the model). Instead of specifying the coefficient numbers, one can specify a string for `btt`. In that case, `grep` will be used to search for all coefficient names that match the string.

Instead, one can also specify one or multiple linear combinations of the coefficients in the model that should be tested to be zero via the `L` argument. If given as a matrix, its rows define the linear combinations to be tested. If the matrix is of full rank, an omnibus Wald-type test of all linear combinations is also provided.

When specifying two models for comparison, the function provides a likelihood ratio test comparing the two models. The two models must be based on the same set of data, must be of the same class, and should be nested for the likelihood ratio test to make sense. Note that likelihood ratio tests are not meaningful when using REML estimation and the two models have different fixed effects.

Value

An object of class "anova.rma". When a single model is specified (without any further arguments or together with the `btt` argument), the object is a list containing the following components:

<code>QM</code>	test statistic for the Wald-type test of model coefficients.
-----------------	--------------------------------------------------------------

QMp	p-value for the Wald-type test of model coefficients.
btt	indices of the coefficients tested by the Wald-type test.
k	number of outcomes included in the model fitting.
p	number of coefficients in the model (including the intercept).
m	number of coefficients included in the Wald-type test of coefficients.
...	some additional elements/values.

When argument `L` is specified, the object is a list containing the following components:

QM	test statistic for the omnibus Wald-type test of all linear combinations.
QMp	p-value for the omnibus Wald-type test.
hyp	description of the linear combinations tested.
Lb	values of the linear combinations.
se	standard errors of the linear combinations.
zval	test statistics of the linear combinations.
pval	p-values for the linear combinations.

When two models are specified, the object is a list containing the following components:

fit.stats.f	log-likelihood, deviance, AIC, BIC, and AICc for the full model.
fit.stats.r	log-likelihood, deviance, AIC, BIC, and AICc for the reduced model.
p.f	number of parameters in the full model.
p.r	number of parameters in the reduced model.
LRT	likelihood ratio test statistic.
pval	p-value for the likelihood ratio test.
QE.f	test statistic for the test of (residual) heterogeneity from the full model.
QE.r	test statistic for the test of (residual) heterogeneity from the reduced model.
tau2.f	estimated τ^2 value from the full model. NA for "rma.mv" objects.
tau2.r	estimated τ^2 value from the reduced model. NA for "rma.mv" objects.
R2	amount (in percent) of the heterogeneity in the reduced model that is accounted for in the full model (NA for fixed-effects models or for "rma.mv" objects). This can be regarded as a pseudo R^2 statistic (Raudenbush, 2009). Note that the value may not be very accurate unless k is large (Lopez-Lopez et al., 2014).
...	some additional elements/values.

The results are formatted and printed with the `print.anova.rma` function.

Note

In principle, one can consider likelihood ratio tests for the amount of (residual) heterogeneity in random- and mixed-effects models. The full model should then be fitted with either `method="ML"` or `method="REML"` and the reduced model with `method="FE"`. The p-value from that test is based on a chi-square distribution with 1 degree of freedom, but actually needs to be adjusted for the fact that the parameter (i.e., τ^2) falls on the boundary of the parameter space under the null hypothesis. Moreover, the Q-test usually keeps better control of the Type I error rate and therefore should be preferred (see Viechtbauer, 2007, for more details).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

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- Huizenga, H. M., Visser, I., & Dolan, C. V. (2011). Testing overall and moderator effects in random effects meta-regression. *British Journal of Mathematical and Statistical Psychology*, **64**, 1–19.
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- Raudenbush, S. W. (2009). Analyzing effect sizes: Random effects models. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (2nd ed., pp. 295–315). New York: Russell Sage Foundation.
- Viechtbauer, W. (2007). Hypothesis tests for population heterogeneity in meta-analysis. *British Journal of Mathematical and Statistical Psychology*, **60**, 29–60.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [print.anova.rma](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model
res1 <- rma(yi, vi, data=dat, method="ML")

### mixed-effects model with two moderators (absolute latitude and publication year)
res2 <- rma(yi, vi, mods = ~ ablat + year, data=dat, method="ML")

### Wald-type test of the two moderators
anova(res2)

### alternative way of specifying the same test
anova(res2, L=rbind(c(0,1,0), c(0,0,1)))

### corresponding likelihood ratio test
anova(res1, res2)

### test of a linear combination
anova(res2, L=c(1,35,1970))

### mixed-effects model with three moderators
res3 <- rma(yi, vi, mods = ~ ablat + year + alloc, data=dat, method="ML")
```

```

res3

### test the 'alloc' factor
anova(res3, btt=4:5)

### instead of specifying the coefficient numbers, grep for "alloc"
anova(res3, btt="alloc")

```

baujat

Baujat Plots for 'rma' Objects

Description

Function to create Baujat plots for objects of class "rma".

Usage

```

baujat(x, ...)

## S3 method for class 'rma'
baujat(x, xlim, ylim, xlab, ylab, cex, symbol, grid=TRUE, progbar=FALSE, ...)

```

Arguments

x	an object of class "rma".
xlim	x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
ylim	y-axis limits. If unspecified, the function tries to set the y-axis limits to some sensible values.
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
ylab	title for the y-axis. If unspecified, the function tries to set an appropriate axis title.
cex	optional character expansion factor. If unspecified, the function tries to set this to a sensible value.
symbol	either an integer to specify the pch value (i.e., plotting symbol), or "slab" to plot the study labels (if specified), or "ids" to plot the study id numbers (if unspecified, this is the default).
grid	logical indicating whether a grid should be added to the plot (can also be a color name).
progbar	logical indicating whether a progress bar should be shown (the default is FALSE).
...	other arguments.

Details

The model specified via `x` must be a model fitted with either the `rma.uni`, `rma.mh`, or `rma.peto` function.

Baujat et al. (2002) proposed a diagnostic plot to detect sources of heterogeneity in meta-analytic data. The plot shows the contribution of each study to the overall Q-test statistic for heterogeneity on the x-axis versus the influence of each study (defined as the standardized squared difference between the overall estimate based on a fixed-effects model with and without the study included in the model fitting) on the y-axis. The same type of plot can be produced by first fitting a fixed-effects model with either the `rma.uni` (using `method="FE"`), `rma.mh`, or `rma.peto` functions and then passing the fitted model object to the `baujat` function.

For models fitted with the `rma.uni` function (which may involve moderators and/or which may be random/mixed-effects models), the idea underlying this type of plot can be generalized as follows: The x-axis then corresponds to the squared Pearson residual of a study, while the y-axis corresponds to the standardized squared difference between the predicted/fitted value for the study with and without the study included in the model fitting. Therefore, for a fixed-effect with moderators model, the x-axis corresponds to the contribution of the study to the QE-test statistic for residual heterogeneity.

By default, the points plotted are the study id numbers, but one can also plot the study labels by setting `symbol="slab"` or one can specify a plotting symbol via the `symbol` argument that gets passed to `pch` (see [points](#)).

Value

A data frame with components:

<code>x</code>	the x coordinates of the points that were plotted.
<code>y</code>	the y coordinates of the points that were plotted.
<code>ids</code>	study id numbers.
<code>slab</code>	study labels.

Note that the data frame is returned invisibly.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Baujat, B., Mahe, C., Pignon, J.-P., & Hill, C. (2002). A graphical method for exploring heterogeneity in meta-analyses: Application to a meta-analysis of 65 trials. *Statistics in Medicine*, **21**(18), 2641–2652.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [influence.rma.uni](#), [radial](#)

Examples

```
### copy data from Pignon et al. (2000) into 'dat'
dat <- dat.pignon2000

### compute estimated log hazard ratios and sampling variances
dat$yi <- with(dat, OmE/V)
dat$vi <- with(dat, 1/V)

### meta-analysis based on all 65 trials
res <- rma(yi, vi, data=dat, method="FE", slab=trial)

### create Baujat plot
baujat(res)

### some variations of the plotting symbol
baujat(res, symbol=19)
baujat(res, symbol="slab")
```

bldiag*Construct Block Diagonal Matrix*

Description

Function to construct a block diagonal matrix from (a list of) matrices.

Usage

```
bldiag(...)
```

Arguments

... individual matrices or a list of matrices.

Author(s)

Posted to R-help by Berton Gunter (2 Sep 2005).

See Also

[rma.mv](#)

Examples

```
### copy data into 'dat'
dat <- dat.berkey1998

### construct list of the variance-covariance matrices of the observed outcomes for the studies
V <- lapply(split(dat[c("v1i", "v2i")], dat$trial), as.matrix)
V
```

```
### construct block diagonal matrix
V <- bldiag(V)
V
```

blup

Best Linear Unbiased Predictions for 'rma.uni' Objects

Description

The function calculates best linear unbiased predictions (BLUPs) of the study-specific true outcomes by combining the fitted values based on the fixed effects and the estimated contributions of the random effects for objects of class "rma.uni". Corresponding standard errors and prediction interval bounds are also provided.

Usage

```
blup(x, ...)

## S3 method for class 'rma.uni'
blup(x, level, digits, transf, targs, ...)
```

Arguments

x	an object of class "rma.uni".
level	numerical value between 0 and 100 specifying the prediction interval level (if unspecified, the default is to take the value from the object).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
transf	optional argument specifying the name of a function that should be used to transform the predicted values and interval bounds (e.g., transf=exp; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified under transf.
...	other arguments.

Value

An object of class "list.rma". The object is a list containing the following components:

pred	predicted values.
se	corresponding standard errors.
pi.lb	lower bound of the prediction intervals.
pi.ub	upper bound of the prediction intervals.
...	some additional elements/values.

The "list.rma" object is formatted and printed with [print.list.rma](#).

Note

For best linear unbiased predictions of only the random effects, see [ranef](#).

For predicted/fitted values that are based only on the fixed effects of the model, see [fitted.rma](#) and [predict.rma](#).

For conditional residuals (the deviations of the observed outcomes from the BLUPs), see `rstandard.rma.uni` with `type="conditional"`.

Fixed-effects models (with or without moderators) do not contain random study effects. The BLUPs for these models will therefore be equal to the usual fitted values, that is, those obtained with [fitted.rma](#) and [predict.rma](#).

When using the `transf` argument, the transformation is applied to the predicted values and the corresponding interval bounds. The standard errors are then set equal to NA and are omitted from the printed output.

The normal distribution is used to calculate the prediction intervals. When the model was fitted with the Knapp and Hartung (2003) method (i.e., `test="knha"` in the [rma.uni](#) function), then the t-distribution with $k - p$ degrees of freedom is used.

To be precise, it should be noted that the function actually calculates empirical BLUPs (eBLUPs), since the predicted values are a function of the estimated value of τ^2 .

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Kacker, R. N., & Harville, D. A. (1981). Unbiasedness of two-stage estimation and prediction procedures for mixed linear models. *Communications in Statistics, Theory and Methods*, **10**, 1249–1261.

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Robinson, G. K. (1991). That BLUP is a good thing: The estimation of random effects. *Statistical Science*, **6**, 15–32.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [predict.rma](#), [fitted.rma](#), [ranef.rma.uni](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### meta-analysis of the log risk ratios using a random-effects model
res <- rma(yi, vi, data=dat)
```

```

### BLUPs of the true risk ratios for each study
blup(res, transf=exp)

### illustrate shrinkage of BLUPs towards the (estimated) population average
res <- rma(yi, vi, data=dat)
blups <- blup(res)$pred
plot(NA, NA, xlim=c(.8,2.4), ylim=c(-2,0.5), pch=19,
     xaxt="n", bty="n", xlab="", ylab="Log Risk Ratio")
segments(rep(1,13), dat$yi, rep(2,13), blups, col="darkgray")
points(rep(1,13), dat$yi, pch=19)
points(rep(2,13), blups, pch=19)
axis(side=1, at=c(1,2), labels=c("Observed\nValues", "BLUPs"), lwd=0)
segments(.7, res$beta, 2.15, res$beta, lty="dotted")
text(2.3, res$beta, expression(hat(mu)==-0.71), cex=1)

```

```
coef.permutest.rma.uni
```

Extract the Model Coefficient Table from 'permutest.rma.uni' Objects

Description

The function extracts the estimated model coefficients, corresponding standard errors, test statistics, p-values (based on the permutation test), and confidence interval bounds from objects of class "permutest.rma.uni".

Usage

```
## S3 method for class 'permutest.rma.uni'
coef(object, ...)
```

Arguments

object	an object of class "permutest.rma.uni".
...	other arguments.

Value

A data frame with the following elements:

estimate	estimated model coefficient(s).
se	corresponding standard error(s).
zval	corresponding test statistic(s).
pval	p-value(s) based on the permutation test.
ci.lb	lower bound of the (permutation-based) confidence interval(s).
ci.ub	upper bound of the (permutation-based) confidence interval(s).

When the model was fitted with the Knapp and Hartung (2003) method (i.e., `test="knha"` in the `rma.uni` function), then `zval` is called `tval` in the data frame that is returned by the function.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[permutest.rma.uni](#), [rma.uni](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects model
### with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)

### permutation test
## Not run:
pres <- permutest(res)
coef(pres)
## End(Not run)
```

coef.rma

Extract the Model Coefficients and Coefficient Table from 'rma' and 'summary.rma' Objects

Description

The coef function extracts the estimated model coefficients from objects of class "rma". For objects of class "summary.rma", the model coefficients, corresponding standard errors, test statistics, p-values, and confidence interval bounds are extracted.

Usage

```
## S3 method for class 'rma'
coef(object, ...)

## S3 method for class 'summary.rma'
coef(object, ...)
```

Arguments

object an object of class "rma" or "summary.rma".
 ... other arguments.

Value

Either a vector with the estimated model coefficient(s) or a data frame with the following elements:

estimate	estimated model coefficient(s).
se	corresponding standard error(s).
zval	corresponding test statistic(s).
pval	corresponding p-value(s).
ci.lb	corresponding lower bound of the confidence interval(s).
ci.ub	corresponding upper bound of the confidence interval(s).

When the model was fitted with the Knapp and Hartung (2003) method (i.e., `test="knha"` in the `rma.uni` function) or with `test="t"` in the `rma.glmm` and `rma.mv` functions, then `zval` is called `tval` in the data frame that is returned by the function.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects model
### with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)
coef(res)
coef(summary(res))
```

confint.rma

Confidence Intervals for 'rma' Objects

Description

The function calculates confidence intervals for the model coefficients and/or for variance/correlation parameters in the model (the latter only for `rma.uni` and `rma.mv` objects).

Usage

```
## S3 method for class 'rma.uni'
confint(object, parm, level, fixed=FALSE, random=TRUE,
        digits, transf, targs, verbose=FALSE, control, ...)

## S3 method for class 'rma.mh'
confint(object, parm, level, digits, transf, targs, ...)

## S3 method for class 'rma.peto'
confint(object, parm, level, digits, transf, targs, ...)

## S3 method for class 'rma.glmm'
confint(object, parm, level, digits, transf, targs, ...)

## S3 method for class 'rma.mv'
confint(object, parm, level, fixed=FALSE, sigma2, tau2, rho, gamma2, phi,
        digits, transf, targs, verbose=FALSE, control, ...)
```

Arguments

object	an object of class "rma.uni", "rma.mh", "rma.peto", or "rma.mv". The method is not yet implemented for objects of class "rma.glmm".
parm	this argument is here for compatibility with the generic function <code>confint</code> , but is (currently) ignored.
fixed	logical indicating whether confidence intervals for the model coefficients should be returned (the default is FALSE).
random	logical indicating whether a confidence interval for the amount of (residual) heterogeneity should be returned (the default is TRUE) (only relevant for "rma.uni" objects).
sigma2	integer specifying for which σ^2 value a confidence interval should be obtained (only relevant for "rma.mv" objects).
tau2	integer specifying for which τ^2 value a confidence interval should be obtained (only relevant for "rma.mv" objects).
rho	integer specifying for which ρ value the confidence interval should be obtained (only relevant for "rma.mv" objects).
gamma2	integer specifying for which γ^2 value a confidence interval should be obtained (only relevant for "rma.mv" objects).
phi	integer specifying for which ϕ value a confidence interval should be obtained (only relevant for "rma.mv" objects).
level	numerical value between 0 and 100 specifying the confidence interval level (if unspecified, the default is to take the value from the object).
digits	integer specifying the number of decimal places to which the results should be rounded (if unspecified, the default is to take the value from the object).
transf	optional argument specifying the name of a function that should be used to transform the model coefficients and interval bounds (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.

targs	optional arguments needed by the function specified under transf.
verbose	logical indicating whether output should be generated on the progress of the iterative algorithms used to obtain the confidence intervals (the default is FALSE). See ‘Note’.
control	list of control values for the iterative algorithms. If unspecified, default values are defined inside the function. See ‘Note’.
...	other arguments.

Details

The confidence intervals for the model coefficients are simply the usual Wald-type intervals which are also shown when printing the fitted object.

For objects of class `"rma.uni"` obtained with the `rma.uni` function, the confidence interval for the amount of (residual) heterogeneity (i.e., τ^2) is obtained iteratively either via the Q-profile method or via the generalized Q-statistic method (Hartung and Knapp, 2005; Viechtbauer, 2007; Jackson, 2013; Jackson et al., 2014). The latter is automatically used when the model was fitted with `method="GENQ"`, the former is used in all other cases. Either method provides an exact confidence interval for τ^2 in random- and mixed-effects models. The square root of the interval bounds is also returned for easier interpretation. Confidence intervals for I^2 and H^2 are also provided (Higgins & Thompson, 2002). Since I^2 and H^2 are just monotonic transformations of τ^2 (for details, see `print.rma.uni`), the confidence intervals for I^2 and H^2 are also exact.

Usually, the estimate of τ^2 from the random/mixed-effects model will fall within the confidence interval provided by the Q-profile method. However, this is not guaranteed. Depending on the method used to estimate τ^2 and the width of the confidence interval, it can happen that the confidence interval does not actually contain the estimate (trying to explain this to reviewers can be tricky). However, using the empirical Bayes or Paule-Mandel estimator of τ^2 when fitting the model (i.e., using `method="EB"` or `method="PM"`) guarantees that the estimate of τ^2 falls within the confidence interval. When `method="GENQ"` was used to fit the model, the corresponding CI obtained via the generalized Q-statistic method is also guaranteed to contain the estimate τ^2 .

For objects of class `"rma.mv"` obtained with the `rma.mv` function, profile likelihood confidence intervals are obtained by default for all (non-fixed) variance and correlation components of the model. Alternatively, one can use the `sigma2`, `tau2`, `rho`, `gamma2`, or `phi` arguments to specify for which variance/correlation parameter a confidence interval should be obtained. Only one of these arguments can be used at a time. A single integer is used to specify the number of the parameter. The function then provides a profile likelihood confidence interval for the specified parameter. It is a good idea to examine the corresponding profile likelihood plot (via the `profile.rma.mv` function) to make sure that the bounds obtained are sensible.

The methods used to find a confidence interval for a variance/correlation component are iterative and require the use of the `uniroot` function. By default, the desired accuracy (`tol`) is set equal to `.Machine$double.eps^0.25` and the maximum number of iterations (`maxiter`) to 1000. These values can be adjusted with `control=list(tol=value,maxiter=value)`, but the defaults should be adequate for most purposes. If `verbose=TRUE`, output is generated on the progress of the iterative algorithm. This is especially useful when model fitting is slow, in which case finding the confidence interval bounds can also take considerable amounts of time.

More problematic when using the `uniroot` function is setting appropriate end points of the interval to be searched for the confidence interval bounds. The function tries to set some sensible defaults

for the end points, but it may happen that the function is only able to determine that a bound is below/above a certain limit (this is indicated in the output accordingly with < or > signs). It can also happen that the model cannot be fitted or does not converge especially at the extremes of the interval to be searched. This will result in missing (NA) bounds and corresponding warnings. It may then be necessary to adjust the end points manually (see ‘Note’).

Finally, it is also possible that the lower and upper confidence interval bounds for a variance component both fall below zero. Since both bounds then fall outside of the parameter space, the confidence interval then consists of the null/empty set. Alternatively, one could interpret this as a CI with bounds $[0, 0]$ or as indicating ‘highly (or overly) homogeneous’ data.

Value

An object of class `"confint.rma"`. The object is a list with either one or two elements (named `fixed` and `random`) with the following elements:

<code>estimate</code>	estimate of the model coefficient or variance component.
<code>ci.lb</code>	lower bound of the confidence interval.
<code>ci.ub</code>	upper bound of the confidence interval.

When obtaining CIs for all variance and correlation components of `"rma.mv"` models, the object is a list of class `"list.confint.rma"`, where each element is a `"confint.rma"` object as described above.

The results are formatted and printed with the `print.confint.rma` and `print.list.confint.rma` functions.

Note

For objects of class `"rma.uni"` with `random=TRUE`, the function provides a confidence interval for τ^2 . The upper end point of the interval to be searched for the confidence interval bounds is set to 100 (which should be large enough for most cases). The upper end point can be adjusted with `control=list(tau2.max=value)`. One can also adjust the lower end point of the interval to be searched with `control=list(tau2.min=value)` (the default is to take that value from the object, which is 0 by default). You should only play around with this value if you know what you are doing.

For objects of class `"rma.mv"`, the function provides confidence intervals for the variance/correlation parameters in the model. For variance components, the lower end point of the interval to be searched is set to 0 and the upper end point to the larger of 10 and 100 times the value of the component. For correlations, the function tries to set the lower end point to a sensible default depending on the type of variance structure chosen, while the upper end point is set to 1. One can adjust the lower and/or upper end points with `control=list(vc.min=value,vc.max=value)`. Also, the function tries to adjust the lower/upper end points when the model does not converge at these extremes (the end points are then moved closer to the estimated value of the component). The total number of tries for setting/adjusting the end points is determined via `control=list(eptries=<value>)`, with the default being 10 tries.

The Q-profile and generalized Q-statistic methods are both exact under the assumptions of the random- and mixed-effects models (i.e., normally distributed observed and true outcomes and known sampling variances). In practice, these assumptions are usually only approximately true, turning confidence intervals for τ^2 also into approximations. Profile likelihood confidence intervals are not exact by construction and rely on the asymptotic behavior of the likelihood ratio statistic, so they may be inaccurate in small samples.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

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See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#)

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### confidence interval for the total amount of heterogeneity
confint(res)

### mixed-effects model with absolute latitude in the model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat, data=dat.bcg)

### confidence interval for the residual amount of heterogeneity
confint(res)

### multilevel random-effects model
res <- rma.mv(yi, vi, random = ~ 1 | district/school, data=dat.konstantopoulos2011)
```

```

### profile plots and confidence intervals for the variance components
## Not run:
par(mfrow=c(2,1))
profile(res, sigma2=1)
abline(h=logLik(res) - qchisq(.95, df=1)/2, lty="dotted")
sav <- confint(res, sigma2=1)
sav
abline(v=sav$random[1,2:3], lty="dotted")
profile(res, sigma2=2)
abline(h=logLik(res) - qchisq(.95, df=1)/2, lty="dotted")
sav <- confint(res, sigma2=2)
sav
abline(v=sav$random[1,2:3], lty="dotted")
## End(Not run)

### multivariate parameterization of the model
res <- rma.mv(yi, vi, random = ~ factor(school) | district, data=dat.konstantopoulos2011)

### profile plots and confidence intervals for the variance component and correlation
## Not run:
par(mfrow=c(2,1))
profile(res, tau2=1)
abline(h=logLik(res) - qchisq(.95, df=1)/2, lty="dotted")
sav <- confint(res, tau2=1)
sav
abline(v=sav$random[1,2:3], lty="dotted")
profile(res, rho=1)
abline(h=logLik(res) - qchisq(.95, df=1)/2, lty="dotted")
sav <- confint(res, rho=1)
sav
abline(v=sav$random[1,2:3], lty="dotted")
## End(Not run)

```

contrmat

Construct Contrast Matrix for Two-Group Comparisons

Description

The function constructs a matrix that indicates which two groups have been contrasted against each other in each row of the dataset.

Usage

```
contrmat(data, grp1, grp2, last, shorten=FALSE, minlen=2, append=TRUE)
```

Arguments

data	a data frame in wide format.
grp1	either the name (given as a character string) or the position (given as a single number) of the first group variable in the data frame.

grp2	either the name (given as a character string) or the position (given as a single number) of the second group variable in the data frame.
last	optional character string to specify which group will be placed in the last column of the matrix (must be one of the groups in the group variables). If not given, the most frequently occurring second group is placed last.
shorten	logical indicating whether the variable names corresponding to the group names should be shortened (default is FALSE).
minlen	integer indicating the minimum length of the shortened variable names (2 by default).
append	logical indicating whether the contrast matrix should be appended to the data frame specified via the data argument (default is TRUE). If append=FALSE, only the contrast matrix is returned.

Details

The function can be used to construct a matrix that indicates which two groups have been contrasted against each other in each row of the data frame (with 1 for the first group, -1 for the second group, and 0 otherwise).

The `grp1` and `grp2` arguments are used to specify the group variables in the dataset (either as character strings or as numbers indicating the column positions of these variables in the dataset). Optional argument `last` is used to specify which group will be placed in the last column of the matrix.

If `shorten=TRUE`, the variable names corresponding to the group names are shortened (to at least `minlen`; the actual length might be longer to ensure uniqueness of the variable names).

The examples below illustrate the use of this function.

Value

A matrix with as many variables as there are groups.

Author(s)

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References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[to.wide](#), [dat.senn2013](#), [dat.hasselblad1998](#)

Examples

```

### restructure to wide format
dat <- dat.senn2013
dat <- dat[c(1,4,3,2,5,6)]
dat <- to.wide(dat, study="study", grp="treatment", ref="placebo", grpvars=4:6)
dat

### add contrast matrix
dat <- contrmat(dat, grp1="treatment.1", grp2="treatment.2")
dat

### data in long format
dat <- dat.hasselblad1998
dat

### restructure to wide format
dat <- to.wide(dat, study="study", grp="trt", ref="no_contact", grpvars=6:7)
dat

### add contrast matrix
dat <- contrmat(dat, grp1="trt.1", grp2="trt.2", shorten=TRUE)
dat

```

cumul

*Cumulative Meta-Analysis for 'rma' Objects***Description**

The functions repeatedly fit the specified model, adding one observation/study at a time to the model.

Usage

```

cumul(x, ...)

## S3 method for class 'rma.uni'
cumul(x, order, digits, transf, targs, progbar=FALSE, ...)
## S3 method for class 'rma.mh'
cumul(x, order, digits, transf, targs, progbar=FALSE, ...)
## S3 method for class 'rma.peto'
cumul(x, order, digits, transf, targs, progbar=FALSE, ...)

```

Arguments

x an object of class "rma.mh", "rma.peto", "rma.uni".

order optional vector with indices giving the desired order for the cumulative meta-analysis.

digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
transf	optional argument specifying the name of a function that should be used to transform the model coefficients and interval bounds (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified under <code>transf</code> .
progbar	logical indicating whether a progress bar should be shown (the default is <code>FALSE</code>).
...	other arguments.

Details

For "rma.uni" objects, the model specified by `x` must be a model without moderators (i.e., either a fixed- or a random-effects model).

Value

An object of class `c("list.rma", "cumul.rma")`. The object is a list containing the following components:

estimate	estimated coefficients of the model.
se	standard errors of the coefficients.
zval	test statistics of the coefficients.
pval	p-values for the test statistics.
ci.lb	lower bounds of the confidence intervals for the coefficients.
ci.ub	upper bounds of the confidence intervals for the coefficients.
QE	test statistics for the tests of heterogeneity.
QEp	p-values for the tests of heterogeneity.
tau2	estimated amounts of (residual) heterogeneity (only for random-effects models).
I2	values of I^2 (only for random-effects models).
H2	values of H^2 (only for random-effects models).

The object is formatted and printed with `print.list.rma`. A forest plot showing the results from the cumulative meta-analysis can be obtained with `forest.cumul.rma`. For random-effects models, `plot.cumul.rma` can also be used to visualize the results.

Note

When using the `transf` option, the transformation is applied to the estimated coefficients and the corresponding interval bounds. The standard errors are then set equal to `NA` and are omitted from the printed output.

Author(s)

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References

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- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest.cumul.rma](#), [plot.cumul.rma](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model
res <- rma(yi, vi, data=dat)

### cumulative meta-analysis (in the order of publication year)
cumul(res, transf=exp, order=order(dat$year))

### meta-analysis of the (log) risk ratios using the Mantel-Haenszel method
res <- rma.mh(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### cumulative meta-analysis
cumul(res, order=order(dat.bcg$year))
cumul(res, order=order(dat.bcg$year), transf=TRUE)

### meta-analysis of the (log) odds ratios using Peto's method
res <- rma.mh(ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### cumulative meta-analysis
cumul(res, order=order(dat.bcg$year))
cumul(res, order=order(dat.bcg$year), transf=TRUE)
```

dat.bangertdrowns2004 *Studies on the Effectiveness of Writing-to-Learn Interventions*

Description

Results from 48 studies on the effectiveness of school-based writing-to-learn interventions on academic achievement.

Usage

```
dat.bangertdrowns2004
```

Format

The data frame contains the following columns:

id	numeric	study number
author	character	study author(s)
year	numeric	publication year
grade	numeric	grade level (1 = elementary; 2 = middle; 3 = high-school; 4 = college)
length	numeric	treatment length (in weeks)
minutes	numeric	minutes per assignment
wic	numeric	writing tasks were completed in class (0 = no; 1 = yes)
feedback	numeric	feedback on writing was provided (0 = no; 1 = yes)
info	numeric	writing contained informational components (0 = no; 1 = yes)
pers	numeric	writing contained personal components (0 = no; 1 = yes)
imag	numeric	writing contained imaginative components (0 = no; 1 = yes)
meta	numeric	prompts for metacognitive reflection (0 = no; 1 = yes)
subject	character	subject matter
ni	numeric	total sample size of the study
yi	numeric	standardized mean difference
vi	numeric	corresponding sampling variance

Details

In each of the studies included in this meta-analysis, an experimental group (i.e., a group of students that received instruction with increased emphasis on writing tasks) was compared against a control group (i.e., a group of students that received conventional instruction) with respect to some content-related measure of academic achievement (e.g., final grade, an exam/quiz/test score). The effect size measure for this meta-analysis was the standardized mean difference (with positive scores indicating a higher mean level of academic achievement in the intervention group).

The standardized mean differences given here are bias-corrected and therefore differ slightly from the values reported in the article. Also, since only the total sample size is given in the article, the estimated sampling variances were computed under the assumption that $n_{i1} = n_{i2} = n_i/2$.

Source

Bangert-Drowns, R. L., Hurley, M. M., & Wilkinson, B. (2004). The effects of school-based writing-to-learn interventions on academic achievement: A meta-analysis. *Review of Educational Research*, **74**, 29–58.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.bangertdrowns2004
dat

### random-effects model
res <- rma(yi, vi, data=dat)
res
```

dat.begg1989 *Studies on Bone-Marrow Transplantation versus Chemotherapy for the Treatment of Leukemia*

Description

Results from controlled and uncontrolled studies on the effectiveness of allogeneic bone-marrow transplantation (BMT) and conventional chemotherapy (CMO) in the treatment of acute nonlymphocytic leukemia.

Usage

dat.begg1989

Format

The data frame contains the following columns:

study	numeric	study number
trt	character	treatment (BMT or CMO)
arms	numeric	number of arms in the study (1 = uncontrolled studies; 2 = controlled studies)
yi	numeric	2-year disease-free survival
sei	numeric	corresponding standard error
vi	numeric	corresponding sampling variance

Details

The dataset includes the results from controlled and uncontrolled studies on the 2-year disease-free survival in patients with acute nonlymphocytic leukemia receiving either allogeneic bone-marrow transplantation (BMT) or conventional chemotherapy (CMO). In the controlled (two-arm) studies (studies 1-4), a cohort of patients in complete remission and potentially eligible for BMT was assembled, and those who consented and for whom a donor could be found received BMT, with the remaining patients used as controls (receiving CMO). In the uncontrolled (one-arm) studies (studies 5-16), only a single group was studied, receiving either BMT or CMO.

The data in this dataset were obtained from Table 1 in Begg & Pilote (1991, p. 902).

Source

Begg, C. B., & Pilote, L. (1991). A model for incorporating historical controls into a meta-analysis. *Biometrics*, **47**, 899–906.

References

Begg, C. B., Pilote, L., & McGlave, P. B. (1989). Bone marrow transplantation versus chemotherapy in acute non-lymphocytic leukemia: A meta-analytic review. *European Journal of Cancer and Clinical Oncology*, **25**, 1519–1523.

Examples

```

### copy data into 'dat' and examine data
dat <- dat.begg1989
dat

### turn trt and arms into factors and set reference levels
dat$trt <- relevel(factor(dat$trt), ref="CMO")
dat$arms <- relevel(factor(dat$arms), ref="2")

### create data frame with the treatment differences for the controlled studies
dat2 <- data.frame(yi = dat$yi[c(1,3,5,7)] - dat$yi[c(2,4,6,8)],
                  vi = dat$vi[c(1,3,5,7)] + dat$vi[c(2,4,6,8)])
dat2

### DerSimonian and Laird method using the treatment differences
res <- rma(yi, vi, data=dat2, method="DL", digits=2)
res

### Begg & Pilote (1991) model incorporating the uncontrolled studies
res <- rma.mv(yi, vi, mods = ~ trt, random = ~ 1 | study,
             data=dat, method="ML", digits=2)
res

### model involving bias terms for the uncontrolled studies
res <- rma.mv(yi, vi, mods = ~ trt + trt:arms, random = ~ 1 | study,
             data=dat, method="ML", digits=2)
res

### model with random treatment effect
res <- rma.mv(yi, vi, mods = ~ trt, random = list(~ 1 | study, ~ trt | study),
             struct="UN", tau2=c(0,NA), rho=0, data=dat, method="ML", digits=2)
res

### model with random treatment effect, but with equal variances in both arms
res <- rma.mv(yi, vi, mods = ~ trt, random = list(~ 1 | study, ~ trt | study),
             struct="CS", rho=0, data=dat, method="ML", digits=2)
res

```

dat.berkey1998

Studies on Treatments for Periodontal Disease

Description

Results from 5 trials comparing surgical and non-surgical treatments for medium-severity periodontal disease one year after treatment.

Usage

```
dat.berkey1998
```

Format

The data frame contains the following columns:

trial	numeric	trial number
author	character	study author(s)
year	numeric	publication year
ni	numeric	number of patients
outcome	character	outcome (PD = probing depth; AL = attachment level)
yi	numeric	observed mean difference in outcome (surgical versus non-surgical)
vi	numeric	corresponding sampling variance
v1i	numeric	variances and covariances of the observed effects
v2i	numeric	variances and covariances of the observed effects

Details

The dataset includes the results from 5 trials that compared surgical and non-surgical methods for the treatment of medium-severity periodontal disease. Reported outcomes include the change in probing depth (PD) and attachment level (AL) one year after the treatment. The effect size measure used for this meta-analysis was the (raw) mean difference, calculated in such a way that positive values indicate that surgery was more effective than non-surgical treatment in decreasing the probing depth and increasing the attachment level (so, the results from the various trials indicate that surgery is preferable for reducing the probing depth, while non-surgical treatment is preferable for increasing the attachment level). Since each trial provides effect size estimates for both outcomes, the estimates are correlated. A multivariate model can be used to meta-analyze the two outcomes simultaneously.

The $v1i$ and $v2i$ values are the variances and covariances of the observed effects. In particular, for each study, variables $v1i$ and $v2i$ form a 2×2 variance-covariance matrix of the observed effects, with the diagonal elements corresponding to the sampling variances of the mean differences (the first for probing depth, the second for attachment level) and the off-diagonal value corresponding to the covariance of the two mean differences. Below, the full (block diagonal) variance-covariance for all studies is constructed from these two variables.

Source

Berkey, C. S., Antczak-Bouckoms, A., Hoaglin, D. C., Mosteller, F., & Pihlstrom, B. L. (1995). Multiple-outcomes meta-analysis of treatments for periodontal disease. *Journal of Dental Research*, **74**, 1030–1039.

Berkey, C. S., Hoaglin, D. C., Antczak-Bouckoms, A., Mosteller, F., & Colditz, G. A. (1998). Meta-analysis of multiple outcomes by regression with random effects. *Statistics in Medicine*, **17**, 2537–2550.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.berkey1998
dat

### construct list of the variance-covariance matrices of the observed outcomes for the studies
```

```

V <- lapply(split(dat[c("v1i", "v2i")], dat$trial), as.matrix)

### construct block diagonal matrix
V <- bldiag(V)

### fit multiple outcomes (meta-regression) model (with REML estimation)
res <- rma.mv(yi, V, mods = ~ outcome - 1, random = ~ outcome | trial, struct="UN", data=dat)
print(res, digits=3)

### test/estimate difference between the two outcomes
anova(res, L=c(1,-1))

### fit model including publication year as moderator for both outcomes (with ML estimation)
res <- rma.mv(yi, V, mods = ~ outcome + outcome:I(year - 1983) - 1,
              random = ~ outcome | trial, struct="UN", data=dat, method="ML")
print(res, digits=3)

```

dat.bonett2010

Studies on the Reliability of the CES-D Scale

Description

Results from 9 studies on the reliability of the Center for Epidemiologic Studies Depression (CES-D) Scale administered to children providing care to an elderly parent.

Usage

```
dat.bonett2010
```

Format

The data frame contains the following columns:

study	numeric	study number
source	character	source of data
ni	numeric	sample size
mi	numeric	number of items in the scale
ai	numeric	observed value of Cronbach's alpha
caregivers	character	gender of the children in the sample

Details

The Center for Epidemiologic Studies Depression (CES-D) Scale is a 20-item questionnaire assessing various symptoms of depression, with each item scored on a 4-point scale. The scale has been used in several studies to examine depressive symptoms in children providing care to an elderly parent. The dataset includes information on the reliability of the scale as measured with Cronbach's alpha in 9 such studies. Also, the gender composition of the children in each sample is indicated.

Source

Bonett, D. G. (2010). Varying coefficient meta-analytic methods for alpha reliability. *Psychological Methods*, **15**, 368–385.

References

Bonett, D. G. (2002). Sample size requirements for testing and estimating coefficient alpha. *Journal of Educational and Behavioral Statistics*, **27**, 335–340.

Hakstian, A. R., & Whalen, T. E. (1976). A k-sample significance test for independent alpha coefficients. *Psychometrika*, **41**, 219–231.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.bonett2010
dat

### meta-analysis using the raw alpha values
res <- rma(measure="ARAW", ai=ai, mi=mi, ni=ni, data=dat)
res

### meta-analysis using transformed alpha values (using the
### transformation suggested by Hakstian & Whalen, 1976)
res <- rma(measure="AHW", ai=ai, mi=mi, ni=ni, data=dat)
res
predict(res, transf=transf.iahw)

### meta-analysis using transformed alpha values (using the
### transformation suggested by Bonett, 2002)
res <- rma(measure="ABT", ai=ai, mi=mi, ni=ni, data=dat)
res
predict(res, transf=transf.iabt)

### examine whether female/mixed samples yield different alphas (with raw alphas)
res <- rma(measure="ARAW", ai=ai, mi=mi, ni=ni, mods = ~ caregivers, data=dat)
res
predict(res, newmods=c(0,1), digits=2)
```

dat.bourassa1996

Studies on the Association between Handedness and Eye-Dominance

Description

Results from 47 studies on the association between handedness and eye-dominance.

Usage

```
dat.bourassa1996
```

Format

The data frame contains the following columns:

study	numeric	study number
sample	numeric	sample number
author	character	(first) author
year	numeric	publication year
selection	character	selection of subjects on the basis of eyedness or handedness
investigator	character	investigator (psychologist, educationalist, or other)
hand_assess	character	method to assess handedness (questionnaire or performance based)
eye_assess	character	method to assess eyedness (see below for classification)
mage	numeric	mean age of sample
lh.le	numeric	number of left-handed left-eyed individuals
lh.re	numeric	number of left-handed right-eyed individuals
rh.le	numeric	number of right-handed left-eyed individuals
rh.re	numeric	number of right-handed right-eyed individuals
sex	character	sex of the sample (combined, male, or female)

Details

The 47 studies included in this meta-analysis examined the association between handedness and eye-dominance (ocular dominance or eyedness). Results are given in terms of 2×2 tables, indicating the number of left-handed left-eyed, left-handed right-eyed, right-handed left-eyed, and right-handed right-eyed individuals. Note that some studies included multiple (independent) samples, so that the meta-analysis included 54 samples in total. Also, for some studies, the combined data of the males and females are further broken down into the two subgroups.

In some studies, there was indication that the selection of subjects was not random with respect to handedness and/or eyedness. While this should not influence the size of the association as measured with the odds ratio, this invalidates those studies for assessing the overall percentage of left-eyed and left-handed individuals.

Handedness was assessed in the individual studies either based on a questionnaire or inventory or based on task performance. Eyedness was assessed based on various methods: E.1 methods are based on task performance, while E.2.a denotes assessment based on a questionnaire. The performance based methods could be further broken down into: E.1.a.i (monocular procedure with object/instrument held in one hand), E.1.a.ii (monocular procedure with object/instrument held in both hands), E.1.b (binocular procedure), E.1.c (a combination of the previous methods), and E.1.d (some other method).

Source

Bourassa, D. C., McManus, I. C., & Bryden, M. P. (1996). Handedness and eye-dominance: A meta-analysis of their relationship. *Laterality*, *1*, 5–34.

Examples

```
### copy data into 'dat'
dat <- dat.bourassa1996
```

```

### calculate log(OR) and corresponding sampling variance with 1/2 correction
dat <- escalc(measure="OR", ai=lh.le, bi=lh.re, ci=rh.le, di=rh.re, data=dat, add=1/2, to="all")
dat

### overall association between handedness and eyedness
res <- rma(yi, vi, data=dat, subset=sex=="combined")
res
predict(res, transf=exp, digits=2)

```

dat.colditz1994

*Studies on the Effectiveness of the BCG Vaccine Against Tuberculosis***Description**

Results from 13 studies examining the effectiveness of the Bacillus Calmette-Guerin (BCG) vaccine against tuberculosis.

Usage

```

dat.colditz1994
dat.bcg

```

Format

The data frame contains the following columns:

trial	numeric	trial number
author	character	author(s)
year	numeric	publication year
tpos	numeric	number of TB positive cases in the treated (vaccinated) group
tneg	numeric	number of TB negative cases in the treated (vaccinated) group
cpos	numeric	number of TB positive cases in the control (non-vaccinated) group
cneg	numeric	number of TB negative cases in the control (non-vaccinated) group
ablat	numeric	absolute latitude of the study location (in degrees)
alloc	character	method of treatment allocation (random, alternate, or systematic assignment)

Details

The 13 studies provide data in terms of 2×2 tables in the form:

	TB positive	TB negative
vaccinated group	tpos	tneg
control group	cpos	cneg

The goal of the meta-analysis was to examine the overall effectiveness of the BCG vaccine for preventing tuberculosis and to examine moderators that may potentially influence the size of the effect.

The dataset has been used in several publications to illustrate meta-analytic methods (see ‘References’).

Source

Colditz, G. A., Brewer, T. F., Berkey, C. S., Wilson, M. E., Burdick, E., Fineberg, H. V., & Mosteller, F. (1994). Efficacy of BCG vaccine in the prevention of tuberculosis: Meta-analysis of the published literature. *Journal of the American Medical Association*, **271**, 698–702.

References

Berkey, C. S., Hoaglin, D. C., Mosteller, F., & Colditz, G. A. (1995). A random-effects regression model for meta-analysis. *Statistics in Medicine*, **14**, 395–411.

van Houwelingen, H. C., Arends, L. R., & Stijnen, T. (2002). Advanced methods in meta-analysis: Multivariate approach and meta-regression. *Statistics in Medicine*, **21**, 589–624.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

Examples

```
### copy data into 'dat'
dat <- dat.bcg

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat)
dat

### random-effects model
res <- rma(yi, vi, data=dat)
res

### average risk ratio with 95% CI
predict(res, transf=exp)

### mixed-effects model with absolute latitude and publication year as moderators
res <- rma(yi, vi, mods = ~ ablat + year, data=dat)
res

### predicted average risk ratios for 10-60 degrees absolute latitude
### holding the publication year constant at 1970
predict(res, newmods=cbind(seq(from=10, to=60, by=10), 1970), transf=exp)

### note: the interpretation of the results is difficult because absolute
### latitude and publication year are strongly correlated (the more recent
### studies were conducted closer to the equator)
plot(dat$ablat, dat$year)
cor(dat$ablat, dat$year)
```

dat.collins1985a *Studies on the Treatment of Upper Gastrointestinal Bleeding by a Histamine H2 Antagonist*

Description

Results from studies examining the effectiveness of histamine H2 antagonists (cimetidine or ranitidine) in treating patients with acute upper gastrointestinal hemorrhage.

Usage

dat.collins1985a

Format

The data frame contains the following columns:

id	numeric	study number
trial	character	first author of trial
year	numeric	year of publication
ref	numeric	reference number
trt	character	C = cimetidine, R = ranitidine
ctrl	character	P = placebo, AA = antacids, UT = usual treatment
nti	numeric	number of patients in treatment group
b.xti	numeric	number of patients in treatment group with persistent or recurrent bleedings
o.xti	numeric	number of patients in treatment group in need of operation
d.xti	numeric	number of patients in treatment group that died
nci	numeric	number of patients in control group
b.xci	numeric	number of patients in control group with persistent or recurrent bleedings
o.xci	numeric	number of patients in control group in need of operation
d.xci	numeric	number of patients in control group that died

Details

The data were obtained from Tables 1 and 2 in Collins and Langman (1985). The authors used Peto's (one-step) method for meta-analyzing the 27 trials. This approach is implemented in the [rma.peto](#) function. Using the same dataset, van Houwelingen, Zwinderman, and Stijnen (1993) describe some alternative approaches for analyzing these data, including fixed and random-effects conditional logistic models. Those are implemented in the [rma.glm](#) function.

Source

Collins, R., & Langman, M. (1985). Treatment with histamine H2 antagonists in acute upper gastrointestinal hemorrhage. *New England Journal of Medicine*, **313**, 660–666.

References

van Houwelingen, H. C., Zwinderman, K. H., & Stijnen, T. (1993). A bivariate approach to meta-analysis. *Statistics in Medicine*, **12**, 2273–2284.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.collins1985a
dat

### meta-analysis of log ORs using Peto's method (outcome: persistent or recurrent bleedings)
res <- rma.peto(ai=b.xti, n1i=nti, ci=b.xci, n2i=nci, data=dat)
print(res, digits=2)

## Not run:
### meta-analysis of log ORs using a conditional logistic regression model (FE model)
res <- rma.glmm(measure="OR", ai=b.xti, n1i=nti, ci=b.xci, n2i=nci, data=dat,
               model="CM.EL", method="FE")
summary(res)
predict(res, transf=exp, digits=2)

### plot the likelihoods of the odds ratios
llplot(measure="OR", ai=b.xti, n1i=nti, ci=b.xci, n2i=nci, data=dat,
       lwd=1, refline=NA, xlim=c(-4,4), drop00=FALSE)

### meta-analysis of log odds ratios using a conditional logistic regression model (RE model)
res <- rma.glmm(measure="OR", ai=b.xti, n1i=nti, ci=b.xci, n2i=nci, data=dat,
               model="CM.EL", method="ML")
summary(res)
predict(res, transf=exp, digits=2)

## End(Not run)

### meta-analysis of log ORs using Peto's method (outcome: need for surgery)
res <- rma.peto(ai=o.xti, n1i=nti, ci=o.xci, n2i=nci, data=dat)
print(res, digits=2)

### meta-analysis of log ORs using Peto's method (outcome: death)
res <- rma.peto(ai=d.xti, n1i=nti, ci=d.xci, n2i=nci, data=dat)
print(res, digits=2)
```

dat.collins1985b

Studies on the Effects of Diuretics in Pregnancy

Description

Results from 9 studies examining the effects of diuretics in pregnancy on various outcomes.

Usage

```
dat.collins1985b
```

Format

The data frame contains the following columns:

id	numeric	study number
author	character	study author(s)
year	numeric	publication year
pre.nti	numeric	number of women in treatment group followed up for pre-eclampsia outcome
pre.nci	numeric	number of women in control/placebo group followed up for pre-eclampsia outcome
pre.xti	numeric	number of women in treatment group with any form of pre-eclampsia
pre.xci	numeric	number of women in control/placebo group with any form of pre-eclampsia
oedema	numeric	dummy variable indicating whether oedema was a diagnostic criterion
fup.nti	numeric	number of women in treatment group followed up for mortality outcomes
fup.nci	numeric	number of women in control/placebo group followed up for mortality outcomes
ped.xti	numeric	number of perinatal deaths in treatment group
ped.xci	numeric	number of perinatal deaths in control/placebo group
stb.xti	numeric	number of stillbirths in treatment group
stb.xci	numeric	number of stillbirths in control/placebo group
ned.xti	numeric	number of neonatal deaths in treatment group
ned.xci	numeric	number of neonatal deaths in control/placebo group

Details

The 9 studies in this dataset examined the effects of diuretics in pregnancy on various outcomes, including the presence of any form of pre-eclampsia, perinatal death, stillbirth, and neonatal death.

Source

Collins, R., Yusuf, S., & Peto, R. (1985). Overview of randomised trials of diuretics in pregnancy. *British Medical Journal*, **290**, 17–23.

Examples

```
### copy data into 'dat'
dat <- dat.collins1985b

### calculate (log) odds ratio and sampling variance
dat <- escalc(measure="OR", n1i=pre.nti, n2i=pre.nci, ai=pre.xti, ci=pre.xci, data=dat)
summary(dat, digits=2, transf=exp)

### meta-analysis using Peto's method for any form of pre-eclampsia
rma.peto(n1i=pre.nti, n2i=pre.nci, ai=pre.xti, ci=pre.xci, data=dat, digits=2)

### meta-analysis including only studies where oedema was not a diagnostic criterion
rma.peto(n1i=pre.nti, n2i=pre.nci, ai=pre.xti, ci=pre.xci, data=dat, digits=2, subset=(oedema==0))

### meta-analyses of mortality outcomes (perinatal deaths, stillbirths, and neonatal deaths)
```

```
rma.peto(n1i=fup.nti, n2i=fup.nci, ai=ped.xti, ci=ped.xci, data=dat, digits=2)
rma.peto(n1i=fup.nti, n2i=fup.nci, ai=stb.xti, ci=stb.xci, data=dat, digits=2)
rma.peto(n1i=fup.nti, n2i=fup.nci, ai=ned.xti, ci=ned.xci, data=dat, digits=2)
```

dat.curtis1998 *Studies on the Effects of Elevated CO2 Levels on Woody Plant Mass*

Description

Results from studies examining the effects of elevated CO2 levels on woody plant mass.

Usage

```
dat.curtis1998
```

Format

The data frame contains the following columns:

id	numeric	observation number
paper	numeric	paper number
genus	character	genus name
species	character	species name
fungrp	character	plant functional group
co2.ambi	numeric	ambient CO2 level (control group)
co2.elev	numeric	elevated CO2 level (treatment group)
units	character	units for CO2 exposure levels
time	numeric	maximum length of time (days) of CO2 exposure
pot	character	growing method (see below)
method	character	CO2 exposure facility (see below)
stock	character	planting stock code
xtrt	character	interacting treatment code (see below)
level	character	interacting treatment level codes (see below)
m1i	numeric	mean plant mass under elevated CO2 level (treatment group)
sd1i	numeric	standard deviation of plant mass under elevated CO2 level (treatment group)
n1i	numeric	number of observations under elevated CO2 level (treatment group)
m2i	numeric	mean plant mass under ambient CO2 level (control group)
sd2i	numeric	standard deviation of plant mass under ambient CO2 level (control group)
n2i	numeric	number of observations under ambient CO2 level (control group)

Details

The studies included in this dataset compared the total above- plus below-ground biomass (in grams) for plants that were either exposed to ambient (around 35 Pa) and elevated CO2 levels (around twice the ambient level). The `co2.ambi` and `co2.elev` variables indicate the CO2 levels in the control and treatment groups, respectively (with the `units` variable specifying the units for the CO2 exposure levels). Many of the studies also varied one or more additional environmental variables (defined by

the xtrt and level variables):

- NONE = no additional treatment factor
- FERT = soil fertility (either a CONTROL, HIGH, or LOW level)
- LIGHT = light treatment (always a LOW light level)
- FERT+L = soil fertility and light (a LOW light and soil fertility level)
- H2O = well watered vs drought (either a WW or DRT level)
- TEMP = temperature treatment (either a HIGH or LOW level)
- OZONE = ozone exposure (either a HIGH or LOW level)
- UVB = ultraviolet-B radiation exposure (either a HIGH or LOW level)

In addition, the studies differed with respect to various design variables, including CO₂ exposure duration (time), growing method (pot: number = pot size in liters; GRND = plants rooted in ground; HYDRO = solution or aeroponic culture), CO₂ exposure facility (method: GC = growth chamber; GH = greenhouse; OTC = field-based open-top chamber), and planting stock (stock: SEED = plants started from seeds; SAP = plants started from cuttings). The goal of the meta-analysis was to examine the effects of elevated CO₂ levels on plant physiology and growth and the interacting effects of the environmental (and design) variables.

Source

Hedges, L. V., Gurevitch, J., & Curtis, P. S. (1999). The meta-analysis of response ratios in experimental ecology. *Ecology*, **80**, 1150–1156. (data obtained from *Ecological Archives*, E080-008-S1, at: <http://www.esapubs.org/archive/ecol/E080/008/>)

References

Curtis, P. S., & Wang, X. (1998). A meta-analysis of elevated CO₂ effects on woody plant mass, form, and physiology. *Oecologia*, **113**, 299–313.

Examples

```
### copy data into 'dat'
dat <- dat.curtis1998

### calculate log ratio of means and corresponding sampling variances
dat <- escalc(measure="ROM", m1i=m1i, sd1i=sd1i, n1i=n1i,
              m2i=m2i, sd2i=sd2i, n2i=n2i, data=dat)
dat

### meta-analysis of log ratio of means using a random-effects model
res <- rma(yi, vi, method="DL", data=dat)
res

### average ratio of means with 95% CI
predict(res, transf=exp, digits=2)

### meta-analysis for plants grown under nutrient stress
res <- rma(yi, vi, method="DL", data=dat, subset=(xtrt=="FERT" & level=="LOW"))
```

```

predict(res, transf=exp, digits=2)

### meta-analysis for plants grown under low light conditions
res <- rma(yi, vi, method="DL", data=dat, subset=(xtrt=="LIGHT" & level=="LOW"))
predict(res, transf=exp, digits=2)

```

dat.debruin2009

Studies on Standard Care Quality and HAART-Adherence

Description

Results from 13 trials providing information about standard care quality and HAART-adherence in control groups.

Usage

```
dat.debruin2009
```

Format

The data frame contains the following columns:

author	character	(first) author of study
year	numeric	publication year
scq	numeric	standard care quality
ni	numeric	number of patients in the standard care group
xi	numeric	number of patients with an undetectable viral load in standard care group
mi	numeric	number of patients with a detectable viral load in standard care group
ethnicity	character	dominant ethnicity of the patients in the standard care group
patients	character	inclusion of patients continuing or starting (a new) treatment
select	character	baseline selection of patients with adherence problems or no selection
sens	character	sensitivity of viral load assessments (<400 vs. >=400 copies/ml)

Details

Highly active antiretroviral therapy (HAART) refers to a combination of multiple antiretroviral drugs that can effectively suppress the HIV virus. However, achieving viral suppression (to the point that the virus becomes essentially undetectable in a blood sample) requires high levels of adherence to an often complicated medication regimen. A number of trials have examined various interventions that aim to increase adherence levels. In each trial, patients receiving the intervention are compared to patients in a control group receiving standard care (often referred to as 'care as usual'). However, the quality of standard care can vary substantially between these studies. de Bruin et al. (2009) assessed the quality of standard care provided (based on a quantification of the number of behavior change techniques applied) and examined to what extent the quality of standard care was related to the proportion of patients achieving effective viral suppression in the control groups.

Source

de Bruin, M., Viechtbauer, W., Hospers, H. J., Schaalma, H. P., & Kok, G. (2009). Standard care quality determines treatment outcomes in control groups of HAART-adherence intervention studies: Implications for the interpretation and comparison of intervention effects. *Health Psychology*, **28**, 668–674.

Examples

```
### copy data into 'dat'
dat <- dat.debruin2009

### calculate proportions and corresponding sampling variances
dat <- escalc(measure="PR", xi=xi, ni=ni, data=dat)
dat

### random-effects model
res <- rma(yi, vi, data=dat)
print(res, digits=2)

### mixed-effects meta-regression model with all predictors/covariates
res <- rma(yi, vi, mods = ~ scq + ethnicity + patients + select + sens, data=dat)
print(res, digits=3)

### mixed-effects meta-regression model with scq and ethnicity as predictors/covariates
res <- rma(yi, vi, mods = ~ scq + ethnicity, data=dat)
print(res, digits=3)
```

dat.egger2001	<i>Studies on the Effectiveness of Intravenous Magnesium in Acute Myocardial Infarction</i>
---------------	---------------------------------------------------------------------------------------------

Description

Results from 16 trials examining the effectiveness of intravenous magnesium in the prevention of death following acute myocardial infarction.

Usage

```
dat.egger2001
```

Format

The data frame contains the following columns:

id	numeric	trial id number
study	character	first author or trial name
year	numeric	publication year
ai	numeric	number of deaths in the magnesium group

n1i	numeric	number of patients in the magnesium group
ci	numeric	number of deaths in the control group
n2i	numeric	number of patients in the control group

Details

The dataset includes the results from 16 randomized clinical trials that examined the effectiveness of intravenous magnesium in the prevention of death following acute myocardial infarction. Studies 1-7 were included in the meta-analyses by Teo et al. (1991) and Horner (1992) and were combined with the results from the LIMIT-2 trial (Woods et al., 1992) in Yusuf et al. (1993), suggesting that magnesium is an effective treatment for reducing mortality. However, the results from the ISIS-4 mega trial (ISIS-4 Collaborative Group, 1995) indicated no reduction in mortality with magnesium treatment. Publication bias has been suggested as one possible explanation for the conflicting findings (Egger & Davey Smith, 1995).

The present dataset includes some additional trials and are based on Table 18.2 from Egger, Davey Smith, and Altman (2001).

Source

Egger, M., Davey Smith, G., & Altman, D. G. (Eds.) (2001). *Systematic reviews in health care: Meta-analysis in context* (2nd ed.). London: BMJ Books.

References

Egger, M., & Davey Smith, G. (1995). Misleading meta-analysis: Lessons from “an effective, safe, simple” intervention that wasn’t. *British Medical Journal*, **310**, 752–754.

Horner, S. M. (1992). Efficacy of intravenous magnesium in acute myocardial infarction in reducing arrhythmias and mortality: Meta-analysis of magnesium in acute myocardial infarction. *Circulation*, **86**, 774–779.

ISIS-4 Collaborative Group (1995). ISIS-4: A randomised factorial trial assessing early oral captopril, oral mononitrate, and intravenous magnesium sulphate in 58,050 patients with suspected acute myocardial infarction. *Lancet*, **345**, 669–685.

Teo, K. K., Yusuf, S., Collins, R., Held, P. H., & Peto, R. (1991). Effects of intravenous magnesium in suspected acute myocardial infarction: Overview of randomised trials. *British Medical Journal*, **303**, 1499–1503.

Woods, K. L., Fletcher, S., Roffe, C., & Haider, Y. (1992). Intravenous magnesium sulphate in suspected acute myocardial infarction: Results of the second Leicester Intravenous Magnesium Intervention Trial (LIMIT-2). *Lancet*, **339**, 1553–1558.

Yusuf, S., Teo, K., & Woods, K. (1993). Intravenous magnesium in acute myocardial infarction: An effective, safe, simple, and inexpensive treatment. *Circulation*, **87**, 2043–2046.

See Also

[dat.li2007](#)

Examples

```

### copy data into 'dat' and examine data
dat <- dat.egger2001
dat

### meta-analysis of trials 1-7 using Peto's method (as in Teo et al., 1991)
res <- rma.peto(ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, subset=1:7)
print(res, digits=2)

### meta-analysis of trials 1-7 and LIMIT-2 (as in Yusuf et al., 1993)
res <- rma.peto(ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, subset=c(1:7,14))
print(res, digits=2)

### meta-analysis of all trials except ISIS-4
res <- rma.peto(ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, subset=-16)
print(res, digits=2)
predict(res, transf=exp, digits=2)

### meta-analysis of all trials including ISIS-4
res <- rma.peto(ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat)
print(res, digits=2)
predict(res, transf=exp, digits=2)

### contour-enhanced funnel plot centered at 0
funnel(res, refline=0, level=c(90, 95, 99), shade=c("white", "gray", "darkgray"))

```

dat.fine1993

*Studies on Radiation Therapy with or without Adjuvant Chemotherapy
in Patients with Malignant Gliomas*

Description

Results from 17 trials comparing post-operative radiation therapy with and without adjuvant chemotherapy in patients with malignant gliomas.

Usage

```
dat.fine1993
```

Format

The data frame contains the following columns:

study	numeric	study number
nei	numeric	sample size in the experimental group receiving radiotherapy plus adjuvant chemotherapy
nci	numeric	sample size in the control group receiving radiotherapy alone
e1i	numeric	number of survivors at 6 months in the experimental group
c1i	numeric	number of survivors at 6 months in the control group
e2i	numeric	number of survivors at 12 months in the experimental group

c2i	numeric	number of survivors at 12 months in the control group
e3i	numeric	number of survivors at 18 months in the experimental group
c3i	numeric	number of survivors at 18 months in the control group
e4i	numeric	number of survivors at 24 months in the experimental group
c4i	numeric	number of survivors at 24 months in the control group

Details

The 17 trials report the post-operative survival of patients with malignant gliomas receiving either radiation therapy with adjuvant chemotherapy or radiation therapy alone. Survival was assessed at 6, 12, 18, and 24 months in all but one study (which assessed survival only at 12 and at 24 months).

The data were reconstructed by Trikalinos and Olkin (2012) based on Table 2 in Fine et al. (1993) and Table 3 in Dear (1994). The data can be used to illustrate how a meta-analysis can be conducted of effect sizes reported at multiple time points using a multivariate model.

Source

Dear, K. B. G. (1994). Iterative generalized least squares for meta-analysis of survival data at multiple times. *Biometrics*, **50**, 989–1002.

Trikalinos, T. A., & Olkin, I. (2012). Meta-analysis of effect sizes reported at multiple time points: A multivariate approach. *Clinical Trials*, **9**, 610–620.

References

Fine, H. A., Dear, K. B., Loeffler, J. S., Black, P. M., & Canellos, G. P. (1993). Meta-analysis of radiation therapy with and without adjuvant chemotherapy for malignant gliomas in adults. *Cancer*, **71**, 2585–2597.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.fine1993
dat

### calculate log(ORs) and sampling variances for each time point
dat <- escalc(measure="OR", ai=e1i, n1i=nei, ci=c1i, n2i=nci, data=dat, var.names=c("y1i", "v1i"))
dat <- escalc(measure="OR", ai=e2i, n1i=nei, ci=c2i, n2i=nci, data=dat, var.names=c("y2i", "v2i"))
dat <- escalc(measure="OR", ai=e3i, n1i=nei, ci=c3i, n2i=nci, data=dat, var.names=c("y3i", "v3i"))
dat <- escalc(measure="OR", ai=e4i, n1i=nei, ci=c4i, n2i=nci, data=dat, var.names=c("y4i", "v4i"))

### calculate the covariances (equations in Appendix of Trikalinos & Olkin, 2012)
dat$v12i <- with(dat, nei / (e1i * (nei - e2i)) + nci / (c1i * (nci - c2i)))
dat$v13i <- with(dat, nei / (e1i * (nei - e3i)) + nci / (c1i * (nci - c3i)))
dat$v14i <- with(dat, nei / (e1i * (nei - e4i)) + nci / (c1i * (nci - c4i)))
dat$v23i <- with(dat, nei / (e2i * (nei - e3i)) + nci / (c2i * (nci - c3i)))
dat$v24i <- with(dat, nei / (e2i * (nei - e4i)) + nci / (c2i * (nci - c4i)))
dat$v34i <- with(dat, nei / (e3i * (nei - e4i)) + nci / (c3i * (nci - c4i)))

### create dataset in long format
dat.long <- data.frame(study=rep(1:nrow(dat), each=4), time=1:4,
```

```

yi=c(t(dat[c("y1i","y2i","y3i","y4i")])),
vi=c(t(dat[c("v1i","v2i","v3i","v4i")])))

### var-cov matrices of the studies
V <- lapply(split(dat, dat$study),
            function(x) matrix(c( x$v1i, x$v12i, x$v13i, x$v14i,
                                x$v12i, x$v2i, x$v23i, x$v24i,
                                x$v13i, x$v23i, x$v3i, x$v34i,
                                x$v14i, x$v24i, x$v34i, x$v4i), nrow=4, ncol=4, byrow=TRUE))

### remove rows for the missing time points in study 17
dat.long <- na.omit(dat.long)

### remove corresponding rows/columns from var-cov matrix
V[[17]] <- V[[17]][c(2,4),c(2,4)]

### make a copy of V
Vc <- V

### replace any (near) singular var-cov matrices with ridge corrected versions
repl.Vi <- function(Vi) {
  res <- eigen(Vi)
  if (any(res$values <= .08)) {
    round(res$vectors %*% diag(res$values + .08) %*% t(res$vectors), 12)
  } else {
    Vi
  }
}
Vc <- lapply(Vc, repl.Vi)

### do not correct var-cov matrix of study 17
Vc[[17]] <- V[[17]]

### construct block diagonal matrix
Vc <- bldiag(Vc)

### multivariate fixed-effects model
res <- rma.mv(yi, Vc, mods = ~ factor(time) - 1, method="FE", data=dat.long)
print(res, digits=3)

### multivariate random-effects model with heteroscedastic AR(1) structure for the true effects
res <- rma.mv(yi, Vc, mods = ~ factor(time) - 1, random = ~ time | study,
             struct="HAR", data=dat.long)
print(res, digits=3)

## Not run:
### profile the variance components
par(mfrow=c(2,2))
profile(res, tau2=1, xlim=c(0,.2))
profile(res, tau2=2, xlim=c(0,.2))
profile(res, tau2=3, xlim=c(0,.2))
profile(res, tau2=4, xlim=c(.1,.3))
## End(Not run)

```

```
## Not run:
### profile the autocorrelation coefficient
par(mfrow=c(1,1))
profile(res, rho=1)
## End(Not run)
```

dat.gibson2002	<i>Studies on the Effectiveness of Self-Management Education and Regular Medical Review for Adults with Asthma</i>
----------------	--------------------------------------------------------------------------------------------------------------------

Description

Results from 15 trials examining the effectiveness of self-management education and regular medical review for adults with asthma.

Usage

```
dat.gibson2002
```

Format

The data frame contains the following columns:

author	character	first author of study
year	numeric	publication year
n1i	numeric	number of participants in the intervention group
m1i	numeric	mean number of days off work/school in the intervention group
sd1i	numeric	standard deviation of the number of days off work/school in the intervention group
n2i	numeric	number of participants in the control/comparison group
m2i	numeric	mean number of days off work/school in the control/comparison group
sd2i	numeric	standard deviation of the number of days off work/school in the control/comparison group
ai	numeric	number of participants who had one or more days off work/school in the intervention group
bi	numeric	number of participants who no days off work/school in the intervention group
ci	numeric	number of participants who had one or more days off work/school in the control/comparison group
di	numeric	number of participants who no days off work/school in the control/comparison group
type	numeric	numeric code for the intervention type (see below)

Details

Asthma management guidelines typically recommend for patients to receive education and regular medical review. While self-management programs have been shown to increase patient knowledge, it is less clear to what extent they actually impact health outcomes. The systematic review by Gibson et al. (2002) examined the effectiveness of self-management education and regular medical review for adults with asthma. In each study, participants receiving a certain management intervention were compared against those in a control/comparison group with respect to a variety of health outcomes. One of the outcomes examined in a number of studies was the number of days off work/school.

The majority of studies reporting this outcome provided means and standard deviations allowing a meta-analysis of standardized mean differences. Seven studies also reported the number of participants who had one or more days off work/school in each group. These studies could be meta-analyzed using, for example, (log) risk ratios. Finally, one could also consider a combined analysis based on standardized mean differences computed from the means and standard deviations where available and using probit transformed risk differences (which also provide estimates of the standardized mean difference) for the remaining studies.

Some degree of patient education was provided in all studies. In addition, the type variable indicates what additional intervention components were included in each study:

1. optimal self-management (writing action plan, self-monitoring, regular medical review),
2. self-monitoring and regular medical review,
3. self-monitoring only,
4. regular medical review only,
5. written action plan only.

Source

Gibson, P. G., Powell, H., Wilson, A., Abramson, M. J., Haywood, P., Bauman, A., et al. (2002). Self-management education and regular practitioner review for adults with asthma. *Cochrane Database of Systematic Reviews*, **3**.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.gibson2002
dat

### fixed-effects model analysis of the standardized mean differences
dat <- escalc(measure="SMD", m1i=m1i, sd1i=sd1i, n1i=n1i, m2i=m2i, sd2i=sd2i, n2i=n2i, data=dat)
res <- rma(yi, vi, data=dat, method="FE")
print(res, digits=2)

### fixed-effects model analysis of the (log) risk ratios
dat <- escalc(measure="RR", ai=ai, bi=bi, ci=ci, di=di, data=dat)
res <- rma(yi, vi, data=dat, method="FE")
print(res, digits=2)
predict(res, transf=exp, digits=2)

### fixed-effects model analysis of the standardized mean differences and the probit transformed
### risk differences (which also provide estimates of the standardized mean difference)
dat <- escalc(measure="SMD", m1i=m1i, sd1i=sd1i, n1i=n1i, m2i=m2i, sd2i=sd2i, n2i=n2i, data=dat)
dat <- escalc(measure="PBIT", ai=ai, bi=bi, ci=ci, di=di, data=dat, replace=FALSE)
dat
res <- rma(yi, vi, data=dat, method="FE")
print(res, digits=2)
```

 dat.graves2010

Studies on the Effectiveness of Injected Cholera Vaccines

Description

Results from 17 studies on the effectiveness of injected vaccines against cholera.

Usage

dat.graves2010

Format

The data frame contains the following columns:

study	character	author/study name and publication year
ai	numeric	number of cholera cases in the vaccinated group
n1i	numeric	number of individuals in the vaccinated group
ci	numeric	number of cholera cases in the placebo group
n2i	numeric	number of individuals in the placebo group

Details

Cholera is an infection caused by certain strains of the bacterium *Vibrio cholerae*. When untreated, mortality rates can be as high as 50-60%. Proper sanitation practices are usually effective in preventing outbreaks, but a number of oral and injectable vaccines have also been developed. The Cochrane review by Graves et al. (2010) examined the effectiveness of injectable vaccines for preventing cholera cases and death. The present dataset includes results from 17 studies that reported the number of cholera cases in vaccinated and placebo/comparison groups up to 7 months after the treatment.

Source

Graves, P. M., Deeks, J. J., Demicheli, V., & Jefferson, T. (2010). Vaccines for preventing cholera: Killed whole cell or other subunit vaccines (injected). *Cochrane Database of Systematic Reviews*, **8**, CD000974.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.graves2010
dat

### analysis using the Mantel-Haenszel method
rma.mh(measure="RR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, digits=2)
```

 dat.hackshaw1998 *Studies on Lung Cancer Risk from ETS Exposure*

Description

Results from 37 studies on the risk of lung cancer from environmental tobacco smoke (ETS) exposure.

Usage

```
dat.hackshaw1998
```

Format

The data frame contains the following columns:

study	numeric	study number
author	character	first author of study
year	numeric	publication year
country	character	country where study was conducted
design	character	study design (either cohort or case-control)
cases	numeric	number of lung cancer cases
yi	numeric	log odds ratio
vi	numeric	corresponding sampling variance

Details

The dataset includes the results from 37 studies (4 cohort, 33 case-control) on the risk of lung cancer from environmental tobacco smoke (ETS) exposure from the spouse in women who are lifelong nonsmokers. Values of the log odds ratio greater than 0 indicate an increased risk of cancer in exposed women compared to women not exposed to ETS from their spouse.

Source

Hackshaw, A. K., Law, M. R., & Wald, N. J. (1997). The accumulated evidence on lung cancer and environmental tobacco smoke. *British Medical Journal*, **315**, 980–988.

Hackshaw, A. K. (1998). Lung cancer and passive smoking. *Statistical Methods in Medical Research*, **7**, 119–136.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.hackshaw1998
dat

### random-effects model using the log odds ratios
res <- rma(yi, vi, data=dat, method="DL")
res
```

```
### estimated average odds ratio with CI (and credibility/prediction interval)
predict(res, transf=exp, digits=2)
```

dat.hart1999

Studies on the Effectiveness of Warfarin for Preventing Strokes

Description

Results from 6 clinical trials examining the effectiveness of adjusted-dose warfarin for preventing strokes in patients with atrial fibrillation.

Usage

```
dat.hart1999
```

Format

The data frame contains the following columns:

trial	numeric	trial number
study	character	study name (abbreviated)
year	numeric	publication year
x1i	numeric	number of strokes in the warfarin group
n1i	numeric	number of patients in the warfarin group
t1i	numeric	total person-time (in years) in the warfarin group
x2i	numeric	number of strokes in the placebo/control group
n2i	numeric	number of patients in the placebo/control group
t2i	numeric	total person-time (in years) in the placebo/control group
compgrp	character	type of comparison group (placebo or control)
prevtype	character	type of prevention (primary or secondary)
trintr	character	target range for the international normalized ratio (INR)

Details

The 6 studies provide data with respect to the number of strokes in the warfarin and the comparison (placebo or control) group. In addition, the number of patients and the total person-time (in years) is provided for the two groups. The goal of the meta-analysis was to examine the effectiveness of adjusted-dose warfarin for preventing strokes in patients with atrial fibrillation.

Source

Hart, R. G., Benavente, O., McBride, R., & Pearce, L. A. (1999). Antithrombotic therapy to prevent stroke in patients with atrial fibrillation: A meta-analysis. *Annals of Internal Medicine*, **131**, 492–501.

Examples

```

### copy data into 'dat'
dat <- dat.hart1999

### calculate log incidence rate ratios and corresponding sampling variances
dat <- escalc(measure="IRR", x1i=x1i, x2i=x2i, t1i=t1i, t2i=t2i, data=dat)
dat

### meta-analysis of log incidence rate ratios using a random-effects model
res <- rma(yi, vi, data=dat)
res

### average incidence rate ratio with 95% CI
predict(res, transf=exp)

### forest plot with extra annotations
par(mar=c(5,4,1,2))
forest(res, xlim=c(-11, 5), at=log(c(.05, .25, 1, 4)), atranf=exp,
       slab=paste0(dat$study, " (", dat$year, ")"),
       ilab=cbind(paste(dat$x1i, "/", dat$t1i, sep=" "),
                 paste(dat$x2i, "/", dat$t2i, sep=" ")),
       ilab.xpos=c(-6.5,-4), cex=.85, header="Study (Year)")
op <- par(cex=.85, font=2)
text(c(-6.5,-4), 8.5, c("Warfarin", "Control"))
text(c(-6.5,-4), 7.5, c("Strokes / PT", "Strokes / PT"))
segments(x0=-8, y0=8, x1=-2.75, y1=8)
par(op)

### meta-analysis of incidence rate differences using a random-effects model
res <- rma(measure="IRD", x1i=x1i, x2i=x2i, t1i=t1i, t2i=t2i, data=dat)
res

```

dat.hasselblad1998 *Studies on the Effectiveness of Counseling for Smoking Cessation*

Description

Results from 24 studies on the effectiveness of various counseling types for smoking cessation.

Usage

```
dat.hasselblad1998
```

Format

The data frame contains the following columns:

id	numeric	id number for each treatment arm
study	numeric	study id number

authors	character	study author(s)
year	numeric	publication year
trt	character	intervention group
xi	numeric	number of individuals abstinent
ni	numeric	number of individuals in group

Details

The dataset includes the results from 24 studies on the effectiveness of various counseling types for smoking cessation (i.e., self-help, individual counseling, group counseling, and no contact). The dataset indicates the total number of individuals within each study arm and the number that were abstinent from 6 to 12 months. The majority of the studies compared two interventions types against each other, while 2 studies compared three types against each other simultaneously.

The data can be used for a ‘network meta-analysis’ (also called ‘mixed treatment comparison meta-analysis’). The code below shows how such an analysis can be conducted using an arm-based and a contrast-based model (see Salanti et al., 2008, for more details).

Source

Hasselblad, V. (1998). Meta-analysis of multitreatment studies. *Medical Decision Making*, **18**, 37–43.

References

Gleser, L. J., & Olkin, I. (2009). Stochastically dependent effect sizes. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (2nd ed., pp. 357–376). New York: Russell Sage Foundation.

Salanti, G., Higgins, J. P. T., Ades, A. E., & Ioannidis, J. P. A. (2008). Evaluation of networks of randomized trials. *Statistical Methods in Medical Research*, **17**, 279–301.

Examples

```
### copy data into 'dat'
dat <- dat.hasselblad1998

### calculate log odds for each study arm
dat <- escalc(measure="PLO", xi=xi, ni=ni, add=1/2, to="all", data=dat)
dat

### create network graph ('plyr' and 'igraph' packages must be installed)
## Not run:
require(plyr)
require(igraph)
pairs <- do.call(rbind, sapply(split(dat$strt, dat$study), function(x) t(combn(x,2))))
pairs <- ddply(data.frame(pairs), .(X1, X2), count)
g <- graph.edgelist(as.matrix(pairs[,1:2]), directed=FALSE)
plot(g, edge.curved=FALSE, edge.width=pairs$freq, vertex.label.dist=.7,
vertex.label=c("Individual\nCounseling", "Group\nCounseling", "No Contact", "Self-Help"))
## End(Not run)
```

```

### convert trt variable to factor with desired ordering of levels
dat$trt <- factor(dat$trt, levels=c("no_contact", "self_help", "ind_counseling", "grp_counseling"))

### add a space before each level (this makes the output a bit more legible)
levels(dat$trt) <- paste0(" ", levels(dat$trt))

### network meta-analysis using an arm-based model with fixed study effects
### by setting rho=1/2, tau^2 reflects the amount of heterogeneity for all treatment comparisons
res <- rma.mv(yi, vi, mods = ~ factor(study) + trt - 1,
             random = ~ trt | study, rho=1/2, data=dat, btt="trt")
res

### all pairwise odds ratios of interventions versus no contact
predict(res, newmods=cbind(matrix(0, nrow=3, ncol=24), diag(3)),
        intercept=FALSE, transf=exp, digits=2)

### all pairwise odds ratios comparing interventions (ic vs sh, gc vs sh, and gc vs ic)
predict(res, newmods=cbind(matrix(0, nrow=3, ncol=24), rbind(c(-1,1,0), c(-1,0,1), c(0,-1,1))),
        intercept=FALSE, transf=exp, digits=2)

### forest plot of ORs of interventions versus no contact
dev.new(width=7, height=4)
par(mar=c(5,4,1,2))
forest(c(0,res$beta[25:27]), sei=c(0,res$sse[25:27]), psize=1, xlim=c(-3,4), digits=c(2,1), efac=2,
       slab=c("No Contact", "Self-Help", "Individual Counseling", "Group Counseling"),
       atranf=exp, at=log(c(.5, 1, 2, 4, 8)), xlab="Odds Ratio for Intervention vs. No Contact",
       header=c("Intervention", "Odds Ratio [95% CI]"))

#####

### restructure dataset to a contrast-based format
dat <- to.wide(dat.hasselblad1998, study="study", grp="trt", ref="no_contact", grpvars=6:7)

### calculate log odds ratios for each treatment comparison
dat <- escalc(measure="OR", ai=xi.1, n1i=ni.1,
             ci=xi.2, n2i=ni.2, add=1/2, to="all", data=dat)
dat

### calculate the variance-covariance matrix of the log odds ratios for multitreatment studies
### see Gleser & Olkin (2009), equation (19.11), for the covariance equation
calc.v <- function(x) {
  v <- matrix(1/(x$xi.2[1]+1/2) + 1/(x$ni.2[1] - x$xi.2[1] + 1/2), nrow=nrow(x), ncol=nrow(x))
  diag(v) <- x$vi
  v
}
V <- bldiag(lapply(split(dat, dat$study), calc.v))

### add contrast matrix to dataset
dat <- contrmat(dat, grp1="trt.1", grp2="trt.2")
dat

### network meta-analysis using a contrast-based random-effects model
### by setting rho=1/2, tau^2 reflects the amount of heterogeneity for all treatment comparisons

```

```
res <- rma.mv(yi, V, mods = ~ self_help + ind_counseling + grp_counseling - 1,
             random = ~ factor(id) | study, rho=1/2, data=dat)
res

### predicted odds ratios of interventions versus no contact
predict(res, newmods=diag(3), transf=exp, digits=2)
```

dat.hine1989

Studies on Prophylactic Use of Lidocaine After a Heart Attack

Description

Results from 6 studies evaluating mortality from prophylactic use of lidocaine in acute myocardial infarction.

Usage

```
dat.hine1989
```

Format

The data frame contains the following columns:

study	numeric	study number
source	character	source of data
n1i	numeric	number of patients in lidocaine group
n2i	numeric	number of patients in control group
ai	numeric	number of deaths in lidocaine group
ci	numeric	number of deaths in control group

Details

Hine et al. (1989) conducted a meta-analysis of death rates in randomized controlled trials in which prophylactic lidocaine was administered to patients with confirmed or suspected acute myocardial infarction. The dataset describes the mortality at the end of the assigned treatment period for control and intravenous lidocaine treatment groups for six studies. The question of interest is whether there is a detrimental effect of lidocaine. Because the studies were conducted to compare rates of arrhythmias following a heart attack, the studies, taken individually, are too small to detect important differences in mortality rates.

The data in this dataset were obtained from Table I in Normand (1999, p. 322).

Source

Normand, S. T. (1999). Meta-analysis: Formulating, evaluating, combining, and reporting. *Statistics in Medicine*, **18**, 321–359.

References

Hine, L. K., Laird, N., Hewitt, P., & Chalmers, T. C. (1989). Meta-analytic evidence against prophylactic use of lidocaine in acute myocardial infarction. *Archives of Internal Medicine*, **149**, 2694–2698.

Examples

```
### copy data into 'dat'
dat <- dat.hine1989

### calculate risk differences and corresponding sampling variances
dat <- escalc(measure="RD", n1i=n1i, n2i=n2i, ai=ai, ci=ci, data=dat)
dat

### meta-analysis of risk differences using a random-effects model
res <- rma(yi, vi, data=dat)
res
```

dat.ishak2007

Studies on Deep-Brain Stimulation

Description

Results from 46 studies examining the effects of deep-brain stimulation on motor skills of patients with Parkinson's disease.

Usage

```
dat.ishak2007
```

Format

The data frame contains the following columns:

study	character	(first) author and year
y1i	numeric	observed mean difference at 3 months
v1i	numeric	sampling variance of the mean difference at 3 months
y2i	numeric	observed mean difference at 6 months
v2i	numeric	sampling variance of the mean difference at 6 months
y3i	numeric	observed mean difference at 12 months
v3i	numeric	sampling variance of the mean difference at 12 months
y4i	numeric	observed mean difference at the long-term follow-up
v4i	numeric	sampling variance of the mean difference at the long-term follow-up
mdur	numeric	mean disease duration (in years)
mbase	numeric	mean baseline UPDRS score

Details

Deep-brain stimulation (DBS), which is delivered through thin surgically implanted wires in specific areas of the brain and controlled by the patient, is meant to provide relief of the debilitating symptoms of Parkinson's disease. The dataset includes the results from 46 studies examining the effects of DBS of the subthalamic nucleus on motor functioning, measured with the Unified Parkinson's Disease Rating Scale (UPDRS). The effect size measure for this meta-analysis was the mean difference of the scores while the stimulator is active and the baseline scores (before implantation of the stimulator). Since lower scores on the UPDRS indicate better functioning, negative numbers indicate improvements in motor skills. Effects were generally measured at 3, 6, and 12 months after implantation of the stimulator, with some studies also including a further long-term follow-up. However, the number of measurements differed between studies - hence the missing data on some of the measurement occasions.

Since the same patients were followed over time within a study, effect size estimates from multiple measurement occasions are likely to be correlated. A multivariate model accounting for the correlation in the effects can be used to meta-analyze these data. A difficulty with this approach is the lack of information about the correlation of the measurements over time in the individual studies. The approach taken by Ishak et al. (2007) was to assume an autoregressive (AR1) structure for the estimates within the individual studies. In addition, the correlation in the true effects was modeled, again using an autoregressive structure.

Source

Ishak, K. J., Platt, R. W., Joseph, L., Hanley, J. A., & Caro, J. J. (2007). Meta-analysis of longitudinal studies. *Clinical Trials*, *4*, 525–539.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.ishak2007
dat

### create long format dataset
dat.long <- reshape(dat, direction="long", idvar="study", v.names=c("yi","vi"),
                    varying=list(c(2,4,6,8), c(3,5,7,9)))
dat.long <- dat.long[order(dat.long$study, dat.long$time),]
rownames(dat.long) <- 1:nrow(dat.long)

### remove missing measurement occasions from dat.long
is.miss <- is.na(dat.long$yi)
dat.long <- dat.long[!is.miss,]

### construct the full (block diagonal) V matrix with an AR(1) structure
rho.within <- .97 ### value as estimated by Ishak et al. (2007)
V <- lapply(split(with(dat, cbind(v1i, v2i, v3i, v4i)), dat$study), diag)
V <- lapply(V, function(v) sqrt(v) %*% toeplitz(ARMAacf(ar=rho.within, lag.max=3)) %*% sqrt(v))
V <- bldiag(V)
V <- V[!is.miss,!is.miss] ### remove missing measurement occasions from V

### plot data
with(dat.long, interaction.plot(time, study, yi, type="b", pch=19, lty="solid", xaxt="n",
```

```

      legend=FALSE, xlab="Time Point", ylab="Mean Difference", bty="l"))
axis(side=1, at=1:4, lab=c("1 (3 months)", "2 (6 months)", "3 (12 months)", "4 (12+ months)"))

### multivariate model with heteroscedastic AR(1) structure for the true effects
res <- rma.mv(yi, V, mods = ~ factor(time) - 1, random = ~ time | study,
             struct = "HAR", data = dat.long)
print(res, digits=2)

```

dat.konstantopoulos2011

Studies on the Effects of Modified School Calendars on Student Achievement

Description

Results from 56 studies on the effects of modified school calendars on student achievement.

Usage

```
dat.konstantopoulos2011
```

Format

The data frame contains the following columns:

district	numeric	district id number
school	numeric	school id number (within district)
study	numeric	study id number
yi	numeric	standardized mean difference
vi	numeric	corresponding sampling variance
year	numeric	year of the study

Details

Instead of following the more traditional school calendar with a long summer break (in addition to a short winter and spring break), some schools have switched to a modified school calendar comprising more frequent but shorter intermittent breaks (e.g., 9 weeks of school followed by 3 weeks off), while keeping the total number of days at school approximately the same. The effects of using such a modified calendar on student achievement have been examined in a number of studies and were meta-analyzed by Cooper et al. (2003).

The dataset (taken from Konstantopoulos, 2011) contains the results from 56 studies, each comparing the level of academic achievement in a group of students following a modified school calendar with that of a group of students following a more traditional school calendar. The difference between the two groups was quantified in terms of a standardized mean difference (with positive values indicating a higher mean level of achievement in the group following the modified school calendar).

The studies were conducted at various schools that were clustered within districts. The data there-

fore have a multilevel structure, with schools nested within districts. A multilevel meta-analysis of these data can be used to estimate and account for the amount of heterogeneity between districts and between schools within districts.

Source

Konstantopoulos, S. (2011). Fixed effects and variance components estimation in three-level meta-analysis. *Research Synthesis Methods*, *2*, 61–76.

References

Cooper, H., Valentine, J. C., Charlton, K., & Melson, A. (2003). The effects of modified school calendars on student achievement and on school and community attitudes. *Review of Educational Research*, *73*, 1–52.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.konstantopoulos2011
dat

### regular random-effects model
res <- rma(yi, vi, data=dat)
print(res, digits=3)

### regular random-effects model using rma.mv()
res <- rma.mv(yi, vi, random = ~ 1 | study, data=dat)
print(res, digits=3)

### multilevel random-effects model
res.ml <- rma.mv(yi, vi, random = ~ 1 | district/school, data=dat)
print(res.ml, digits=3)

### profile variance components
profile(res.ml, progbar=FALSE)

### multivariate parameterization of the model
res.mv <- rma.mv(yi, vi, random = ~ factor(school) | district, data=dat)
print(res.mv, digits=3)

### tau^2 from multivariate model = sum of the two variance components from the multilevel model
round(sum(res.ml$sigma2), 3)

### rho from multivariate model = intraclass correlation coefficient based on the multilevel model
round(res.ml$sigma2[1] / sum(res.ml$sigma2), 3)
```

dat.laopaiboon2015 *Studies on the Effectiveness of Azithromycin for Treating Lower Respiratory Tract Infections*

Description

Results from 15 studies on the effectiveness of azithromycin versus amoxicillin or amoxicillin/clavulanic acid (amoxyclav) in the treatment of acute lower respiratory tract infections.

Usage

dat.laopaiboon2015

Format

The data frame contains the following columns:

author	character	author(s)
year	numeric	publication year
ai	numeric	number of clinical failures in the group treated with azithromycin
n1i	numeric	number of patients in the group treated with azithromycin
ci	numeric	number of clinical failures in the group treated with amoxicillin or amoxyclav
n2i	numeric	number of patients in the group treated with amoxicillin or amoxyclav
age	character	whether the trial included adults or children
diag.ab	numeric	trial included patients with a diagnosis of acute bacterial bronchitis
diag.cb	numeric	trial included patients with a diagnosis of chronic bronchitis with acute exacerbation
diag.pn	numeric	trial included patients with a diagnosis of pneumonia
ctrl	character	antibiotic in control group (amoxicillin or amoxyclav)

Details

Azithromycin is an antibiotic useful for the treatment of a number of bacterial infections. Laopaiboon et al. (2015) conducted a meta-analysis of trials comparing the effectiveness of azithromycin versus amoxicillin or amoxicillin/clavulanic acid (amoxyclav) in the treatment of acute lower respiratory tract infections, including acute bacterial bronchitis, acute exacerbations of chronic bronchitis, and pneumonia. The results from 15 trials are included in this dataset.

Source

Laopaiboon, M., Panpanich, R., & Swa Mya, K. (2015). Azithromycin for acute lower respiratory tract infections. *Cochrane Database of Systematic Reviews*, **3**, CD001954.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.laopaiboon2015
dat
```

```

### analysis using the Mantel-Haenszel method
rma.mh(measure="RR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, digits=3)

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat)

### random-effects model
res <- rma(yi, vi, data=dat)
res

### average risk ratio with 95% CI
predict(res, transf=exp)

```

dat.lee2004

Studies on Acupoint P6 Stimulation for Preventing Nausea

Description

Results from studies examining the effectiveness of wrist acupuncture point P6 stimulation for preventing postoperative nausea.

Usage

dat.lee2004

Format

The data frame contains the following columns:

id	numeric	trial id number
study	character	first author
year	numeric	study year
ai	numeric	number of patients experiencing nausea in the treatment group
n1i	numeric	total number of patients in treatment group
ci	numeric	number of patients experiencing nausea in the sham group
n2i	numeric	total number of patients in the sham group

Details

Postoperative nausea and vomiting are common complications following surgery and anaesthesia. As an alternative to drug therapy, acupuncture has been studied as a potential treatment in several trials. The dataset contains the results from 16 clinical trials examining the effectiveness of wrist acupuncture point P6 stimulation for preventing postoperative nausea.

Source

Lee, A., & Done, M. L. (2004). Stimulation of the wrist acupuncture point P6 for preventing postoperative nausea and vomiting. *Cochrane Database of Systematic Reviews*, **3**, CD003281.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.lee2004
dat

### meta-analysis based on log risk ratios
res <- rma(measure="RR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat)
res
predict(res, transf=exp, digits=2)
```

dat.li2007	<i>Studies on the Effectiveness of Intravenous Magnesium in Acute Myocardial Infarction</i>
------------	---------------------------------------------------------------------------------------------

Description

Results from 22 trials examining the effectiveness of intravenous magnesium in the prevention of death following acute myocardial infarction.

Usage

```
dat.li2007
```

Format

The data frame contains the following columns:

id	numeric	trial id number
study	character	first author or trial name
year	numeric	publication year
ai	numeric	number of deaths in the magnesium group
n1i	numeric	number of patients in the magnesium group
ci	numeric	number of deaths in the control group
n2i	numeric	number of patients in the control group

Details

The dataset includes the results from 22 randomized clinical trials that examined the effectiveness of intravenous magnesium in the prevention of death following acute myocardial infarction. It is similar to the dataset [dat.egger2001](#), with some slight differences in the included trials and data used.

Source

Li, J., Zhang, Q., Zhang, M., & Egger, M. (2007). Intravenous magnesium for acute myocardial infarction. *Cochrane Database of Systematic Reviews*, **2**, CD002755.

See Also[dat.egger2001](#)**Examples**

```
### copy data into 'dat' and examine data
dat <- dat.li2007
dat

### meta-analysis of all trials except ISIS-4
res <- rma(measure="OR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, method="FE", subset=-14)
print(res, digits=2)
predict(res, transf=exp, digits=2)

### meta-analysis of all trials including ISIS-4
res <- rma(measure="OR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, method="FE")
print(res, digits=2)
predict(res, transf=exp, digits=2)

### contour-enhanced funnel plot centered at 0
funnel(res, refline=0, level=c(90, 95, 99), shade=c("white", "gray", "darkgray"))
```

dat.linde2005

*Studies on the Effectiveness of St. John's Wort for Treating Depression***Description**

Results from 26 studies on the effectiveness of *Hypericum perforatum* extracts (St. John's wort) for treating depression.

Usage

dat.linde2005

Format

The data frame contains the following columns:

id	numeric	study number
study	character	study author(s)
year	numeric	publication year
country	character	study location
ni	numeric	total sample size
major	numeric	sample restricted to patients who met criteria for major depression
baseline	numeric	HRSD baseline score
version	numeric	HRSD version (17 or 21 items)
duration	numeric	study duration (in weeks)
prep	character	Hypericum extract preparation

dosage	numeric	dosage (in mg)
response	numeric	definition of response (1 = HRSD score reduction of at least 50% or HRSDscore after therapy <10;
ai	numeric	number of responses in treatment group
n1i	numeric	number of patients in treatment group
ci	numeric	number of responses in placebo group
n2i	numeric	number of patients in placebo group
group	numeric	stratification variable used by the authors (1 = smaller trials restricted to major depression; 2 = large

Details

The dataset includes the results from 26 double-blind placebo-controlled trials on the effectiveness of *Hypericum perforatum* extracts (St. John's wort) for treating depression (note that 2 studies did not provide sufficient response information).

Data were extracted from Table 1 and Figure 3. For study duration, the assessment week (instead of the total study duration) was coded for Philipp et al. (1999) and Montgomery et al. (2000). For dosage, the midpoint was coded when a range of values was given.

Source

Linde, K., Berner, M., Egger, M., & Mulrow, C. (2005). St John's wort for depression: Meta-analysis of randomised controlled trials. *British Journal of Psychiatry*, **186**, 99–107.

References

Viechtbauer, W. (2007). Accounting for heterogeneity via random-effects models and moderator analyses in meta-analysis. *Zeitschrift für Psychologie / Journal of Psychology*, **215**, 104–121.

Examples

```
### copy data into 'dat'
dat <- dat.linde2005

### remove studies with no response information and study with no responses in either group
dat <- dat[-c(5,6,26),]

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=ai, ci=ci, n1i=n1i, n2i=n2i, data=dat)
dat

### meta-analysis of the log risk ratios using a random-effects model
res <- rma(yi, vi, data=dat, method="DL")
res

### mixed-effects meta-regression model with stratification variable
res <- rma(yi, vi, mods = ~ factor(group) - 1, data=dat, method="DL")
res

### predicted average risk ratio for each level of the stratification variable
predict(res, newmods=diag(4), transf=exp, digits=2)
```

 dat.mcdaniel1994 *Studies on the Validity of Employment Interviews*

Description

Results from 160 studies on the correlation between employment interview assessments and job performance.

Usage

dat.mcdaniel1994

Format

The data frame contains the following columns:

study	numeric	study number
ni	numeric	sample size of the study
ri	numeric	observed correlation
type	character	interview type (j = job-related, s = situational, p = psychological)
struct	character	interview structure (u = unstructured, s = structured)

Details

The 160 studies provide data in terms of the correlation between employment interview performance and actual job performance. In addition, the interview type and the interview structure are indicated.

McDaniel et al. (1994) describe the interview type and structure variables as follows. "Questions in situational interviews [...] focus on the individual's ability to project what his or her behavior would be in a given situation. [...] Job-related interviews are those in which the interviewer is a personnel officer or hiring authority and the questions attempt to assess past behaviors and job-related information, but most questions are not considered situational. Psychological interviews are conducted by a psychologist, and the questions are intended to assess personal traits, such as dependability." In structured interviews, "the questions and acceptable responses were specified in advance and the responses were rated for appropriateness of content. [...] Unstructured interviews gather applicant information in a less systematic manner than do structured interviews. Although the questions may be specified in advance, they usually are not, and there is seldom a formalized scoring guide. Also, all persons being interviewed are not typically asked the same questions."

The goal of the meta-analysis was to examine the overall criterion-related validity of employment interviews and to examine whether the validity depends on the type and structure of the interview.

The data in this dataset were obtained from Table A.2 in Rothstein, Sutton, and Borenstein (2005, p. 325-329). Note that the type and struct variables contain some NAs.

Source

Rothstein, H. R., Sutton, A. J., & Borenstein, M. (Eds.). (2005). *Publication bias in meta-analysis: Prevention, assessment, and adjustments*. Chichester, England: Wiley.

References

McDaniel, M. A., Whetzel, D. L., Schmidt, F. L., & Maurer, S. D. (1994). The validity of employment interviews: A comprehensive review and meta-analysis. *Journal of Applied Psychology*, **79**, 599–616.

Examples

```
### copy data into 'dat'
dat <- dat.mcdaniel1994

### calculate r-to-z transformed correlations and corresponding sampling variances
dat <- escalc(measure="ZCOR", ri=ri, ni=ni, data=dat)
dat

### meta-analysis of the transformed correlations using a random-effects model
res <- rma(yi, vi, data=dat)
res

### average correlation with 95% CI
predict(res, transf=transf.ztor)

### mixed-effects model with interview type as factor
### note: job-related interviews is the reference level
rma(yi, vi, mods = ~ factor(type), data=dat)

### mixed-effects model with interview structure as factor
### note: structured interviews is the reference level
rma(yi, vi, mods = ~ factor(struct), data=dat)

### note: the interpretation of the results is difficult since all
### situational interviews were structured, almost all psychological
### interviews were unstructured, and actually for the majority of
### the psychological interviews it was unknown whether the interview
### was structured or unstructured
table(dat$type, dat$struct, useNA="always")

### meta-analysis of raw correlations using a random-effects model
res <- rma(measure="COR", ri=ri, ni=ni, data=dat.mcdaniel1994)
res
```

dat.molloy2014

Studies on the Relationship between Conscientiousness and Medication Adherence

Description

Results from 16 studies on the correlation between conscientiousness and medication adherence.

Usage

dat.molloy2014

Format

The data frame contains the following columns:

authors	character	study authors
year	numeric	publication year
ni	numeric	sample size of the study
ri	numeric	observed correlation
controls	character	number of variables controlled for
design	character	whether a cross-sectional or prospective design was used
a_measure	character	type of adherence measure (self-report or other)
c_measure	character	type of conscientiousness measure (NEO or other)
meanage	numeric	mean age of the sample
quality	numeric	methodological quality

Details

Conscientiousness, one of the big-5 personality traits, can be defined as “socially prescribed impulse control that facilitates task- and goal-directed behaviour, such as thinking before acting, delaying gratification, following norms and rules and planning, organising and prioritising tasks” (John & Srivastava, 1999). Conscientiousness has been shown to be related to a number of health-related behaviors (e.g., tobacco/alcohol/drug use, diet and activity patterns, risky behaviors). A recent meta-analysis by Molloy et al. (2014) examined to what extent conscientiousness is related to medication adherence, that is, the extent to which (typically chronically ill) patients follow a prescribed medication regimen (e.g., taking a daily dose of a cholesterol lowering drug in patients with high LDL serum cholesterol levels). The results from the 16 studies included in this meta-analysis are provided in this dataset.

Variable `a_measure` indicates whether adherence was measured based on self-reports or a more ‘objective’ measure (e.g., electronic monitoring of pill bottle openings, pill counts). Variable `c_measure` indicates whether conscientiousness was measured with some version of the NEO personality inventory or some other scale. Methodological quality was scored by the authors on a 1 to 4 scale with higher scores indicating higher quality (see article for details on how this score was derived).

Source

Molloy, G. J., O’Carroll, R. E., & Ferguson, E. (2014). Conscientiousness and medication adherence: A meta-analysis. *Annals of Behavioral Medicine*, *47*, 92–101.

References

John, O. P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (2nd ed., pp. 102-138). New York: Guilford Press.

Examples

```
### copy data into 'dat'
dat <- dat.molloy2014

### calculate r-to-z transformed correlations and corresponding sampling variances
dat <- escalc(measure="ZCOR", ri=ri, ni=ni, data=dat, slab=paste(authors, year, sep=", "))
dat

### meta-analysis of the transformed correlations using a random-effects model
res <- rma(yi, vi, data=dat)
res

### average correlation with 95% CI
predict(res, digits=3, transf=transf.ztor)

### forest plot
forest(res, addcred=TRUE, xlim=c(-1.6,1.6), attransf=transf.ztor,
       at=transf.rtoz(c(-.4,-.2,0,.2,.4,.6)), digits=c(2,1), cex=.8,
       header="Author(s), Year")

### funnel plot
funnel(res)
```

dat.nielweise2007	<i>Studies on Anti-Infective-Treated Central Venous Catheters for Prevention of Catheter-Related Bloodstream Infections</i>
-------------------	-----------------------------------------------------------------------------------------------------------------------------

Description

Results from 18 studies comparing the risk of catheter-related bloodstream infection when using anti-infective-treated versus standard catheters in the acute care setting.

Usage

```
dat.nielweise2007
```

Format

The data frame contains the following columns:

study	numeric	study number
author	character	(first) author
year	numeric	publication year
ai	numeric	number of CRBSIs in patients receiving an anti-infective catheter
n1i	numeric	number of patients receiving an anti-infective catheter
ci	numeric	number of CRBSIs in patients receiving a standard catheter
n2i	numeric	number of patients receiving a standard catheter

Details

The use of a central venous catheter may lead to a catheter-related bloodstream infection (CRBSI), which in turn increases the risk of morbidity and mortality. Anti-infective-treated catheters have been developed that are meant to reduce the risk of CRBSIs. Niel-Weise et al. (2007) conducted a meta-analysis of studies comparing infection risk when using anti-infective-treated versus standard catheters in the acute care setting. The results from 18 such studies are included in this dataset.

The dataset was used in the article by Stijnen et al. (2010) to illustrate various generalized linear mixed-effects models for the meta-analysis of proportions and odds ratios (see ‘References’).

Source

Niel-Weise, B. S., Stijnen, T., & van den Broek, P. J. (2007). Anti-infective-treated central venous catheters: A systematic review of randomized controlled trials. *Intensive Care Medicine*, **33**, 2058–2068.

References

Stijnen, T., Hamza, T. H., & Ozdemir, P. (2010). Random effects meta-analysis of event outcome in the framework of the generalized linear mixed model with applications in sparse data. *Statistics in Medicine*, **29**, 3046–3067.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.nielweise2007
dat

### standard (inverse-variance) random-effects model
res <- rma(measure="OR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, drop00=TRUE)
print(res, digits=3)
predict(res, transf=exp, digits=2)

### random-effects conditional logistic model
## Not run:
res <- rma.glmm(measure="OR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, model="CM.EL")
print(res, digits=3)
predict(res, transf=exp, digits=2)
## End(Not run)
```

dat.nielweise2008

Studies on Anti-Infective-Treated Central Venous Catheters for Prevention of Catheter-Related Bloodstream Infections

Description

Results from 18 studies comparing the risk of catheter-related bloodstream infection when using anti-infective-treated versus standard catheters for total parenteral nutrition or chemotherapy.

Usage

```
dat.nielweise2008
```

Format

The data frame contains the following columns:

study	numeric	study number
authors	character	study authors
year	numeric	publication year
x1i	numeric	number of CRBSIs in patients receiving an anti-infective catheter
t1i	numeric	total number of catheter days for patients receiving an anti-infective catheter
x2i	numeric	number of CRBSIs in patients receiving a standard catheter
t2i	numeric	total number of catheter days for patients receiving a standard catheter

Details

The use of a central venous catheter may lead to a catheter-related bloodstream infection (CRBSI), which in turn increases the risk of morbidity and mortality. Anti-infective-treated catheters have been developed that are meant to reduce the risk of CRBSIs. Niel-Weise et al. (2008) conducted a meta-analysis of studies comparing infection risk when using anti-infective-treated versus standard catheters for total parenteral nutrition or chemotherapy. The results from 9 such studies are included in this dataset.

The dataset was used in the article by Stijnen et al. (2010) to illustrate various generalized linear mixed-effects models for the meta-analysis of incidence rates and incidence rate ratios (see ‘References’).

Source

Niel-Weise, B. S., Stijnen, T., & van den Broek, P. J. (2008). Anti-infective-treated central venous catheters for total parenteral nutrition or chemotherapy: A systematic review. *Journal of Hospital Infection*, **69**, 114–123.

References

Stijnen, T., Hamza, T. H., & Ozdemir, P. (2010). Random effects meta-analysis of event outcome in the framework of the generalized linear mixed model with applications in sparse data. *Statistics in Medicine*, **29**, 3046–3067.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.nielweise2008
dat

### standard (inverse-variance) random-effects model
res <- rma(measure="IRR", x1i=x1i, t1i=t1i, x2i=x2i, t2i=t2i, data=dat)
print(res, digits=3)
predict(res, transf=exp, digits=2)
```

```
### random-effects conditional Poisson model
## Not run:
res <- rma.glm(mmeasure="IRR", x1i=x1i, t1i=t1i, x2i=x2i, t2i=t2i, data=dat, model="CM.EL")
print(res, digits=3)
predict(res, transf=exp, digits=2)
## End(Not run)
```

dat.normand1999

Studies on the Length of Hospital Stay of Stroke Patients

Description

Results from 9 studies on the length of the hospital stay of stroke patients under specialized care and under conventional/routine (non-specialist) care.

Usage

```
dat.normand1999
```

Format

The data frame contains the following columns:

study	numeric	study number
source	character	source of data
n1i	numeric	number of patients under specialized care
m1i	numeric	mean length of stay (in days) under specialized care
sd1i	numeric	standard deviation of the length of stay under specialized care
n2i	numeric	number of patients under routine care
m2i	numeric	mean length of stay (in days) under routine care
sd2i	numeric	standard deviation of the length of stay under routine care

Details

The 9 studies provide data in terms of the mean length of the hospital stay (in days) of stroke patients under specialized care and under conventional/routine (non-specialist) care. The goal of the meta-analysis was to examine the hypothesis whether specialist stroke unit care will result in a shorter length of hospitalization compared to routine management.

Source

Normand, S. T. (1999). Meta-analysis: Formulating, evaluating, combining, and reporting. *Statistics in Medicine*, **18**, 321–359.

Examples

```
### copy data into 'dat'
```



```

dat <- dat.normand1999

### calculate mean differences and corresponding sampling variances
dat <- escalc(measure="MD", m1i=m1i, sd1i=sd1i, n1i=n1i, m2i=m2i, sd2i=sd2i, n2i=n2i, data=dat)
dat

### meta-analysis of mean differences using a random-effects model
res <- rma(yi, vi, data=dat)
res

### meta-analysis of standardized mean differences using a random-effects model
res <- rma(measure="SMD", m1i=m1i, sd1i=sd1i, n1i=n1i, m2i=m2i, sd2i=sd2i, n2i=n2i,
           data=dat, slab=source)
res

### draw forest plot
forest(res, xlim=c(-7,5), alim=c(-3,1), cex=.8, header="Study/Source")

```

dat.pagliaro1992

Studies on the Effectiveness of Nonsurgical Treatments in Cirrhosis

Description

Results from 26 trials examining the effectiveness of beta-blockers and sclerotherapy for the prevention of first bleeding in patients with cirrhosis

Usage

```
dat.pagliaro1992
```

Format

The data frame contains the following columns:

study	numeric	study id
trt	character	either beta-blockers, sclerotherapy, or control
xi	numeric	number of patients with first bleeding
ni	numeric	number of patients treated

Details

The dataset includes the results from 26 randomized controlled trials examining the effectiveness of nonsurgical treatments for the prevention of first bleeding in patients with cirrhosis. Patients were either treated with beta-blockers, endoscopic sclerotherapy, or with a nonactive treatment (control). Two trials included all three treatment conditions, 7 trials compared beta-blockers against control, and 17 trials compared sclerotherapy against control. The dataset has been used in various papers to illustrate methods for conducting a network meta-analysis / mixed treatment comparison.

Source

Pagliari, L., D'Amico, G., Sørensen, T. I. A., Lebec, D., Burroughs, A. K., Morabito, A., Tiné, F., Politi, F., & Traina, M. (1992). Prevention of first bleeding in cirrhosis: A meta-analysis of randomized trials of nonsurgical treatment. *Annals of Internal Medicine*, **117**, 59–70.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.pagliari1992
dat

### restructure dataset to a contrast-based format
dat.c <- to.wide(dat, study="study", grp="trt", grpvars=3:4)
dat.c

### Mantel-Haenszel results for beta-blockers and sclerotherapy versus control, respectively
rma.mh(measure="OR", ai=xi.1, n1i=ni.1, ci=xi.2, n2i=ni.2,
       data=dat.c, subset=(trt.1=="beta-blockers"), digits=2)
rma.mh(measure="OR", ai=xi.1, n1i=ni.1, ci=xi.2, n2i=ni.2,
       data=dat.c, subset=(trt.1=="sclerotherapy"), digits=2)

### calculate log odds for each study arm
dat <- escalc(measure="PLO", xi=xi, ni=ni, data=dat)
dat

### turn treatment variable into factor and set reference level
dat$trt <- relevel(factor(dat$trt), ref="control")

### add a space before each level (this makes the output a bit more legible)
levels(dat$trt) <- paste0(" ", levels(dat$trt))

### network meta-analysis using an arm-based random-effects model with fixed study effects
### (by setting rho=1/2, tau^2 reflects the amount of heterogeneity for all treatment comparisons)
res <- rma.mv(yi, vi, mods = ~ factor(study) + trt - 1, random = ~ trt | study, rho=1/2, data=dat)
res

### average odds ratio comparing beta-blockers and sclerotherapy versus control, respectively
predict(res, newmods=c(rep(0,26), 1, 0), transf=exp, digits=2)
predict(res, newmods=c(rep(0,26), 0, 1), transf=exp, digits=2)

### average odds ratio comparing beta-blockers versus sclerotherapy
predict(res, newmods=c(rep(0,26), 1, -1), transf=exp, digits=2)
```

Description

Results from studies examining mortality risk in patients with nonmetastatic head and neck squamous-cell carcinoma receiving either locoregional treatment plus chemotherapy versus locoregional treatment alone.

Usage

```
dat.pignon2000
```

Format

The data frame contains the following columns:

id	numeric	study id number
trial	character	trial abbreviation
OmE	numeric	observed minus expected number of deaths in the locoregional treatment plus chemotherapy group
V	numeric	corresponding variance
grp	numeric	timing of chemotherapy: 1 = adjuvant, 2 = neoadjuvant, 3 = concomitant

Details

The purpose of this meta-analysis was to examine the mortality risk in patients with nonmetastatic head and neck squamous-cell carcinoma receiving either locoregional treatment plus chemotherapy versus locoregional treatment alone. For 65 trials, the dataset provides the observed minus expected number of deaths and corresponding variances in the locoregional treatment plus chemotherapy group. Based on these values, we can estimate the log hazard ratios with OmE/V and the corresponding sampling variance with $1/V$.

The trials were also divided according to the timing of the chemotherapy: (1) adjuvant, after the locoregional treatment, (2) neoadjuvant, before the locoregional treatment, and (3) concomitant, chemotherapy given concomitantly or alternating with radiotherapy.

Source

Pignon, J. P., Bourhis, J., Domenge, C., & Designe, L. (2000). Chemotherapy added to locoregional treatment for head and neck squamous-cell carcinoma: Three meta-analyses of updated individual data. *Lancet*, **355**(9208), 949–955.

Examples

```
### copy data into 'dat'
dat <- dat.pignon2000

### compute estimated log hazard ratios and sampling variances
dat$yi <- with(dat, OmE/V)
dat$vi <- with(dat, 1/V)
dat

### meta-analysis based on all 65 trials
res <- rma(yi, vi, data=dat, method="FE", digits=2)
res
```

```

predict(res, transf=exp)

### only adjuvant trials
res <- rma(yi, vi, data=dat, method="FE", subset=grp==1, digits=2)
res
predict(res, transf=exp)

### only neoadjuvant trials
res <- rma(yi, vi, data=dat, method="FE", subset=grp==2, digits=2)
res
predict(res, transf=exp)

### only concomitant trials
res <- rma(yi, vi, data=dat, method="FE", subset=grp==3, digits=2)
res
predict(res, transf=exp)

```

dat.pritz1997	<i>Studies on the Effectiveness of Hyperdynamic Therapy for Treating Cerebral Vasospasm</i>
---------------	---------------------------------------------------------------------------------------------

Description

Results from 14 studies on the effectiveness of hyperdynamic therapy for treating cerebral vasospasm.

Usage

```
dat.pritz1997
```

Format

The data frame contains the following columns:

study	numeric	study number
authors	character	study authors
xi	numeric	number of patients that improved with hyperdynamic therapy
ni	numeric	total number of patients treated

Details

As described in Zhou et al. (1999), "hyperdynamic therapy refers to induced hypertension and hypervolaemia (volume expansion) to treat ischaemic symptoms due to vasospasm, and the success of this therapy is defined as clinical improvement in terms of neurologic deficits." For each study that was included in the meta-analysis, the dataset includes information on the number of patients that improved under this form of therapy and the total number of patients that were treated. The goal of the meta-analysis is to estimate the true (average) success rate of hyperdynamic therapy.

Source

Zhou, X.-H., Brizendine, E. J., & Pritz, M. B. (1999). Methods for combining rates from several studies. *Statistics in Medicine*, **18**, 557–566.

References

Pritz, M. B. (1997). Treatment of cerebral vasospasm due to aneurysmal subarachnoid hemorrhage: Past, present, and future of hyperdynamic therapy. *Neurosurgery Quarterly*, **7**, 273–285.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.pritz1997
dat

### computation of "weighted average" in Zhou et al. (1999), Table IV
dat <- escalc(measure="PR", xi=xi, ni=ni, data=dat, add=0)
theta.hat <- sum(dat$ni * dat$yi) / sum(dat$ni)
se.theta.hat <- sqrt(sum(dat$ni^2 * dat$vi) / sum(dat$ni)^2)
ci.lb <- theta.hat - 1.96 * se.theta.hat
ci.ub <- theta.hat + 1.96 * se.theta.hat
round(c(estimate = theta.hat, se = se.theta.hat, ci.lb = ci.lb, ci.ub = ci.ub), 4)

### this is identical to a FE model with sample size weights
rma(yi, vi, weights=ni, method="FE", data=dat)

### random-effects model with raw proportions
dat <- escalc(measure="PR", xi=xi, ni=ni, data=dat)
res <- rma(yi, vi, data=dat)
predict(res)

### random-effects model with logit transformed proportions
dat <- escalc(measure="PLO", xi=xi, ni=ni, data=dat)
res <- rma(yi, vi, data=dat)
predict(res, transf=transf.ilogit)

### mixed-effects logistic regression model
res <- rma.glmm(measure="PLO", xi=xi, ni=ni, data=dat)
predict(res, transf=transf.ilogit)
```

dat.raudenbush1985 *Studies on Assessing the Effects of Teacher Expectations on Pupil IQ*

Description

Results from 19 studies examining how teachers' expectations about their pupils can influence actual IQ levels.

Usage

```
dat.raudenbush1985
```

Format

The data frame contains the following columns:

study	numeric	study number
author	character	study author(s)
year	numeric	publication year
weeks	numeric	weeks of contact prior to expectancy induction
setting	character	whether tests were group or individually administered
tester	character	whether test administrator was aware or blind
n1i	numeric	sample size of experimental group
n2i	numeric	sample size of control group
yi	numeric	standardized mean difference
vi	numeric	corresponding sampling variance

Details

In the so-called ‘Pygmalion study’ (Rosenthal & Jacobson, 1968), “all of the predominantly poor children in the so-called Oak elementary school were administered a test pretentiously labeled the ‘Harvard Test of Inflected Acquisition.’ After explaining that this newly designed instrument had identified those children most likely to show dramatic intellectual growth during the coming year, the experimenters gave the names of these ‘bloomers’ to the teachers. In truth, the test was a traditional IQ test and the ‘bloomers’ were a randomly selected 20% of the student population. After retesting the children 8 months later, the experimenters reported that those predicted to bloom had in fact gained significantly more in total IQ (nearly 4 points) and reasoning IQ (7 points) than the control group children. Further, at the end of the study, the teachers rated the experimental children as intellectually more curious, happier, better adjusted, and less in need of approval than their control group peers” (Raudenbush, 1984).

In the following years, a series of studies were conducted attempting to replicate this rather controversial finding. However, the great majority of those studies were unable to demonstrate a statistically significant difference between the two experimental groups in terms of IQ scores. Raudenbush (1984) conducted a meta-analysis based on 19 such studies to further examine the evidence for the existence of the ‘Pygmalion effect’. The dataset includes the results from these studies.

The effect size measure used for the meta-analysis was the standardized mean difference (y_i), with positive values indicating that the supposed ‘bloomers’ had, on average, higher IQ scores than those in the control group. The weeks variable indicates the number of weeks of prior contact between teachers and students before the expectancy induction. Testing was done either in a group setting or individually, which is indicated by the setting variable. Finally, the tester variable indicates whether the test administrators were either aware or blind to the researcher-provided designations of the children’s intellectual potential.

The data in this dataset were obtained from Raudenbush and Bryk (1985) with information on the setting and tester variables extracted from Raudenbush (1984).

Source

Raudenbush, S. W. (1984). Magnitude of teacher expectancy effects on pupil IQ as a function of the credibility of expectancy induction: A synthesis of findings from 18 experiments. *Journal of Educational Psychology*, **76**, 85–97.

Raudenbush, S. W., & Bryk, A. S. (1985). Empirical Bayes meta-analysis. *Journal of Educational Statistics*, **10**, 75–98.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.raudenbush1985
dat

### random-effects model
res <- rma(yi, vi, data=dat)
res

### create weeks variable where values larger than 3 are set to 3
dat$weeks.c <- ifelse(dat$week > 3, 3, dat$week)

### mixed-effects model with weeks.c variable as moderator
res <- rma(yi, vi, mods=~weeks.c, data=dat, digits=3)
res
```

dat.riley2003

Studies on MYC-N as a Prognostic Marker for Neuroblastoma

Description

Results from 81 studies examining overall and disease-free survival in neuroblastoma patients with amplified versus normal MYC-N protein levels.

Usage

```
dat.riley2003
```

Format

The data frame contains the following columns:

study	numeric	study number
yi	numeric	log hazard ratio of the outcome in those with amplified versus normal MYC-N protein levels
sei	numeric	standard error of the log hazard ratio
outcome	character	outcome (OS = overall survival; DFS = disease-free survival)

Details

The meta-analysis by Riley et al. (2003) examined a variety of prognostic markers for overall and disease-free survival in patients with neuroblastoma. One of the markers examined was amplified levels of the MYC-N protein, with is associated with poorer outcomes.

The dataset given here was extracted from Riley (2011) and has been used in several other publications (e.g., Riley et al., 2004, 2007). The dataset provides the (log) hazard ratios (and corresponding standard errors) with respect to these two outcomes in 81 studies, with positive values indicating a greater risk of death (for OS) or disease recurrence/death (for DFS) for patients with high MYC-N levels compared to those with normal/low levels. Note that information on both outcomes could only be extracted from 17 studies (39 studies only provided sufficient information to extract the OS estimate, while 25 studies only allowed for extraction of the DFS estimate).

Source

Riley, R. D., Sutton, A. J., Abrams, K. R., & Lambert, P. C. (2004). Sensitivity analyses allowed more appropriate and reliable meta-analysis conclusions for multiple outcomes when missing data was present. *Journal of Clinical Epidemiology*, **57**, 911–924.

Riley, R. D., Abrams, K. R., Lambert, P. C., Sutton, A. J., & Thompson, J. R. (2007). An evaluation of bivariate random-effects meta-analysis for the joint synthesis of two correlated outcomes. *Statistics in Medicine*, **26**, 78–97.

Riley, R. D. (2011). Erratum. *Statistics in Medicine*, **30**, 400.

References

Riley, R. D., Burchill, S. A., Abrams, K. R., Heney, D., Lambert, P. C., Jones, D. R., et al. (2003). A systematic review and evaluation of the use of tumour markers in paediatric oncology: Ewing's sarcoma and neuroblastoma. *Health Technology Assessment*, **7**, 1–162.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.riley2003
dat

### random-effects model analysis for outcome DFS
res <- rma(yi, sei=sei, data=dat, subset=(outcome == "DFS"), method="DL")
res
predict(res, transf=exp, digits=2)

### random-effects model analysis for outcome OS
res <- rma(yi, sei=sei, data=dat, subset=(outcome == "OS"), method="DL")
res
predict(res, transf=exp, digits=2)
```

 dat.senn2013

Studies on the Effectiveness of Glucose-Lowering Agents

Description

Results from 26 trials examining the effectiveness of glucose-lowering agents in patients with type 2 diabetes

Usage

dat.senn2013

Format

The data frame contains the following columns:

study	character	(first) author and year of study
ni	numeric	sample size of the study arm
treatment	character	treatment given
comment	character	whether figures given are based on raw values at outcome or on change from baseline
mi	numeric	mean score
sdi	numeric	standard deviation

Details

The dataset includes the results from 26 randomized controlled trials examining the effectiveness of adding various oral glucose-lowering agents to a baseline sulfonylurea therapy in patients with type 2 diabetes. The outcome measured in the studies was either the mean HbA1c level at follow-up or the mean change in HbA1c level from baseline to follow-up. A total of 10 different treatment types were examined in these studies: acarbose, benfluorex, metformin, miglitol, pioglitazone, placebo, rosiglitazone, sitagliptin, sulfonylurea alone, and vildagliptin. One study included three treatment arms (Willms, 1999), while the rest of the studies included two treatment arms (hence, the dataset includes the results from 53 treatment arms).

The data can be used for a network meta-analysis, either using an arm-based or a contrast-based model. See 'Examples' below.

Source

Senn, S., Gavini, F., Magrez, D., & Scheen, A. (2013). Issues in performing a network meta-analysis. *Statistical Methods in Medical Research*, **22**, 169–189.

Examples

```
### copy data into 'dat' and examine data
dat <- dat.senn2013
dat
```

```

### create network graph ('plyr' and 'igraph' packages must be installed)
## Not run:
require(plyr)
require(igraph)
pairs <- do.call(rbind, sapply(split(dat$treatment, dat$study), function(x) t(combn(x,2))))
pairs <- ddply(data.frame(pairs), .(X1, X2), count)
g <- graph.edgelist(as.matrix(pairs[,1:2]), directed=FALSE)
plot(g, edge.curved=FALSE, edge.width=pairs$freq, vertex.label.dist=.8)
## End(Not run)

### table of studies versus treatments examined
print(addmargins(table(dat$study, dat$treatment)), zero.print="")

### table of frequencies with which treatment pairs were studied
print(as.table(crossprod(table(dat$study, dat$treatment))), zero.print="")

### add means and sampling variances of the means to the dataset
dat <- escalc(measure="MN", mi=mi, sdi=sdi, ni=ni, data=dat)

### turn treatment variable into factor and set reference level
dat$treatment <- relevel(factor(dat$treatment), ref="placebo")

### add a space before each level (this makes the output a bit more legible)
levels(dat$treatment) <- paste0(" ", levels(dat$treatment))

### network meta-analysis using an arm-based fixed-effects model with fixed study effects
res.fe <- rma.mv(yi, vi, mods = ~ study + treatment - 1, data=dat, slab=paste0(study, treatment))
res.fe

### test if treatment factor as a whole is significant
anova(res.fe, btt="treatment")

### forest plot of the contrast estimates (treatments versus placebos)
dev.new(width=7, height=5)
forest(tail(coef(res.fe), 9), tail(diag(vcov(res.fe)), 9), slab=levels(dat$treatment)[-1],
       xlim=c(-2.5, 2.0), alim=c(-1.5, 0.5), psize=1, xlab="Estimate", header="Treatment")

### weight matrix for the estimation of the fixed effects (leaving out study effects)
w <- t(tail(vcov(res.fe)) %*% t(model.matrix(res.fe)) %*% weights(res.fe, type="matrix"), 9)
rownames(w) <- res.fe$slab

### create shade plot for the diabetes network with placebo as the reference treatment
### negative values in blue shades, positive values in red shades
dev.new()
cols <- colorRampPalette(c("blue", "gray95", "red"))(9)
heatmap(w, Rowv=NA, Colv=NA, scale="none", margins=c(6,11), col=cols,
       cexRow=.7, cexCol=1, labCol=levels(dat$treatment)[-1])

### network meta-analysis using an arm-based random-effects model with fixed study effects
### by setting rho=1/2, tau^2 reflects the amount of heterogeneity for all treatment comparisons
res.re <- rma.mv(yi, vi, mods = ~ study + treatment - 1, random = ~ treatment | study, rho=1/2,
               data=dat, slab=paste0(study, treatment))
res.re

```

```

### test if treatment factor as a whole is significant
anova(res.re, btt="treatment")

### forest plot of the contrast estimates (treatments versus placebos)
forest(tail(coef(res.re), 9), tail(diag(vcov(res.re)), 9), slab=levels(dat$treatment)[-1],
       xlim=c(-3.0, 2.5), alim=c(-1.5, 0.5), psize=1, xlab="Estimate", header="Treatment")

### compute contribution of each study to the overall Q-test value
qi <- sort(by((resid(res.fe) / sqrt(dat$vi))^2, dat$study, sum))

### check that the values add up
sum(qi)
res.fe$QE

### plot the values
s <- length(qi)
par(mar=c(5,10,2,1))
plot(qi, 1:s, pch=19, xaxt="n", yaxt="n", xlim=c(0,40), xlab="Chi-Square Contribution", ylab="")
axis(side=1)
axis(side=2, at=1:s, labels=names(qi), las=1, tcl=0)
segments(rep(0,s), 1:s, qi, 1:s)

#####

### restructure dataset to a contrast-based format
dat <- dat.senn2013[c(1,4:2,5:6)] # reorder variables first
dat <- to.wide(dat, study="study", grp="treatment", ref="placebo", grpvars=4:6)
dat

### calculate mean difference and corresponding sampling variance for each treatment comparison
dat <- escalc(measure="MD", m1i=mi.1, sdi1=sdi.1, ni1=ni.1,
             m2i=mi.2, sdi2=sdi.2, ni2=ni.2, data=dat)
dat

### calculate the variance-covariance matrix of the mean differences for the multitreatment studies
calc.v <- function(x) {
  v <- matrix(x$sdi.2[1]^2 / x$ni.2[1], nrow=nrow(x), ncol=nrow(x))
  diag(v) <- x$vi
  v
}
V <- bldiag(lapply(split(dat, dat$study), calc.v))

### add contrast matrix to dataset
dat <- contrmat(dat, grp1="treatment.1", grp2="treatment.2")
dat

### network meta-analysis using a contrast-based random-effects model
### by setting rho=1/2, tau^2 reflects the amount of heterogeneity for all treatment comparisons
### the treatment left out (placebo) becomes the reference level for the treatment comparisons
res.cb <- rma.mv(yi, V, mods = ~ acarbose + benfluorex + metformin + miglitol + pioglitazone +
                rosiglitazone + sitagliptin + sulfonylurea + vildagliptin - 1,
                random = ~ factor(id) | study, rho=1/2, data=dat)

```

```

res.cb

### estimate all pairwise differences between treatments (using the 'multcomp' package)
if (require(multcomp)) {
  contr <- contrMat(setNames(rep(1,res.cb$p), colnames(res.cb$X)), type="Tukey")
  sav <- predict(res.cb, newmods=contr)
  sav[["slab"]] <- rownames(contr)
  sav
}

```

dat.yusuf1985

Studies of Beta Blockers During and After Myocardial Infarction

Description

Results from studies examining the effectiveness of beta blockers for reducing mortality and reinfarction.

Usage

```
dat.yusuf1985
```

Format

The data frame contains the following columns:

table	character	table number
id	character	trial id number
trial	character	trial name or first author
ai	numeric	number of deaths/reinfarctions in treatment group
n1i	numeric	number of patients in treatment group
ci	numeric	number of deaths/reinfarctions in control group
n2i	numeric	number of patients in control group

Details

The dataset contains table 6 (total mortality from short-term trials of oral beta blockers), 9 (total mortality at one week from trials with an initial IV dose of a beta blocker), 10 (total mortality from long-term trials with treatment starting late and mortality from day 8 onwards in long-term trials that began early and continued after discharge), 11 (nonfatal reinfarction from long-term trials of beta blockers), 12a (sudden death in long-term beta blocker trials), and 12b (nonsudden death in long-term beta blocker trials) from the meta-analysis by Yusuf et al. (1985) on the effectiveness of beta blockers for reducing mortality and reinfarction.

The article also describes what is sometimes called Peto's one-step method for meta-analyzing 2×2 table data. This method is implemented in the [rma.peto](#) function.

Source

Yusuf, S., Peto, R., Lewis, J., Collins, R., & Sleight, P. (1985). Beta blockade during and after myocardial infarction: An overview of the randomized trials. *Progress in Cardiovascular Disease*, 27, 335–371.

Examples

```
### copy data into 'dat'
dat <- dat.yusuf1985

### to select a table for the analysis
tab <- "6" ### either: 6, 9, 10, 11, 12a, 12b

### to double-check total counts as reported in article
apply(dat[dat$table==tab,4:7], 2, sum, na.rm=TRUE)

### meta-analysis using Peto's one-step method
res <- rma.peto(ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat, subset=(table==tab))
res
predict(res, transf=exp, digits=2)
```

escalc

Calculate Effect Sizes and Outcome Measures

Description

The function can be used to calculate various effect sizes or outcome measures (and the corresponding sampling variances) that are commonly used in meta-analyses.

Usage

```
escalc(measure, ai, bi, ci, di, n1i, n2i, x1i, x2i, t1i, t2i,
       m1i, m2i, sd1i, sd2i, xi, mi, ri, ti, sdi, r2i, ni, yi, vi, sei,
       data, slab, subset, include,
       add=1/2, to="only0", drop00=FALSE, vtype="LS",
       var.names=c("yi", "vi"), add.measure=FALSE,
       append=TRUE, replace=TRUE, digits, ...)
```

Arguments

measure	a character string indicating which effect size or outcome measure should be calculated. See ‘Details’ for possible options and how the data should be specified.
ai	vector to specify the 2×2 table frequencies (upper left cell).
bi	vector to specify the 2×2 table frequencies (upper right cell).
ci	vector to specify the 2×2 table frequencies (lower left cell).
di	vector to specify the 2×2 table frequencies (lower right cell).

<code>n1i</code>	vector to specify the group sizes or row totals (first group/row).
<code>n2i</code>	vector to specify the group sizes or row totals (second group/row).
<code>x1i</code>	vector to specify the number of events (first group).
<code>x2i</code>	vector to specify the number of events (second group).
<code>t1i</code>	vector to specify the total person-times (first group).
<code>t2i</code>	vector to specify the total person-times (second group).
<code>m1i</code>	vector to specify the means (first group or time point).
<code>m2i</code>	vector to specify the means (second group or time point).
<code>sd1i</code>	vector to specify the standard deviations (first group or time point).
<code>sd2i</code>	vector to specify the standard deviations (second group or time point).
<code>xi</code>	vector to specify the frequencies of the event of interest.
<code>mi</code>	vector to specify the frequencies of the complement of the event of interest or the group means.
<code>ri</code>	vector to specify the raw correlation coefficients.
<code>ti</code>	vector to specify the total person-times.
<code>sdi</code>	vector to specify the standard deviations.
<code>r2i</code>	vector to specify the R^2 values.
<code>ni</code>	vector to specify the sample/group sizes.
<code>yi</code>	vector to specify the observed effect size or outcomes.
<code>vi</code>	vector to specify the corresponding sampling variances.
<code>sei</code>	vector to specify the corresponding standard errors.
<code>data</code>	optional data frame containing the variables given to the arguments above.
<code>slab</code>	optional vector with labels for the studies.
<code>subset</code>	optional (logical or numeric) vector indicating the subset of studies that will be included in the data frame returned by the function.
<code>include</code>	optional (logical or numeric) vector indicating the subset of studies for which the measure should be calculated. See the ‘Value’ section for more details.
<code>add</code>	a non-negative number indicating the amount to add to zero cells, counts, or frequencies. See ‘Details’.
<code>to</code>	a character string indicating when the values under <code>add</code> should be added (either “all”, “only0”, “if0all”, or “none”). See ‘Details’.
<code>drop00</code>	logical indicating whether studies with no cases/events (or only cases) in both groups should be dropped when calculating the observed outcomes of the individual studies. See ‘Details’.
<code>vtype</code>	a character string indicating the type of sampling variances to calculate (either “LS”, “UB”, “HO”, “ST”, or <code>vtype="CS"</code>). See ‘Details’.
<code>var.names</code>	a character string with two elements, specifying the name of the variable for the observed outcomes and the name of the variable for the corresponding sampling variances (the default is “yi” and “vi”).

<code>add.measure</code>	logical indicating whether a variable should be added to the data frame (with default name "measure") that indicates the type of outcome measure computed. When using this option, <code>var.names</code> can have a third element to change this variable name.
<code>append</code>	logical indicating whether the data frame specified via the <code>data</code> argument (if one has been specified) should be returned together with the observed outcomes and corresponding sampling variances (the default is TRUE).
<code>replace</code>	logical indicating whether existing values for <code>yi</code> and <code>vi</code> in the data frame should be replaced or not. Only relevant when <code>append=TRUE</code> and the data frame already contains the <code>yi</code> and <code>vi</code> variables. If <code>replace=TRUE</code> (the default), all of the existing values will be overwritten. If <code>replace=FALSE</code> , only NA values will be replaced. See the 'Value' section for more details.
<code>digits</code>	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is 4). Note that the values are stored without rounding in the returned object.
<code>...</code>	other arguments.

Details

Before a meta-analysis can be conducted, the relevant results from each study must be quantified in such a way that the resulting values can be further aggregated and compared. Depending on (a) the goals of the meta-analysis, (b) the design and types of studies included, and (c) the information provided therein, one of the various effect size or outcome measures described below may be appropriate for the meta-analysis and can be computed with the `escalc` function.

The `measure` argument is a character string specifying which outcome measure should be calculated (see below for the various options), arguments `ai` through `ni` are then used to specify the information needed to calculate the various measures (depending on the chosen outcome measure, different arguments need to be specified), and `data` can be used to specify a data frame containing the variables given to the previous arguments. The `add`, `to`, and `drop00` arguments may be needed when dealing with frequency or count data that may need special handling when some of the frequencies or counts are equal to zero (see below for details). Finally, the `vtype` argument is used to specify how to estimate the sampling variances (again, see below for details).

To provide a structure to the various effect size or outcome measures that can be calculated with the `escalc` function, we can distinguish between measures that are used to:

- contrast two independent (either experimentally created or naturally occurring) groups,
- describe the direction and strength of the association between two variables,
- summarize some characteristic or attribute of individual groups, or
- quantify change within a single group or the difference between two matched pairs samples.

Furthermore, where appropriate, we can further distinguish between measures that are applicable when the characteristic, response, or dependent variable assessed in the individual studies is:

- a dichotomous (binary) variable (e.g., remission versus no remission),
- a count of events per time unit (e.g., number of migraines per year),
- a quantitative variable (e.g., amount of depression as assessed by a rating scale).

Outcome Measures for Two-Group Comparisons:

In many meta-analyses, the goal is to synthesize the results from studies that compare or contrast two groups. The groups may be experimentally defined (e.g., a treatment and a control group created via random assignment) or may occur naturally (e.g., men and women, employees working under high- versus low-stress conditions, people exposed to some environmental risk factor versus those not exposed).

Measures for Dichotomous Variables:

In various fields (such as the health and medical sciences), the response or outcome variable measured is often dichotomous (binary), so that the data from a study comparing two different groups can be expressed in terms of a 2×2 table, such as:

	outcome 1	outcome 2	total
group 1	ai	bi	n1i
group 2	ci	di	n2i

where a_i , b_i , c_i , and d_i denote the cell frequencies (i.e., the number of people falling into a particular category) and n_{1i} and n_{2i} are the row totals (i.e., the group sizes).

For example, in a set of randomized clinical trials, group 1 and group 2 may refer to the treatment and placebo/control group, respectively, with outcome 1 denoting some event of interest (e.g., death, complications, failure to improve under the treatment) and outcome 2 its complement. Similarly, in a set of cohort studies, group 1 and group 2 may denote those who engage in and those who do not engage in a potentially harmful behavior (e.g., smoking), with outcome 1 denoting the development of a particular disease (e.g., lung cancer) during the follow-up period. Finally, in a set of case-control studies, group 1 and group 2 may refer to those with the disease (i.e., cases) and those free of the disease (i.e., controls), with outcome 1 denoting, for example, exposure to some risk environmental risk factor in the past and outcome 2 non-exposure. Note that in all of these examples, the stratified sampling scheme fixes the row totals (i.e., the group sizes) by design.

A meta-analysis of studies reporting results in terms of 2×2 tables can be based on one of several different outcome measures, including the risk ratio (also called the relative risk), the odds ratio, the risk difference, and the arcsine square root transformed risk difference (e.g., Fleiss & Berlin, 2009, Rücker et al., 2009). For any of these outcome measures, one needs to specify the cell frequencies via the a_i , b_i , c_i , and d_i arguments (or alternatively, one can use the a_i , c_i , n_{1i} , and n_{2i} arguments).

The options for the measure argument are then:

- "RR" for the *log risk ratio*.
- "OR" for the *log odds ratio*.
- "RD" for the *risk difference*.
- "AS" for the *arcsine square root transformed risk difference* (Rücker et al., 2009).
- "PETO" for the *log odds ratio* estimated with Peto's method (Yusuf et al., 1985).

Note that the log is taken of the risk ratio and the odds ratio, which makes these outcome measures symmetric around 0 and yields corresponding sampling distributions that are closer to normality.

Cell entries with a zero count can be problematic, especially for the risk ratio and the odds ratio. Adding a small constant to the cells of the 2×2 tables is a common solution to this problem. When `to="only0"` (the default), the value of `add` (the default is 1/2; but see 'Note') is added to each cell of those 2×2 tables with at least one cell equal to 0. When `to="all"`, the value of `add`

is added to each cell of all 2×2 tables. When `to="if0all"`, the value of `add` is added to each cell of all 2×2 tables, but only when there is at least one 2×2 table with a zero cell. Setting `to="none"` or `add=0` has the same effect: No adjustment to the observed table frequencies is made. Depending on the outcome measure and the data, this may lead to division by zero inside of the function (when this occurs, the resulting value is recoded to NA). Also, studies where `ai=ci=0` or `bi=di=0` may be considered to be uninformative about the size of the effect and dropping such studies has sometimes been recommended (Higgins & Green, 2008). This can be done by setting `drop00=TRUE`. The values for such studies will then be set to NA.

Datasets corresponding to data of this type are provided in [dat.bcg](#), [dat.collins1985a](#), [dat.collins1985b](#), [dat.egger2001](#), [dat.hine1989](#), [dat.laopaiboon2015](#), [dat.lee2004](#), [dat.li2007](#), [dat.linde2005](#), [dat.nielweise2007](#), and [dat.yusuf1985](#).

Assuming that the dichotomous outcome is actually a dichotomized version of the responses on an underlying quantitative scale, it is also possible to estimate the standardized mean difference based on 2×2 table data, using either the probit transformed risk difference or a transformation of the odds ratio (e.g., Cox & Snell, 1989; Chinn, 2000; Hasselblad & Hedges, 1995; Sánchez-Meca et al., 2003). The options for the `measure` argument are then:

- "PBIT" for the *probit transformed risk difference* as an estimate of the standardized mean difference.
- "OR2DN" for the *transformed odds ratio* as an estimate of the standardized mean difference (normal distributions).
- "OR2DL" for the *transformed odds ratio* as an estimate of the standardized mean difference (logistic distributions).

The probit transformation assumes that the responses on the underlying quantitative scale are normally distributed. There are two versions of the odds ratio transformation, the first also assuming normal distributions within the two groups, while the second assumes that the responses follow logistic distributions.

A dataset corresponding to data of this type is provided in [dat.gibson2002](#).

Measures for Event Counts:

In medical and epidemiological studies comparing two different groups (e.g., treated versus untreated patients, exposed versus unexposed individuals), results are sometimes reported in terms of event counts (i.e., the number of events, such as strokes or myocardial infarctions) over a certain period of time. Data of this type are also referred to as 'person-time data'. In particular, assume that the studies report data in the form:

	number of events	total person-time
group 1	x_{1i}	t_{1i}
group 2	x_{2i}	t_{2i}

where x_{1i} and x_{2i} denote the number of events in the first and the second group, respectively, and t_{1i} and t_{2i} the corresponding total person-times at risk. Often, the person-time is measured in years, so that t_{1i} and t_{2i} denote the total number of follow-up years in the two groups.

This form of data is fundamentally different from what was described in the previous section, since the total follow-up time may differ even for groups of the same size and the individuals studied may experience the event of interest multiple times. Hence, different outcome measures than the ones described in the previous section must be considered when data are reported in this format. These include the incidence rate ratio, the incidence rate difference, and the square root transformed incidence rate difference (Bagos & Nikolopoulos, 2009; Rothman et al., 2008). For any of these outcome measures, one needs to specify the total number of events via the x_{1i} and

x_{2i} arguments and the corresponding total person-time values via the t_{1i} and t_{2i} arguments. The options for the measure argument are then:

- "IRR" for the *log incidence rate ratio*.
- "IRD" for the *incidence rate difference*.
- "IRSD" for the *square root transformed incidence rate difference*.

Note that the log is taken of the incidence rate ratio, which makes this outcome measure symmetric around 0 and yields a corresponding sampling distribution that is closer to normality.

Studies with zero events in one or both groups can be problematic, especially for the incidence rate ratio. Adding a small constant to the number of events is a common solution to this problem. When $to="only0"$ (the default), the value of add (the default is $1/2$; but see 'Note') is added to x_{1i} and x_{2i} only in the studies that have zero events in one or both groups. When $to="all"$, the value of add is added to x_{1i} and x_{2i} in all studies. When $to="if0all"$, the value of add is added to x_{1i} and x_{2i} in all studies, but only when there is at least one study with zero events in one or both groups. Setting $to="none"$ or $add=0$ has the same effect: No adjustment to the observed number of events is made. Depending on the outcome measure and the data, this may lead to division by zero inside of the function (when this occurs, the resulting value is recoded to NA). Like for 2×2 table data, studies where $x_{1i}=x_{2i}=0$ may be considered to be uninformative about the size of the effect and dropping such studies has sometimes been recommended. This can be done by setting $drop00=TRUE$. The values for such studies will then be set to NA.

Datasets corresponding to data of this type are provided in [dat.hart1999](#) and [dat.nielweise2008](#).

Measures for Quantitative Variables:

When the response or dependent variable assessed in the individual studies is measured on some quantitative scale, it is customary to report certain summary statistics, such as the mean and standard deviation of the observations. The data layout for a study comparing two groups with respect to such a variable is then of the form:

	mean	standard deviation	group size
group 1	m_{1i}	sd_{1i}	n_{1i}
group 2	m_{2i}	sd_{2i}	n_{2i}

where m_{1i} and m_{2i} are the observed means of the two groups, sd_{1i} and sd_{2i} are the observed standard deviations, and n_{1i} and n_{2i} denote the number of individuals in each group. Again, the two groups may be experimentally created (e.g., a treatment and control group based on random assignment) or naturally occurring (e.g., men and women). In either case, the raw mean difference, the standardized mean difference, and the (log transformed) ratio of means (also called log response ratio) are useful outcome measures when meta-analyzing studies of this type (e.g., Borenstein, 2009).

The options for the measure argument are then:

- "MD" for the *raw mean difference*.
- "SMD" for the *standardized mean difference*.
- "SMDH" for the *standardized mean difference* with heteroscedastic population variances in the two groups (Bonett, 2008, 2009).
- "ROM" for the *log transformed ratio of means* (Hedges et al., 1999; Lajeunesse, 2011).

Note that the log is taken of the ratio of means, which makes this outcome measures symmetric around 0 and yields a corresponding sampling distribution that is closer to normality. However, note that if m_{1i} and m_{2i} have opposite signs, this outcome measure cannot be computed.

The positive bias in the standardized mean difference is automatically corrected for within the

function, yielding Hedges' g for `measure="SMD"` (Hedges, 1981). Similarly, the same bias correction is applied for `measure="SMDH"` (Bonett, 2009). For `measure="SMD"`, one can choose between `vtype="LS"` (the default) and `vtype="UB"`. The former uses the usual large-sample approximation to compute the sampling variances. The latter provides unbiased estimates of the sampling variances. Finally, for `measure="MD"` and `measure="ROM"`, one can choose between `vtype="LS"` (the default) and `vtype="HO"`. The former computes the sampling variances without assuming homoscedasticity (i.e., that the true variances of the measurements are the same in group 1 and group 2 within each study), while the latter assumes homoscedasticity.

A dataset corresponding to data of this type is provided in [dat.normand1999](#) (for mean differences and standardized mean differences). A dataset showing the use of the ratio of means measure is provided in [dat.curtis1998](#).

It is also possible to transform standardized mean differences into log odds ratios (e.g., Cox & Snell, 1989; Chinn, 2000; Hasselblad & Hedges, 1995; Sánchez-Meca et al., 2003). The options for the `measure` argument are then:

- `"D2ORN"` for the *transformed standardized mean difference* as an estimate of the log odds ratio (normal distributions).
- `"D2ORL"` for the *transformed standardized mean difference* as an estimate of the log odds ratio (logistic distributions).

Both of these transformations provide an estimate of the log odds ratio, the first assuming that the responses within the two groups are normally distributed, while the second assumes that the responses follow logistic distributions.

A dataset illustrating the combined analysis of standardized mean differences and probit transformed risk differences is provided in [dat.gibson2002](#).

Finally, interest may also be focused on differences between the two groups with respect to their variability. Here, the (log transformed) ratio of the coefficient of variation of the two groups (also called the coefficient of variation ratio) can be a useful measure (Nakagawa et al., 2015). If focus is solely on the variability of the measurements within the two groups, then the (log transformed) ratio of the standard deviations (also called the variability ratio) can be used (Nakagawa et al., 2015). For the latter, one only needs to specify `sd1i`, `sd2i`, `n1i`, and `n2i`. The options for the `measure` argument are:

- `"CVR"` for the *log transformed coefficient of variation ratio*.
- `"VR"` for the *log transformed variability ratio*.

Note that a slight bias correction is applied for both of these measures (Nakagawa et al., 2015). Also, the sampling variance for `measure="CVR"` is computed as given by equation 12 in Nakagawa et al. (2015), but without the $-2\rho \dots$ terms, since for normally distributed data (which we assume here) the mean and variance (and transformations thereof) are independent.

Outcome Measures for Variable Association:

Meta-analyses are often used to synthesize studies that examine the direction and strength of the association between two variables measured concurrently and/or without manipulation by experimenters. In this section, a variety of outcome measures will be discussed that may be suitable for a meta-analyses with this purpose. We can distinguish between measures that are applicable when both variables are measured on quantitative scales, when both variables measured are dichotomous, and when the two variables are of mixed types.

Measures for Two Quantitative Variables:

The (Pearson or product moment) correlation coefficient quantifies the direction and strength of the (linear) relationship between two quantitative variables and is therefore frequently used as

the outcome measure for meta-analyses (e.g., Borenstein, 2009). Two alternative measures are a bias-corrected version of the correlation coefficient and Fisher's *r*-to-*z* transformed correlation coefficient.

For these measures, one needs to specify *ri*, the vector with the raw correlation coefficients, and *ni*, the corresponding sample sizes. The options for the measure argument are then:

- "COR" for the *raw correlation coefficient*.
- "UCOR" for the *raw correlation coefficient* corrected for its slight negative bias (based on equation 2.3 in Olkin & Pratt, 1958).
- "ZCOR" for *Fisher's r-to-z transformed correlation coefficient* (Fisher, 1921).

For `measure="UCOR"`, one can choose between `vtype="LS"` (the default) and `vtype="UB"`. The former uses the usual large-sample approximation to compute the sampling variances. The latter provides unbiased estimates of the sampling variances (see Hedges, 1989, but using the exact equation instead of the approximation).

Datasets corresponding to data of this type are provided in [dat.mcdaniel1994](#) and [dat.molloy2014](#).

Measures for Two Dichotomous Variables:

When the goal of a meta-analysis is to examine the relationship between two dichotomous variables, the data for each study can again be presented in the form of a 2×2 table, except that there may not be a clear distinction between the group (i.e., the row) and the outcome (i.e., the column) variable. Moreover, the table may be a result of cross-sectional (i.e., multinomial) sampling, where none of the table margins (except the total sample size) are fixed by the study design.

The phi coefficient and the odds ratio are commonly used measures of association for 2×2 table data (e.g., Fleiss & Berlin, 2009). The latter is particularly advantageous, as it is directly comparable to values obtained from stratified sampling (as described earlier). Yule's *Q* and Yule's *Y* (Yule, 1912) are additional measures of association for 2×2 table data (although they are not typically used in meta-analyses). Finally, assuming that the two dichotomous variables are actually dichotomized versions of the responses on two underlying quantitative scales (and assuming that the two variables follow a bivariate normal distribution), it is also possible to estimate the correlation between the two variables using the tetrachoric correlation coefficient (Pearson, 1900; Kirk, 1973).

For any of these outcome measures, one needs to specify the cell frequencies via the *ai*, *bi*, *ci*, and *di* arguments (or alternatively, one can use the *ai*, *ci*, *n1i*, and *n2i* arguments). The options for the measure argument are then:

- "OR" for the *log odds ratio*.
- "PHI" for the *phi coefficient*.
- "YUQ" for *Yule's Q* (Yule, 1912).
- "YUY" for *Yule's Y* (Yule, 1912).
- "RTET" for the *tetrachoric correlation*.

Tables with one or two zero counts are handled as described earlier. For `measure="PHI"`, one must indicate via `vtype="ST"` or `vtype="CS"` whether the data for the studies were obtained using stratified or cross-sectional (i.e., multinomial) sampling, respectively (it is also possible to specify an entire vector for the `vtype` argument in case the sampling schemes differed for the various studies).

A dataset corresponding to data of this type is provided in [dat.bourassa1996](#).

Measures for Mixed Variable Types:

Finally, we can consider outcome measures that can be used to describe the relationship between two variables, where one variable is dichotomous and the other variable measures some

quantitative characteristic. In that case, it is likely that study authors again report summary statistics, such as the mean and standard deviation of the measurements within the two groups (defined by the dichotomous variable). In that case, one can compute the point-biserial correlation (Tate, 1954) as a measure of association between the two variables. If the dichotomous variable is actually a dichotomized version of the responses on an underlying quantitative scale (and assuming that the two variables follow a bivariate normal distribution), it is also possible to estimate the correlation between the two variables using the biserial correlation coefficient (Pearson, 1909; Soper, 1914; Jacobs & Viechtbauer, 2017).

Here, one again needs to specify $m1i$ and $m2i$ for the observed means of the two groups, $sd1i$ and $sd2i$ for the observed standard deviations, and $n1i$ and $n2i$ for the number of individuals in each group. The options for the measure argument are then:

- "RPB" for the *point-biserial correlation*.
- "RBIS" for the *biserial correlation*.

For measure="RPB", one must indicate via vtype="ST" or vtype="CS" whether the data for the studies were obtained using stratified or cross-sectional (i.e., multinomial) sampling, respectively (it is also possible to specify an entire vector for the vtype argument in case the sampling schemes differed for the various studies).

Outcome Measures for Individual Groups:

In this section, outcome measures will be described which may be useful when the goal of a meta-analysis is to synthesize studies that characterize some property of individual groups. We will again distinguish between measures that are applicable when the characteristic of interest is a dichotomous variable, when the characteristic represents an event count, or when the characteristic assessed is a quantitative variable.

Measures for Dichotomous Variables:

A meta-analysis may be conducted to aggregate studies that provide data for individual groups with respect to a dichotomous dependent variable. Here, one needs to specify x_i and n_i , denoting the number of individuals experiencing the event of interest and the total number of individuals, respectively. Instead of specifying n_i , one can use m_i to specify the number of individuals that do not experience the event of interest. The options for the measure argument are then:

- "PR" for the *raw proportion*.
- "PLN" for the *log transformed proportion*.
- "PLO" for the *logit transformed proportion* (i.e., log odds).
- "PAS" for the *arcsine square root transformed proportion* (i.e., the angular transformation).
- "PFT" for the *Freeman-Tukey double arcsine transformed proportion* (Freeman & Tukey, 1950).

Zero cell entries can be problematic for certain outcome measures. When to="only0" (the default), the value of add (the default is 1/2; but see 'Note') is added to x_i and m_i only for studies where x_i or m_i is equal to 0. When to="all", the value of add is added to x_i and m_i in all studies. When to="if0all", the value of add is added in all studies, but only when there is at least one study with a zero value for x_i or m_i . Setting to="none" or add=0 has the same effect: No adjustment to the observed values is made. Depending on the outcome measure and the data, this may lead to division by zero inside of the function (when this occurs, the resulting value is recoded to NA).

Datasets corresponding to data of this type are provided in [dat.pritz1997](#) and [dat.debruin2009](#).

Measures for Event Counts:

Various measures can be used to characterize individual groups when the dependent variable assessed is an event count. Here, one needs to specify x_i and t_i , denoting the number of events that occurred and the total person-times at risk, respectively. The options for the measure argument are then:

- "IR" for the *raw incidence rate*.
- "IRLN" for the *log transformed incidence rate*.
- "IRS" for the *square root transformed incidence rate*.
- "IRFT" for the *Freeman-Tukey transformed incidence rate* (Freeman & Tukey, 1950).

Studies with zero events can be problematic, especially for the log transformed incidence rate. Adding a small constant to the number of events is a common solution to this problem. When `to="only0"` (the default), the value of `add` (the default is 1/2; but see 'Note') is added to x_i only in the studies that have zero events. When `to="all"`, the value of `add` is added to x_i in all studies. When `to="if0all"`, the value of `add` is added to x_i in all studies, but only when there is at least one study with zero events. Setting `to="none"` or `add=0` has the same effect: No adjustment to the observed number of events is made. Depending on the outcome measure and the data, this may lead to division by zero inside of the function (when this occurs, the resulting value is recoded to NA).

Measures for Quantitative Variables:

The goal of a meta-analysis may also be to characterize individual groups, where the response, characteristic, or dependent variable assessed in the individual studies is measured on some quantitative scale. In the simplest case, the raw mean for the quantitative variable is reported for each group, which then becomes the observed outcome for the meta-analysis. Here, one needs to specify m_i , sdi , and n_i for the observed means, the observed standard deviations, and the sample sizes, respectively. For ratio scale measurements, the log transformed mean or the log transformed coefficient of variation (with bias correction) may also be of interest (Nakagawa et al., 2015). If focus is solely on the variability of the measurements, then the log transformed standard deviation (with bias correction) is a useful measure (Nakagawa et al., 2015; Raudenbush & Bryk, 1987). Here, one only needs to specify sdi and n_i .

The options for the measure argument are:

- "MN" for the *raw mean*.
- "MNLN" for the *log transformed mean*.
- "CVLN" for the *log transformed coefficient of variation*.
- "SDLN" for the *log transformed standard deviation*.

Note that sdi is used to specify the standard deviations of the observed values of the response, characteristic, or dependent variable and not the standard errors of the means. Also, the sampling variance for `measure="CVLN"` is computed as given by equation 27 in Nakagawa et al. (2015), but without the $'-2\rho \dots'$ term, since for normally distributed data (which we assume here) the mean and variance (and transformations thereof) are independent.

Outcome Measures for Change or Matched Pairs:

A more complicated situation arises when the purpose of the meta-analysis is to assess the amount of change within individual groups (e.g., before and after a treatment or under two different treatments) or when dealing with matched pairs designs.

Measures for Dichotomous Variables:

For dichotomous variables, the data for a study of this type gives rise to a paired 2×2 table, which is of the form:

	trt 2 outcome 1	trt 2 outcome 2
trt 1 outcome 1	ai	bi
trt 1 outcome 2	ci	di

where a_i , b_i , c_i , and d_i denote the cell frequencies. Note that ‘trt1’ and ‘trt2’ may be applied to a single group of subjects or to matched pairs of subjects. The data from such a study can be rearranged into a marginal table of the form:

	outcome 1	outcome 2
trt 1	a_i+b_i	c_i+d_i
trt 2	a_i+c_i	b_i+d_i

which is of the same form as a 2×2 table that would arise in a study comparing/contrasting two independent groups.

The options for the measure argument that will compute outcome measures based on the marginal table are:

- "MPRR" for the matched pairs *marginal log risk ratio*.
- "MPOR" for the matched pairs *marginal log odds ratio*.
- "MPRD" for the matched pairs *marginal risk difference*.

See Becker and Balagtas (1993), Curtin et al. (2002), Elbourne et al. (2002), Fagerland et al. (2014), May and Johnson (1997), Newcombe (1998), Stedman et al. (2011), and Zou (2007) for discussions of these measures.

The options for the measure argument that will compute outcome measures based on the paired table are:

- "MPORC" for the *conditional log odds ratio*.
- "MPPETO" for the *conditional log odds ratio* estimated with Peto’s method.

See Curtin et al. (2002) and Zou (2007) for discussions of these measures.

Measures for Quantitative Variables:

When the response or dependent variable assessed in the individual studies is measured on some quantitative scale, the raw mean change, standardized versions thereof, or the (log transformed) ratio of means (log response ratio) can be used as outcome measures (Becker, 1988; Gibbons et al., 1993; Lajeunesse, 2011; Morris, 2000). Here, one needs to specify $m1_i$ and $m2_i$, the observed means at the two measurement occasions, $sd1_i$ and $sd2_i$ for the corresponding observed standard deviations, r_i for the correlation between the scores observed at the two measurement occasions, and n_i for the sample size. The options for the measure argument are then:

- "MC" for the *raw mean change*.
- "SMCC" for the *standardized mean change* using change score standardization.
- "SMCR" for the *standardized mean change* using raw score standardization.
- "SMCRH" for the *standardized mean change* using raw score standardization with heteroscedastic population variances at the two measurement occasions (Bonett, 2008).
- "ROMC" for the *log transformed ratio of means* (Lajeunesse, 2011).

See also Morris and DeShon (2002) for a thorough discussion of the difference between the change score measures.

A few notes about the change score measures. In practice, one often has a mix of information available from the individual studies to compute these measures. In particular, if $m1_i$ and $m2_i$ are unknown, but the raw mean change is directly reported in a particular study, then you can

set $m1i$ to that value and $m2i$ to 0 (making sure that the raw mean change was computed as $m1i - m2i$ within that study and not the other way around). Also, for the raw mean change ("MC") or the standardized mean change using change score standardization ("SMCC"), if $sd1i$, $sd2i$, and ri are unknown, but the standard deviation of the change scores is directly reported, then you can set $sd1i$ to that value and both $sd2i$ and ri to 0. Finally, for the standardized mean change using raw score standardization ("SMCR"), argument $sd2i$ is actually not needed, as the standardization is only based on $sd1i$ (Becker, 1988; Morris, 2000), which is usually the pre-test standard deviation (if the post-test standard deviation should be used, then set $sd1i$ to that). Note all of these measures are also applicable for matched-pairs designs (subscripts 1 and 2 then simply denote the first and second group that are formed by the matching).

Finally, interest may also be focused on differences in the variability of the measurements at the two measurement occasions (or between the two matched groups). Here, the (log transformed) ratio of the coefficient of variation (also called the coefficient of variation ratio) can be a useful measure (Nakagawa et al., 2015). If focus is solely on the variability of the measurements, then the (log transformed) ratio of the standard deviations (also called the variability ratio) can be used (Nakagawa et al., 2015). For the latter, one only needs to specify $sd1i$, $sd2i$, ni , and ri . The options for the measure argument are:

- "CVRC" for the *log transformed coefficient of variation ratio*.
- "VRC" for the *log transformed variability ratio*.

The definitions of these measures are the same as given in Nakagawa et al. (2015) but are here computed for two sets of dependent measurements. Hence, the computation of the sampling variances are adjusted to take the correlation between the measurements into consideration.

Other Outcome Measures for Meta-Analyses:

Other outcome measures are sometimes used for meta-analyses that do not directly fall into the categories above. These are described in this section.

Cronbach's alpha and Transformations Thereof:

Meta-analytic methods can also be used to aggregate Cronbach's alpha values. This is usually referred to as a 'reliability generalization meta-analysis' (Vacha-Haase, 1998). Here, one needs to specify ai , mi , and ni for the observed alpha values, the number of items/replications/parts of the measurement instrument, and the sample sizes, respectively. One can either directly analyze the raw Cronbach's alpha values or transformations thereof (Bonett, 2002, 2010; Hakstian & Whalen, 1976). The options for the measure argument are then:

- "ARAW" for *raw alpha* values.
- "AHW" for *transformed alpha values* (Hakstian & Whalen, 1976).
- "ABT" for *transformed alpha values* (Bonett, 2002).

Note that the transformations implemented here are slightly different from the ones described by Hakstian and Whalen (1976) and Bonett (2002). In particular, for "AHW", the transformation $1 - (1 - \alpha)^{1/3}$ is used, while for "ABT", the transformation $-\ln(1 - \alpha)$ is used. This ensures that the transformed values are monotonically increasing functions of α .

A dataset corresponding to data of this type is provided in [dat.bonett2010](#).

Partial and Semi-Partial Correlations:

Aloe and Becker (2012), Aloe and Thompson (2013), and Aloe (2014) describe the use of partial and semi-partial correlation coefficients as a method for meta-analyzing the results from regression models (when the focus is on a common regression coefficient of interest across studies). To compute these measures, one needs to specify ti for the test statistics (i.e., t-tests) of the regression coefficient of interest, ni for the sample sizes of the studies, mi for the number

of predictors in the regression models, and r^2_i for the R^2 value of the regression models (the latter is only needed when `measure="SPCOR"`). The options for the `measure` argument are then:

- "PCOR" for the *partial correlation coefficient*.
- "ZPCOR" for *Fisher's r-to-z transformed partial correlation coefficient*.
- "SPCOR" for the *semi-partial correlation coefficient*.

Note that the sign of the (semi-)partial correlation coefficients is determined based on the signs of the values specified via the `ti` argument. Also, Fisher's variance stabilizing transformation can only be applied to partial correlation coefficient, not semi-partial coefficients.

Converting a Data Frame to an 'escalc' Object:

The function can also be used to convert a regular data frame to an 'escalc' object. One simply sets the `measure` argument to one of the options described above (or to `measure="GEN"` for a generic outcome measure not further specified) and passes the observed effect sizes or outcomes via the `yi` argument and the corresponding sampling variances via the `vi` argument (or the standard errors via the `sei` argument).

Value

An object of class `c("escalc", "data.frame")`. The object is a data frame containing the following components:

<code>yi</code>	observed outcomes or effect size estimates.
<code>vi</code>	corresponding (estimated) sampling variances.

If `append=TRUE` and a data frame was specified via the `data` argument, then `yi` and `vi` are appended to this data frame. Note that the `var.names` argument actually specifies the names of these two variables.

If the data frame already contains two variables with names as specified by the `var.names` argument, the values for these two variables will be overwritten when `replace=TRUE` (which is the default). By setting `replace=FALSE`, only values that are NA will be replaced.

The `subset` argument can be used to select the studies that will be included in the data frame returned by the function. On the other hand, the `include` argument simply selects for which studies the measure will be computed (if it shouldn't be computed for all of them).

The object is formatted and printed with the `print.escalc` function. The `summary.escalc` function can be used to obtain confidence intervals for the individual outcomes.

Note

The variable names specified under `var.names` should be syntactically valid variable names. If necessary, they are adjusted so that they are.

Although the default value for `add` is $1/2$, for certain measures the use of such a bias correction makes little sense and for these measures, the function internally sets `add = 0`. This applies to the following measures: "AS", "PHI", "RTET", "IRSD", "PAS", "PFT", "IRS", and "IRFT". One can still force the use of the bias correction by explicitly setting the `add` argument to some non-zero value.

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See Also

[print.escalc](#), [summary.escalc](#), [rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
dat

### suppose that for a particular study, yi and vi are known (i.e., have
### already been calculated) but the 2x2 table counts are not known; with
### replace=FALSE, the yi and vi values for that study are not replaced
dat[1:12,10:11] <- NA
dat[13,4:7] <- NA
dat
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat, replace=FALSE)
dat

### illustrate difference between 'subset' and 'include' arguments
escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg, subset=1:6)
escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg, include=1:6)

### convert a regular data frame to an 'escalc' object
```

```
### dataset from Lipsey & Wilson (2001), Table 7.1, page 130
dat <- data.frame(id = c(100, 308, 1596, 2479, 9021, 9028, 161, 172, 537, 7049),
  yi = c(-0.33, 0.32, 0.39, 0.31, 0.17, 0.64, -0.33, 0.15, -0.02, 0.00),
  vi = c(0.084, 0.035, 0.017, 0.034, 0.072, 0.117, 0.102, 0.093, 0.012, 0.067),
  random = c(0, 0, 0, 0, 0, 0, 1, 1, 1, 1),
  intensity = c(7, 3, 7, 5, 7, 7, 4, 4, 5, 6))
dat <- escalc(measure="SMD", yi=yi, vi=vi, data=dat, slab=paste("Study ID:", id), digits=3)
dat
```

Description

Functions to extract the log-likelihood, deviance, AIC, BIC, and AICc values from objects of class "rma".

Usage

```
fitstats(object, ...)

## S3 method for class 'rma'
fitstats(object, ..., REML)

## S3 method for class 'rma'
logLik(object, REML, ...)
## S3 method for class 'rma'
deviance(object, REML, ...)

## S3 method for class 'rma'
AIC(object, ..., k=2, correct=FALSE)
## S3 method for class 'rma'
BIC(object, ...)
```

Arguments

object	an object of class "rma".
...	optionally more fitted model objects.
REML	logical indicating whether the regular or restricted likelihood function should be used to obtain the fit statistics and information criteria. Defaults to the method of estimation used, that is TRUE if object was fitted with method="REML" and FALSE otherwise.
k	numeric value specifying the penalty per parameter to use. The default (k=2) is the classical AIC. See AIC for more details.
correct	logical indicating whether the regular (default) or corrected (i.e., AICc) should be extracted.

Value

For `fitstats`, a data frame with the (restricted) log-likelihood, deviance, AIC, BIC, and AICc values for each model passed to the function.

For `logLik`, an object of class "logLik", providing the (restricted) log-likelihood of the model evaluated at the estimated coefficient(s).

For deviance, a numeric value with the corresponding deviance.

For AIC and BIC, either a numeric value with the corresponding AIC, AICc, or BIC or a data frame with rows corresponding to the models and columns representing the number of parameters in the model (`df`) and the AIC, AICc, or BIC.

Note

Variance components in the model (e.g., τ^2 in random/mixed-effects models) are counted as additional parameters in the calculation of the AIC, BIC, and AICc. Also, the fixed effects are counted as parameters in the calculation of the AIC, BIC, and AICc even when using REML estimation.

Author(s)

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References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#), [anova.rma](#)

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res1 <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
           data=dat.bcg, method="ML")

### mixed-effects model with two moderators (latitude and publication year)
res2 <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, mods = ~ ablat + year,
           data=dat.bcg, method="ML")

fitstats(res1, res2)

logLik(res1)
logLik(res2)

deviance(res1)
deviance(res2)

AIC(res1, res2)
AIC(res1, res2, correct=TRUE)
BIC(res1, res2)
```

`fitted.rma`*Fitted Values for 'rma' Objects*

Description

The function computes the fitted values for objects of class "rma".

Usage

```
## S3 method for class 'rma'  
fitted(object, ...)
```

Arguments

<code>object</code>	an object of class "rma".
<code>...</code>	other arguments.

Value

A vector with the fitted values.

Note

The `predict.rma` function also provides standard errors and confidence intervals for the fitted values. Best linear unbiased predictions (BLUPs) that combine the fitted values based on the fixed effects and the estimated contributions of the random effects can be obtained with `blup.rma.uni` (only for objects of class "rma.uni").

For objects not involving moderators, the fitted values are all identical to the estimated value of the model intercept.

Author(s)

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References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[predict.rma](#), [blup.rma.uni](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects model
### with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)
fitted(res)
```

forest

*Forest Plots***Description**

The function `forest` is generic. It can be used to create forest plots.

Usage

```
forest(x, ...)
```

Arguments

`x` either an object of class "rma", a vector with the observed effect size or outcomes, or an object of class "cumul.rma". See 'Details'.

`...` other arguments.

Details

Currently, methods exist for three types of situations.

In the first case, object `x` is a fitted model object coming from the `rma.uni`, `rma.mh`, or `rma.peto` functions. The corresponding method is then `forest.rma`.

Alternatively, object `x` can be a vector with observed effect size or outcomes. The corresponding method is then `forest.default`.

Finally, object `x` could be an object coming from the `cumul.rma.uni`, `cumul.rma.mh`, or `cumul.rma.peto` functions. The corresponding method is then `forest.cumul.rma`.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Lewis, S., & Clarke, M. (2001). Forest plots: Trying to see the wood and the trees. *British Medical Journal*, **322**, 1479–1480.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest.rma](#), [forest.default](#), [forest.cumul.rma](#)

 forest.cumul.rma *Forest Plots (Method for 'cumul.rma' Objects)*

Description

Function to create forest plots for objects of class "cumul.rma".

Usage

```
## S3 method for class 'cumul.rma'
forest(x, annotate=TRUE, header=FALSE,
       xlim, alim, clim, ylim, top=3, at, steps=5,
       level=x$level, refline=0, digits=2L, width,
       xlab, ilab, ilab.xpos, ilab.pos,
       transf, atransf, targ, rows,
       efac=1, pch=15, psize=1, col, lty, fonts,
       cex, cex.lab, cex.axis, annosym, ...)
```

Arguments

x	an object of class "cumul.rma".
annotate	logical specifying whether annotations should be added to the plot (the default is TRUE).
header	logical specifying whether column headings should be added to the plot (the default is FALSE). Can also be a character vector to specify the left and right headings.
xlim	horizontal limits of the plot region. If unspecified, the function tries to set the horizontal plot limits to some sensible values.
alim	the actual x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
clim	limits for the confidence intervals. If unspecified, no limits are used.
ylim	the y limits of the plot. If unspecified, the function tries to set the y-axis limits to some sensible values.
top	the amount of space to leave empty at the top of the plot (e.g., for adding headers) (the default is 3 rows).
at	position of the x-axis tick marks and corresponding labels. If unspecified, the function tries to set the tick mark positions/labels to some sensible values.
steps	the number of tick marks for the x-axis (the default is 5). Ignored when the user specifies the positions via the at argument.
level	numerical value between 0 and 100 specifying the confidence interval level (the default is to take the value from the object).
refline	value at which a vertical 'reference' line should be drawn (the default is 0). The line can be suppressed by setting this argument to NA.

digits	integer specifying the number of decimal places to which the tick mark labels of the x-axis and the annotations should be rounded (the default is 2L). Can also be a vector of two integers, the first specifying the number of decimal places for the annotations, the second for the x-axis labels. When specifying an integer (e.g., 2L), trailing zeros after the decimal mark are dropped for the x-axis labels. When specifying a numerical value (e.g., 2), trailing zeros are retained.
width	optional integer to manually adjust the width of the columns for the annotations.
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
ilab	optional vector, matrix, or data frame providing additional information about the studies that should be added to the plot.
ilab.xpos	vector of numerical value(s) specifying the x-axis position(s) of the variable(s) given via ilab (must be specified if ilab is specified).
ilab.pos	integer(s) (either 1, 2, 3, or 4) specifying the alignment of the vector(s) given via ilab (2 means right, 4 mean left aligned). If unspecified, the default is to center the labels.
transf	optional argument specifying the name of a function that should be used to transform the observed effect sizes, summary estimates, fitted values, and confidence interval bounds (e.g., transf=exp; see also transf). If unspecified, no transformation is used.
atransf	optional argument specifying the name of a function that should be used to transform the x-axis labels and annotations (e.g., atransf=exp; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified via transf or atransf.
rows	optional vector specifying the rows (or more generally, the horizontal positions) for plotting the outcomes. If unspecified, the function sets this value automatically. Can also be a single value specifying the row (horizontal position) of the first outcome (the remaining outcomes are then plotted below this starting row).
efac	vertical expansion factor for confidence interval limits and arrows. The default value of 1 should usually work okay. Can also be a vector of two numbers, the first for CI limits, the second for arrows.
pch	plotting symbol to use for the observed effect sizes or outcomes. By default, a filled square is used. See points for other options. Can also be a vector of values.
psize	optional vector with point sizes for the observed effect sizes or outcomes. Default is 1.
col	optional character string specifying the name of a color to use for plotting ("black" is used by default if not specified). Can also be a vector of color names.
lty	optional character string specifying the line type for the confidence intervals (if unspecified, the function sets this to "solid" by default).
fonts	optional character string specifying the font to use for the study labels, annotations, and the extra information (if specified via ilab). If unspecified, the default font is used.

cex	optional character and symbol expansion factor. If unspecified, the function tries to set this to a sensible value.
cex.lab	optional expansion factor for the x-axis title. If unspecified, the function tries to set this to a sensible value.
cex.axis	optional expansion factor for the x-axis labels. If unspecified, the function tries to set this to a sensible value.
annosym	optional vector of length 3 to change the left bracket, separation, and right bracket symbols for the annotations.
...	other arguments.

Details

The plot shows the estimated (average) outcome with corresponding confidence interval as one study at a time is added to the analysis.

Note

The function tries to set some sensible values for the optional arguments, but it may be necessary to tweak these in certain circumstances.

The function actually returns some information about the chosen defaults invisibly. Printing this information is useful as a starting point to make adjustments to the plot.

If the number of studies is quite large, the labels, annotations, and symbols may become quite small and impossible to read. Stretching the plot window vertically may then provide a more readable figure (one should call the function again after adjusting the window size, so that the label/symbol sizes can be properly adjusted). Also, the `cex`, `cex.lab`, and `cex.axis` arguments are then useful to adjust the symbol and text sizes.

If the horizontal plot and/or x-axis limits are set by the user, then the horizontal plot limits (`xlim`) must be at least as wide as the x-axis limits (`alim`). This restriction is enforced inside the function.

If the outcome measure used for creating the plot is bounded (e.g., correlations are bounded between -1 and 1, proportions are bounded between 0 and 1), one can use the `clim` argument to enforce those limits (confidence intervals cannot exceed those bounds then).

The `lty` argument can also be a vector of two elements, the first for specifying the line type of the individual CIs ("solid" by default), the second for the line type of the horizontal line that is automatically added to the plot ("solid" by default; set to "blank" to remove it).

Author(s)

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Lewis, S., & Clarke, M. (2001). Forest plots: Trying to see the wood and the trees. *British Medical Journal*, **322**, 1479–1480.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest, cumul](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model
res <- rma(yi, vi, data=dat, slab=paste(author, year, sep=" "))

x <- cumul(res, order=order(dat$year))
forest(x, cex=.8)
forest(x, alim=c(-2,1), cex=.8)

### meta-analysis of the (log) risk ratios using the Mantel-Haenszel method
res <- rma.mh(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
             slab=paste(author, year, sep=" "))
x <- cumul(res, order=order(dat$year))
forest(x, alim=c(-2,1), cex=.8)
```

forest.default

Forest Plots (Default Method)

Description

Function to create forest plots for a given set of data.

Usage

```
## Default S3 method:
forest(x, vi, sei, ci.lb, ci.ub,
       annotate=TRUE, showweights=FALSE, header=FALSE,
       xlim, alim, clim, ylim, top=3, at, steps=5,
       level=95, refline=0, digits=2L, width,
       xlab, slab, ilab, ilab.xpos, ilab.pos,
       subset, transf, atranf, targs, rows,
       efac=1, pch=15, psize, col, lty, fonts,
       cex, cex.lab, cex.axis, annosym, ...)
```

Arguments

<code>x</code>	vector of length k with the observed effect sizes or outcomes.
<code>vi</code>	vector of length k with the corresponding sampling variances.
<code>sei</code>	vector of length k with the corresponding standard errors (note: only one of the two, <code>vi</code> or <code>sei</code> , needs to be specified).
<code>ci.lb</code>	vector of length k with the corresponding lower confidence interval bounds. Not needed if <code>vi</code> or <code>sei</code> is specified. See ‘Details’.
<code>ci.ub</code>	vector of length k with the corresponding upper confidence interval bounds. Not needed if <code>vi</code> or <code>sei</code> is specified. See ‘Details’.
<code>annotate</code>	logical specifying whether annotations should be added to the plot (the default is TRUE).
<code>showweights</code>	logical specifying whether the annotations should also include inverse variance weights (the default is FALSE).
<code>header</code>	logical specifying whether column headings should be added to the plot (the default is FALSE). Can also be a character vector to specify the left and right headings.
<code>xlim</code>	horizontal limits of the plot region. If unspecified, the function tries to set the horizontal plot limits to some sensible values.
<code>alim</code>	the actual x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
<code>clim</code>	limits for the confidence intervals. If unspecified, no limits are used.
<code>ylim</code>	the y limits of the plot. If unspecified, the function tries to set the y-axis limits to some sensible values.
<code>top</code>	the amount of space to leave empty at the top of the plot (e.g., for adding headers) (the default is 3 rows).
<code>at</code>	position of the x-axis tick marks and corresponding labels. If unspecified, the function tries to set the tick mark positions/labels to some sensible values.
<code>steps</code>	the number of tick marks for the x-axis (the default is 5). Ignored when the user specifies the positions via the <code>at</code> argument.
<code>level</code>	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
<code>refline</code>	value at which a vertical ‘reference’ line should be drawn (the default is 0). The line can be suppressed by setting this argument to NA.
<code>digits</code>	integer specifying the number of decimal places to which the tick mark labels of the x-axis and the annotations should be rounded (the default is 2L). Can also be a vector of two integers, the first specifying the number of decimal places for the annotations, the second for the x-axis labels. When specifying an integer (e.g., 2L), trailing zeros after the decimal mark are dropped for the x-axis labels. When specifying a numerical value (e.g., 2), trailing zeros are retained.
<code>width</code>	optional integer to manually adjust the width of the columns for the annotations.
<code>xlab</code>	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.

slab	optional vector with labels for the k studies. If unspecified, simple labels are created within the function. To suppress labels, set this argument to NA.
ilab	optional vector, matrix, or data frame providing additional information about the studies that should be added to the plot.
ilab.xpos	vector of numerical value(s) specifying the x-axis position(s) of the variable(s) given via <code>ilab</code> (must be specified if <code>ilab</code> is specified).
ilab.pos	integer(s) (either 1, 2, 3, or 4) specifying the alignment of the vector(s) given via <code>ilab</code> (2 means right, 4 mean left aligned). If unspecified, the default is to center the labels.
subset	optional (logical or numeric) vector indicating the subset of studies that should be included in the plot. Note that this argument can also be used for reordering the studies.
transf	optional argument specifying the name of a function that should be used to transform the observed effect sizes or outcomes and corresponding confidence interval bounds (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.
atransf	optional argument specifying the name of a function that should be used to transform the x-axis labels and annotations (e.g., <code>atransf=exp</code> ; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified via <code>transf</code> or <code>atransf</code> .
rows	optional vector specifying the rows (or more generally, the horizontal positions) for plotting the outcomes. If unspecified, the function sets this value automatically. Can also be a single value specifying the row (horizontal position) of the first outcome (the remaining outcomes are then plotted below this starting row).
efac	vertical expansion factor for confidence interval limits and arrows. The default value of 1 should usually work okay. Can also be a vector of two numbers, the first for CI limits, the second for arrows.
pch	plotting symbol to use for the observed effect sizes or outcomes. By default, a filled square is used. See points for other options. Can also be a vector of values.
psize	optional vector with point sizes for the observed effect sizes or outcomes. If unspecified, the point sizes are an inverse function of the precision of the estimates.
col	optional character string specifying the name of a color to use for plotting ("black" is used by default if not specified). Can also be a vector of color names.
lty	optional character string specifying the line type for the confidence intervals (if unspecified, the function sets this to "solid" by default).
fonts	optional character string specifying the font to use for the study labels, annotations, and the extra information (if specified via <code>ilab</code>). If unspecified, the default font is used.
cex	optional character and symbol expansion factor. If unspecified, the function tries to set this to a sensible value.
cex.lab	optional expansion factor for the x-axis title. If unspecified, the function tries to set this to a sensible value.

<code>cex.axis</code>	optional expansion factor for the x-axis labels. If unspecified, the function tries to set this to a sensible value.
<code>annosym</code>	optional vector of length 3 to change the left bracket, separation, and right bracket symbols for the annotations.
<code>...</code>	other arguments.

Details

The plot shows the individual observed effect sizes or outcomes with corresponding confidence intervals. To use the function, one should specify the observed effect sizes or outcomes (via the `x` argument) together with the corresponding sampling variances (via the `vi` argument) or with the corresponding standard errors (via the `sei` argument). Alternatively, one can specify the observed effect sizes or outcomes together with the corresponding confidence interval bounds (via the `ci.lb` and `ci.ub` arguments).

With the `transf` argument, the observed effect sizes or outcomes and corresponding confidence interval bounds can be transformed with some suitable function. For example, when plotting log odds ratios, then one could use `transf=exp` to obtain a forest plot showing the odds ratios. Alternatively, one can use the `atransf` argument to transform the x-axis labels and annotations (e.g., `atransf=exp`). See also [transf](#) for some transformation functions useful for meta-analyses. The examples below illustrate the use of these arguments.

By default, the studies are ordered from top to bottom (i.e., the first study in the dataset will be placed in row k , the second study in row $k - 1$, and so on, until the last study, which is placed in the first row). The studies can be reordered with the `subset` argument (by specifying a vector with indices with the desired order).

Summary estimates can also be added to the plot with the [addpoly](#) function. See the documentation for that function for examples.

Note

The function tries to set some sensible values for the optional arguments, but it may be necessary to tweak these in certain circumstances.

The function actually returns some information about the chosen defaults invisibly. Printing this information is useful as a starting point to make adjustments to the plot.

If the number of studies is quite large, the labels, annotations, and symbols may become quite small and impossible to read. Stretching the plot window vertically may then provide a more readable figure (one should call the function again after adjusting the window size, so that the label/symbol sizes can be properly adjusted). Also, the `cex`, `cex.lab`, and `cex.axis` arguments are then useful to adjust the symbol and text sizes.

If the horizontal plot and/or x-axis limits are set by the user, then the horizontal plot limits (`xlim`) must be at least as wide as the x-axis limits (`alim`). This restriction is enforced inside the function.

If the outcome measure used for creating the plot is bounded (e.g., correlations are bounded between -1 and 1 , proportions are bounded between 0 and 1), one can use the `clim` argument to enforce those limits (confidence intervals cannot exceed those bounds then).

The `lty` argument can also be a vector of two elements, the first for specifying the line type of the individual CIs ("solid" by default), the second for the line type of the horizontal line that is automatically added to the plot ("solid" by default; set to "blank" to remove it).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Lewis, S., & Clarke, M. (2001). Forest plots: Trying to see the wood and the trees. *British Medical Journal*, **322**, 1479–1480.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest](#), [forest.rma](#), [addpoly](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### default forest plot of the observed log risk ratios
forest(dat$yi, dat$vi)

### forest plot of the observed risk ratios
forest(dat$yi, dat$vi, slab=paste(dat$author, dat$year, sep=", "), transf=exp,
       alim=c(0,2), steps=5, xlim=c(-2.5,4), refline=1, cex=.9)

### forest plot of the observed risk ratios
forest(dat$yi, dat$vi, slab=paste(dat$author, dat$year, sep=", "), atranf=exp,
       at=log(c(.05,.25,1,4,20)), xlim=c(-10,8), cex=.9)

### forest plot of the observed risk ratios with studies ordered by the RRs
forest(dat$yi, dat$vi, slab=paste(dat$author, dat$year, sep=", "), atranf=exp,
       at=log(c(.05,.25,1,4,20)), xlim=c(-10,8), cex=.9, subset=order(dat$yi))

### see also examples for the forest.rma function
```

forest.rma

Forest Plots (Method for 'rma' Objects)

Description

Function to create forest plots for objects of class "rma".

Usage

```
## S3 method for class 'rma'
forest(x, annotate=TRUE, addfit=TRUE, addcred=FALSE,
       showweights=FALSE, header=FALSE,
       xlim, alim, clim, ylim, top=3, at, steps=5,
       level=x$level, reflate=0, digits=2L, width,
       xlab, slab, mlab, ilab, ilab.xpos, ilab.pos,
       order, transf, atranf, targs, rows,
       efac=1, pch=15, psize, col, border, lty, fonts,
       cex, cex.lab, cex.axis, annosym, ...)
```

Arguments

x	an object of class "rma".
annotate	logical specifying whether annotations should be added to the plot (the default is TRUE).
addfit	logical specifying whether the summary estimate (for models without moderators) or fitted values (for models with moderators) should be added to the plot (the default is TRUE). See 'Details'.
addcred	logical specifying whether the bounds of the credibility/prediction interval should be added to the plot (the default is FALSE). See 'Details'.
showweights	logical specifying whether the annotations should also include the weights given to the observed effects or outcomes during the model fitting (the default is FALSE).
header	logical specifying whether column headings should be added to the plot (the default is FALSE). Can also be a character vector to specify the left and right headings.
xlim	horizontal limits of the plot region. If unspecified, the function tries to set the horizontal plot limits to some sensible values.
alim	the actual x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
clim	limits for the confidence/credibility/prediction intervals. If unspecified, no limits are used.
ylim	the y limits of the plot. If unspecified, the function tries to set the y-axis limits to some sensible values.
top	the amount of space to leave empty at the top of the plot (e.g., for adding headers) (the default is 3 rows).
at	position of the x-axis tick marks and corresponding labels. If unspecified, the function tries to set the tick mark positions/labels to some sensible values.
steps	the number of tick marks for the x-axis (the default is 5). Ignored when the user specifies the positions via the at argument.
level	numerical value between 0 and 100 specifying the confidence interval level (the default is to take the value from the object).

refline	value at which a vertical ‘reference’ line should be drawn (the default is 0). The line can be suppressed by setting this argument to NA.
digits	integer specifying the number of decimal places to which the tick mark labels of the x-axis and the annotations should be rounded (the default is 2L). Can also be a vector of two integers, the first specifying the number of decimal places for the annotations, the second for the x-axis labels. When specifying an integer (e.g., 2L), trailing zeros after the decimal mark are dropped for the x-axis labels. When specifying a numerical value (e.g., 2), trailing zeros are retained.
width	optional integer to manually adjust the width of the columns for the annotations.
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
slab	optional vector with labels for the k studies. If unspecified, the labels are either taken from the object (if study labels were specified) or simple labels are created within the function. To suppress labels, set this argument to NA.
mlab	optional character string giving a label to the summary estimate from a fixed- or random-effects model. If unspecified, the label is created within the function.
ilab	optional vector, matrix, or data frame providing additional information about the studies that should be added to the plot.
ilab.xpos	vector of numerical value(s) specifying the x-axis position(s) of the variable(s) given via <code>ilab</code> (must be specified if <code>ilab</code> is specified).
ilab.pos	integer(s) (either 1, 2, 3, or 4) specifying the alignment of the vector(s) given via <code>ilab</code> (2 means right, 4 mean left aligned). If unspecified, the default is to center the labels.
order	optional character string specifying how the studies should be ordered. See ‘Details’.
transf	optional argument specifying the name of a function that should be used to transform the observed effect sizes, summary estimates, fitted values, and confidence interval bounds (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.
atransf	optional argument specifying the name of a function that should be used to transform the x-axis labels and annotations (e.g., <code>atransf=exp</code> ; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified via <code>transf</code> or <code>atransf</code> .
rows	optional vector specifying the rows (or more generally, the horizontal positions) for plotting the outcomes. If unspecified, the function sets this value automatically. Can also be a single value specifying the row (horizontal position) of the first outcome (the remaining outcomes are then plotted below this starting row).
efac	vertical expansion factor for confidence interval limits, arrows, and the symbol used to denote summary estimates. The default value of 1 should usually work okay. Can also be a vector of two numbers, the first for CI limits and arrows, the second for summary estimates. Can also be a vector of three numbers, the first for CI limits, the second for arrows, the third for summary estimates.
pch	plotting symbol to use for the observed effect sizes or outcomes. By default, a filled square is used. See points for other options. Can also be a vector of values.

<code>psize</code>	optional vector with point sizes for the observed effect sizes or outcomes. If unspecified, the point sizes are an inverse function of the model weights.
<code>cex</code>	optional character and symbol expansion factor. If unspecified, the function tries to set this to a sensible value.
<code>cex.lab</code>	optional expansion factor for the x-axis title. If unspecified, the function tries to set this to a sensible value.
<code>cex.axis</code>	optional expansion factor for the x-axis labels. If unspecified, the function tries to set this to a sensible value.
<code>col</code>	optional character string specifying the name of a color to use for the summary polygon or fitted values. If unspecified, the function sets a default color.
<code>border</code>	optional character string specifying the name of a color to use for the border of the summary polygon or fitted values. If unspecified, the function sets a default color.
<code>lty</code>	optional character string specifying the line type for the confidence intervals (if unspecified, the function sets this to "solid" by default).
<code>fonts</code>	optional character string specifying the font to use for the study labels, annotations, and the extra information (if specified via <code>ilab</code>). If unspecified, the default font is used.
<code>annosym</code>	optional vector of length 3 to change the left bracket, separation, and right bracket symbols for the annotations.
<code>...</code>	other arguments.

Details

The plot shows the individual observed effect sizes or outcomes with corresponding confidence intervals.

For fixed- and random-effects models (i.e., for models without moderators), a polygon is added to the bottom of the forest plot, showing the summary estimate based on the model (with the outer edges of the polygon indicating the confidence interval limits). The `col` and `border` arguments can be used to adjust the (border) color of the polygon.

For random-effects models and if `addcred=TRUE`, a dotted line indicates the (approximate) bounds of the credibility/credible or prediction interval (the interval indicates where `level %` of the true effects are expected to fall) (Riley et al., 2011). For random-effects models of class `"rma.mv"` (see [rma.mv](#)) with multiple τ^2 values, the `addcred` argument can be used to specify for which level of the inner factor the credibility/prediction intervals should be provided (since the credibility/prediction intervals differ depending on the τ^2 value). If the model should also contain multiple γ^2 values, the `addcred` argument should then be of length 2 to specify the levels of both inner factors.

For models involving moderators, the fitted value for each study is added as a polygon to the plot. By default, the width of the polygons corresponds to the confidence interval limits for the fitted values. By setting `addcred=TRUE`, the width reflects the credibility/prediction interval limits. Again, the `col` and `border` arguments can be used to adjust the (border) color of the polygons. These polygons can be suppressed by setting `addfit=FALSE`.

With the `transf` argument, the observed effect sizes or outcomes, summary estimate, fitted values, confidence interval bounds, and credibility/prediction interval bounds can be transformed with some suitable function. For example, when plotting log odds ratios, one could use `transf=exp` to obtain

a forest plot showing the odds ratios. Alternatively, one can use the `atransf` argument to transform the x-axis labels and annotations (e.g., `atransf=exp`). See also [transf](#) for some transformation functions useful for meta-analyses. The examples below illustrate the use of these arguments.

By default, the studies are ordered from top to bottom (i.e., the first study in the dataset will be placed in row k , the second study in row $k - 1$, and so on, until the last study, which is placed in the first row). The studies can be reordered with the `order` argument:

- `order="obs"`: the studies are ordered by the observed effect sizes,
- `order="fit"`: the studies are ordered by the fitted values,
- `order="prec"`: the studies are ordered by their sampling variances,
- `order="resid"`: the studies are ordered by the size of their residuals,
- `order="rstandard"`: the studies are ordered by the size of their standardized residuals,
- `order="abs.resid"`: the studies are ordered by the size of their absolute residuals,
- `order="abs.rstandard"`: the studies are ordered by the size of their absolute standardized residuals.

Alternatively, it is also possible to set `order` equal to a vector with indices specifying the desired order (see examples below).

Additional summary estimates can also be added to the plot with the [addpoly](#) function. See the documentation for that function for examples.

Note

The function tries to set some sensible values for the optional arguments, but it may be necessary to tweak these in certain circumstances.

The function actually returns some information about the chosen defaults invisibly. Printing this information is useful as a starting point to make adjustments to the plot (see examples below).

If the number of studies is quite large, the labels, annotations, and symbols may become quite small and impossible to read. Stretching the plot window vertically may then provide a more readable figure (one should call the function again after adjusting the window size, so that the label/symbol sizes can be properly adjusted). Also, the `cex`, `cex.lab`, and `cex.axis` arguments are then useful to adjust the symbol and text sizes.

If the horizontal plot and/or x-axis limits are set by the user, then the horizontal plot limits (`xlim`) must be at least as wide as the x-axis limits (`xlim`). This restriction is enforced inside the function.

If the outcome measure used for creating the plot is bounded (e.g., correlations are bounded between -1 and 1 , proportions are bounded between 0 and 1), one can use the `ylim` argument to enforce those limits (confidence/credibility/prediction intervals cannot exceed those bounds then).

The models without moderators, the `col` argument can also be a vector of two elements, the first for specifying the color of the summary polygon, the second for specifying the color of the line for the credibility/prediction interval.

The `lty` argument can also be a vector of up to three elements, the first for specifying the line type of the individual CIs (`"solid"` by default), the second for the line type of the credibility/prediction interval (`"dotted"` by default), the third for the line type of the horizontal lines that are automatically added to the plot (`"solid"` by default; set to `"blank"` to remove them).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Lewis, S., & Clarke, M. (2001). Forest plots: Trying to see the wood and the trees. *British Medical Journal*, **322**, 1479–1480.
- Riley, R. D., Higgins, J. P. T., & Deeks, J. J. (2011). Interpretation of random effects meta-analyses. *British Medical Journal*, **342**, d549.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest](#), [forest.default](#), [addpoly](#)

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
          slab=paste(author, year, sep=" ", ""))

### default forest plot of the log risk ratios and summary estimate
forest(res, header=TRUE)

### summary estimate in row -1; studies in rows k=13 through 1; horizontal
### lines in rows 0 and k+1; two extra lines of space at the top for headings,
### and other annotations; headings (if requested) in line k+2
op <- par(xpd=TRUE)
text(x=-8.5, y=-1:16, -1:16, pos=4, cex=.5)
par(op)

### can also inspect defaults chosen
defaults <- forest(res)
defaults

### several forest plots illustrating the use of various arguments
forest(res, cex=.8)
forest(res, cex=.8, addcred=TRUE)
forest(res, cex=.8, alim=c(-3,3))
forest(res, cex=.8, order="prec", alim=c(-3,3))
forest(res, cex=.8, order=order(dat.bcg$ablat), addcred=TRUE)

### adjust xlim values to see how that changes the plot
forest(res)
par("usr")[1:2] ### this shows what xlim values were chosen by default
forest(res, xlim=c(-16,14))
forest(res, xlim=c(-18,10))
forest(res, xlim=c(-10,10))

### illustrate transf argument
```

```

forest(res, transf=exp, at=c(0,1,2,4,6), xlim=c(-8,12), cex=.8, refline=1, header=TRUE)

### illustrate atranf argument
forest(res, atranf=exp, at=log(c(.05,.25,1,4,20)), xlim=c(-8,7), cex=.8, header=TRUE)

### showweights argument
forest(res, atranf=exp, at=log(c(.05,.25,1,4,20)), xlim=c(-8,8),
       order="prec", showweights=TRUE, cex=.8)

### forest plot with extra annotations
### note: may need to widen plotting device to avoid overlapping text
forest(res, atranf=exp, at=log(c(.05, .25, 1, 4)), xlim=c(-16,6),
       ilab=cbind(dat.bcg$tpos, dat.bcg$tneg, dat.bcg$cpos, dat.bcg$cneg),
       ilab.xpos=c(-9.5,-8,-6,-4.5), cex=.75, header="Author(s) and Year")
op <- par(cex=.75, font=2)
text(c(-9.5,-8,-6,-4.5), 15, c("TB+", "TB-", "TB+", "TB-"))
text(c(-8.75,-5.25), 16, c("Vaccinated", "Control"))
par(op)

### mixed-effects model with absolute latitude in the model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, mods = ~ ablat,
          data=dat.bcg, slab=paste(author, year, sep=", "))

### forest plot with observed and fitted values
forest(res, xlim=c(-9,5), order="fit", cex=.8, ilab=dat.bcg$ablat,
       ilab.xpos=-4, atranf=exp, at=log(c(.05,.25,1,4)),
       header="Author(s) and Year")
text(-4, 15, "Latitude", cex=.8, font=2)

### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg,
          slab=paste(author, year, sep=", "))

### for more complicated plots, the ylim and rows arguments may be useful
forest(res)
forest(res, ylim=c(-1.5, 16)) ### the default
forest(res, ylim=c(-1.5, 20)) ### extra space in plot
forest(res, ylim=c(-1.5, 20), rows=c(17:15, 12:6, 3:1)) ### set positions

### forest plot with subgrouping of studies
### note: may need to widen plotting device to avoid overlapping text
forest(res, xlim=c(-16, 6), at=log(c(.05, .25, 1, 4)), atranf=exp,
       ilab=cbind(dat.bcg$tpos, dat.bcg$tneg, dat.bcg$cpos, dat.bcg$cneg),
       ilab.xpos=c(-9.5,-8,-6,-4.5), cex=.75, ylim=c(-1, 21),
       order=order(dat.bcg$alloc), rows=c(1:2,5:11,14:17),
       header="Author(s) and Year")
op <- par(cex=.75, font=4)
text(-16, c(18,12,3), c("Systematic Allocation", "Random Allocation",
                      "Alternate Allocation"), pos=4)
par(cex=.75, font=2)
text(c(-9.5,-8,-6,-4.5), 20, c("TB+", "TB-", "TB+", "TB-"))
text(c(-8.75,-5.25), 21, c("Vaccinated", "Control"))
par(op)

```

```
### see also the addpoly.rma function for an example where summaries
### for the three subgroups are added to such a forest plot

### illustrate use of clim argument with a meta-analysis of raw correlation
### coefficients (data from Pritz, 1997); without clim=c(0,1), some of the
### CIs would have upper bounds larger than 1
dat <- escalc(measure="PR", xi=xi, ni=ni, data=dat.pritz1997)
res <- rma(yi, vi, data=dat, slab=paste0(study, " ", authors))
forest(res, xlim=c(-1,2), alim=c(0,1), psize=1, refline=coef(res), clim=c(0,1), header=TRUE)
```

 formula.rma

Model Formulae for 'rma' Objects

Description

The function extracts model formulae for objects of class "rma".

Usage

```
## S3 method for class 'rma'
formula(x, type="mods", ...)
```

Arguments

x	an object of class "rma".
type	the formula which should be returned; either "mods" (default), "yi" (in case argument yi was used to specify a formula), or "scale" (only for location-scale models).
...	other arguments.

Value

The requested formula.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mv](#)

Examples

```

### copy BCG vaccine data into 'dat'
dat <- dat.bcg

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat,
             slab=paste(author, ", ", year, sep=""))

### mixed-effects meta-regression model
res <- rma(yi, vi, mods = ~ ablat + alloc, data=dat)
formula(res, type="mods")

### specify moderators via 'yi' argument
res <- rma(yi ~ ablat + alloc, vi, data=dat)
formula(res, type="yi")

```

fsn

*Fail-Safe N Analysis (File Drawer Analysis)***Description**

Function to compute the fail-safe N (also called file drawer analysis).

Usage

```
fsn(yi, vi, sei, data, type="Rosenthal", alpha=.05, target, subset, digits)
```

Arguments

yi	vector with the observed effect sizes or outcomes. See ‘Details’
vi	vector with the corresponding sampling variances. See ‘Details’
sei	vector with the corresponding standard errors. See ‘Details’
data	optional data frame containing the variables given to the arguments above.
type	character string indicating the method to use for the calculation of the fail-safe N. Possible options are "Rosenthal", "Orwin", or "Rosenberg". See below for more details.
alpha	target alpha level to use for the Rosenthal and Rosenberg methods (.05 by default).
target	target average effect size to use for the Orwin method. If undefined, then the target average effect size will be equal to the observed average effect size divided by 2.
subset	optional (logical or numeric) vector indicating the subset of studies that should be used for the calculation.
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is 4).

Details

The function can be used in conjunction with any of the usual effect size or outcome measures used in meta-analyses (e.g., log risk ratios, log odds ratios, risk differences, mean differences, standardized mean differences, raw correlation coefficients, correlation coefficients transformed with Fisher's r-to-z transformation, and so on). Simply specify the observed outcomes via the `yi` argument and the corresponding sampling variances via the `vi` argument (instead of specifying `vi`, one can specify the standard errors via the `sei` argument). The `escalc` function can be used to compute a wide variety of effect size and outcome measures (and the corresponding sampling variances) based on summary statistics.

The Rosenthal method (sometimes called a 'file drawer analysis') calculates the number of studies averaging null results that would have to be added to the given set of observed outcomes to reduce the combined significance level (p-value) to a target alpha level (e.g., .05). The calculation is based on Stouffer's method to combine p-values and is described in Rosenthal (1979).

The Orwin method calculates the number of studies averaging null results that would have to be added to the given set of observed outcomes to reduce the (unweighted) average effect size to a target (unweighted) average effect size. The method is described in Orwin (1983).

The Rosenberg method calculates the number of studies averaging null results that would have to be added to the given set of observed outcomes to reduce significance level (p-value) of the (weighted) average effect size (based on a fixed-effects model) to a target alpha level (e.g., .05). The method is described in Rosenberg (2005).

Value

An object of class "fsn". The object is a list containing the following components:

<code>type</code>	the method used.
<code>fnum</code>	the calculated fail-safe N.
<code>alpha</code>	the target alpha level.
<code>pval</code>	the p-value of the observed results. NA for the Orwin method.
<code>meanes</code>	the average effect size of the observed results. NA for the Rosenthal method.
<code>target</code>	the target effect size. NA for the Rosenthal and Rosenberg methods.

The results are formatted and printed with the `print.fsn` function.

Note

For the Rosenberg method, the p-value is calculated based on a standard normal distribution (instead of a t-distribution, as suggested by Rosenberg, 2005).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Rosenthal, R. (1979). The "file drawer problem" and tolerance for null results. *Psychological Bulletin*, **86**, 638–641.
- Orwin, R. G. (1983). A fail-safe N for effect size in meta-analysis. *Journal of Educational Statistics*, **8**, 157–159.
- Rosenberg, M. S. (2005). The file-drawer problem revisited: A general weighted method for calculating fail-safe numbers in meta-analysis. *Evolution*, **59**, 464–468.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[ranktest](#), [regtest](#), [trimfill](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

fsn(yi, vi, data=dat)
fsn(yi, vi, data=dat, type="Orwin")
fsn(yi, vi, data=dat, type="Rosenberg")
```

funnel

Funnel Plots

Description

Function to create funnel plots.

Usage

```
funnel(x, ...)
```

```
## S3 method for class 'rma'
funnel(x, yaxis="sei",
       xlim, ylim, xlab, ylab,
       steps=5, at, atranf, targ, digits, level=x$level,
       addtau2=FALSE, type="rstandard",
       back="lightgray", shade="white", hlines="white",
       refline, pch=19, pch.fill=21, col, bg, legend=FALSE, ci.res=1000, ...)
```

```
## Default S3 method:
funnel(x, vi, sei, ni, subset, yaxis="sei",
       xlim, ylim, xlab, ylab,
       steps=5, at, atranf, targ, digits, level=95,
       back="lightgray", shade="white", hlines="white",
       refline=0, pch=19, col, bg, legend=FALSE, ci.res=1000, ...)
```

Arguments

x	an object of class "rma" or a vector with the observed effect sizes or outcomes.
vi	vector with the corresponding sampling variances.
sei	vector with the corresponding standard errors.
ni	vector with the corresponding sample sizes.
subset	optional (logical or numeric) vector indicating the subset of studies that should be included in the plot. Only relevant when passing a vector via x.
yaxis	either "sei", "vi", "seinv", "vinv", "ni", "ninv", "sqrtni", "sqrtninv", "lni", or "wi" to indicate what values should be placed on the y-axis. See 'Details'.
xlim	x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
ylim	y-axis limits. If unspecified, the function tries to set the y-axis limits to some sensible values.
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
ylab	title for the y-axis. If unspecified, the function tries to set an appropriate axis title.
steps	the number of tick marks for the y-axis (the default is 5).
at	position of the x-axis tick marks and corresponding labels. If unspecified, the function tries to set the tick mark positions/labels to some sensible values.
atransf	optional argument specifying the name of a function that should be used to transform the x-axis labels (e.g., atransf=exp; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified via atransf.
digits	integer specifying the number of decimal places to which the tick mark labels of the x- and y-axis should be rounded. Can also be a vector of two integers, the first specifying the number of decimal places for the x-axis, the second for the y-axis labels (e.g., c(2, 3)). If unspecified, the function tries to set the argument to some sensible values.
level	numerical value between 0 and 100 specifying the level of the pseudo confidence interval region (for "rma" objects, the default is to take the value from the object). May also be a vector of values to obtain multiple regions. See 'Examples'.
addtau2	logical to indicate whether the amount of heterogeneity should be accounted for when drawing the pseudo confidence interval region (the default is FALSE). Ignored when the model includes moderators and residuals are plotted. See 'Details'.
type	either "rstandard" (default) or "rstudent" indicating whether the usual or deleted residuals should be used in creating the funnel plot when the model involves moderators. See 'Details'.
back	color to use for the background of the plotting region.

shade	color to use for shading the pseudo confidence interval region. When level is a vector of values, different shading colors can be specified for each region.
hlines	color of the horizontal reference lines.
refline	value at which to draw the vertical reference line and, if drawn, where the pseudo confidence interval should be centered. If unspecified, the reference line is drawn at the fixed- or random-effects model estimate when the model does not include moderators and at zero when moderators are included (and therefore residuals are plotted) or when directly plotting observed effect sizes or outcomes.
pch	plotting symbol to use for the observed effect sizes or outcomes. By default, a solid circle is used. Can also be a vector of values. See points for other options.
pch.fill	plotting symbol to use for the effect sizes or outcomes filled in by the trim and fill method. By default, a circle is used. Only relevant when plotting an object created by the trimfill function.
col	optional character string specifying the name of a color to use for the points ("black" is used by default if not specified). Can also be a vector of color names.
bg	optional character string specifying the name of a background color for open plot symbols ("white" is used by default if not specified). Can also be a vector of color names.
legend	logical to indicate whether a legend should be added to the plot (can also be a keyword to indicate the position of the legend; see as in legend).
ci.res	integer specifying the number of y-axis values at which to calculate the bounds of the pseudo confidence interval. The default is 1000, which usually provides a sufficient resolution for the plotting.
...	other arguments.

Details

For fixed- and random-effects models (i.e., models not involving moderators), the plot shows the individual observed effect sizes or outcomes on the x-axis against the corresponding standard errors (i.e., the square root of the sampling variances) on the y-axis. A vertical line indicates the estimate based on the model. A pseudo confidence interval region is drawn around this value with bounds equal to $\pm 1.96SE$, where SE is the standard error value from the y-axis (assuming level=95). If `addtau2=TRUE` (only for models of class "rma.uni"), then the bounds of the pseudo confidence interval region are equal to $\pm 1.96\sqrt{SE^2 + \tau^2}$, where τ^2 is the amount of heterogeneity as estimated by the model.

For models involving moderators, the plot shows the residuals on the x-axis against their corresponding standard errors. Either the usual or deleted residuals can be used for that purpose (set via the type argument). See [residuals.rma](#) for more details on the different types of residuals.

With the `atransf` argument, the labels of the observed effect sizes or outcomes on the x-axis can be transformed with some suitable function. For example, when plotting log odds ratios, one could use `transf=exp` to obtain a funnel plot with the values on the x-axis corresponding to the odds ratios. See also [transf](#) for some transformation functions useful for meta-analyses.

Instead of placing the standard error value on the y-axis, several other options are available by setting the `yaxis` argument to:

- `yaxis="vi"` for the sampling variance,
- `yaxis="seinv"` for the inverse of the standard error,
- `yaxis="vinv"` for the inverse of the sampling variance,
- `yaxis="ni"` for the sample size,
- `yaxis="ninv"` for the inverse of the sample size,
- `yaxis="sqrtni"` for the square root sample size,
- `yaxis="sqrtninv"` for the inverse of the square root sample size,
- `yaxis="lni"` for the log of the sample size,
- `yaxis="wi"` for the weights.

However, only when `yaxis="sei"` (the default) will the pseudo confidence region have the expected (upside-down) funnel shape with straight lines. Also, when placing (a function of) the sample size on the y-axis or the weights, then the pseudo confidence region cannot be drawn. See Sterne and Egger (2001) for more details on the choice of the y-axis.

If the object passed to the function comes from the `trimfill` function, the effect sizes or outcomes that are filled in by the trim and fill method are also added to the funnel plot. The symbol to use for plotting the filled in values can then be specified via the `pch.fill` argument.

One can also directly pass a vector of observed effect sizes or outcomes (via `x`) and the corresponding sampling variances (via `vi`), standard errors (via `sei`), and/or sample sizes (via `ni`) to the function. By default, the vertical reference line is then drawn at zero.

The arguments `back`, `shade`, and `hlines` can be set to `NULL` to suppress the shading and the horizontal reference lines.

Value

A data frame with components:

<code>x</code>	the x coordinates of the points that were plotted.
<code>y</code>	the y coordinates of the points that were plotted.
<code>slab</code>	study labels of the points that were plotted.

Note that the data frame is returned invisibly.

Note

Placing (a function of) the sample size on the y-axis (i.e., using `yaxis="ni"`, `yaxis="ninv"`, `yaxis="sqrtni"`, `yaxis="sqrtninv"`, or `yaxis="lni"`) is only possible when information about the sample sizes is actually stored within the object passed to the funnel function. That should automatically be the case when the observed outcomes were computed with the `escalc` function or when the observed outcomes were computed within the model fitting function. On the other hand, this will not automatically be the case when `rma.uni` was used together with the `yi` and `vi` arguments and the `yi` and `vi` values were *not* computed with `escalc`. In that case, it is still possible to pass information about the sample sizes to the `rma.uni` function (i.e., use `rma.uni(yi, vi, ni)`).

When using unweighted estimation, using `yaxis="wi"` will place all points on a horizontal line. When directly passing a vector of observed effect sizes or outcomes to the function, `yaxis="wi"` is equivalent to `yaxis="vinv"`, except that the weights are expressed in percent.

When specifying vectors for `pch`, `col`, and/or `bg`, the variables specified are assumed to be of the same length as the data passed to the `funnel` function or the model fitting function (when using `funnel` on a model object). Any subsetting and removal of studies with missing values is automatically applied to the variables specified via `pch`, `col`, and `bg`.

Author(s)

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References

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Peters, J. L., Sutton, A. J., Jones, D. R., Abrams, K. R., & Rushton, L. (2008). Contour-enhanced meta-analysis funnel plots help distinguish publication bias from other causes of asymmetry. *Journal of Clinical Epidemiology*, **61**, 991–996.

Sterne, J. A. C., & Egger, M. (2001). Funnel plots for detecting bias in meta-analysis: Guidelines on choice of axis. *Journal of Clinical Epidemiology*, **54**, 1046–1055.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#), [influence.rma.uni](#), [trimfill](#)

Examples

```
### copy BCG vaccine data into 'dat'
dat <- dat.bcg

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat)

### random-effects model
res <- rma(yi, vi, data=dat)

### standard funnel plot
funnel(res)

### show risk ratio values on x-axis (log scale)
funnel(res, attransf=exp)

### passing log risk ratios and sampling variances directly to the function
### note: essentially the same plot, except that reference line is centered at zero
funnel(dat$yi, dat$vi)
funnel(res, refline=0)

### funnel plot with risk ratio values on the x-axis (log scale)
funnel(res, attransf=exp, at=log(c(.12, .25, .5, 1, 2)))
```

```

### contour-enhanced funnel plot centered at 0 (see Peters et al., 2008)
funnel(res, level=c(90, 95, 99), shade=c("white", "gray55", "gray75"), refline=0, legend=TRUE)

### same, but show risk ratio values on the x-axis
funnel(res, level=c(90, 95, 99), shade=c("white", "gray55", "gray75"),
       refline=0, legend=TRUE, attransf=exp, at=log(c(.10, .25, .5, 1, 2, 4, 10)))

### illustrate the use of vectors for 'pch' and 'col'
res <- rma(yi, vi, data=dat, subset=2:10)
funnel(res, pch=ifelse(dat$yi > -1, 19, 21), col=ifelse(sqrt(dat$vi) > .3, "red", "blue"))

### mixed-effects model with absolute latitude in the model
res <- rma(yi, vi, mods = ~ ablat, data=dat)

### funnel plot of the residuals
funnel(res)

### simulate a large meta-analytic dataset (correlations with rho = 0.2)
### with no heterogeneity or publication bias; then try out different
### versions of the funnel plot

gencor <- function(rhoi, ni) {
  x1 <- rnorm(ni, mean=0, sd=1)
  x2 <- rnorm(ni, mean=0, sd=1)
  x3 <- rhoi*x1 + sqrt(1-rhoi^2)*x2
  cor(x1, x3)
}

set.seed(1234)
k <- 200                                     ### number of studies to simulate
ni <- round(rchisq(k, df=2) * 20 + 20)      ### simulate sample sizes (skewed distribution)
ri <- mapply(gencor, rep(0.2,k), ni)       ### simulate correlations

res <- rma(measure="ZCOR", ri=ri, ni=ni, method="FE") ### use r-to-z transformed correlations

funnel(res, yaxis="sei")
funnel(res, yaxis="vi")
funnel(res, yaxis="seinv")
funnel(res, yaxis="vinv")
funnel(res, yaxis="ni")
funnel(res, yaxis="ninv")
funnel(res, yaxis="sqrtni")
funnel(res, yaxis="sqrtninv")
funnel(res, yaxis="lni")
funnel(res, yaxis="wi")

```

Description

Function to create GOSH plots for objects of class "rma".

Usage

```
gosh(x, ...)

## S3 method for class 'rma'
gosh(x, subsets, progbar=TRUE, parallel="no", ncpus=1, cl=NULL, ...)
```

Arguments

x	an object of class "rma".
subsets	optional integer to specify the number of subsets.
progbar	logical indicating whether a progress bar should be shown (the default is TRUE). Ignored when using parallel processing.
parallel	character string indicating whether parallel processing should be used (the default is "no"). For parallel processing, set to either "snow" or "multicore". See 'Details'.
ncpus	integer specifying the number of processes to use in the parallel processing.
cl	optional snow cluster to use if parallel="snow". If not supplied, a cluster on the local machine is created for the duration of the call.
...	other arguments.

Details

The model specified via `x` must be a model fitted with either the `rma.uni`, `rma.mh`, or `rma.peto` function.

Olkin et al. (2012) proposed the GOSH (graphical display of study heterogeneity) plot, which is based on examining the results of a fixed-effects model in all possible subsets of size $1, \dots, k$ of the k studies included in a meta-analysis. In a homogeneous set of studies, the model estimates obtained this way should form a roughly symmetric, contiguous, and unimodal distribution. On the other hand, when the distribution is multimodal, then this suggests the presence of heterogeneity, possibly due to outliers and/or distinct subgroupings of studies. Plotting the estimates against some measure of heterogeneity (e.g., I^2 , H^2 , or the Q -statistic) can also help to reveal subclusters, which are indicative of heterogeneity. The same type of plot can be produced by first fitting a fixed-effects model with either the `rma.uni` (using `method="FE"`), `rma.mh`, or `rma.peto` functions and then passing the fitted model object to the `gosh` function and then plotting the results.

For models fitted with the `rma.uni` function (which may involve moderators and/or may be random/mixed-effects models), the idea underlying this type of plot can be generalized by examining the distribution of all model coefficients, plotting them against each other, and against some measure of (residual) heterogeneity (including the estimate of τ^2).

Note that for models without moderators, application of the method requires fitting a total of $2^k - 1$ models, which could be an excessively large number when k is large. For example, for $k = 10$, there are only 1023 possible subsets, but for $k = 20$, this number has already grown to 1048575. For even larger k , it may become computationally infeasible to consider all possible subsets (and even storage of the results could become an issue). Instead, we can then examine (a sufficiently large number of) random subsets.

By default, if the number of possible subsets is $\leq 10^6$, the function will consider all possible subsets and otherwise 10^6 random subsets. One can use the `subsets` argument to specify a different number

of subsets to consider. If `subsets` is specified and it is actually larger than the number of possible subsets, then the function automatically only considers the possible subsets and does not use random subsets.

On machines with multiple cores, one can try to speed things up by delegating the model fitting to separate worker processes, that is, by setting `parallel="snow"` or `parallel="multicore"` and `ncpus` to some value larger than 1. Parallel processing makes use of the `parallel` package, using the `makePSOCKcluster` and `parLapply` functions when `parallel="snow"` or using `mclapply` when `parallel="multicore"` (the latter only works on Unix/Linux-alikes). With `parallel::detectCores()`, one can check on the number of available cores on the local machine. Note that no progress bar will be shown when using parallel processing.

Value

An object of class `"gosh.rma"`. The object is a list containing the following components:

<code>res</code>	a data frame with the results for each subset (various heterogeneity statistics and the model coefficient(s)).
<code>incl</code>	a matrix indicating which studies were included in which subset.
<code>...</code>	some additional elements/values.

The results can be printed with the `print.gosh.rma` function and plotted with the `plot.gosh.rma` function.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Olkin, I., Dahabreh, I. J., & Trikalinos, T. A. (2012). GOSH - a graphical display of study heterogeneity. *Research Synthesis Methods*, **3**, 214–223.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [influence.rma.uni](#),

Examples

```
### meta-analysis of all trials including ISIS-4 using a FE model
res <- rma(measure="OR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat.egger2001, method="FE")

## Not run:
### fit FE model to all possible subsets (65535 models)
sav <- gosh(res)
sav

### create GOSH plot
### red points for subsets that include and blue points
```

```
### for subsets that exclude study 16 (the ISIS-4 trial)
plot(sav, out=16, breaks=100)
## End(Not run)
```

 hc

Meta-Analysis based on the Method by Henmi and Copas (2010)

Description

The function can be used to obtain an estimate of the average true effect and corresponding confidence interval under a random-effects model using the method described by Henmi and Copas (2010).

Usage

```
hc(object, ...)

## S3 method for class 'rma.uni'
hc(object, digits, transf, targs, control, ...)
```

Arguments

object	an object of class "rma.uni".
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
transf	optional argument specifying the name of a function that should be used to transform the estimated true effect and the corresponding interval bounds (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified under <code>transf</code> .
control	list of control values for the iterative algorithm. If unspecified, default values are defined inside the function. See 'Note'.
...	other arguments.

Details

The model specified via `object` must be a model without moderators (i.e., either a fixed- or a random-effects model and not a fixed-effects with moderators or mixed-effects model).

When using the usual method for fitting a random-effects model (i.e., weighted estimation with inverse-variance weights), the weights assigned to smaller and larger studies become more uniform as the amount of heterogeneity increases. As a consequence, the estimated average effect could become increasingly biased under certain forms of publication bias (where smaller studies on one side of the funnel plot are missing). The method by Henmi and Copas (2010) tries to counteract this problem by providing an estimate of the average true effect that is based on inverse-variance weights as used under a fixed-effects model (which do not take the amount of heterogeneity into

consideration). The amount of heterogeneity is still estimated (with the DerSimonian-Laird estimator) and incorporated into the standard error of the estimated average effect and the corresponding confidence interval.

Currently, there is only a method for handling objects of class "rma.uni" with the hc function. It therefore provides a method for conducting a sensitivity analysis after the model has been fitted with the `rma.uni` function.

Value

An object of class "hc.rma.uni". The object is a list containing the following components:

beta	estimated average true effect.
se	corresponding standard error.
ci.lb	lower bound of the confidence intervals for the average true effect.
ci.ub	upper bound of the confidence intervals for the average true effect.
...	some additional elements/values.

The results are formatted and printed with the `print.hc.rma.uni` function.

Note

The method makes use of the `uniroot` function. By default, the desired accuracy is set equal to `.Machine$double.eps^0.25` and the maximum number of iterations to `1000`. The desired accuracy (`tol`) and the maximum number of iterations (`maxiter`) can be adjusted with the `control` argument (i.e., `control=list(tol=value,maxiter=value)`).

Author(s)

Original code by Henmi and Copas (2010). Corrected for typos by Michael Dewey (<lists@dewey.myzen.co.uk>). Incorporated into the package with some small adjustments for consistency with the other functions in the package by Wolfgang Viechtbauer (<wvb@metafor-project.org>).

References

Henmi, M., & Copas, J. B. (2010). Confidence intervals for random effects meta-analysis and robustness to publication bias. *Statistics in Medicine*, **29**, 2969–2983.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

`rma.uni`

Examples

```

### meta-analysis based on log odds ratios
res <- rma(measure="OR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat.lee2004)
res

### funnel plot as in Henmi and Copas (2010)
funnel(res, yaxis="seinv", refline=0, xlim=c(-3,3), ylim=c(.5,3.5), steps=7, digits=1)

### use method by Henmi and Copas (2010) as a sensitivity analysis
hc(res)

### back-transform results to odds ratio scale
hc(res, transf=exp)

```

influence.rma.mv

Outlier and Influential Case Diagnostics for 'rma.mv' Objects

Description

The functions compute various outlier and influential case diagnostics (some of which indicate the influence of deleting one case/study at a time on the model fit and the fitted/residual values) for objects of class "rma.mv".

Usage

```

## S3 method for class 'rma.mv'
cooks.distance(model, progbar=FALSE, cluster,
               reestimate=TRUE, parallel="no", ncpus=1, cl=NULL, ...)
## S3 method for class 'rma.mv'
dfbetas(model, progbar=FALSE, cluster,
         reestimate=TRUE, parallel="no", ncpus=1, cl=NULL, ...)
## S3 method for class 'rma.mv'
hatvalues(model, type="diagonal", ...)

```

Arguments

model	an object of class "rma.mv".
progbar	logical indicating whether a progress bar should be shown (the default is FALSE). Ignored when using parallel processing.
cluster	optional vector specifying a clustering variable to use for computing the Cook's distances. If not specified, Cook's distances are computed for all individual observed outcomes.
reestimate	logical indicating whether variance/correlation components should be re-estimated after deletion of the <i>i</i> th study/cluster (the default is TRUE).
parallel	character string indicating whether parallel processing should be used (the default is "no"). For parallel processing, set to either "snow" or "multicore". See 'Details'.

ncpus	integer specifying the number of processes to use in the parallel processing.
cl	optional snow cluster to use if parallel="snow". If not supplied, a cluster on the local machine is created for the duration of the call.
type	character string indicating whether to return only the diagonal of the hat matrix ("diagonal") or the entire hat matrix ("matrix").
...	other arguments.

Details

Cook's distance for the i th study/cluster can be interpreted as the Mahalanobis distance between the entire set of predicted values once with the i th study/cluster included and once with the i th study/cluster excluded from the model fitting.

The DFBETAS value(s) essentially indicate(s) how many standard deviations the estimated coefficient(s) change(s) after excluding the i th study/cluster from the model fitting.

Value

The `cooks.distance` function returns a vector. The `dfbetas` function returns a data frame. The `hatvalues` function returns either a vector with the diagonal elements of the hat matrix or the entire hat matrix.

Note

Right now, leave-one-out diagnostics are calculated by refitting the model k times (where k is the number of studies/clusters). Depending on how large k is, it may take a few moments to finish the calculations. For complex models fitted with `rma.mv`, this can become computationally expensive.

On machines with multiple cores, one can usually speed things up by delegating the model fitting to separate worker processes, that is, by setting `parallel="snow"` or `parallel="multicore"` and `ncpus` to some value larger than 1. Parallel processing makes use of the `parallel` package, using the `makePSOCKcluster` and `parLapply` functions when `parallel="snow"` or using `mclapply` when `parallel="multicore"` (the latter only works on Unix/Linux-alikes). With `parallel::detectCores()`, one can check on the number of available cores on the local machine.

Alternatively (or in addition to using parallel processing), one can also set `reestimate=FALSE`, in which case any variance/correlation components in the model are not re-estimated after deleting the i th study/cluster from the dataset. Doing so only yields an approximation to the Cook's distances and DFBETAS values that ignores the influence of the i th study/cluster on the variance/correlation components, but is considerably faster (and often yields similar results).

It may not be possible to fit the model after deletion of the i th study/cluster from the dataset. This will result in NA values for that study/cluster.

Author(s)

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References

- Belsley, D. A., Kuh, E., & Welsch, R. E. (1980). *Regression diagnostics*. New York: Wiley.
- Cook, R. D., & Weisberg, S. (1982). *Residuals and influence in regression*. London: Chapman and Hall.
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- Viechtbauer, W., & Cheung, M. W.-L. (2010). Outlier and influence diagnostics for meta-analysis. *Research Synthesis Methods*, **1**, 112–125.

See Also

[rstudent.rma.mv](#), [weights.rma.mv](#)

Examples

```
### copy data from Konstantopoulos (2011) into 'dat'
dat <- dat.konstantopoulos2011

### multilevel random-effects model
res <- rma.mv(yi, vi, random = ~ 1 | district/school, data=dat)
print(res, digits=3)

### Cook's distances for each observed outcome
x <- cooks.distance(res)
x
plot(x, type="o", pch=19, xlab="Observed Outcome", ylab="Cook's Distance")

### Cook's distances for each district
x <- cooks.distance(res, cluster=dat$district)
x
plot(x, type="o", pch=19, xlab="District", ylab="Cook's Distance", xaxt="n")
axis(side=1, at=seq_along(x), labels=as.numeric(names(x)))

### hat values
hatvalues(res)
```

Description

The functions compute various outlier and influential case diagnostics (some of which indicate the influence of deleting one case/study at a time on the model fit and the fitted/residual values) for objects of class "rma.uni".

Usage

```
## S3 method for class 'rma.uni'
influence(model, digits, progbar=FALSE, ...)

## S3 method for class 'infl.rma.uni'
print(x, digits=x$digits, infonly=FALSE, ...)

## S3 method for class 'rma.uni'
cooks.distance(model, progbar=FALSE, ...)
## S3 method for class 'rma.uni'
dfbetas(model, progbar=FALSE, ...)
## S3 method for class 'rma.uni'
hatvalues(model, type="diagonal", ...)
```

Arguments

model	an object of class "rma.uni".
x	an object of class "infl.rma.uni" (for print).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
progbar	logical indicating whether a progress bar should be shown (the default is FALSE).
infonly	logical indicating whether only the influential cases should be printed (the default is FALSE).
type	character string indicating whether to return only the diagonal of the hat matrix ("diagonal") or the entire hat matrix ("matrix").
...	other arguments.

Details

The influence function calculates the following leave-one-out diagnostics for each study:

- externally standardized residual,
- DFFITS value,
- Cook's distance,
- covariance ratio,
- the leave-one-out amount of (residual) heterogeneity,
- the leave-one-out test statistic for the test of (residual) heterogeneity,
- DFBETAS value(s).

The diagonal elements of the hat matrix and the weights (in %) given to the observed effects or outcomes during the model fitting are also provided (except for their scaling, the hat values and weights are the same for models without moderators, but will differ when moderators are included).

For details on externally standardized residuals, see [rstudent.rma.uni](#).

The DFFITS value essentially indicates how many standard deviations the predicted (average) effect for the i th study changes after excluding the i th study from the model fitting.

Cook's distance can be interpreted as the Mahalanobis distance between the entire set of predicted values once with the i th study included and once with the i th study excluded from the model fitting.

The covariance ratio is defined as the determinant of the variance-covariance matrix of the parameter estimates based on the dataset with the i th study removed divided by the determinant of the variance-covariance matrix of the parameter estimates based on the complete dataset. A value below 1 therefore indicates that removal of the i th study yields more precise estimates of the model coefficients.

The leave-one-out amount of (residual) heterogeneity is the estimated value of τ^2 based on the dataset with the i th study removed. Note that this is always equal to 0 for fixed-effects models.

Similarly, the leave-one-out test statistic for the test of (residual) heterogeneity is the value of the test statistic of the test for (residual) heterogeneity calculated based on the dataset with the i th study removed.

Finally, the DFBETAS value(s) essentially indicate(s) how many standard deviations the estimated coefficient(s) change(s) after excluding the i th study from the model fitting.

A study may be considered to be 'influential' if at least one of the following is true:

- The absolute DFFITS value is larger than $3\sqrt{p/(k-p)}$, where p is the number of model coefficients and k the number of studies.
- The lower tail area of a chi-square distribution with p degrees of freedom cut off by the Cook's distance is larger than 50%.
- The hat value is larger than $3(p/k)$.
- Any DFBETAS value is larger than 1.

Studies which are considered influential with respect to any of these measures are marked with an asterisk. Note that the chosen cut-offs are (somewhat) arbitrary. Substantively informed judgment should always be used when examining the influence of each study on the results.

Value

An object of class "infl.rma.uni", which is a list containing the following components:

inf	an element of class "list.rma" with the externally standardized residuals, DFFITS values, Cook's distances, covariance ratios, leave-one-out τ^2 estimates, leave-one-out (residual) heterogeneity test statistics, hat values, weights, and an indicator whether a study is influential or not.
dfbs	an element of class "list.rma" with the the DFBETAS values.
...	some additional elements/values.

The results are printed with `print.infl.rma.uni` and plotted with `plot.infl.rma.uni`.

Note

Right now, leave-one-out diagnostics are calculated by refitting the model k times. Depending on how large k is, it may take a few moments to finish the calculations. There are shortcuts for calculating at least some of these values without refitting the model each time, but these are currently not implemented (and may not exist for all of the leave-one-out diagnostics calculated by the function).

It may not be possible to fit the model after deletion of the i th study from the dataset. This will result in NA values for that study.

Certain relationships between the leave-one-out diagnostics and the (internally or externally) standardized residuals (Belsley, Kuh, & Welsch, 1980; Cook & Weisberg, 1982) no longer hold for the meta-analytic models. Maybe there are other relationships. These remain to be determined.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Belsley, D. A., Kuh, E., & Welsch, R. E. (1980). *Regression diagnostics*. New York: Wiley.
- Cook, R. D., & Weisberg, S. (1982). *Residuals and influence in regression*. London: Chapman and Hall.
- Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. San Diego, CA: Academic Press.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.
- Viechtbauer, W., & Cheung, M. W.-L. (2010). Outlier and influence diagnostics for meta-analysis. *Research Synthesis Methods*, **1**, 112–125.

See Also

[plot.infl.rma.uni](#), [rstudent.rma.uni](#), [weights.rma.uni](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects model
### with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)
influence(res)
plot(influence(res))

cooks.distance(res)
dfbetas(res)
hatvalues(res)
```

Description

Function to create L'Abbé plots for objects of class "rma".

Usage

```
labbe(x, ...)

## S3 method for class 'rma'
labbe(x, xlim, ylim, xlab, ylab,
      add=x$add, to=x$to, transf, targs,
      pch=21, psize, bg="gray", grid=FALSE, lty, ...)
```

Arguments

x	an object of class "rma". See 'Details'.
xlim	x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
ylim	y-axis limits. If unspecified, the function tries to set the y-axis limits to some sensible values.
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
ylab	title for the y-axis. If unspecified, the function tries to set an appropriate axis title.
add	See below and the documentation of the escalc function for more details.
to	See below and the documentation of the escalc function for more details.
transf	optional argument specifying the name of a function that should be used to transform the outcomes (e.g., transf=exp; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified under transf.
pch	plotting symbol to use for the outcomes. By default, a filled circle is used. Can also be a vector of values. See points for other options.
psize	optional vector with point sizes for the outcomes. If unspecified, the point sizes are an inverse function of the precision of the estimates.
bg	color to use for filling the plotting symbol (the default is "gray"). Can also be a vector of values. Set to NA to make the plotting symbols transparent.
grid	logical indicating whether a grid should be added to the plot.
lty	optional character vector specifying the line type for the diagonal reference line of no effect and the line that indicates the estimated effect based on the fitted model (if unspecified, the function sets this to c("solid", "dashed") by default; use "blank" to suppress a line).
...	other arguments.

Details

The model specified via x must be a model without moderators (i.e., either a fixed- or a random-effects model) fitted with either the [rma.uni](#), [rma.mh](#), [rma.peto](#), or [rma.glmm](#) function. Moreover, the model must be fitted with measure set equal to "RD" (for risk differences), "RR" (for risk ratios),

"OR" (for odds ratios), "AS" (for arcsine square root transformed risk differences), "IRR" (for incidence rate ratios), "IRD" (for incidence rate differences), or "IRSD" (for square root transformed incidence rate differences).

The function calculates the arm-level outcomes for the two experimental groups (e.g., treatment and control groups) and plots them against each other. In particular, the function plots the raw proportions of the two groups against each other when analyzing risk differences, the log of the proportions when analyzing (log) risk ratios, the log odds when analyzing (log) odds ratios, the arcsine square root transformed proportions when analyzing arcsine square root transformed risk differences, the raw incidence rates when analyzing incidence rate differences, the log of the incidence rates when analyzing (log) incidence rate ratios, and the square root transformed incidence rates when analyzing square root transformed incidence rate differences. The `transf` argument can be used to transform these values (for example, `transf=exp` to transform the log of the proportions back to raw proportions; see also `transf`).

As described under the documentation for the `escalc` function, zero cells can lead to problems when calculating particular outcomes. Adding a small constant to the cells of the 2×2 tables is a common solution to this problem. By default, the functions adopt the same method for handling zero cells as was done when fitting the model.

By default (i.e., if `psize` is not specified), the size of the points is an inverse function of the precision (inverse standard errors) of the outcomes. The solid line corresponds to identical outcomes in the two groups (i.e., the absence of a difference between the two groups). The dashed line indicates the estimated effect based on the fitted model.

Value

A data frame with components:

<code>x</code>	the x coordinates of the points that were plotted.
<code>y</code>	the y coordinates of the points that were plotted.
<code>psize</code>	the point sizes.

Note that the data frame is returned invisibly.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- L'Abbé, K. A., Detsky, A. S., & O'Rourke, K. (1987). Meta-analysis in clinical research. *Annals of Internal Medicine*, **107**, 224–233.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#)

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### default plot
labbe(res)

### funnel plot with risk values on the x- and y-axis
labbe(res, transf=exp)
```

leave1out

Leave-One-Out Diagnostics for 'rma' Objects

Description

The functions repeatedly fit the specified model, leaving out one observation/study at a time.

Usage

```
leave1out(x, ...)

## S3 method for class 'rma.uni'
leave1out(x, digits, transf, targs, progbar=FALSE, ...)
## S3 method for class 'rma.mh'
leave1out(x, digits, transf, targs, progbar=FALSE, ...)
## S3 method for class 'rma.peto'
leave1out(x, digits, transf, targs, progbar=FALSE, ...)
```

Arguments

x	an object of class "rma.mh", "rma.peto", or "rma.uni".
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
transf	an optional argument specifying the name of a function that should be used to transform the model coefficients and interval bounds (e.g., transf=exp; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified under transf.
progbar	logical indicating whether a progress bar should be shown (the default is FALSE).
...	other arguments.

Details

The model specified via x must be a model without moderators (i.e., either a fixed- or a random-effects model and not a fixed-effects with moderators or mixed-effects model).

Value

An object of class "list.rma". The object is a list containing the following components:

estimate	estimated coefficients of the model.
se	standard errors of the coefficients.
zval	test statistics of the coefficients.
pval	p-values for the test statistics.
ci.lb	lower bounds of the confidence intervals for the coefficients.
ci.ub	upper bounds of the confidence intervals for the coefficients.
Q	test statistics for the tests of heterogeneity.
Qp	p-values for the tests of heterogeneity.
tau2	estimated amounts of (residual) heterogeneity (only for random-effects models).
I2	values of I^2 (only for random-effects models).
H2	values of H^2 (only for random-effects models).

The "list.rma" object is formatted and printed with `print.list.rma`.

Note

When using the `transf` option, the transformation is applied to the estimated coefficients and the corresponding interval bounds. The standard errors are then set equal to NA and are omitted from the printed output.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.
- Viechtbauer, W., & Cheung, M. W.-L. (2010). Outlier and influence diagnostics for meta-analysis. *Research Synthesis Methods*, **1**, 112–125.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model
res <- rma(yi, vi, data=dat)

### leave-one-out analysis
```

```

leave1out(res)
leave1out(res, transf=exp)

### meta-analysis of the (log) risk ratios using the Mantel-Haenszel method
res <- rma.mh(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### leave-one-out analysis
leave1out(res)
leave1out(res, transf=exp)

### meta-analysis of the (log) odds ratios using Peto's method
res <- rma.peto(ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### leave-one-out analysis
leave1out(res)
leave1out(res, transf=exp)

```

llplot	<i>Likelihood Plot of a Parameter Corresponding to an Effect Size or Outcome Measure</i>
--------	------------------------------------------------------------------------------------------

Description

Function to plot the likelihood of a certain parameter corresponding to an effect size or outcome measure given the study data.

Usage

```
llplot(measure, yi, vi, sei, ai, bi, ci, di, n1i, n2i, data, subset, drop00=TRUE,
       xvals=1000, xlim, ylim, xlab, ylab, scale=TRUE,
       lty, lwd, col, level=99.99, refline=0, ...)
```

Arguments

measure	a character string indicating for which effect size or outcome measure the likelihoods should be calculated. See ‘Details’ for possible options and how the data should be specified.
yi	vector with the observed effect sizes or outcomes.
vi	vector with the corresponding sampling variances.
sei	vector to specify the corresponding standard.
ai	vector to specify the 2×2 table frequencies (upper left cell).
bi	vector to specify the 2×2 table frequencies (upper right cell).
ci	vector to specify the 2×2 table frequencies (lower left cell).
di	vector to specify the 2×2 table frequencies (lower right cell).
n1i	vector to specify the group sizes or row totals (first group/row).
n2i	vector to specify the group sizes or row totals (second group/row).

data	optional data frame containing the variables given to the arguments above.
subset	optional (logical or numeric) vector indicating the subset of studies that should be included in the plot.
drop00	logical indicating whether studies with no cases (or only cases) in both groups should be dropped. See ‘Details’.
xvals	integer specifying for how many distinct values the likelihood should be evaluated.
xlim	x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
ylim	y-axis limits. If unspecified, the function tries to set the y-axis limits to some sensible values.
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
ylab	title for the y-axis. If unspecified, the function tries to set an appropriate axis title.
scale	logical indicating whether the likelihood values should be scaled, so that the total area under each curve is (approximately) equal to 1.
lty	the line types (either a single value or a vector of length k). If unspecified, the function sets the line types according to some characteristics of the likelihood function. See ‘Details’.
lwd	the line widths (either a single value or a vector of length k). If unspecified, the function sets the widths according to the sampling variances (so that the line is thicker for more precise studies and vice-versa).
col	the line colors (either a single value or a vector of length k). If unspecified, the function uses various shades of gray according to the sampling variances (so that darker shades are used for more precise studies and vice-versa).
level	numerical value between 0 and 100 specifying the plotting limits for each likelihood line in terms of the confidence interval (the default is 99.99).
refline	value at which a vertical ‘reference’ line should be drawn (the default is 0). The line can be suppressed by setting this argument to NA.
...	other arguments.

Details

At the moment, the function only accepts `measure="GEN"` or `measure="OR"`.

For `measure="GEN"`, one must specify arguments y_i for the observed effect sizes or outcomes and v_i for the corresponding sampling variances (instead of specifying v_i , one can specify the standard errors via the `sei` argument). The function then plots the likelihood of the true outcome based on a normal sampling distribution with observed outcome as given by y_i and variance as given by v_i for each study.

For `measure="OR"`, one must specify arguments a_i , b_i , c_i , and d_i , which denote the cell frequencies of the 2×2 tables. Alternatively, one can specify a_i , c_i , $n1_i$, and $n2_i$. See [escalc](#) function for more details. The function then plots the likelihood of the true log odds ratio based on the non-central hypergeometric distribution for each 2×2 table. Since studies with no cases (or only

cases) in both groups have a flat likelihood and are not informative about the odds ratio, they are dropped by default (i.e., `drop00=TRUE`) and are hence not drawn (if `drop00=FALSE`, these likelihood are indicated by dotted lines). For studies that have a single zero count, the MLE of the odds ratio is infinite and these likelihoods are indicated by dashed lines.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- van Houwelingen, H. C., Zwinderman, K. H., & Stijnen, T. (1993). A bivariate approach to meta-analysis. *Statistics in Medicine*, **12**, 2273–2284.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.glm](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### draw likelihoods
llplot(measure="GEN", yi=yi, vi=vi, data=dat, lwd=1, refline=NA, xlim=c(-3,2))

### create plot (Figure 2 in van Houwelingen, Zwinderman, & Stijnen, 1993)
llplot(measure="OR", ai=b.xci, n1i=nci, ci=b.xti, n2i=nti, data=dat.collins1985a,
       lwd=1, refline=NA, xlim=c(-4,4), drop00=FALSE)
```

metafor.news

Read News File of the Metafor Package

Description

Read news file of the [metafor-package](#).

Usage

```
metafor.news()
```

Details

The function is just a wrapper for `news(package="metafor")` which parses and displays the ‘NEWS’ file of the package.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

Examples

```
## Not run:  
metafor.news()  
## End(Not run)
```

model.matrix.rma *Model Matrix for 'rma' Objects*

Description

The function extracts the model matrix for objects of class "rma".

Usage

```
## S3 method for class 'rma'  
model.matrix(object, ...)
```

Arguments

object	an object of class "rma".
...	other arguments.

Value

The model matrix.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[fitted.rma](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects meta-regression model
### with multiple moderators (absolute latitude, publication year, and allocation method)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year + alloc, data=dat.bcg)
model.matrix(res)
```

permutest

*Permutation Tests for 'rma.uni' Objects***Description**

The function carries out permutation tests for objects of class "rma.uni".

Usage

```
permutest(x, ...)

## S3 method for class 'rma.uni'
permutest(x, exact=FALSE, iter=1000, permci=FALSE,
          progbar=TRUE, retpermdist=FALSE, digits, control, ...)
```

Arguments

x	an object of class "rma.uni".
exact	logical indicating whether an exact permutation test should be carried out or not (the default is FALSE). See 'Details'.
iter	integer specifying the number of iterations for the permutation test when not doing an exact test (the default is 1000 iterations).
permci	logical indicating whether permutation-based CIs should also be calculated (the default is FALSE). Can also be a vector of indices specifying for which coefficients a permutation-based CI should be obtained.
progbar	logical indicating whether a progress bar should be shown (the default is TRUE).
retpermdist	logical indicating whether the permutation distributions of the test statistics should be returned (the default is FALSE).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
control	list of control values for numerical comparisons (comptol) and for uniroot (i.e., tol and maxiter). The latter is only relevant when permci=TRUE. See 'Note'.
...	other arguments.

Details

For models without moderators, the permutation test is carried out by permuting the signs of the observed effect sizes or outcomes. The (two-sided) p-value of the permutation test is then equal to the proportion of times that the absolute value of the test statistic under the permuted data is as extreme or more extreme than under the actually observed data. See Follmann and Proschan (1999) for more details.

For models with moderators, the permutation test is carried out by permuting the rows of the model matrix (i.e., X). The (two-sided) p-value for a particular model coefficient is then equal to the proportion of times that the absolute value of the test statistic for the coefficient under the permuted data is as extreme or more extreme than under the actually observed data. Similarly, for the omnibus test, the p-value is the proportion of times that the test statistic for the omnibus test is as extreme or more extreme than the actually observed one. See Higgins and Thompson (2004) and Viechtbauer et al. (2015) for more details.

If `exact=TRUE`, the function will try to carry out an exact permutation test. An exact permutation test requires fitting the model to each possible permutation once. However, the number of possible permutations increases rapidly with the number of outcomes/studies (i.e., k). For models without moderators, there are 2^k possible permutations of the signs. Therefore, for $k = 5$, there are 32 possible permutations, for $k = 10$, there are already 1024, and for $k = 20$, there are over one million permutations of the signs.

For models with moderators, the increase in the number of possible permutations may be even more severe. The total number of possible permutations of the model matrix is $k!$. Therefore, for $k = 5$, there are 120 possible permutations, for $k = 10$, there are 3,628,800, and for $k = 20$, there are over 10^{18} permutations of the model matrix.

Therefore, going through all possible permutations may become infeasible. Instead of using an exact permutation test, one can set `exact=FALSE` (which is also the default). In that case, the function approximates the exact permutation-based p-value(s) by going through a smaller number (as specified by the `iter` argument) of *random* permutations. Therefore, running the function twice on the same data can yield (slightly) different p-values. Setting `iter` sufficiently large ensures that the results become stable. Note that if `exact=FALSE` and `iter` is actually larger than the number of iterations required for an exact permutation test, then an exact test will be carried out.

For models with moderators, the exact permutation test actually only requires fitting the model to each *unique* permutation of the model matrix. The number of unique permutations will be smaller than $k!$ when the model matrix contains recurring rows. This may be the case when only including categorical moderators (i.e., factors) in the model or when any quantitative moderators included in the model only take on a small number of unique values. When `exact=TRUE`, the function therefore uses an algorithm to restrict the test to only the unique permutations of the model matrix, which may make the use of the exact test feasible even when k is large.

When using random permutations, the function ensures that the very first permutation will always correspond to the original data. This avoids p-values equal to 0.

When `permc1=TRUE`, the function also tries to obtain permutation-based CIs of the model coefficient(s). This is done by shifting the observed effect sizes or outcomes and finding the most extreme values for which the permutation-based test would just lead to non-rejection. This is computationally expensive and may take a long time to complete. For models with moderators, one can also set `permc1` to a vector of indices specifying for which coefficient(s) a permutation-based CI should be obtained. When the algorithm fails to determine a particular CI bound, it will be shown as NA in the output.

Value

An object of class "permutest.rma.uni". The object is a list containing the following components:

pval	p-value(s) based on the permutation test.
QMp	p-value for the omnibus test of coefficients based on the permutation test.
zval.perm	values of the test statistics of the coefficients under the various permutations (only when retpermdist=TRUE).
b.perm	values of the model coefficients under the various permutations (only when retpermdist=TRUE).
QM.perm	values of the test statistic for the omnibus test of coefficients under the various permutations (only when retpermdist=TRUE).
ci.lb	lower bound of the confidence intervals for the coefficients (permutation-based when permci=TRUE).
ci.ub	upper bound of the confidence intervals for the coefficients (permutation-based when permci=TRUE).
...	some additional elements/values are passed on.

The results are formatted and printed with the `print.permutest.rma.uni` function. One can also use `coef.permutest.rma.uni` to obtain the table with the model coefficients, corresponding standard errors, test statistics, p-values, and confidence interval bounds.

Note

It is important to note that the p-values obtained with permutation tests cannot reach conventional levels of statistical significance (i.e., $p \leq .05$) when k is very small. In particular, for models without moderators, the smallest possible (two-sided) p-value is .0625 when $k = 5$ and .03125 when $k = 6$. Therefore, the permutation test is only able to reject the null hypothesis at $\alpha = .05$ when k is at least equal to 6. For models with moderators, the smallest possible (two-sided) p-value for a particular model coefficient is .0833 when $k = 4$ and .0167 when $k = 5$ (assuming that each row in the model matrix is unique). Therefore, the permutation test is only able to reject the null hypothesis at $\alpha = .05$ when k is at least equal to 5. Consequently, permutation-based CIs can also only be obtained when k is sufficiently large.

When the number of permutations required for the exact test is so large as to be essentially indistinguishable from infinity (e.g., `factorial(200)`), the function will terminate with an error.

Determining whether a test statistic under the permuted data is as extreme or more extreme than under the actually observed data requires making \geq or \leq comparisons. To avoid problems due to the finite precision with which computers generally represent numbers, the function uses a numerical tolerance (control argument `comptol`, which is set by default equal to `.Machine$double.eps^0.5`) when making such comparisons (e.g., instead of `sqrt(3)^2 - 3 >= 0`, which may evaluate to FALSE, we can use `sqrt(3)^2 - 3 >= 0 - .Machine$double.eps^0.5`, which should evaluate to TRUE).

When obtaining permutation-based CIs, the function makes use of `uniroot`. By default, the desired accuracy is set equal to `.Machine$double.eps^0.25` and the maximum number of iterations to 100. The desired accuracy and the maximum number of iterations can be adjusted with the control argument (i.e., `control=list(tol=value,maxiter=value)`).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Follmann, D. A., & Proschan, M. A. (1999). Valid inference in random effects meta-analysis. *Biometrics*, **55**, 732–737.
- Good, P. I. (2009). *Permutation, parametric, and bootstrap tests of hypotheses* (3rd ed.). New York: Springer.
- Higgins, J. P. T., & Thompson, S. G. (2004). Controlling the risk of spurious findings from meta-regression. *Statistics in Medicine*, **23**, 1663–1682.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.
- Viechtbauer, W., López-López, J. A., Sánchez-Meca, J., & Marín-Martínez, F. (2015). A comparison of procedures to test for moderators in mixed-effects meta-regression models. *Psychological Methods*, **20**, 360–374.

See Also

[rma.uni](#), [print.permutest.rma.uni](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model
res <- rma(yi, vi, data=dat)
res

### permutation test (approximate and exact)
## Not run:
permutest(res)
permutest(res, exact=TRUE)
## End(Not run)

### mixed-effects model with two moderators (absolute latitude and publication year)
res <- rma(yi, vi, mods = ~ ablat + year, data=dat)
res

### permutation test (approximate only; exact not feasible)
## Not run:

permres <- permutest(res, iter=10000, retpermdist=TRUE)
permres

### histogram of permutation distribution for absolute latitude
### dashed horizontal line: the observed value of the test statistic
### red curve: standard normal density
### blue curve: kernel density estimate of the permutation distribution
```

```

### note that the tail area under the permutation distribution is larger
### than under a standard normal density (hence, the larger p-value)
hist(permmres$zval.perm[,2], breaks=120, freq=FALSE, xlim=c(-5,5), ylim=c(0,.4),
     main="Permutation Distribution", xlab="Value of Test Statistic", col="gray90")
abline(v=res$zval[2], lwd=2, lty="dashed")
abline(v=0, lwd=2)
curve(dnorm, from=-5, to=5, add=TRUE, lwd=2, col=rgb(1,0,0,alpha=.7))
lines(density(permmres$zval.perm[,2]), lwd=2, col=rgb(0,0,1,alpha=.7))

## End(Not run)

```

plot.cumul.rma

Plot Method for 'cumul.rma' Objects

Description

Plot method for objects of class "cumul.rma".

Usage

```

## S3 method for class 'cumul.rma'
plot(x, yaxis="tau2", xlim, ylim, xlab, ylab,
     at, transf, atransf, targ, digits, cols=c("gray90","gray10"),
     addgrid=TRUE, pch=19, cex=1, lwd=2, ...)

```

Arguments

x	an object of class "cumul.rma".
yaxis	either "tau2", "I2", or "H2" to indicate what values should be placed on the y-axis. See 'Details'.
xlim	x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
ylim	y-axis limits. If unspecified, the function tries to set the y-axis limits to some sensible values.
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
ylab	title for the y-axis. If unspecified, the function tries to set an appropriate axis title.
at	position of the x-axis tick marks and corresponding labels. If unspecified, the function tries to set the tick mark positions/labels to some sensible values.
transf	optional argument specifying the name of a function that should be used to transform the summary estimates (e.g., transf=exp; see also transf). If unspecified, no transformation is used.
atransf	optional argument specifying the name of a function that should be used to transform the x-axis labels (e.g., atransf=exp; see also transf). If unspecified, no transformation is used.

targs	optional arguments needed by the function specified via transf or atranf.
digits	integer specifying the number of decimal places to which the tick mark labels of the x- and y-axis should be rounded. Can also be a vector of two integers, the first specifying the number of decimal places for the x-axis, the second for the y-axis labels (e.g., c(2, 3)). If unspecified, the function tries to set the argument to some sensible values.
cols	vector with two or more colors to use for indicating the order of the cumulative results.
addgrid	logical specifying whether a grid should be added to the plot (the default is TRUE).
pch	plotting symbol to use. By default, a solid circle is used. See points for other options.
cex	symbol expansion factor.
lwd	line width.
...	other arguments.

Details

The function is meant to be used for cumulative random-effects models results as obtained with the [cumul.rma.uni](#) function.

By default, the plot shows the model estimate on the x-axis and the corresponding estimate of τ^2 on the y-axis in the cumulative order of the results in the "cumul.rma" object. Alternatively, one can also place the value of I^2 (yaxis="I2") or H^2 (yaxis="H2") on the y-axis.

The color gradient of the points/lines indicates the order of the cumulative results (by default, light gray at the beginning, dark gray at the end). A different set of colors can be chosen via the cols argument. See 'Examples'.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[cumul.rma.uni](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model
res <- rma(yi, vi, data=dat)
```

```

### cumulative meta-analysis (in the order of publication year)
sav <- cumul(res, transf=exp, order=order(dat$year))

### plot of model estimate and tau^2 over time
plot(sav)

### illustrate some other plot options
plot(sav, yaxis="I2", ylim=c(0,100), atranf=exp, at=log(seq(1.3, 1.6, by=.1)),
      lwd=5, cex=0, cols=c("green", "blue", "red"))

```

plot.gosh.rma

Plot Method for 'gosh.rma' Objects

Description

Plot method for objects of class "gosh.rma".

Usage

```

## S3 method for class 'gosh.rma'
plot(x, het="I2", pch=16, cex=0.5, out, col, alpha, border,
      xlim, ylim, xhist=TRUE, yhist=TRUE, hh=.3, breaks,
      adjust, lwd, labels, ...)

```

Arguments

x	an object of class "gosh.rma".
het	character string indicating the heterogeneity measure to plot. Either "I2", "H2", "QE", or "tau2" (the last only for random/mixed-effects models).
pch	plotting symbol to use. By default, a borderless filled circle is used. See points for other options.
cex	symbol expansion factor.
out	optional integer indicating the number of a study that may be a potential outlier. If specified, subsets containing the specified study are drawn in a different color than those not containing the study.
col	optional character string specifying the name of a color to use for the points (if not provided, points are drawn in black). When out is used, two colors should be specified (if not provided, red is used for subsets containing the specified study and blue otherwise).
alpha	optional alpha transparency value for the points (0 means fully transparent and 1 means opaque). If unspecified, the function tries to set this to a sensible value.
border	optional character string specifying the name of a color to use for the borders of the histogram (if not provided, borders are drawn in white). Set to FALSE to omit the borders.

xlim	x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
ylim	y-axis limits. If unspecified, the function tries to set the y-axis limits to some sensible values.
xhist	logical specifying whether a histogram should be drawn for the x-axis (the default is TRUE).
yhist	logical specifying whether a histogram should be drawn for the y-axis (the default is TRUE).
hh	optional numerical value (or vector of two values) to adjust the height of the histogram(s). Must be between 0 and 1, but should not be too close to 0 or 1, as otherwise the plot cannot be drawn.
breaks	optional argument passed on to <code>hist</code> for choosing the (number of) breakpoints of the histogram(s).
adjust	optional argument passed on to <code>density</code> for adjusting the bandwidth of the kernel density estimate(s) (values larger than 1 result in more smoothing).
lwd	optional numeric value to specify the line width of the estimated densities. Set to 0 to omit the line(s).
labels	optional argument to specify the x-axis and y-axis labels (or passed on to <code>pairs</code> for specifying the names of the variables in the scatterplot matrix).
...	other arguments.

Details

For models without moderators, the function draws a scatterplot of the model estimates on the x-axis against the chosen measure of heterogeneity on the y-axis. Histograms of the respective distributions (with kernel density estimates superimposed) are shown in the margins (when `xhist=TRUE` and `yhist=TRUE`).

For models with moderators, the function draws a scatterplot matrix (with the `pairs` function) of the chosen measure of heterogeneity and each of the model coefficients. Histograms of the variables plotted are shown along the diagonal, with kernel density estimates of the distributions superimposed. Arguments `xlim`, `ylim`, `xhist`, and `yhist` are then ignored (argument `hh` can then be used to compress/stretch the height of the distributions shown along the diagonal).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Olkin, I., Dahabreh, I. J., & Trikalinos, T. A. (2012). GOSH - a graphical display of study heterogeneity. *Research Synthesis Methods*, *3*, 214–223.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[gosh.rma](#)

Examples

```

### meta-analysis of all trials including ISIS-4 using a FE model
res <- rma(measure="OR", ai=ai, n1i=n1i, ci=ci, n2i=n2i, data=dat.egger2001, method="FE")

## Not run:
### fit FE model to all possible subsets (65535 models)
sav <- gosh(res)

### create GOSH plot
### red points for subsets that include and blue points
### for subsets that exclude study 16 (the ISIS-4 trial)
plot(sav, out=16, breaks=100)
## End(Not run)

```

plot.infl.rma.uni *Plot Method for 'infl.rma.uni' Objects*

Description

Plot method for objects of class "infl.rma.uni".

Usage

```

## S3 method for class 'infl.rma.uni'
plot(x, plotinf=TRUE, plotdfbs=FALSE, dfbsnew=FALSE, logcov=TRUE,
     layout, slab.style=1, las=0, pch=21, bg="black",
     bg.infl="red", col.na="lightgray", ...)

```

Arguments

x	an object of class "infl.rma.uni".
plotinf	logical indicating whether the various case diagnostics should be plotted (the default is TRUE). Can also be a vector of up to 8 integers indicating which plots to draw (see 'Details' for the numbers corresponding to the various plots).
plotdfbs	logical indicating whether the DFBETAS values should be plotted (the default is FALSE). Can also be a vector of integers to indicate for which coefficient(s) to plot the DFBETAS values.
dfbsnew	logical indicating whether a new device should be opened for plotting the DFBETAS values (the default is FALSE).
logcov	logical indicating whether the covariance ratios should be plotted on a log scale (the default is TRUE).
layout	optional vector of two numbers, indicating the number of rows and columns for the layout of the figure.
slab.style	integer to indicate the style of the x-axis labels: 1 = study number, 2 = study label, 3 = abbreviated study label. Note that study labels, even when abbreviated, may be too long to fit in the margin.)

las	integer between 0 and 3 to specify the alignment of the axis labels (see par). The most useful alternative to 0 is 3, so that the x-axis labels are drawn vertical to the axis.
pch	plotting symbol to use. By default, a filled circle is used. See points for other options.
bg	color to use for filling the plotting symbol (the default is "black").
bg.infl	color to use for filling the plotting symbol when the point is considered influential (the default is "red").
col.na	color to use for lines connecting two points with NA values in between (the default is "lightgray").
...	other arguments.

Details

When `plotinf=TRUE`, the function plots the (1) externally standardized residuals, (2) DFFITS values, (3) Cook's distances, (4) covariance ratios, (5) leave-one-out τ^2 estimates, (6) leave-one-out (residual) heterogeneity test statistics, (7) hat values, and (8) weights. If `plotdfbs=TRUE`, the DFBETAS values are also plotted either after confirming the page change (if `dfbsnew=FALSE`) or on a separate device (if `dfbsnew=TRUE`).

A study may be considered to be 'influential' if at least one of the following is true:

- The absolute DFFITS value is larger than $3\sqrt{p/(k-p)}$, where p is the number of model coefficients and k the number of studies.
- The lower tail area of a chi-square distribution with p degrees of freedom cut off by the Cook's distance is larger than 50%.
- The hat value is larger than $3(p/k)$.
- Any DFBETAS value is larger than 1.

Studies which are considered influential with respect to any of these measures are indicated by the color specified for the `bg.infl` argument (the default is "red").

The cut-offs described above are indicated in the plot with horizontal reference lines. In addition, on the plot of the externally standardized residuals, horizontal reference lines are drawn at -1.96, 0, and 1.96. On the plot of the hat values, a horizontal reference line is drawn at p/k . Since the sum of the hat values is equal to p , the value p/k indicates equal hat values for all k studies. Finally, on the plot of weights, a horizontal reference line is drawn at $100/k$, corresponding to the value for equal weights (in %) for all k studies. Note that all weights will automatically be equal to each other when using unweighted model fitting. Also, the hat values will be equal to the weights values (except for their scaling) in models without moderators.

The chosen cut-offs are (somewhat) arbitrary. Substantively informed judgment should always be used when examining the influence of each study on the results.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.
- Viechtbauer, W., & Cheung, M. W.-L. (2010). Outlier and influence diagnostics for meta-analysis. *Research Synthesis Methods*, **1**, 112–125.

See Also

[influence.rma.uni](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects model
### with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)
plot(influence(res))
plot(influence(res), plotinf=1:4)
plot(influence(res), plotinf=1:4, layout=c(4,1))
plot(influence(res), plotdfbs=TRUE, dfbsnew=TRUE)
```

plot.rma

Plot Method for 'rma' Objects

Description

Plot method for objects of class "rma.uni", "rma.mh", "rma.peto", and "rma.glmm".

Usage

```
## S3 method for class 'rma.uni'
plot(x, qqplot=FALSE, ...)

## S3 method for class 'rma.mh'
plot(x, qqplot=FALSE, ...)

## S3 method for class 'rma.peto'
plot(x, qqplot=FALSE, ...)

## S3 method for class 'rma.glmm'
plot(x, qqplot=FALSE, ...)
```

Arguments

x	an object of class "rma.uni", "rma.mh", or "rma.peto". The method is not yet implemented for objects of class "rma.glmm".
qqplot	logical indicating whether a normal QQ plot should be drawn (the default is FALSE).
...	other arguments.

Details

Four plots are produced. If the model does not contain any moderators, then a forest plot, funnel plot, radial plot, and a plot of the standardized residuals is provided. If qqplot=TRUE, the last plot is replaced by a normal QQ plot of the standardized residuals.

If the model contains moderators, then a forest plot, funnel plot, plot of the standardized residuals against the fitted values, and a plot of the standardized residuals is provided. If qqplot=TRUE, the last plot is replaced by a normal QQ plot of the standardized residuals.

Note

If the number of studies is large, the forest plot may become quite impossible to read due to the small font size. Stretching the plotting device vertically should provide more room.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[forest](#), [funnel](#), [radial](#), [qqnorm.rma.uni](#)

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
plot(res, qqplot=TRUE)

### mixed-effects model with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)
plot(res, qqplot=TRUE)
```

predict.rma

Predicted Values for 'rma' Objects

Description

The function computes predicted values, corresponding standard errors, confidence intervals, and (approximate) credibility/prediction intervals for objects of class "rma".

Usage

```
## S3 method for class 'rma'
predict(object, newmods, intercept, tau2.levels, gamma2.levels,
        addx=FALSE, level, digits, transf, targs, vcov=FALSE, ...)
```

Arguments

object	an object of class "rma".
newmods	optional vector or matrix specifying the values of the moderator values for which the predicted values should be calculated. See 'Details'.
intercept	logical specifying whether the intercept should be included when calculating the predicted values for newmods. If unspecified, the intercept is automatically added when the original model also included an intercept.
tau2.levels	vector specifying the levels of the inner factor when computing credibility/prediction intervals. Only relevant for models of class "rma.mv" (see rma.mv) and when the model includes more than a single τ^2 value. See 'Details'.
gamma2.levels	vector specifying the levels of the inner factor when computing credibility/prediction intervals. Only relevant for models of class "rma.mv" (see rma.mv) and when the model includes more than a single γ^2 value. See 'Details'.
addx	logical specifying whether the values of the moderator variables should be added to the returned object. See 'Examples'.
level	numerical value between 0 and 100 specifying the confidence and credibility/prediction interval level (if unspecified, the default is to take the value from the object).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
transf	optional argument specifying the name of a function that should be used to transform the predicted values and interval bounds (e.g., <code>transf=exp</code> ; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified under <code>transf</code> .
vcov	logical specifying whether the variance-covariance matrix of the predicted values should also be returned (the default is FALSE).
...	other arguments.

Details

For a fixed-effects model, `predict(object)` returns the estimated (average) outcome in the set of studies included in the meta-analysis. This is the same as the estimated intercept in the fixed-effects model.

For a random-effects model, `predict(object)` returns the estimated (average) outcome in the hypothetical population of studies from which the set of studies included in the meta-analysis are assumed to be a random selection. This is the same as the estimated intercept in the random-effects model.

For models including one or more moderators, `predict(object)` returns the estimated (average) outcomes for values of the moderator(s) equal to those of the k studies included in the meta-analysis (i.e., the fitted values for the k studies).

For models including q moderator variables, new moderator values for k_{new} new studies can be specified by setting `newmods` equal to an $k_{new} \times q$ matrix with the corresponding new moderator values. If the original model includes an intercept, then it should not be explicitly specified under `newmods`, as it will be added by default (unless one sets `intercept=FALSE`). Also, any factors in the original model get turned into the appropriate contrast variables within the `rma` function, so that `newmods` should actually include the values for the contrast variables. Examples are shown below.

For random/mixed-effects models, an approximate credibility/credible or prediction interval is also calculated (Raudenbush, 2009; Riley et al., 2011). The interval estimates where level % of the true outcomes fall in the hypothetical population of studies. Note that this interval is calculated under the assumption that the value of τ^2 is known (and not estimated). A method for calculating a credibility/prediction interval that accounts for the uncertainty in the estimate of τ^2 may be implemented in the future.

For random-effects models of class `"rma.mv"` (see `rma.mv`) with multiple τ^2 values (i.e., when the random argument includes a `~ inner | outer` term and `struct="HCS"`, `struct="HAR"`, or `struct="UN"`), the function will provide credibility/prediction intervals for each level of the inner factor (since the credibility/prediction intervals differ depending on the τ^2 value). Alternatively, one can use the `tau2.levels` argument to specify for which level(s) the credibility/prediction interval should be provided.

If the model includes a second `~ inner | outer` term with multiple γ^2 values, credibility/prediction intervals for each combination of levels of the inner factors will be provided. Alternatively, one can use the `tau2.levels` and `gamma2.levels` arguments to specify for which level combination(s) the credibility/prediction interval should be provided.

When using the `newmods` argument for mixed-effects models of class `"rma.mv"` with multiple τ^2 (and multiple γ^2) values, one must use the `tau2.levels` (and `gamma2.levels`) argument to specify the levels of the inner factor(s) (i.e., a vector of length k_{new}) to obtain the appropriate credibility/prediction interval(s).

Value

An object of class `"list.rma"`. The object is a list containing the following components:

<code>pred</code>	predicted value(s).
<code>se</code>	corresponding standard error(s).
<code>ci.lb</code>	lower bound of the confidence interval(s).
<code>ci.ub</code>	upper bound of the confidence interval(s).
<code>cr.lb</code>	lower bound of the credibility/prediction interval(s) (only random/mixed-effects models).
<code>cr.ub</code>	upper bound of the credibility/prediction interval(s) (only random/mixed-effects models).
<code>tau2.level</code>	the level(s) of the inner factor (only for models of class <code>"rma.mv"</code> with multiple τ^2 values).
<code>gamma2.level</code>	the level(s) of the inner factor (only for models of class <code>"rma.mv"</code> with multiple γ^2 values).

X the moderator value(s) used to calculate the predicted values (only when addx=TRUE).
 ... some additional elements/values.

If vcov=TRUE, then the returned object is a list with the first element equal to the one as described above and the second element equal to the variance-covariance matrix of the predicted values.

The "list.rma" object is formatted and printed with `print.list.rma`.

Note

The predicted values are based only on the fixed effects of the model. Best linear unbiased predictions (BLUPs) that combine the fitted values based on the fixed effects and the estimated contributions of the random effects can be obtained with `blup.rma.uni` (currently only for objects of class "rma.uni").

When using the `transf` option, the transformation is applied to the predicted values and the corresponding interval bounds. The standard errors are then set equal to NA and are omitted from the printed output. Also, `vcov=TRUE` is ignored when using the `transf` option.

Confidence and credibility/prediction intervals are calculated based on the critical values from a standard normal distribution (i.e., ± 1.96 for `level=95`). When the model was fitted with the Knapp and Hartung (2003) method (i.e., `test="knha"` in the `rma.uni` function) or with `test="t"` in the `rma.glmm` and `rma.mv` functions, then the t-distribution with $k - p$ degrees of freedom is used.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. San Diego, CA: Academic Press.
- Raudenbush, S. W. (2009). Analyzing effect sizes: Random effects models. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (2nd ed., pp. 295–315). New York: Russell Sage Foundation.
- Riley, R. D., Higgins, J. P. T., & Deeks, J. J. (2011). Interpretation of random effects meta-analyses. *British Medical Journal*, **342**, d549.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

`fitted.rma`, `blup.rma.uni`

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### average risk ratio with 95% CI
predict(res, transf=exp)
```



```

### mixed-effects model with absolute latitude as a moderator
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, mods = ~ ablat,
          data=dat.bcg)

### predicted average risk ratios for given absolute latitude values
predict(res, transf=exp, addx=TRUE)

### predicted average risk ratios for 10-60 degrees absolute latitude
predict(res, newmods=c(10, 20, 30, 40, 50, 60), transf=exp)

### mixed-effects model with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)

### predicted average risk ratios for 10 and 60 degrees latitude in 1950 and 1980
predict(res, newmods=cbind(c(10,60,10,60),c(1950,1950,1980,1980)), transf=exp, addx=TRUE)

### mixed-effects model with two moderators (one of which is a factor)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + factor(alloc), data=dat.bcg)

### examine how the factor was actually coded for the studies in the dataset
predict(res, addx=TRUE)

### predicted average risk ratios at 30 degrees for the three factor levels
### note: the contrast (dummy) variables need to be specified explicitly here
predict(res, newmods=c(30, 0, 0), addx=TRUE) # for alternate allocation
predict(res, newmods=c(30, 1, 0), addx=TRUE) # for random allocation
predict(res, newmods=c(30, 0, 1), addx=TRUE) # for systematic allocation

### can also use named vector with arbitrary order and abbreviated variable names
predict(res, newmods=c(sys=0, ran=0, abl=30))
predict(res, newmods=c(sys=0, ran=1, abl=30))
predict(res, newmods=c(sys=1, ran=0, abl=30))

```

print.anova.rma

Print Method for 'anova.rma' Objects

Description

Print method for objects of class "anova.rma".

Usage

```

## S3 method for class 'anova.rma'
print(x, digits=x$digits, ...)

```

Arguments

x	an object of class "anova.rma".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
...	other arguments.

Details

The output includes:

- the number of parameters in the full and the reduced model.
- the AIC, BIC, AICc, and log-likelihood of the full and the reduced model.
- the value of the likelihood ratio test statistic.
- the p-value for the likelihood ratio test.
- the test statistic for the test of (residual) heterogeneity for the full and the reduced model.
- the estimate of τ^2 from the full and the reduced model. Suppressed for fixed-effects models.
- R2amount (in percent) of heterogeneity in the reduced model that is accounted for in the full model (NA for fixed-effects models or for "rma.mv" objects). This can be regarded as a pseudo R^2 statistic (Raudenbush, 2009). Note that the value may not be very accurate unless k is large (Lopez-Lopez et al., 2014).

The last two items are not provided when comparing "rma.mv" models.

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- López-López, J. A., Marín-Martínez, F., Sánchez-Meca, J., Van den Noortgate, W., & Viechtbauer, W. (2014). Estimation of the predictive power of the model in mixed-effects meta-regression: A simulation study. *British Journal of Mathematical and Statistical Psychology*, **67**, 30–48.
- Raudenbush, S. W. (2009). Analyzing effect sizes: Random effects models. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (2nd ed., pp. 295–315). New York: Russell Sage Foundation.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[anova.rma](#)

print.confint.rma *Print Methods for 'confint.rma' and 'list.confint.rma' Objects*

Description

Print methods for objects of class "confint.rma" and "list.confint.rma".

Usage

```
## S3 method for class 'confint.rma'  
print(x, digits=x$digits, ...)  
## S3 method for class 'list.confint.rma'  
print(x, digits=x$digits, ...)
```

Arguments

x	an object of class "confint.rma" or "list.confint.rma".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
...	other arguments.

Details

The output includes:

- estimate of the model coefficient or variance/correlation parameter
- lower bound of the confidence interval
- upper bound of the confidence interval

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[confint.rma.uni](#), [confint.rma.mv](#)

print.escalc

Print and Summary Methods for 'escalc' Objects

Description

Print and summary methods for objects of class "escalc".

Usage

```
## S3 method for class 'escalc'
print(x, digits=attr(x,"digits"), ...)

## S3 method for class 'escalc'
summary(object, out.names=c("sei","zi","ci.lb","ci.ub"), var.names,
        H0=0, append=TRUE, replace=TRUE, level=95, clim, digits, transf, ...)
```

Arguments

x	an object of class "escalc".
object	an object of class "escalc".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
out.names	character string with four elements, specifying the variable names for the standard errors, test statistics, and lower/upper confidence interval bounds.
var.names	character string with two elements, specifying the variable names for the observed outcomes and the sampling variances (the default is to take the value from the object if possible).
H0	numeric value specifying the value of the outcome under the null hypothesis.
append	logical indicating whether the data frame specified via the object argument should be returned together with the additional variables that are calculated by the summary function (the default is TRUE).
replace	logical indicating whether existing values for sei, zi, ci.lb, and ci.ub in the data frame should be replaced or not. Only relevant when the data frame already contains these variables. If replace=TRUE (the default), all of the existing values will be overwritten. If replace=FALSE, only NA values will be replaced.
level	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
clim	limits for the confidence intervals. If unspecified, no limits are used.
transf	optional argument specifying the name of a function that should be used to transform the observed outcomes and interval bounds (e.g., transf=exp; see also transf). If unspecified, no transformation is used. Any additional arguments needed for the function specified here can be passed via . . .
. . .	other arguments.

Value

The `print.escalc` function formats and prints the data frame, so that the observed outcomes and sampling variances are rounded (to the number of digits specified).

The `summary.escalc` function creates an object that is a data frame containing the original data (if `append=TRUE`) and the following components:

<code>yi</code>	observed outcomes or effect size estimates (transformed if <code>transf</code> is specified).
<code>vi</code>	corresponding (estimated) sampling variances.
<code>sei</code>	standard errors of the observed outcomes or effect size estimates.
<code>zi</code>	test statistics for testing $H_0 : \theta_i = H_0$ (i.e., $(y_i - H_0) / sei$).
<code>ci.lb</code>	lower confidence interval bounds (transformed if <code>transf</code> is specified).
<code>ci.ub</code>	upper confidence interval bounds (transformed if <code>transf</code> is specified).

Note that the actual variable names above depend on the `out.names` (and `var.names`) arguments. If the data frame already contains variables with names as specified by the `out.names` argument, the values for these variables will be overwritten when `replace=TRUE` (which is the default). By setting `replace=FALSE`, only values that are NA will be replaced.

The `print.escalc` function again formats and prints the data frame, rounding the added variables to the number of digits specified.

Note

If some transformation function has been specified for the `transf` argument, then `yi`, `ci.lb`, and `ci.ub` will be transformed accordingly. However, `vi` and `sei` then still reflect the sampling variances and standard errors of the untransformed values.

The `summary.escalc` function computes level % Wald-type confidence intervals, which may or may not be the most accurate method for computing confidence intervals for the chosen outcome or effect size measure.

If the outcome measure used is bounded (e.g., correlations are bounded between -1 and 1, proportions are bounded between 0 and 1), one can use the `clim` argument to enforce those limits (confidence intervals cannot exceed those bounds then).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[escalc](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
dat

### apply summary function
summary(dat)
summary(dat, transf=exp)
```

print.fsn

Print Method for 'fsn' Objects

Description

Print method for objects of class "fsn".

Usage

```
## S3 method for class 'fsn'
print(x, digits=x$digits, ...)
```

Arguments

x	an object of class "fsn".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
...	other arguments.

Details

The output shows the results from the fail-safe N calculation.

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[fsn](#)

print.gosh.rma *Print Method for 'gosh.rma' Objects*

Description

Print method for objects of class "gosh.rma".

Usage

```
## S3 method for class 'gosh.rma'  
print(x, digits=x$digits, ...)
```

Arguments

x	an object of class "gosh.rma".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
...	other arguments.

Details

The output shows how many model fits were attempted, how many succeeded, and summary statistics (i.e., the mean and the five-number summary) for the various measures of (residual) heterogeneity and the model coefficient(s) computed across all of the subsets.

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[gosh.rma](#)

print.hc.rma.uni *Print Method for 'hc.rma.uni' Objects*

Description

Print method for objects of class "hc.rma.uni".

Usage

```
## S3 method for class 'hc.rma.uni'  
print(x, digits=x$digits, ...)
```

Arguments

x	an object of class "hc.rma.uni".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
...	other arguments.

Details

The output is a data frame with two rows, the first (labeled rma) corresponding to the results based on the usual estimation method, the second (labeled hc) corresponding to the results based on the method by Henmi and Copas (2010). The data frame includes the following variables:

- the method used to estimate τ^2 (always DL for hc)
- the estimated amount of heterogeneity
- the estimated average true effect
- the corresponding standard error (NA when transf argument has been used)
- the lower and upper confidence interval bounds

Value

The function returns the data frame invisibly.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[hc.rma.uni](#)

print.list.rma *Print method for 'list.rma' Objects*

Description

Print method for objects of class "list.rma".

Usage

```
## S3 method for class 'list.rma'  
print(x, digits=x$digits, ...)
```

Arguments

x	an object of class "list.rma".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
...	other arguments.

Value

See the documentation of the function that creates the "list.rma" object for details on what is printed. Regardless of what is printed, a data frame with the results is also returned invisibly.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

print.permutest.rma.uni
Print Method for 'permutest.rma.uni' Objects

Description

Print method for objects of class "permutest.rma.uni".

Usage

```
## S3 method for class 'permutest.rma.uni'  
print(x, digits=x$digits, signif.stars=getOption("show.signif.stars"),  
      signif.legend=signif.stars, ...)
```

Arguments

<code>x</code>	an object of class "permutest.rma.uni".
<code>digits</code>	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
<code>signif.stars</code>	logical indicating whether p-values should be encoded visually with 'significance stars'. Defaults to the <code>show.signif.stars</code> slot of options .
<code>signif.legend</code>	logical indicating whether the legend for the 'significance stars' should be printed. Defaults to the value for <code>signif.stars</code> .
<code>...</code>	other arguments.

Details

The output includes:

- the results of the omnibus test of the coefficients in the model. Suppressed if the model includes only one coefficient (e.g., only an intercept, like in the fixed- and random-effects model). The p-value based on the permutation test is indicated by `p-val*`.
- a table with the estimated coefficients, corresponding standard errors, test statistics, p-values, and confidence interval bounds. The p-values based on the permutation test are indicated by `pval*`. When permutation-based CIs have been obtained, then the CI bounds are indicated with `ci.lb*` and `ci.ub*`.

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[permutest.rma.uni](#)

print.ranktest.rma *Print Method for 'ranktest.rma' Objects*

Description

Print method for objects of class "ranktest.rma".

Usage

```
## S3 method for class 'ranktest.rma'  
print(x, digits=x$digits, ...)
```

Arguments

x	an object of class "ranktest.rma".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
...	other arguments.

Details

The output includes:

- the estimated value of Kendall's tau rank correlation coefficient
- the corresponding p-value for the test that the true tau is equal to zero

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[ranktest.rma](#)

print.regtest.rma *Print Method for 'regtest.rma' Objects*

Description

Print method for objects of class "regtest.rma".

Usage

```
## S3 method for class 'regtest.rma'  
print(x, digits=x$digits, ret.fit=x$ret.fit, ...)
```

Arguments

x	an object of class "regtest.rma".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
ret.fit	logical indicating whether the full results from the fitted model should also be returned (if unspecified, the default is to take the value from the object).
...	other arguments.

Details

The output includes:

- the model used for the regression test
- the predictor used for the regression test
- the results from the fitted model (only when `ret.fit=TRUE`)
- the value of the test statistic for the test that the predictor is unrelated to the outcomes
- the degrees of freedom of the test statistic (only if the test statistic follows a t-distribution)
- the p-value for the test statistic

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[regtest.rma](#)

print.rma

Print and Summary Methods for 'rma' Objects

Description

Print and summary methods for objects of class "rma.uni", "rma.mh", "rma.peto", "rma.glmm", and "rma.glmm".

Usage

```
## S3 method for class 'rma.uni'
print(x, digits, showfit=FALSE, signif.stars=getOption("show.signif.stars"),
      signif.legend=signif.stars, ...)

## S3 method for class 'rma.mh'
print(x, digits, showfit=FALSE, ...)

## S3 method for class 'rma.peto'
print(x, digits, showfit=FALSE, ...)

## S3 method for class 'rma.glmm'
print(x, digits, showfit=FALSE, signif.stars=getOption("show.signif.stars"),
      signif.legend=signif.stars, ...)

## S3 method for class 'rma.mv'
print(x, digits, showfit=FALSE, signif.stars=getOption("show.signif.stars"),
      signif.legend=signif.stars, ...)

## S3 method for class 'rma'
summary(object, digits, showfit=TRUE, ...)

## S3 method for class 'summary.rma'
print(x, digits, showfit=TRUE, signif.stars=getOption("show.signif.stars"),
      signif.legend=signif.stars, ...)
```

Arguments

x	an object of class "rma.uni", "rma.mh", "rma.peto", "rma.glmm", "rma.mv", or "summary.rma" (for print).
object	an object of class "rma" (for summary).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
showfit	logical indicating whether the fit statistics and information criteria should be printed (the default is FALSE for print and TRUE for summary).

signif.stars	logical indicating whether p-values should be encoded visually with ‘significance stars’. Defaults to the show.signif.stars slot of <code>options</code> .
signif.legend	logical indicating whether the legend for the ‘significance stars’ should be printed. Defaults to the value for signif.stars.
...	other arguments.

Details

The output includes:

- the log-likelihood, deviance, AIC, BIC, and AICc value (when setting `showfit=TRUE` or by default for summary).
- for objects of class `"rma.uni"` and `"rma.glm"`, the amount of (residual) heterogeneity in the random/mixed-effects model (i.e., the estimate of τ^2 and its square root). Suppressed for fixed-effects models. The (asymptotic) standard error of the estimate of τ^2 is also provided (where possible).
- for objects of `"rma.mv"`, a table providing information about the variance components and correlations in the model. For σ^2 components, the estimate and its square root are provided, in addition to the number of values/levels, whether the component was fixed or estimated, and the name of the grouping variable/factor. If the `R` argument was used to specify known correlation matrices, this is also indicated. For models with an `~ inner | outer` formula term, the name of the inner and outer grouping variable/factor are given and the number of values/levels of these variables/factors. In addition, for each τ^2 component, the estimate and its square root are provided, the number of effects or outcomes observed at each level of the inner grouping variable/factor (only for `struct="HCS"`, `struct="DIAG"`, `struct="HAR"`, and `struct="UN"`), and whether the component was fixed or estimated. Finally, either the estimate of ρ (for `struct="CS"`, `struct="AR"`, `struct="CAR"`, `struct="HAR"`, or `struct="HCS"`) or the entire estimated correlation matrix (for `struct="UN"`) between the levels of the inner grouping variable/factor is provided, again with information whether a particular correlation was fixed or estimated, and how often each combination of levels of the inner grouping variable/factor was observed across the levels of the outer grouping variable/factor. If there is a second `~ inner | outer` formula term, the same information as described above will be provided, but now for the γ^2 and ϕ components.
- the I^2 statistic, which estimates (in percent) how much of the total variability in the effect size estimates (which is composed of heterogeneity plus sampling variability) can be attributed to heterogeneity among the true effects. For a meta-regression model, I^2 estimates how much of the unaccounted variability (which is composed of residual heterogeneity plus sampling variability) can be attributed to residual heterogeneity. See ‘Note’ for how I^2 is computed.
- the H^2 statistic, which estimates the ratio of the total amount of variability in the effect size estimates to the amount of sampling variability. For a meta-regression model, H^2 estimates the ratio of the unaccounted variability in the effect size estimates to the amount of sampling variability. See ‘Note’ for how H^2 is computed.
- for objects of class `"rma.uni"`, the R^2 statistic, which estimates the amount of heterogeneity accounted for by the moderators included in the model and can be regarded as a pseudo R^2 statistic (Raudenbush, 2009). Only provided when fitting a mixed-effects models (i.e., for models including moderators). This is suppressed (and set to `NULL`) for models without moderators, fixed-effects models, or if the model does not contain an intercept. See ‘Note’ for how R^2 is computed.

- for objects of class "rma.glm", the amount of study level variability (only when using a model that models study level differences as a random effect).
- the results of the test for (residual) heterogeneity. This is the usual Q -test for heterogeneity when not including moderators in the model and the Q_E -test for residual heterogeneity when moderators are included. For objects of class "rma.glm", the results from a Wald-type test and a likelihood ratio test are provided (see `rma.glm` for more details).
- the results of the omnibus (Wald-type) test of the coefficients in the model (the indices of the coefficients tested are also indicated). Suppressed if the model includes only one coefficient (e.g., only an intercept, like in the fixed- and random-effects model).
- a table with the estimated coefficients, corresponding standard errors, test statistics, p-values, and confidence interval bounds.
- the Cochran-Mantel-Haenszel test and Tarone's test for heterogeneity (only when analyzing odds ratios using the Mantel-Haenszel method, i.e., "rma.mh").

Value

The print functions do not return an object. The summary function returns the object passed to it (with additional class "summary.rma").

Note

For random-effects models, the I^2 statistic is computed with

$$I^2 = 100\% \times \frac{\hat{\tau}^2}{\hat{\tau}^2 + s^2},$$

where $\hat{\tau}^2$ is the estimated value of τ^2 and

$$s^2 = \frac{(k-1) \sum w_i}{(\sum w_i)^2 - \sum w_i^2},$$

where w_i is the inverse of the sampling variance of the i th study (s^2 is equation 9 in Higgins & Thompson, 2002, and can be regarded as the 'typical' within-study variance of the observed effect sizes or outcomes). The H^2 statistic is computed with

$$H^2 = \frac{\hat{\tau}^2 + s^2}{s^2}.$$

Analogous equations are used for mixed-effects models.

Therefore, depending on the estimator of τ^2 used, the values of I^2 and H^2 will change. For random-effects models, I^2 and H^2 are typically computed in practice with $I^2 = (Q - (k - 1))/Q$ and $H^2 = Q/(k - 1)$, where Q denotes the statistic for the test of heterogeneity and k the number of studies (i.e., observed effects or outcomes) included in the meta-analysis. The equations used in the metafor package to compute these statistics are more general and have the advantage that the values of I^2 and H^2 will be consistent with the estimated value of τ^2 (i.e., if $\hat{\tau}^2 = 0$, then $I^2 = 0$ and $H^2 = 1$ and if $\hat{\tau}^2 > 0$, then $I^2 > 0$ and $H^2 > 1$).

The two definitions of I^2 and H^2 actually coincide when using the DerSimonian-Laird estimator of τ^2 (i.e., the commonly used equations are actually special cases of the more general definitions given above). Therefore, if you prefer the more conventional definitions of these statistics,

use `method="DL"` when fitting the random/mixed-effects model with the `rma.uni` function. The conventional definitions are also automatically used when fitting fixed-effects models.

The pseudo R^2 statistic (Raudenbush, 2009) is computed with

$$R^2 = \frac{\hat{\tau}_{RE}^2 - \hat{\tau}_{ME}^2}{\hat{\tau}_{RE}^2},$$

where $\hat{\tau}_{RE}^2$ denotes the estimated value of τ^2 based on the random-effects model (i.e., the total amount of heterogeneity) and $\hat{\tau}_{ME}^2$ denotes the estimated value of τ^2 based on the mixed-effects model (i.e., the residual amount of heterogeneity). It can happen that $\hat{\tau}_{RE}^2 < \hat{\tau}_{ME}^2$, in which case R^2 is set to zero (also if $\hat{\tau}_{RE}^2 = 0$). Again, the value of R^2 will change depending on the estimator of τ^2 used. Also note that this statistic is only computed when the mixed-effects model includes an intercept (so that the random-effects model is clearly nested within the mixed-effects model). You can also use the `anova.rma` function to compute R^2 for any two models that are known to be nested. Note that the pseudo R^2 statistic may not be very accurate unless k is large (Lopez-Lopez et al., 2014).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

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- Raudenbush, S. W. (2009). Analyzing effect sizes: Random effects models. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (2nd ed., pp. 295–315). New York: Russell Sage Foundation.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#)

print.robust.rma

Print Method for 'robust.rma' Objects

Description

Print method for objects of class "robust.rma".

Usage

```
## S3 method for class 'robust.rma'  
print(x, digits=x$digits, signif.stars=getOption("show.signif.stars"),  
      signif.legend=signif.stars, ...)
```

Arguments

x	an object of class "robust.rma".
digits	integer specifying the number of decimal places to which the printed results should be rounded (the default is to take the value from the object).
signif.stars	logical indicating whether p-values should be encoded visually with 'significance stars'. Defaults to the show.signif.stars slot of options .
signif.legend	logical indicating whether the legend for the 'significance stars' should be printed. Defaults to the value for signif.stars.
...	other arguments.

Details

The output includes:

- information on the number of outcomes, number of clusters, and the number of outcomes per cluster.
- the results of the omnibus (Wald-type) test of the coefficients in the model (the indices of the coefficients tested are also indicated). Suppressed if the model includes only one coefficient (e.g., only an intercept, like in the fixed- and random-effects model).
- a table with the estimated coefficients, corresponding standard errors, test statistics, p-values, and confidence interval bounds.

Value

The function does not return an object.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[robust.rma.uni](#), [robust.rma.mv](#)

profile.rma.uni *Profile Plots for 'rma' Objects*

Description

Function to profile the (restricted) log-likelihood for objects of class "rma.uni" and "rma.mv".

Usage

```
## S3 method for class 'rma.uni'
profile(fitted, xlim, ylim, steps=20,
        progbar=TRUE, parallel="no", ncpus=1, cl=NULL,
        plot=TRUE, pch=19, cline=FALSE, ...)

## S3 method for class 'rma.mv'
profile(fitted, sigma2, tau2, rho, gamma2, phi,
        xlim, ylim, steps=20, lltol=1e-06, startmethod="init",
        progbar=TRUE, parallel="no", ncpus=1, cl=NULL,
        plot=TRUE, pch=19, cline=FALSE, ...)

## S3 method for class 'profile.rma'
print(x, ...)
## S3 method for class 'profile.rma'
plot(x, xlim, ylim, pch=19,
      xlab, ylab, main, cline=FALSE, ...)
```

Arguments

fitted	an object of class "rma.uni" or "rma.mv".
x	an object of class "profile.rma" (for plot and print).
sigma2	integer specifying for which σ^2 value the likelihood should be profiled (only relevant for "rma.mv" objects).
tau2	integer specifying for which τ^2 value the likelihood should be profiled (only relevant for "rma.mv" objects).
rho	integer specifying for which ρ value the likelihood should be profiled (only relevant for "rma.mv" objects).
gamma2	integer specifying for which γ^2 value the likelihood should be profiled (only relevant for "rma.mv" objects).
phi	integer specifying for which ϕ value the likelihood should be profiled (only relevant for "rma.mv" objects).
xlim	optional vector specifying the lower and upper limit of the parameter over which the profiling should be done. If unspecified, the function tries to set these limits automatically.
ylim	optional vector specifying the y-axis limits when plotting the profiled likelihood. If unspecified, the function tries to set these limits automatically.

steps	number of points between xlim[1] and xlim[2] (inclusive) for which the likelihood should be evaluated (the default is 20).
lltol	numerical tolerance used when comparing values of the profiled log-likelihood with the log-likelihood of the fitted model (the default is 1e-06).
startmethod	method for picking starting values for the optimization. Default is "init", which starts each model fit at the default initial values. The alternative is "prev", which starts at the estimates from the previous model fit (usually faster, but also less stable for ill-defined models).
progbar	logical indicating whether a progress bar should be shown (the default is TRUE). Ignored when using parallel processing.
parallel	character string indicating whether parallel processing should be used (the default is "no"). For parallel processing, set to either "snow" or "multicore". See 'Details'.
ncpus	integer specifying the number of processes to use in the parallel processing.
cl	optional snow cluster to use if parallel="snow". If not supplied, a cluster on the local machine is created for the duration of the call.
plot	logical indicating whether the profile plot should be drawn after profiling is finished (the default is TRUE).
pch	plotting symbol to use. By default, a filled circle is used. See points for other options.
cline	logical indicating whether a horizontal reference line should be added to the plot that indicates the log-likelihood value corresponding to the 95% profile confidence interval (the default is FALSE).
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.
ylab	title for the y-axis. If unspecified, the function tries to set an appropriate axis title.
main	title for the plot. If unspecified, the function tries to set an appropriate title.
...	other arguments.

Details

The function fixes a particular variance component or correlation parameter of the model and then computes the maximized (restricted) log-likelihood over the remaining parameters of the model. By doing this for a range of values for the parameter that was fixed, a profile of the (restricted) log-likelihood is constructed.

For objects of class "rma.uni" obtained with the [rma.uni](#) function, the function profiles over parameter τ^2 . If the model was fitted with `method="ML"` or `method="REML"`, the profiled (restricted) log-likelihood should be maximized at the ML/REML estimate of τ^2 .

For objects of class "rma.mv" obtained with the [rma.mv](#) function, profiling is done by default over all (non-fixed) variance and correlation components of the model. Alternatively, one can use the `sigma2`, `tau2`, `rho`, `gamma2`, or `phi` arguments to specify over which parameter the profiling should be done. Only one of these arguments can be used at a time. A single integer is used to specify the number of the parameter. Each profile plot should show a peak at the corresponding ML/REML

estimate (the function checks whether any of the profiled log-likelihood values is larger than the log-likelihood of the fitted model, using a numerical tolerance of `lltol`; if so, a warning is issued as this might indicate that the optimizer did not identify the actual ML/REML estimates). If the profiled likelihood is flat (over the entire parameter space or large portions of it), then this suggests that at least some of the parameters of the model are not identifiable (and the parameter estimates obtained are to some extent arbitrary).

Profiling requires repeatedly refitting the same model, which can be slow when k is large and/or the model is complex (the latter especially applies to `"rma.mv"` objects). On machines with multiple cores, one can usually speed things up by delegating the model fitting to separate worker processes, that is, by setting `parallel="snow"` or `parallel="multicore"` and `ncpus` to some value larger than 1. Parallel processing makes use of the `parallel` package, using the `makePSOCKcluster` and `parLapply` functions when `parallel="snow"` or using `mclapply` when `parallel="multicore"` (the latter only works on Unix/Linux-alikes). With `parallel::detectCores()`, one can check on the number of available cores on the local machine. Note that argument `startmethod` is ignored when using parallel processing and no progress bar will be shown.

Value

An object of class `"profile.rma"`. The object is a list (or list of lists) containing the following components:

<code>sigma2</code>	values of σ^2 over which the likelihood was profiled (only when profiling was actually done over σ^2).
<code>tau2</code>	values of τ^2 over which the likelihood was profiled (only when profiling was actually done over τ^2).
<code>rho</code>	values of ρ over which the likelihood was profiled (only when profiling was actually done over ρ).
<code>gamma2</code>	values of γ^2 over which the likelihood was profiled (only when profiling was actually done over γ^2).
<code>phi</code>	values of ϕ over which the likelihood was profiled (only when profiling was actually done over ϕ).
<code>ll</code>	(restricted) log-likelihood at the corresponding parameter value.
<code>beta</code>	a matrix with the estimated model coefficients at the corresponding parameter value.
<code>ci.lb</code>	a matrix with the lower confidence interval bounds for the model coefficients at the corresponding parameter value.
<code>ci.ub</code>	a matrix with the upper confidence interval bounds for the model coefficients at the corresponding parameter value.
<code>...</code>	some additional elements/values.

Note that the list is returned invisibly.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mv](#)

Examples

```
### calculate log odds ratios and corresponding sampling variances
dat <- escalc(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model using rma.uni()
res <- rma(yi, vi, data=dat)

### profile over tau^2
profile(res, progbar=FALSE)

### change data into long format
dat.long <- to.long(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### set levels of group variable ("exp" = experimental/vaccinated; "con" = control/non-vaccinated)
levels(dat.long$group) <- c("exp", "con")

### set "con" to reference level
dat.long$group <- relevel(dat.long$group, ref="con")

### calculate log odds and corresponding sampling variances
dat.long <- escalc(measure="PLO", xi=out1, mi=out2, data=dat.long)

### bivariate random-effects model using rma.mv()
res <- rma.mv(yi, vi, mods = ~ group, random = ~ group | study, struct="UN", data=dat.long)
res

### profile over tau^2_1, tau^2_2, and rho
### note: for rho, adjust region over which profiling is done ('zoom in' on area around estimate)
## Not run:
par(mfrow=c(3,1))
profile(res, tau2=1)
profile(res, tau2=2)
profile(res, rho=1, xlim=c(.90, .98))
## End(Not run)
```

Description

Function to create normal QQ plots for objects of class "rma.uni", "rma.mh", and "rma.peto".

Usage

```
## S3 method for class 'rma.uni'
qqnorm(y, type="rstandard", pch=19, envelope=TRUE,
        level=y$level, bonferroni=FALSE, reps=1000, smooth=TRUE, bass=0,
        label=FALSE, offset=0.3, pos=13, lty, ...)
## S3 method for class 'rma.mh'
qqnorm(y, type="rstandard", pch=19, label=FALSE, offset=0.3, pos=13, ...)
## S3 method for class 'rma.peto'
qqnorm(y, type="rstandard", pch=19, label=FALSE, offset=0.3, pos=13, ...)
## S3 method for class 'rma.glmm'
qqnorm(y, ...)
## S3 method for class 'rma.mv'
qqnorm(y, ...)
```

Arguments

<code>y</code>	an object of class "rma.uni", "rma.mh", or "rma.peto". The method is not yet implemented for objects of class "rma.glmm" or "rma.mv".
<code>type</code>	either "rstandard" (default) or "rstudent" indicating whether standardized residuals or studentized deleted residuals should be used in creating the plot. See 'Details'.
<code>pch</code>	plotting symbol to use for the observed effect sizes or outcomes. By default, a solid circle is used. See points for other options.
<code>envelope</code>	logical indicating whether a pseudo confidence envelope should be simulated and added to the plot (the default is TRUE). Only for objects of class "rma.uni". See 'Details'.
<code>level</code>	numerical value between 0 and 100 specifying the level of the pseudo confidence envelope (the default is to take the value from the object).
<code>bonferroni</code>	logical indicating whether the bounds of the envelope should be Bonferroni corrected.
<code>reps</code>	numerical value indicating the number of iterations to use for simulating the pseudo confidence envelope (the default is 1000).
<code>smooth</code>	logical indicating whether the results from the simulation should be smoothed (the default is TRUE).
<code>bass</code>	numerical value that controls the degree of smoothing (the default is 0).
<code>label</code>	argument to control the labeling of the points (the default is FALSE). See 'Details'.
<code>offset</code>	argument to control the distance between the points and the corresponding labels.
<code>pos</code>	argument to control the position of the labels.
<code>lty</code>	optional character string specifying the line type for the diagonal line and the pseudo confidence envelope (if unspecified, the function sets this to c("solid", "dotted") by default).
<code>...</code>	other arguments.

Details

The plot shows the theoretical quantiles of a normal distribution on the horizontal axis against the observed quantiles for either the standardized residuals (type="rstandard", the default) or the externally standardized residuals (type="rstudent") on the vertical axis (see [residuals.rma](#) for details on the definition of these residual types).

For reference, a line is added to the plot with slope of 1, going through the (0,0) point.

For objects of class "rma.uni", it is also possible to add a pseudo confidence envelope to the plot. The envelope is created based on the quantiles of sets of pseudo residuals simulated from the given model (for details, see Cook & Weisberg, 1982). The number of sets simulated can be controlled with the reps argument. When smooth=TRUE, the simulated bounds are smoothed with Friedman's SuperSmother (see [supsmu](#)). The bass argument can be set to a number between 0 and 10, with higher numbers indicating increasing smoothness. If bonferroni=TRUE, the envelope bounds are Bonferroni corrected, so that the envelope can be regarded as a confidence region for all k residuals simultaneously. The default however is bonferroni=FALSE, which makes the plot more sensitive to deviations from normality.

With the label argument, one can control whether points in the plot will be labeled (e.g., to identify outliers). If label="all" (or label=TRUE), all points in the plot will be labeled. If label="out", points falling outside of the confidence envelope will be labeled (only available for objects of class "rma.uni"). Finally, one can also set this argument to a numeric value (between 1 and k), indicating how many of the most extreme points should be labeled (for example, with label=1 only the most extreme point would be labeled, while with label=3, the most extreme, and the second and third most extreme points would be labeled). With the offset argument, the distance between the labels and the corresponding points can be controlled. The pos argument is the position specifier for the labels (1, 2, 3, and 4, respectively indicate positions below, to the left of, above, and to the right of the points; 13 places the labels below the points for points that fall below the reference line and above otherwise; 24 places the labels to the left of the points for points that fall above the reference line and to the right otherwise).

Value

A list with components:

- x the x coordinates of the points that were plotted.
- y the y coordinates of the points that were plotted.

Note that the list is returned invisibly.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Cook, R. D., & Weisberg, S. (1982). *Residuals and influence in regression*. London: Chapman and Hall.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

Wang, M. C., & Bushman, B. J. (1998). Using the normal quantile plot to explore meta-analytic data sets. *Psychological Methods*, **3**, 46–54.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#)

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
qqnorm(res)

### mixed-effects model with absolute latitude as a moderator
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, mods = ~ ablat,
           data=dat.bcg)
qqnorm(res)
```

radial

Radial (Galbraith) Plots for 'rma' Objects

Description

Function to create radial (also called Galbraith) plots for objects of class "rma".

Usage

```
radial(x, ...)
galbraith(x, ...)

## S3 method for class 'rma'
radial(x, center=FALSE, xlim, zlim, xlab, zlab,
       atz, aty, steps=7, level=x$level, digits=2, back="lightgray",
       transf, targ, pch=19, arc.res=100, cex, ...)
```

Arguments

x	an object of class "rma".
center	logical to indicate whether the plot should be centered horizontally at the model estimate (the default is FALSE).
xlim	x-axis limits. If unspecified, the function tries to set the x-axis limits to some sensible values.
zlim	z-axis limits. If unspecified, the function tries to set the z-axis limits to some sensible values (note that the z-axis limits are the actual vertical limit of the plotting region).
xlab	title for the x-axis. If unspecified, the function tries to set an appropriate axis title.

zlab	title for the z-axis. If unspecified, the function tries to set an appropriate axis title.
atz	position for the z-axis tick marks and labels. If unspecified, these values are set by the function.
aty	position for the y-axis tick marks and labels. If unspecified, these values are set by the function.
steps	the number of tick marks for the y-axis (the default is 7). Ignored when argument aty is used.
level	numerical value between 0 and 100 specifying the level of the z-axis error region (the default is to take the value from the object).
digits	integer specifying the number of decimal places to which the tick mark labels of the y-axis should be rounded (the default is 2).
back	color of the z-axis error region. Set to NA to suppress shading of the region.
transf	optional argument specifying the name of a function that should be used to transform the y-axis labels (e.g., transf=exp; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified via transf.
pch	plotting symbol. By default, a solid circle is used. See points for other options.
arc.res	integer specifying the number of line segments to use when drawing the y-axis and confidence interval arcs (the default is 100).
cex	optional character and symbol expansion factor. If unspecified, the function tries to set this to a sensible value.
...	other arguments.

Details

For a fixed-effects model, the plot shows the inverse of the standard errors on the horizontal axis against the individual observed effect sizes or outcomes standardized by their corresponding standard errors on the vertical axis. Since the vertical axis corresponds to standardized values, it is referred to as the z-axis within this function. On the right hand side of the plot, an arc is drawn (referred to as the y-axis within this function) corresponding to the individual observed effect sizes or outcomes. A line projected from (0,0) through a particular point within the plot onto this arc indicates the value of the individual observed effect size or outcome for that point.

For a random-effects model, the function uses $1/\sqrt{v_i + \tau^2}$ for the horizontal axis, where v_i is the sampling variance of the observed effect size or outcome and τ^2 is the amount of heterogeneity as estimated based on the model. For the z-axis, $\sqrt{v_i + \tau^2}$ is used to standardize the individual observed effect sizes or outcomes.

If the model contains moderators, the function returns an error.

Value

A data frame with components:

x	the x coordinates of the points that were plotted.
y	the y coordinates of the points that were plotted.

slab study labels of the points that were plotted.

Note that the data frame is returned invisibly.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Galbraith, R. F. (1988). Graphical display of estimates having differing standard errors. *Technometrics*, **30**, 271–281.

Galbraith, R. F. (1988). A note on graphical presentation of estimated odds ratios from several clinical trials. *Statistics in Medicine*, **7**, 889–894.

Galbraith, R. F. (1994). Some applications of radial plots. *Journal of the American Statistical Association*, **89**, 1232–1242.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#)

Examples

```
### meta-analysis of the log risk ratios using a fixed-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg, method="FE")
radial(res)
```

```
### line from (0,0) with slope equal to the log risk ratio from the 4th study
abline(a=0, b=-1.44155119, lty="dotted")
```

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
radial(res)
```

ranef

Best Linear Unbiased Predictions for 'rma.uni' and 'rma.mv' Objects

Description

The function calculates best linear unbiased predictions (BLUPs) of the random effects for objects of class "rma.uni" and "rma.mv". Corresponding standard errors and prediction interval bounds are also provided.

Usage

```
## S3 method for class 'rma.uni'
ranef(object, level, digits, transf, targs, ...)
## S3 method for class 'rma.mv'
ranef(object, level, digits, transf, targs, verbose=FALSE, ...)
```

Arguments

object	an object of class "rma.uni" or "rma.mv".
level	numerical value between 0 and 100 specifying the prediction interval level (if unspecified, the default is to take the value from the object).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
transf	optional argument specifying the name of a function that should be used to transform the predicted values and interval bounds (e.g., transf=exp; see also transf). If unspecified, no transformation is used.
targs	optional arguments needed by the function specified under transf.
verbose	logical indicating whether output should be generated on the progress of the computations (the default is FALSE).
...	other arguments.

Value

For objects of class "rma.uni", an object of class "list.rma". The object is a list containing the following components:

pred	predicted values.
se	corresponding standard errors.
pi.lb	lower bound of the prediction intervals.
pi.ub	upper bound of the prediction intervals.
...	some additional elements/values.

The "list.rma" object is formatted and printed with [print.list.rma](#).

For objects of class "rma.mv", a list of data frames with the same components as described above.

Note

For best linear unbiased predictions that combine the fitted values based on the fixed effects and the estimated contributions of the random effects, see [blup](#).

For predicted/fitted values that are based only on the fixed effects of the model, see [fitted.rma](#) and [predict.rma](#).

Fixed-effects models (with or without moderators) do not contain random study effects. The BLUPs for these models will therefore be 0.

When using the `transf` argument, the transformation is applied to the predicted values and the corresponding interval bounds. The standard errors are then set equal to NA and are omitted from the printed output.

The normal distribution is used to calculate the prediction intervals. When the model was fitted with the Knapp and Hartung (2003) method (i.e., `test="knha"` in the `rma.uni` function), then the t-distribution with $k - p$ degrees of freedom is used.

To be precise, it should be noted that the function actually calculates empirical BLUPs (eBLUPs), since the predicted values are a function of the estimated variance component(s).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Kacker, R. N., & Harville, D. A. (1981). Unbiasedness of two-stage estimation and prediction procedures for mixed linear models. *Communications in Statistics, Theory and Methods*, **10**, 1249–1261.
- Raudenbush, S. W., & Bryk, A. S. (1985). Empirical Bayes meta-analysis. *Journal of Educational Statistics*, **10**, 75–98.
- Robinson, G. K. (1991). That BLUP is a good thing: The estimation of random effects. *Statistical Science*, **6**, 15–32.
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- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [predict.rma](#), [fitted.rma](#), [blup.rma.uni](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### meta-analysis of the log risk ratios using a random-effects model
res <- rma(yi, vi, data=dat)

### BLUPs of the random effects
ranef(res)
```

`ranktest`*Rank Correlation Test for Funnel Plot Asymmetry*

Description

The function can be used to carry out the rank correlation test for funnel plot asymmetry.

Usage

```
ranktest(x, ...)  
  
## S3 method for class 'rma'  
ranktest(x, digits, ...)  
  
## Default S3 method:  
ranktest(x, vi, sei, subset, digits, ...)
```

Arguments

<code>x</code>	an object of class "rma" or a vector with the observed effect sizes or outcomes.
<code>vi</code>	vector with the corresponding sampling variances.
<code>sei</code>	vector with the corresponding standard errors.
<code>subset</code>	optional (logical or numeric) vector indicating the subset of studies that should be included in the test. Only relevant when passing a vector via <code>x</code> .
<code>digits</code>	integer specifying the number of decimal places to which the printed results should be rounded (the default is 4).
<code>...</code>	other arguments.

Details

The function carries out the rank correlation test as described by Begg and Mazumdar (1994). The test can be used to examine whether the observed outcomes and the corresponding sampling variances are correlated. A high correlation would indicate that the funnel plot is asymmetric, which may be a result of publication bias.

One can either pass an object of class "rma" to the function or a vector of observed effect sizes or outcomes (via `x`) and the corresponding sampling variances via `vi` (or the standard errors via `sei`).

Value

An object of class "ranktest.rma". The object is a list containing the following components:

<code>tau</code>	the estimated value of Kendall's tau rank correlation coefficient
<code>pval</code>	the corresponding p-value for the test that the true tau is equal to zero

The results are formatted and printed with the `print.ranktest.rma` function.

Note

The method does not depend on the model fitted. Therefore, regardless of the model passed to the function, the results of the rank test will always be the same. See [regtest](#) for tests of funnel plot asymmetry that are based on regression models and model dependent.

The function makes use of the [cor.test](#) function with `method="kendall"`. If possible, an exact p-value is provided; otherwise, a large-sample approximation is used.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Begg, C. B., & Mazumdar, M. (1994). Operating characteristics of a rank correlation test for publication bias. *Biometrics*, **50**, 1088–1101.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[regtest](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model
res <- rma(yi, vi, data=dat)

ranktest(res)
ranktest(dat$yi, dat$vi)
```

regtest

Regression Test for Funnel Plot Asymmetry

Description

The function can be used to carry out (various versions of) Egger's regression test for funnel plot asymmetry.

Usage

```
regtest(x, ...)

## S3 method for class 'rma'
regtest(x, model="rma", predictor="sei", ret.fit=FALSE, digits, ...)

## Default S3 method:
regtest(x, vi, sei, ni, subset, model="rma", predictor="sei", ret.fit=FALSE, digits, ...)
```

Arguments

<code>x</code>	an object of class "rma" or a vector with the observed effect sizes or outcomes.
<code>vi</code>	vector with the corresponding sampling variances.
<code>sei</code>	vector with the corresponding standard errors.
<code>ni</code>	vector with the corresponding sample sizes.
<code>subset</code>	optional (logical or numeric) vector indicating the subset of studies that should be included in the test. Only relevant when passing a vector via <code>x</code> .
<code>model</code>	either "rma" or "lm" to indicate the type of model to use for the regression test. See 'Details'.
<code>predictor</code>	either "sei" "vi", "ni", "ninv", "sqrtni", or "sqrtninv" to indicate the predictor to use for the regression test. See 'Details'.
<code>ret.fit</code>	logical indicating whether the full results from the fitted model should also be returned.
<code>digits</code>	integer specifying the number of decimal places to which the printed results should be rounded (the default is 4).
<code>...</code>	other arguments.

Details

Various tests for funnel plot asymmetry have been suggested in the literature, including the rank correlation test by Begg and Mazumdar (1994) and the regression test by Egger et al. (1997). Extensions, modifications, and further developments of the regression test are described (among others) by Macaskill, Walter, and Irwig (2001), Sterne and Egger (2005), Harbord, Egger, and Sterne (2006), Peters et al. (2006), Rücker et al. (2008), and Moreno et al. (2009). The various versions of the regression test differ in terms of the model (either a weighted regression model with a multiplicative dispersion term or a fixed/random/mixed-effects meta-regression model is used), in terms of the predictor variable that the observed outcomes are hypothesized to be related to when publication bias is present (suggested predictors include the standard error, the sampling variance, and the sample size – or transformations thereof), and in terms of the outcome measure used (e.g., for 2×2 table data, one has the choice between various outcome measures). The idea behind the various tests is the same though: If there is a relationship between the observed outcomes and the chosen predictor, then this usually implies asymmetry in the funnel plot, which in turn may be an indication of publication bias.

The `regtest.rma` function can be used to carry out various versions of the regression test. The model is chosen via the `model` argument, with `model="lm"` for weighted regression with a multiplicative dispersion term or `model="rma"` for the meta-analytic models. In the latter case, arguments such as `method`, `weighted`, and `test` used during the initial model fitting are also used for

the regression test. Therefore, if one wants to conduct the regression test with a random/mixed-effects model, one should first fit a random-effects model with the `rma` function and then use the `regtest.rma` function on the fitted model object.

The predictor is chosen via the `predictor` argument:

- `predictor="sei"` for the standard error,
- `predictor="vi"` for the sampling variance,
- `predictor="ni"` for the sample size,
- `predictor="ninv"` for the inverse of the sample size,
- `predictor="sqrtni"` for the square root transformed sample size, and
- `predictor="sqrtninv"` for the inverse of the square root transformed sample size.

For predictors based on the sample size, the object `x` obviously must contain the information about the sample sizes. This will automatically be the case when `measure` was *not* equal to "GEN" or the `ni` values were explicitly specified during the initial model fitting.

If the model passed to the `regtest.rma` function already included one or more moderators, then `regtest.rma` will add the chosen predictor to the moderator(s) already included in the model. This way, one can test for funnel plot asymmetry after accounting first for the influence of the moderator(s) already included.

One can also pass a vector of observed effect sizes or outcomes (via `x`) and the corresponding sampling variances via `vi` (or the standard errors via `sei`) directly to the function (in this case, the `regtest.default` function is used). When the predictor is the sample size or a transformation thereof, then `ni` needs to be specified here as well.

The outcome measure used for the regression test is simply determined by what `measure` was used in fitting the original model (or what values are passed to `regtest.default`).

Value

An object of class "regtest.rma". The object is a list containing the following components:

<code>model</code>	the model used for the regression test.
<code>predictor</code>	the predictor used for the regression test.
<code>zval</code>	the value of the test statistic.
<code>pval</code>	the corresponding p-value
<code>dfs</code>	the degrees of freedom of the test statistic (if the test is based on a t-distribution).
<code>fit</code>	the full results from the fitted model.

The results are formatted and printed with the `print.regtest.rma` function.

Note

The classical "Egger test" is obtained by setting `model="lm"` and `predictor="sei"`. For the random/mixed-effects version of the Egger test, one should first fit a random-effects model to the data and then set `model="rma"` and `predictor="sei"` when using the `regtest.rma` function. See Sterne and Egger (2005) for details on these two types of models/tests.

All of the tests do not directly test for publication bias, but for a relationship between the observed outcomes and the chosen predictor. If such a relationship is present, then this usually implies asymmetry in the funnel plot, which in turn may be an indication of publication bias. However, it is important to keep in mind that there can be other reasons besides publication bias that could lead to asymmetry in the funnel plot.

Author(s)

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See Also

[ranktest](#)

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### fit random-effects model
res <- rma(yi, vi, data=dat)

### classical Egger test
```

```

regtest(res, model="lm")

### random/mixed-effects version of the Egger test
regtest(res)

### same tests, but passing outcomes directly
regtest(dat$yi, dat$vi, model="lm")
regtest(dat$yi, dat$vi)

### examples using the sample size (or a transformation thereof) as predictor
regtest(res, model="lm", predictor="ni")
regtest(res, model="lm", predictor="ninv")
regtest(res, model="rma", predictor="ni")
regtest(res, model="rma", predictor="ninv")

### if dat$yi is computed with escalc(), sample size information is stored in attributes
dat$yi

### then this will work
regtest(dat$yi, dat$vi, predictor="ni")

### otherwise have to supply sample sizes manually
dat$ni <- with(dat, tpos + tneg + cpos + cneg)
regtest(dat$yi, dat$vi, dat$ni, predictor="ni")

### testing for asymmetry after accounting for the influence of a moderator
res <- rma(yi, vi, mods = ~ ablat, data=dat)
regtest(res, model="lm")
regtest(res)

```

replmiss

Replace Missing Values in a Vector

Description

Function to replace missing (NA) values in a vector.

Usage

```
replmiss(x, y)
```

Arguments

x	vector that may include one or more missing values.
y	either a scalar or a vector of the same length as x with the value(s) to replace missing values with.

Value

Vector x with the missing values replaced based on the scalar or vector y.

Author(s)

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Examples

```
x <- c(4,2,7,NA,1,NA,5)
x <- replmiss(x,0)
x

x <- c(4,2,7,NA,1,NA,5)
y <- c(2,3,6,5,8,1,2)
x <- replmiss(x,y)
x
```

 reporter

Dynamically Generated Analysis Reports for 'rma.uni' Objects

Description

The function dynamically generates analysis reports for objects of class "rma.uni".

Usage

```
reporter(x, ...)

## S3 method for class 'rma.uni'
reporter(x, dir, filename, format="html_document", open=TRUE,
         digits, forest, funnel, footnotes=FALSE, verbose=TRUE, ...)
```

Arguments

x	an object of class "rma.uni".
dir	optional character string specifying the directory for creating the report (by default, <code>tempdir</code> will be used).
filename	optional character string specifying the filename (without file extension) for the report (by default, the function sets a filename automatically).
format	output format for the report (either <code>html_document</code> , <code>pdf_document</code> , or <code>word_document</code>). Can be abbreviated. See 'Note'.
open	logical indicating whether the report should be opened after it has been generated (default is TRUE). See 'Note'.
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
forest	optional character string with arguments to be added to the call to <code>forest.rma</code> for generating the forest plot.

funnel	optional character string with arguments to be added to the call to <code>funnel.rma</code> for generating the funnel plot.
footnotes	logical indicating whether additional explanatory footnotes should be added to the report (default is FALSE).
verbose	logical indicating whether information on the progress of the report generation should be provided (default is TRUE).
...	other arguments.

Details

The function dynamically generates an analysis report based on the model object. The report includes information about the model that was fitted, the distribution of the observed outcomes, the estimate of the average outcome based on the fitted model, tests and statistics that are informative about potential (residual) heterogeneity in the outcomes, checks for outliers and/or influential studies, and tests for funnel plot asymmetry. A forest plot and a funnel plot are also provided.

Value

The function generates either a html, pdf, or docx file and returns (invisibly) the path to the generated document.

Note

Since the report is created based on an R markdown document that is generated by the function, the rmarkdown package (<https://cran.r-project.org/package=rmarkdown>) and pandoc (<http://pandoc.org>) must be installed.

To render the report into a pdf document (i.e., using `format="pdf_document"`) requires a LaTeX installation. If LaTeX is not already installed, you could try using the tinytex package (<https://yihui.name/tinytex/>) to install a lightweight LaTeX distribution based on TeX Live.

Once the report is generated, the function tries to open the output file (either a .html, .pdf, or .docx file) with an appropriate application (if `open=TRUE`). This will only work when an appropriate application for the file type is installed and associated with the extension.

If `filename` is unspecified, the default is to use `report`, followed by an underscore (i.e., `_`) and the name of the object passed to the function. Both the R markdown file (with extension `.rmd`) and the actual report (with extension `.html`, `.pdf`, or `.docx`) are named accordingly. To generate the report, the model object is also saved to a file (with the same filename as above, but with extension `.rdata`). Also, files `references.bib` and `apa.csl` are copied to the same directory (these files are needed to generate the references in APA format).

Since the report is put together based on predefined text blocks, the writing is not very elegant. Also, using personal pronouns ('I' or 'we') does not make sense for such a report, so a lot of passive voice is used.

The generated report provides an illustration of how the results of the model can be reported, but is not a substitute for a careful examination of the results.

Author(s)

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References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#)

Examples

```
### copy BCG vaccine data into 'dat'
dat <- dat.bcg

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat,
             slab=paste(author, ", ", ", ", year, sep=""))

### random-effects model
res <- rma(yi, vi, data=dat)

## Not run:
### generate pdf report
reporter(res)
## End(Not run)
```

residuals.rma

Residual Values based on 'rma' Objects

Description

The `residuals`, `rstandard`, and `rstudent` functions compute residuals, corresponding standard errors, and standardized residuals for models fitted with the [rma.uni](#), [rma.mh](#), [rma.peto](#), and [rma.mv](#) functions.

Usage

```
## S3 method for class 'rma'
residuals(object, type="response", ...)

## S3 method for class 'rma.uni'
rstandard(model, digits, type="marginal", ...)
## S3 method for class 'rma.mh'
rstandard(model, digits, ...)
## S3 method for class 'rma.peto'
rstandard(model, digits, ...)
## S3 method for class 'rma.mv'
rstandard(model, digits, cluster, ...)
```

```
## S3 method for class 'rma.uni'
rstudent(model, digits, progbar=FALSE, ...)
## S3 method for class 'rma.mh'
rstudent(model, digits, progbar=FALSE, ...)
## S3 method for class 'rma.peto'
rstudent(model, digits, progbar=FALSE, ...)
## S3 method for class 'rma.mv'
rstudent(model, digits, progbar=FALSE, cluster,
          reestimate=TRUE, parallel="no", ncpus=1, cl=NULL, ...)
```

Arguments

object	an object of class "rma" (for residuals).
type	the type of residuals which should be returned. For residuals, the alternatives are: "response" (default), "rstandard", "rstudent", and "pearson". For rstandard.rma.uni, the alternatives are: "marginal" (default) and "conditional". See 'Details'.
model	an object of class "rma" (for residuals) or an object of class "rma.uni", "rma.mh", "rma.peto", or "rma.mv" (for rstandard and rstudent).
cluster	optional vector specifying a clustering variable to use for computing cluster-level multivariate standardized residuals (only for "rma.mv" objects).
reestimate	logical indicating whether variance/correlation components should be re-estimated after deletion of the <i>i</i> th study/cluster when computing externally standardized residuals (the default is TRUE).
parallel	character string indicating whether parallel processing should be used (the default is "no"). For parallel processing, set to either "snow" or "multicore". See 'Details'.
ncpus	integer specifying the number of processes to use in the parallel processing.
cl	optional snow cluster to use if parallel="snow". If not supplied, a cluster on the local machine is created for the duration of the call.
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
progbar	logical indicating whether a progress bar should be shown (only for rstudent) (the default is FALSE).
...	other arguments.

Details

The observed residuals (obtained with residuals) are simply equal to the 'observed - fitted' values. These can be obtained with residuals(object) (using the default type="response").

Dividing the observed residuals by the model-implied standard errors of the observed effect sizes or outcomes yields Pearson (or semi-standardized) residuals. These can be obtained with residuals(object, type="pearson").

Dividing the observed residuals by their corresponding standard errors yields (internally) standardized residuals. These can be obtained with rstandard or residuals(object, type="rstandard").

The `rstudent` function (or `residuals(object, type="rstudent")`) calculates externally standardized residuals (also called standardized deleted residuals or (externally) studentized residuals). The externally standardized residual for the i th case is obtained by deleting the i th case from the dataset, fitting the model based on the remaining cases, calculating the predicted value for the i th case based on the fitted model, taking the difference between the observed and the predicted value for the i th case (which yields the deleted residual), and then standardizing the deleted residual based on its standard error.

If a particular study fits the model, its standardized residual follows (asymptotically) a standard normal distribution. A large standardized residual for a study therefore may suggest that the study does not fit the assumed model (i.e., it may be an outlier).

For "rma.uni" objects, `rstandard.rma.uni` also can compute conditional residuals (when `type="conditional"`), which are the deviations of the observed outcomes from the best linear unbiased predictions (BLUPs) of the study-specific true outcomes (see [blup.rma.uni](#)).

For "rma.mv" objects, one can specify a clustering variable (via the `cluster` argument). If specified, `rstandard` and `rstudent` also compute cluster-level multivariate (internally or externally) standardized residuals. If all outcomes within a cluster fit the model, then the multivariate standardized residual for the cluster follows (asymptotically) a chi-square distribution with k_i degrees of freedom (where k_i denotes the number of outcomes within the cluster).

See also [influence.rma.uni](#) and [influence.rma.mv](#) for other leave-one-out diagnostics that are useful for detecting influential cases in models fitted with the [rma.uni](#) and [rma.mv](#) functions.

Value

Either a vector with the residuals of the requested type (for `residuals`) or an object of class "list.rma", which is a list containing the following components:

<code>resid</code>	observed residuals (for <code>rstandard</code>) or deleted residuals (for <code>rstudent</code>).
<code>se</code>	corresponding standard errors.
<code>z</code>	standardized residuals (internally standardized for <code>rstandard</code> or externally standardized for <code>rstudent</code>).

When a clustering variable is specified for "rma.mv" objects, the returned object is a list with the first element (named `obs`) as described above and a second element (named `cluster` of class "list.rma" with:

<code>X2</code>	cluster-level multivariate standardized residuals.
<code>k</code>	number of outcomes within the clusters.

The "list.rma" object is formatted and printed with [print.list.rma](#).

Note

Right now, the externally standardized residuals (obtained with `rstudent`) are calculated by refitting the model k times (where k is the number of studies/clusters). Depending on how large k is, it may take a few moments to finish the calculations. For complex models fitted with [rma.mv](#), this can become computationally expensive.

On machines with multiple cores, one can usually speed things up by delegating the model fitting to separate worker processes, that is, by setting `parallel="snow"` or `parallel="multicore"`

and `ncpus` to some value larger than 1 (only for objects of class "rma.mv"). Parallel processing makes use of the `parallel` package, using the `makePSOCKcluster` and `parLapply` functions when `parallel="snow"` or using `mclapply` when `parallel="multicore"` (the latter only works on Unix/Linux-alikes). With `parallel::detectCores()`, one can check on the number of available cores on the local machine.

Alternatively (or in addition to using parallel processing), one can also set `reestimate=FALSE`, in which case any variance/correlation components in the model are not re-estimated after deleting the i th study/cluster from the dataset. Doing so only yields an approximation to the externally standardized residuals (and the cluster-level multivariate standardized residuals) that ignores the influence of the i th study/cluster on the variance/correlation components, but is considerably faster (and often yields similar results).

It may not be possible to fit the model after deletion of the i th study/cluster from the dataset. This will result in NA values for that study/cluster when calling `rstudent`.

Also, for "rma.mv" objects with a clustering variable specified, it may not be possible to compute the cluster-level multivariate standardized residual for a particular cluster (if the var-cov matrix of the residuals within a cluster is not of full rank). This will result in NA for that cluster.

For objects of class "rma.mh" and "rma.peto", `rstandard` actually computes Pearson (or semi-standardized) residuals.

Author(s)

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References

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- Viechtbauer, W., & Cheung, M. W.-L. (2010). Outlier and influence diagnostics for meta-analysis. *Research Synthesis Methods*, **1**, 112–125.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#), [influence.rma.uni](#), [influence.rma.mv](#)

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
rstudent(res)

### mixed-effects model with absolute latitude as a moderator
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, mods = ~ ablat,
          data=dat.bcg)
rstudent(res)
```


Description

Function to fit meta-analytic fixed- and random/mixed-effects models with or without moderators via generalized linear (mixed-effects) models. See below and the documentation of the [metafor-package](#) for more details on these models.

Usage

```
rma.glmm(ai, bi, ci, di, n1i, n2i, x1i, x2i, t1i, t2i, xi, mi, ti, ni,
         mods, measure, intercept=TRUE, data, slab, subset,
         add=1/2, to="only0", drop00=TRUE, vtype="LS",
         model="UM.FS", method="ML", test="z",
         level=95, digits, btt, nAGQ=7, verbose=FALSE, control, ...)
```

Arguments

ai	see below and the documentation of the escalc function for more details.
bi	see below and the documentation of the escalc function for more details.
ci	see below and the documentation of the escalc function for more details.
di	see below and the documentation of the escalc function for more details.
n1i	see below and the documentation of the escalc function for more details.
n2i	see below and the documentation of the escalc function for more details.
x1i	see below and the documentation of the escalc function for more details.
x2i	see below and the documentation of the escalc function for more details.
t1i	see below and the documentation of the escalc function for more details.
t2i	see below and the documentation of the escalc function for more details.
xi	see below and the documentation of the escalc function for more details.
mi	see below and the documentation of the escalc function for more details.
ti	see below and the documentation of the escalc function for more details.
ni	see below and the documentation of the escalc function for more details.
mods	optional argument to include one or more moderators in the model. A single moderator can be given as a vector of length k specifying the values of the moderator. Multiple moderators are specified by giving a matrix with k rows and as many columns as there are moderator variables. Alternatively, a model formula can be used to specify the model. See ‘Details’.
measure	character string indicating the outcome measure to use for the meta-analysis. Possible options are the odds ratio ("OR"), the incidence rate ratio ("IRR"), the logit transformed proportion ("PLO"), or the log transformed incidence rate ("IRLN").

intercept	logical indicating whether an intercept should be added to the model (the default is TRUE).
data	optional data frame containing the data supplied to the function.
slab	optional vector with labels for the k studies.
subset	optional (logical or numeric) vector indicating the subset of studies that should be used for the analysis.
add	non-negative number indicating the amount to add to zero cells, counts, or frequencies when calculating the observed outcomes of the individual studies. See below and the documentation of the <code>escalc</code> function for more details.
to	character string indicating when the values under add should be added (either "only0", "all", "if0all", or "none"). See below and the documentation of the <code>escalc</code> function for more details.
drop00	logical indicating whether studies with no cases/events (or only cases) in both groups should be dropped. See the documentation of the <code>escalc</code> function for more details.
vtype	character string indicating the type of sampling variances to calculate when calculating the observed outcomes. See the documentation of the <code>escalc</code> function for more details.
model	character string specifying the general model type to use for the analysis (either "UM.FS" (the default), "UM.RS", "CM.EL", or "CM.AL"). See 'Details'.
method	character string specifying whether a fixed- or a random/mixed-effects model should be fitted. A fixed-effects model (with or without moderators) is fitted when using <code>method="FE"</code> . Random/mixed-effects models are fitted by setting <code>method="ML"</code> (the default). See 'Details'.
test	character string specifying how test statistics and confidence intervals for the fixed effects should be computed. By default (<code>test="z"</code>), Wald-type tests and CIs are obtained, which are based on a standard normal distribution. When <code>test="t"</code> , a t-distribution is used instead. See 'Details'.
level	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is 4).
btt	optional vector of indices specifying which coefficients to include in the omnibus test of moderators. Can also be a string to grep for. See 'Details'.
nAGQ	positive integer specifying the number of points per axis for evaluating the adaptive Gauss-Hermite approximation to the log-likelihood. The default is 7. Setting this to 1 corresponds to the Laplacian approximation. See 'Note'.
verbose	logical indicating whether output should be generated on the progress of the model fitting (the default is FALSE). Can also be an integer. Values > 1 generate more verbose output. See 'Note'.
control	optional list of control values for the estimation algorithms. If unspecified, default values are defined inside the function. See 'Note'.
...	additional arguments.

Details

Specifying the Data

The function can be used in conjunction with the following effect size or outcome measures:

- `measure="OR"` for odds ratios (analyzed in log units)
- `measure="IRR"` for incidence rate ratios (analyzed in log units)
- `measure="PLO"` for logit transformed proportions (i.e., log odds)
- `measure="IRLN"` for log transformed incidence rates.

The `escalc` function describes the data/arguments that should be specified/used for these measures.

Specifying the Model

A variety of model types are available when analyzing 2×2 table data (i.e., when `measure="OR"`) or two-group event count data (i.e., when `measure="IRR"`):

- `model="UM.FS"` for an unconditional generalized linear mixed-effects model with fixed study effects
- `model="UM.RS"` for an unconditional generalized linear mixed-effects model with random study effects
- `model="CM.AL"` for a conditional generalized linear mixed-effects model (approximate likelihood)
- `model="CM.EL"` for a conditional generalized linear mixed-effects model (exact likelihood).

For `measure="OR"`, models `"UM.FS"` and `"UM.RS"` are essentially (mixed-effects) logistic regression models, while for `measure="IRR"`, these models are (mixed-effects) Poisson regression models. A choice must be made on how to model study level variability (i.e., differences in outcomes across studies irrespective of group membership). One can choose between using fixed study effects (which means that k dummy variables are added to the model) or random study effects (which means that random effects corresponding to the levels of the study factor are added to the model).

The conditional model (`model="CM.EL"`) avoids having to model study level variability by conditioning on the total numbers of cases/events in each study. For `measure="OR"`, this leads to a non-central hypergeometric distribution for the data within each study and the corresponding model is then a (mixed-effects) conditional logistic model. Fitting this model can be difficult and computationally expensive. When the number of cases in each study is small relative to the group sizes, one can approximate the exact likelihood by a binomial distribution, which leads to a regular (mixed-effects) logistic regression model (`model="CM.AL"`). For `measure="IRR"`, the conditional model leads directly to a binomial distribution for the data within each study and the resulting model is again a (mixed-effects) logistic regression model (no approximate likelihood model is needed here).

When analyzing proportions (i.e., `measure="PLO"`) or incidence rates (i.e., `measure="IRLN"`) of individual groups, the model type is always a (mixed-effects) logistic or Poisson regression model, respectively (i.e., the `model` argument is not relevant here).

Aside from choosing the general model type, one has to decide whether to fit a fixed- or random-effects model to the data. A *fixed-effects model* is fitted by setting `method="FE"`. A *random-effects model* is fitted by setting `method="ML"` (the default). Note that random-effects models with dichotomous data are often referred to as ‘binomial-normal’ models in the meta-analytic literature. Analogously, for event count data, such models could be referred to as ‘Poisson-normal’ models.

One or more moderators can be included in all of these models via the `mods` argument. A single moderator can be given as a (row or column) vector of length k specifying the values of the moderator. Multiple moderators are specified by giving an appropriate model matrix (i.e., X) with k rows and as many columns as there are moderator variables (e.g., `mods = cbind(mod1, mod2, mod3)`, where `mod1`, `mod2`, and `mod3` correspond to the names of the variables for three moderator variables). The intercept is added to the model matrix by default unless `intercept=FALSE`.

Alternatively, one can use the standard `formula` syntax to specify the model. In this case, the `mods` argument should be set equal to a one-sided formula of the form `mods = ~ model` (e.g., `mods = ~ mod1 + mod2 + mod3`). Interactions, polynomial terms, and factors can be easily added to the model in this manner. When specifying a model formula via the `mods` argument, the `intercept` argument is ignored. Instead, the inclusion/exclusion of the intercept is controlled by the specified formula (e.g., `mods = ~ mod1 + mod2 + mod3 - 1` would lead to the removal of the intercept). With moderators, a *fixed-effects with moderators model* is then fitted by setting `method="FE"`, while a *mixed-effects model* is fitted by setting `method="ML"`.

Fixed-, Saturated-, and Random/Mixed-Effects Models

When fitting a particular model, actually up to three different models are fitted within the function:

- the fixed-effects model (i.e., where τ^2 is set to 0),
- the saturated model (i.e., the model with a deviance of 0), and
- the random/mixed-effects model (i.e., where τ^2 is estimated) (only if `method="ML"`).

The saturated model is obtained by adding as many dummy variables to the model as needed so that the model deviance is equal to zero. Even when `method="ML"`, the fixed-effects and saturated models are fitted, as they are used to compute the test statistics for the Wald-type and likelihood ratio tests for (residual) heterogeneity (see below).

Omnibus Test of Parameters

For models including moderators, an omnibus test of all the model coefficients is conducted that excludes the intercept (the first coefficient) if it is included in the model. If no intercept is included in the model, then the omnibus test includes all of the coefficients in the model including the first. Alternatively, one can manually specify the indices of the coefficients to test via the `btt` argument. For example, with `btt=c(3,4)`, only the third and fourth coefficient from the model would be included in the test (if an intercept is included in the model, then it corresponds to the first coefficient in the model). Instead of specifying the coefficient numbers, one can specify a string for `btt`. In that case, `grep` will be used to search for all coefficient names that match the string.

Categorical Moderators

Categorical moderator variables can be included in the model via the `mods` argument in the same way that appropriately (dummy) coded categorical independent variables can be included in linear models. One can either do the dummy coding manually or use a model formula together with the `factor` function to let R handle the coding automatically.

Tests and Confidence Intervals

By default, the test statistics of the individual coefficients in the model (and the corresponding confidence intervals) are based on a standard normal distribution, while the omnibus test is based on a chi-square distribution with m degrees of freedom (m being the number of coefficients tested). As an alternative, one can set `test="t"`, which slightly mimics the Knapp and Hartung (2003) method by using a t-distribution with $k - p$ degrees of freedom for tests of individual coefficients and confidence intervals and an F-distribution with m and $k - p$ degrees of freedom (p being the total

number of model coefficients including the intercept if it is present) for the omnibus test statistic (but note that `test="t"` is not the same as `test="knha"` in `rma.uni`, as no adjustment to the standard errors of the estimated coefficients is made).

Tests for (Residual) Heterogeneity

Two different tests for (residual) heterogeneity are automatically carried out by the function. The first is a Wald-type test, which tests the coefficients corresponding to the dummy variables added in the saturated model for significance. The second is a likelihood ratio test, which tests the same set of coefficients, but does so by computing -2 times the difference in the log-likelihood of the fixed-effects and the saturated model. These two tests are not identical for the types of models fitted by the `rma.glm` function and may even lead to conflicting conclusions.

Observed Outcomes of the Individual Studies

The various models do not require the calculation of the observed outcomes of the individual studies (e.g., the observed odds ratios of the k studies) and directly make use of the table/event counts. Zero cells/events are not a problem (except in extreme cases, such as when one of the two outcomes never occurs or when there are no events in any of the studies). Therefore, it is unnecessary to add some constant to the cell/event counts when there are zero cells/events.

However, for plotting and various other functions, it is necessary to calculate the observed outcomes for the k studies. Here, zero cells/events can be problematic, so adding a constant value to the cell/event counts ensures that all k values can be calculated. The `add` and `to` arguments are used to specify what value should be added to the cell/event counts and under what circumstances when calculating the observed outcomes. The documentation of the `escal` function explains how the `add` and `to` arguments work. Note that `drop00` is set to `TRUE` by default, since studies where $a_i=c_i=0$ or $b_i=d_i=0$ or studies where $x_{1i}=x_{2i}=0$ are uninformative about the size of the effect.

Value

An object of class `c("rma.glm", "rma")`. The object is a list containing the following components:

<code>beta</code>	estimated coefficients of the model.
<code>se</code>	standard errors of the coefficients.
<code>zval</code>	test statistics of the coefficients.
<code>pval</code>	p-values for the test statistics.
<code>ci.lb</code>	lower bound of the confidence intervals for the coefficients.
<code>ci.ub</code>	upper bound of the confidence intervals for the coefficients.
<code>vb</code>	variance-covariance matrix of the estimated coefficients.
<code>tau2</code>	estimated amount of (residual) heterogeneity. Always 0 when <code>method="FE"</code> .
<code>sigma2</code>	estimated amount of study level variability (only for <code>model="UM.RS"</code>).
<code>k</code>	number of studies included in the model.
<code>p</code>	number of coefficients in the model (including the intercept).
<code>m</code>	number of coefficients included in the omnibus test of coefficients.
<code>QE.wld</code>	Wald-type test statistic for the test of (residual) heterogeneity.
<code>QE.p.wld</code>	p-value for the Wald-type test of (residual) heterogeneity.
<code>QE.lrt</code>	likelihood ratio test statistic for the test of (residual) heterogeneity.

QEp.LRT	p-value for the likelihood ratio test of (residual) heterogeneity.
QM	test statistic for the omnibus test of coefficients.
QMp	p-value for the omnibus test of coefficients.
I2	value of I^2 .
H2	value of H^2 .
int.only	logical that indicates whether the model is an intercept-only model.
yi, vi, X	the vector of outcomes, the corresponding sampling variances, and the model matrix.
fit.stats	a list with the log-likelihood, deviance, AIC, BIC, and AICc values.
...	some additional elements/values.

Methods

The results of the fitted model are formatted and printed with the `print.rma.glmm` function. If fit statistics should also be given, use `summary.rma` (or use the `fitstats.rma` function to extract them).

Note

Fitting the various types of models requires several different iterative algorithms:

- For `model="UM.FS"` and `model="CM.AL"`, iteratively reweighted least squares (IWLS) as implemented in the `glm` function is used for fitting the fixed-effects and the saturated models. For `method="ML"`, adaptive Gauss-Hermite quadrature as implemented in the `glmer` function is used. The same applies when `model="CM.EL"` is used in combination with `measure="IRR"` or when `measure="PLO"` or `measure="IRLN"` (regardless of the model type).
- For `model="UM.RS"`, adaptive Gauss-Hermite quadrature as implemented in the `glmer` function is used to fit all of the models.
- For `model="CM.EL"` and `measure="OR"`, the quasi-Newton method ("BFGS") as implemented in the `optim` function is used by default for fitting the fixed-effects and the saturated models. For `method="ML"`, the same algorithm is used, together with adaptive quadrature as implemented in the `integrate` function (for the integration over the density of the non-central hypergeometric distribution). Standard errors of the parameter estimates are obtained by inverting the Hessian, which is numerically approximated using the `hessian` function.

When `model="CM.EL"` and `measure="OR"`, actually `model="CM.AL"` is used first to obtain starting values for `optim`, so either 4 (if `method="FE"`) or 6 (if `method="ML"`) models need to be fitted in total.

Various control parameters can be adjusted via the `control` argument:

- `optimizer` is set by default to `"optim"`, but can be set to `"nlminb"` or one of the optimizers from the `minqa` package (i.e., `"bobyqa"`, `"newuoa"`, or `"uobyqa"`),
- `optmethod` is used to set the method argument for `optim` (the default is "BFGS"),
- `optCtrl` is a list of named arguments to be passed on to the `control` argument of the chosen optimizer,

- `glmCtrl` is a list of named arguments to be passed on to the `control` argument of the `glm` function,
- `glmerCtrl` is a list of named arguments to be passed on to the `control` argument of the `glmer` function, and
- `intCtrl` is a list of named arguments (i.e., `rel.tol` and `subdivisions`) to be passed on to the `integrate` function.
- `hessianCtrl` is a list of named arguments to be passed on to the `method.args` argument of the `hessian` function. For some borderline cases, it may be necessary to bump up the `r` argument to a higher number to get sufficient accuracy when approximating the Hessian numerically (the default is `control=list(hessianCtrl=list(r=16))`).

Also, for `glmer`, the `nAGQ` argument is used to specify the number of quadrature points. The default value is 7, which should provide sufficient accuracy in the evaluation of the log-likelihood in most cases, but at the expense of speed. Setting this to 1 corresponds to the Laplacian approximation (which is faster, but less accurate).

Information on the progress of the various algorithms can be obtained by setting `verbose=TRUE`. Since fitting the various models can be computationally expensive, this option is useful to determine how the model fitting is progressing. One can also set `verbose` to an integer (`verbose=2` yields even more information and `verbose=3` also sets `option(warn=1)` temporarily).

For `model="CM.EL"` and `measure="OR"`, optimization involves repeated calculation of the density of the non-central hypergeometric distribution. When `method="ML"`, this also requires integration over the same density. This is currently implemented in a rather brute-force manner and may not be numerically stable, especially when models with moderators are fitted. Stability can be improved by scaling the moderators in a similar manner (i.e., don't use a moderator that is coded 0 and 1, while another uses values in the 1000s). For models with an intercept and moderators, the function actually rescales (non-dummy) variables to z-scores during the model fitting (results are given after back-scaling, so this should be transparent to the user). For models without an intercept, this is not done, so sensitivity analyses are highly recommended here (to ensure that the results do not depend on the scaling of the moderators).

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Code for computing the density of the non-central hypergeometric distribution from package **MCM-Cpack**, which in turn is based on Liao and Rosen (2001).

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See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), and [rma.mv](#) for other model fitting functions.

[dat.nielweise2007](#), [dat.nielweise2008](#), [dat.collins1985a](#), and [dat.pritz1997](#) for further examples of the use of the `rma.glmm` function.

Examples

```
### random-effects model using rma.uni() (standard RE model analysis)
rma(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
    data=dat.bcg, method="ML", verbose=TRUE)

### random-effects models using rma.glmm() (require 'lme4' package)

### unconditional model with fixed study effects
## Not run:
rma.glmm(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
    data=dat.bcg, model="UM.FS", verbose=TRUE)
## End(Not run)

### unconditional model with random study effects
## Not run:
rma.glmm(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
    data=dat.bcg, model="UM.RS", verbose=TRUE)
## End(Not run)

### conditional model with approximate likelihood
## Not run:
rma.glmm(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
    data=dat.bcg, model="CM.AL", verbose=TRUE)
## End(Not run)

### conditional model with exact likelihood (be patient!)
### note: fitting this model is very slow, so be patient
## Not run:
rma.glmm(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
    data=dat.bcg, model="CM.EL", verbose=TRUE)
## End(Not run)
```


rma.mh

*Meta-Analysis via the Mantel-Haenszel Method***Description**

Function to fit fixed-effects models to 2×2 table and person-time data via the Mantel-Haenszel method. See below and the documentation of the [metafor-package](#) for more details on these models.

Usage

```
rma.mh(ai, bi, ci, di, n1i, n2i, x1i, x2i, t1i, t2i,
       measure="OR", data, slab, subset,
       add=1/2, to="only0", drop00=TRUE,
       correct=TRUE, level=95, digits, verbose=FALSE, ...)
```

Arguments

ai	vector to specify the 2×2 table frequencies (upper left cell). See below and the documentation of the escalc function for more details.
bi	vector to specify the 2×2 table frequencies (upper right cell). See below and the documentation of the escalc function for more details.
ci	vector to specify the 2×2 table frequencies (lower left cell). See below and the documentation of the escalc function for more details.
di	vector to specify the 2×2 table frequencies (lower right cell). See below and the documentation of the escalc function for more details.
n1i	vector to specify the group sizes or row totals (first group). See below and the documentation of the escalc function for more details.
n2i	vector to specify the group sizes or row totals (second group). See below and the documentation of the escalc function for more details.
x1i	vector to specify the number of events (first group). See below and the documentation of the escalc function for more details.
x2i	vector to specify the number of events (second group). See below and the documentation of the escalc function for more details.
t1i	vector to specify the total person-times (first group). See below and the documentation of the escalc function for more details.
t2i	vector to specify the total person-times (second group). See below and the documentation of the escalc function for more details.
measure	character string indicating the outcome measure to use for the meta-analysis. Possible options are the risk ratio ("RR"), the odds ratio ("OR"), the risk difference ("RD"), the incidence rate ratio ("IRR"), or the incidence rate difference ("IRD").
data	optional data frame containing the data supplied to the function.

slab	optional vector with labels for the k studies.
subset	optional (logical or numeric) vector indicating the subset of studies that should be used for the analysis.
add	non-negative number indicating the amount to add to zero cells, counts, or frequencies when calculating the observed outcomes of the individual studies. Can also be a vector of two numbers, where the first number is used in the calculation of the observed outcomes and the second number is used when applying the Mantel-Haenszel method. See below and the documentation of the escalc function for more details.
to	character string indicating when the values under add should be added (either "only0", "all", "if0all", or "none"). Can also be a character vector, where the first string again applies when calculating the observed outcomes and the second string when applying the Mantel-Haenszel method. See below and the documentation of the escalc function for more details.
drop00	logical indicating whether studies with no cases/events (or only cases) in both groups should be dropped when calculating the observed outcomes (the outcomes for such studies are set to NA). Can also be a vector of two logicals, where the first applies to the calculation of the observed outcomes and the second when applying the Mantel-Haenszel method. See below and the documentation of the escalc function for more details.
correct	logical indicating whether to apply a continuity correction when computing the Cochran-Mantel-Haenszel test statistic.
level	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is 4).
verbose	logical indicating whether output should be generated on the progress of the model fitting (the default is FALSE).
...	additional arguments.

Details

Specifying the Data

When the outcome measure is either the risk ratio (measure="RR"), odds ratio (measure="OR"), or risk difference (measure="RD"), the studies are assumed to provide data in terms of 2×2 tables of the form:

	outcome 1	outcome 2	total
group 1	ai	bi	n1i
group 2	ci	di	n2i

where ai, bi, ci, and di denote the cell frequencies and n1i and n2i the row totals. For example, in a set of randomized clinical trials (RCTs) or cohort studies, group 1 and group 2 may refer to the treatment (exposed) and placebo/control (not exposed) group, with outcome 1 denoting some event of interest (e.g., death) and outcome 2 its complement. In a set of case-control studies, group 1 and

group 2 may refer to the group of cases and the group of controls, with outcome 1 denoting, for example, exposure to some risk factor and outcome 2 non-exposure. For these outcome measures, one needs to specify either a_i , b_i , c_i , and d_i or alternatively a_i , c_i , $n1_i$, and $n2_i$.

Alternatively, when the outcome measure is the incidence rate ratio (`measure="IRR"`) or the incidence rate difference (`measure="IRD"`), the studies are assumed to provide data in terms of tables of the form:

	events	person-time
group 1	$x1_i$	$t1_i$
group 2	$x2_i$	$t2_i$

where $x1_i$ and $x2_i$ denote the number of events in the first and the second group, respectively, and $t1_i$ and $t2_i$ the corresponding total person-times at risk.

Mantel-Haenszel Method

An approach for aggregating table data of these types was suggested by Mantel and Haenszel (1959) and later extended by various authors (see references). The Mantel-Haenszel method provides a weighted estimate under a fixed-effects model. The method is particularly advantageous when aggregating a large number of studies with small sample sizes (the so-called sparse data or increasing strata case).

When analyzing odds ratios, the Cochran-Mantel-Haenszel (CMH) test (Cochran, 1954; Mantel & Haenszel, 1959) and Tarone's test for heterogeneity (Tarone, 1985) are also provided (by default, the CMH test statistic is computed with the continuity correction; this can be switched off with `correct=FALSE`). When analyzing incidence rate ratios, the Mantel-Haenszel (MH) test (Rothman et al., 2008) for person-time data is also provided (again, the `correct` argument controls whether the continuity correction is applied). When analyzing risk ratios, odds ratios, or incidence rate ratios, the printed results are given both in terms of the log and the raw units (for easier interpretation).

Observed Outcomes of the Individual Studies

The Mantel-Haenszel method itself does not require the calculation of the observed outcomes of the individual studies (e.g., the observed odds or incidence rate ratios of the k studies) and directly makes use of the table/event counts. Zero cells/events are not a problem (except in extreme cases, such as when one of the two outcomes never occurs in any of the 2×2 tables or when there are no events for one of the two groups in any of the tables). Therefore, it is unnecessary to add some constant to the cell/event counts when there are zero cells/events.

However, for plotting and various other functions, it is necessary to calculate the observed outcomes for the k studies. Here, zero cells/events can be problematic, so adding a constant value to the cell/event counts ensures that all k values can be calculated. The `add` and `to` arguments are used to specify what value should be added to the cell/event counts and under what circumstances when calculating the observed outcomes and when applying the Mantel-Haenszel method. Similarly, the `drop00` argument is used to specify how studies with no cases/events (or only cases) in both groups should be handled. The documentation of the `escalc` function explains how the `add`, `to`, and `drop00` arguments work. If only a single value for these arguments is specified (as per default), then these values are used when calculating the observed outcomes and no adjustment to the cell/event counts is made when applying the Mantel-Haenszel method. Alternatively, when specifying two values for these arguments, the first value applies when calculating the observed outcomes and the second value when applying the Mantel-Haenszel method.

Note that `drop00` is set to `TRUE` by default. Therefore, the observed outcomes for studies where $a_i=c_i=0$ or $b_i=d_i=0$ or studies where $x_{1i}=x_{2i}=0$ are set to `NA`. When applying the Mantel-Haenszel method, such studies are not explicitly dropped (unless the second value of `drop00` argument is also set to `TRUE`), but this is practically not necessary, as they do not actually influence the results (assuming no adjustment to the cell/event counts are made when applying the Mantel-Haenszel method).

Value

An object of class `c("rma.mh", "rma")`. The object is a list containing the following components:

<code>beta</code>	aggregated log risk ratio, log odds ratio, risk difference, log rate ratio, or rate difference.
<code>se</code>	standard error of the aggregated value.
<code>zval</code>	test statistics of the aggregated value.
<code>pval</code>	p-value for the test statistic.
<code>ci.lb</code>	lower bound of the confidence interval.
<code>ci.ub</code>	upper bound of the confidence interval.
<code>QE</code>	test statistic for the test of heterogeneity.
<code>QEp</code>	p-value for the test of heterogeneity.
<code>MH</code>	Cochran-Mantel-Haenszel test statistic (<code>measure="OR"</code>) or Mantel-Haenszel test statistic (<code>measure="IRR"</code>).
<code>MHp</code>	corresponding p-value.
<code>TA</code>	Tarone's heterogeneity test statistic (only when <code>measure="OR"</code>).
<code>TAp</code>	corresponding p-value (only when <code>measure="OR"</code>).
<code>k</code>	number of tables included in the analysis.
<code>yi, vi</code>	the vector of outcomes and corresponding sampling variances.
<code>fit.stats</code>	a list with the log-likelihood, deviance, AIC, BIC, and AICc values under the unrestricted and restricted likelihood.
<code>...</code>	some additional elements/values.

Methods

The results of the fitted model are formatted and printed with the `print.rma.mh` function. If fit statistics should also be given, use `summary.rma` (or use the `fitstats.rma` function to extract them).

The `residuals.rma`, `rstandard.rma.mh`, and `rstudent.rma.mh` functions extract raw and standardized residuals. Leave-one-out diagnostics can be obtained with `leave1out.rma.mh`.

Forest, funnel, radial, L'Abbé, and Baujat plots can be obtained with `forest.rma`, `funnel.rma`, `radial.rma`, `labbe.rma`, and `baujat`. The `qqnorm.rma.mh` function provides normal QQ plots of the standardized residuals. One can also just call `plot.rma.mh` on the fitted model object to obtain various plots at once.

A cumulative meta-analysis (i.e., adding one observation at a time) can be obtained with `cumul.rma.mh`.

Other extractor functions include `coef.rma`, `vcov.rma`, `logLik.rma`, `deviance.rma`, `AIC.rma`, and `BIC.rma`.

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See Also

[rma.uni](#), [rma.glm](#), [rma.peto](#), and [rma.mv](#) for other model fitting functions.

Examples

```
### meta-analysis of the (log) odds ratios using the Mantel-Haenszel method
rma.mh(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### meta-analysis of the (log) risk ratios using the Mantel-Haenszel method
rma.mh(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
```

rma.mv

Meta-Analysis via Multivariate/Multilevel Linear (Mixed-Effects) Models

Description

Function to fit meta-analytic multivariate/multilevel fixed- and random/mixed-effects models with or without moderators via linear (mixed-effects) models. See below and the documentation of the [metafor-package](#) for more details on these models.

Usage

```
rma.mv(yi, V, W, mods, random, struct="CS", intercept=TRUE,
       data, slab, subset, method="REML", test="z",
       level=95, digits, btt, R, Rscale="cor",
       sigma2, tau2, rho, gamma2, phi, sparse=FALSE, verbose=FALSE, control, ...)
```

Arguments

<code>yi</code>	vector of length k with the observed effect sizes or outcomes. See ‘Details’.
<code>V</code>	vector of length k with the corresponding sampling variances or a $k \times k$ variance-covariance matrix of the sampling errors. See ‘Details’.
<code>W</code>	optional argument to specify a vector of length k with user-defined weights or a $k \times k$ user-defined weight matrix. See ‘Details’.
<code>mods</code>	optional argument to include one or more moderators in the model. A single moderator can be given as a vector of length k specifying the values of the moderator. Multiple moderators are specified by giving a matrix with k rows and as many columns as there are moderator variables. Alternatively, a model formula can be used to specify the model. See ‘Details’.
<code>random</code>	either a single one-sided formula or list of one-sided formulas to specify the random-effects structure of the model. See ‘Details’.
<code>struct</code>	character string to specify the variance structure of an <code>~ inner outer</code> formula in the random argument. Either "CS" for compound symmetry, "HCS" for heteroscedastic compound symmetry, "UN" for an unstructured variance-covariance matrix, "ID" for a scaled identity matrix, "DIAG" for a diagonal matrix, "AR" for an AR(1) autoregressive structure, "HAR" for a heteroscedastic AR(1) autoregressive structure, "CAR" for a continuous-time autoregressive structure, or one of "SPEXP", "SPGAU", "SPLIN", "SPRAT", or "SPSPH" for one of the spatial correlation structures. See ‘Details’.
<code>intercept</code>	logical indicating whether an intercept should be added to the model (the default is TRUE). Ignored when <code>mods</code> is a formula.
<code>data</code>	optional data frame containing the data supplied to the function.
<code>slab</code>	optional vector with labels for the k outcomes/studies.
<code>subset</code>	optional (logical or numeric) vector indicating the subset of studies (or more precisely, rows of the dataset) that should be used for the analysis.
<code>method</code>	character string specifying whether the model should be fitted via maximum-likelihood ("ML") or via restricted maximum-likelihood ("REML") estimation. Default is "REML".
<code>test</code>	character string specifying how test statistics and confidence intervals for the fixed effects should be computed. By default (<code>test="z"</code>), Wald-type tests and CIs are obtained, which are based on a standard normal distribution. When <code>test="t"</code> , a t-distribution is used instead. See ‘Details’.
<code>level</code>	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
<code>digits</code>	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is 4).

btt	optional vector of indices specifying which coefficients to include in the omnibus test of moderators. Can also be a string to grep for. See ‘Details’.
R	an optional named list of known correlation matrices corresponding to (some of) the components specified via the random argument. See ‘Details’.
Rscale	character string, integer, or logical indicating how matrices specified via the R argument should be scaled. See ‘Details’.
sigma2	optional numerical vector (of the same length as the number of random intercept components specified via the random argument) to fix the corresponding σ^2 value(s). A specific σ^2 value can be fixed by setting the corresponding element of this argument to the desired value. A specific σ^2 value will be estimated if the corresponding element is set equal to NA. See ‘Details’.
tau2	optional numerical value (for struct="CS", "AR", "CAR", or a spatial correlation structure) or vector (for struct="HCS", "UN", or "HAR") to fix the amount of (residual) heterogeneity for the levels of the inner factor corresponding to an \sim inner outer formula specified in the random argument. A numeric value fixes a particular τ^2 value, while NA means that the value should be estimated. See ‘Details’.
rho	optional numerical value (for struct="CS", "HCS", "AR", "HAR", "CAR", or a spatial correlation structure) or vector (for struct="UN") to fix the correlation between the levels of the inner factor corresponding to an \sim inner outer formula specified in the random argument. A numeric value fixes a particular ρ value, while NA means that the value should be estimated. See ‘Details’.
gamma2	as tau2 argument, but for a second \sim inner outer formula specified in the random argument. See ‘Details’.
phi	as rho argument, but for a second \sim inner outer formula specified in the random argument. See ‘Details’.
sparse	logical indicating whether the function should use sparse matrix objects to the extent possible (can speed up model fitting substantially for certain models). See ‘Note’.
verbose	logical indicating whether output should be generated on the progress of the model fitting (the default is FALSE). Can also be an integer. Values > 1 generate more verbose output. See ‘Note’.
control	optional list of control values for the estimation algorithms. If unspecified, default values are defined inside the function. See ‘Note’.
...	additional arguments.

Details

Specifying the Data

The function can be used in conjunction with any of the usual effect size or outcome measures used in meta-analyses (e.g., log risk ratios, log odds ratios, risk differences, mean differences, standardized mean differences, raw correlation coefficients, correlation coefficients transformed with Fisher’s r-to-z transformation, and so on). Simply specify the observed outcomes via the `yi` argument and the corresponding sampling variances via the `V` argument. In case the sampling errors

are correlated, then one can specify the entire variance-covariance matrix of the sampling errors via the `V` argument.

The `escalc` function can be used to compute a wide variety of effect size and outcome measures (and the corresponding sampling variances) based on summary statistics. Equations for computing the covariance between sampling errors for a variety of different effect size or outcome measures can be found, for example, in Gleser and Olkin (2009). For raw and Fisher's *r*-to-*z* transformed correlations, one can find suitable equations, for example, in Steiger (1980).

Specifying Fixed Effects

With `rma.mv(yi, V)`, a fixed-effects model is fitted to the data (note: arguments `struct`, `sigma2`, `tau2`, `rho`, `gamma2`, `phi`, `R`, and `Rscale` are not relevant then and are ignored). The model is then simply given by $y \sim N(1\beta_0, V)$, where y is the (column) vector with the observed effect sizes or outcomes, 1 is a column vector of 1's, β_0 is the (average) true effect size or outcome, and V is the variance-covariance matrix of the sampling errors (if a vector of sampling variances is provided via the `V` argument, then V is assumed to be diagonal).

One or more moderators can be included in the model via the `mods` argument. A single moderator can be given as a (row or column) vector of length k specifying the values of the moderator. Multiple moderators are specified by giving an appropriate model matrix (i.e., X) with k rows and as many columns as there are moderator variables (e.g., `mods = cbind(mod1, mod2, mod3)`, where `mod1`, `mod2`, and `mod3` correspond to the names of the variables for the three moderator variables). The intercept is added to the model matrix by default unless `intercept=FALSE`.

Alternatively, one can use the standard `formula` syntax to specify the model. In this case, the `mods` argument should be set equal to a one-sided formula of the form `mods = ~ model` (e.g., `mods = ~ mod1 + mod2 + mod3`). Interactions, polynomial terms, and factors can be easily added to the model in this manner. When specifying a model formula via the `mods` argument, the `intercept` argument is ignored. Instead, the inclusion/exclusion of the intercept is controlled by the specified formula (e.g., `mods = ~ mod1 + mod2 + mod3 - 1` would lead to the removal of the intercept). One can also directly specify moderators via the `yi` argument (e.g., `rma.mv(yi ~ mod1 + mod2 + mod3, V)`). In that case, the `mods` argument is ignored and the inclusion/exclusion of the intercept again is controlled by the specified formula.

With moderators included, the model is then given by $y \sim N(X\beta, V)$, where X denotes the model matrix containing the moderator values (and possibly the intercept) and β is a column vector containing the corresponding model coefficients. The model coefficients (i.e., β) are then estimated with $b = (X'WX')^{-1}X'Wy$, where $W = V^{-1}$ is the weight matrix. With the `W` argument, one can also specify user-defined weights (or a weight matrix).

Specifying Random Effects

One can fit random/mixed-effects models to the data by specifying the desired random effects structure via the `random` argument. The `random` argument is either a single one-sided formula or a list of one-sided formulas. One formula type that can be specified via this argument is of the form `random = ~ 1 | id`. Such a formula adds random effects/intercepts corresponding to the grouping variable/factor `id` to the model. Effects or outcomes with the same value/level of the `id` variable/factor receive the same random effect, while effects or outcomes with different values/levels of the `id` variable/factor are assumed to be independent. The variance component corresponding to such a formula is denoted by σ^2 . An arbitrary number of such formulas can be specified as a list of formulas (e.g., `random = list(~ 1 | id1, ~ 1 | id2)`), with variance components σ_1^2 , σ_2^2 , and so on. Nested random effects of this form can also be added using `random = ~ 1 | id1/id2`, which

adds random effects/intercepts for each level of id1 and random effects/intercepts for each level of id2 within id1.

Random effects of this form are useful to model clustering (and hence non-independence) induced by a multilevel structure in the data (e.g., effects derived from the same paper, lab, research group, or species may be more similar to each other than effects derived from different papers, labs, research groups, or species). See, for example, Konstantopoulos (2011) and Nakagawa and Santos (2012) for more details.

See [dat.konstantopoulos2011](#) for an example analysis with multilevel meta-analytic data.

In addition or alternatively to specifying one or multiple $\sim 1 | id$ terms, the random argument can also contain a formula of the form $\sim inner | outer$. Effects or outcomes with different values/levels of the outer grouping variable/factor are assumed to be independent, while effects or outcomes with the same value/level of the outer grouping variable/factor share correlated random effects corresponding to the levels of the inner grouping variable/factor (note that the inner grouping variable must either be a factor or a character variable). The `struct` argument is used to specify the variance structure corresponding to the inner variable/factor. With `struct="CS"`, a compound symmetric structure is assumed (i.e., a single variance component τ^2 corresponding to all values/levels of the inner variable/factor and a single correlation coefficient ρ for the correlation between the different values/levels). With `struct="HCS"`, a heteroscedastic compound symmetric structure is assumed (with variance components τ_1^2, τ_2^2 , and so on, corresponding to the values/levels of the inner variable/factor and a single correlation coefficient ρ for the correlation between the different values/levels). With `struct="UN"`, an unstructured variance-covariance matrix is assumed (with variance components τ_1^2, τ_2^2 , and so on, corresponding to the values/levels of the inner variable/factor and correlation coefficients $\rho_{12}, \rho_{13}, \rho_{23}$, and so on, for the various combinations of the values/levels of the inner variable/factor). For example, for an inner grouping variable/factor with four levels, the three structures correspond to variance-covariance matrices of the form:

$$\begin{array}{ccc}
 \text{struct}=\text{"CS"} & \text{struct}=\text{"HCS"} & \text{struct}=\text{"UN"} \\
 \begin{bmatrix} \tau^2 & \rho\tau^2 & \rho\tau^2 & \rho\tau^2 \\ & \tau^2 & \rho\tau^2 & \rho\tau^2 \\ & & \tau^2 & \rho\tau^2 \\ & & & \tau^2 \end{bmatrix} & \begin{bmatrix} \tau_1^2 & \rho\tau_1\tau_2 & \rho\tau_1\tau_3 & \rho\tau_1\tau_4 \\ & \tau_2^2 & \rho\tau_2\tau_3 & \rho\tau_2\tau_4 \\ & & \tau_3^2 & \rho\tau_3\tau_4 \\ & & & \tau_4^2 \end{bmatrix} & \begin{bmatrix} \tau_1^2 & \rho_{12}\tau_1\tau_2 & \rho_{13}\tau_1\tau_3 & \rho_{14}\tau_1\tau_4 \\ & \tau_2^2 & \rho_{23}\tau_2\tau_3 & \rho_{24}\tau_2\tau_4 \\ & & \tau_3^2 & \rho_{34}\tau_3\tau_4 \\ & & & \tau_4^2 \end{bmatrix}
 \end{array}$$

Structures `struct="ID"` and `struct="DIAG"` are just like `struct="CS"` and `struct="HCS"`, respectively, except that ρ is automatically set to 0, so that we either get a scaled identity matrix or a diagonal matrix.

With the outer factor corresponding to a study identification variable and the inner factor corresponding to a variable indicating the treatment type or study arm, such a random effects component could be used to estimate how strongly different true effects or outcomes within the same study are correlated and/or whether the amount of heterogeneity differs across different treatment types/arms. Network meta-analyses (also known as mixed treatment comparison meta-analyses) will also typically require such a random effects component (e.g., Salanti et al., 2008). The meta-analytic bivariate model (e.g., van Houwelingen, Arends, & Stijnen, 2002) can also be fitted in this manner (see the examples below). The inner factor could also correspond to a variable indicating the outcome variable, which allows for fitting multivariate models when there are multiple correlated effects per study (e.g., Berkey et al., 1998; Kalaian & Raudenbush, 1996).

See [dat.berkey1998](#) for an example of a multivariate meta-analysis with multiple outcomes. See [dat.hasselblad1998](#) and [dat.senn2013](#) for examples of network meta-analyses.

For meta-analyses of studies reporting outcomes at multiple time points, it may also be reasonable to assume that the true effects are correlated over time according to an autoregressive structure (Ishak et al., 2007; Trikalinos & Olkin, 2012). For this purpose, one can also choose `struct="AR"`, corresponding to a structure with a single variance component τ^2 and AR(1) autocorrelation among the random effects. The values of the inner variable (which does not have to be a factor here) should then reflect the various time points, with increasing values reflecting later time points. Note that this structure assumes equally spaced time points, so the actual values of the inner variable are not relevant, only their ordering. One can also use `struct="HAR"`, which allows for fitting a heteroscedastic AR(1) structure (with variance components τ_1^2 , τ_2^2 , and so on). Finally, when time points are not evenly spaced, one might consider using `struct="CAR"` for a continuous-time autoregressive structure. For example, for an inner grouping variable with four time points, these structures correspond to variance-covariance matrices of the form:

$$\begin{array}{ccc} \text{struct}=\text{"AR"} & \text{struct}=\text{"HAR"} & \text{struct}=\text{"CAR"} \\ \begin{bmatrix} \tau^2 & \rho\tau^2 & \rho^2\tau^2 & \rho^3\tau^2 \\ & \tau^2 & \rho\tau^2 & \rho^2\tau^2 \\ & & \tau^2 & \rho\tau^2 \\ & & & \tau^2 \end{bmatrix} & \begin{bmatrix} \tau_1^2 & \rho\tau_1\tau_2 & \rho^2\tau_1\tau_3 & \rho^3\tau_1\tau_4 \\ & \tau_2^2 & \rho\tau_2\tau_3 & \rho^2\tau_2\tau_4 \\ & & \tau_3^2 & \rho\tau_3\tau_4 \\ & & & \tau_4^2 \end{bmatrix} & \begin{bmatrix} \tau^2 & \tau^2\rho^{|t_1-t_2|} & \tau^2\rho^{|t_1-t_3|} & \tau^2\rho^{|t_1-t_4|} \\ & \tau^2 & \tau^2\rho^{|t_2-t_3|} & \tau^2\rho^{|t_2-t_4|} \\ & & \tau^2 & \tau^2\rho^{|t_3-t_4|} \\ & & & \tau^2 \end{bmatrix} \end{array}$$

See [dat.fine1993](#) and [dat.ishak2007](#) for examples involving such structures.

For outcomes that have a known spatial configuration, various spatial correlation structures are also available. For these structures, the formula is of the form `random = ~ var1 + var2 + . . . | outer`, where `var1`, `var2`, and so on are variables to indicate the spatial coordinates (e.g., longitude and latitude) based on which distances (by default Euclidean) will be computed. Let d denote the distance between two points that share the same level of the outer variable (if all true effects are allowed to be spatially correlated, simply set `outer` to a constant). Then the correlation between the true effects corresponding to these two points is a function of d and the parameter ρ . The following table shows the types of spatial correlation structures that can be specified and the equations for the correlation. The covariance between the true effects is then the correlation times τ^2 .

structure	struct	correlation
exponential	"SPEXP"	$\exp(-d/\rho)$
Gaussian	"SPGAU"	$\exp(-d^2/\rho^2)$
linear	"SPLIN"	$(1 - d/\rho)I(d < \rho)$
rational quadratic	"SPRAT"	$1 - (d/\rho)^2/(1 + (d/\rho)^2)$
spherical	"SPSPH"	$(1 - 1.5(d/\rho) + 0.5(d/\rho)^3)I(d < \rho)$

Note that $I(d < \rho)$ is equal to 1 if $d < \rho$ and 0 otherwise. The parameterization of the various structures is based on Pinheiro and Bates (2000). Instead of Euclidean distances, one can also use other distance measures by setting (the undocumented) argument `dist` to either `"maximum"` for the maximum distance between two points (supremum norm), to `"manhattan"` for the absolute distance between the coordinate vectors (L1 norm), or to `"gcd"` for the great-circle distance (WGS84 ellipsoid method). In the latter case, only two variables, namely the longitude and latitude (in decimal degrees, with minus signs for West and South), must be specified.

The `random` argument can also contain a second formula of the form `~ inner | outer` (but no more!). A second formula of this form works exactly described as above, but its variance components are denoted by γ^2 and its correlation components by ϕ . The `struct` argument should then be of length 2 to specify the variance-covariance structure for the first and second component, respectively.

When the random argument contains a formula of the form $\sim 1 \mid \text{id}$, one can use the (optional) argument *R* to specify a corresponding known correlation matrix of the random effects (i.e., $R = \text{list}(\text{id} = \text{Cor})$, where *Cor* is the correlation matrix). In that case, effects or outcomes with the same value/level of the *id* variable/factor receive the same random effect, while effects or outcomes with different values/levels of the *id* variable/factor receive random effects that are correlated as specified in the corresponding correlation matrix given via the *R* argument. The column/row names of the correlation matrix given via the *R* argument must therefore contain all of the values/levels of the *id* variable/factor. When the random argument contains multiple formulas of the form $\sim 1 \mid \text{id}$, one can specify known correlation matrices for none, some, or all of those terms (e.g., with $\text{random} = \text{list}(\sim 1 \mid \text{id1}, \sim 1 \mid \text{id2})$, one could specify $R = \text{list}(\text{id1} = \text{Cor1})$ or $R = \text{list}(\text{id1} = \text{Cor1}, \text{id2} = \text{Cor2})$, where *Cor1* and *Cor2* are the correlation matrices corresponding to the grouping variables/factors *id1* and *id2*, respectively).

Random effects with a known (or at least approximately known) correlation structure are useful in a variety of contexts. For example, such components can be used to account for the correlations induced by a shared phylogenetic history among organisms (e.g., plants, fungi, animals). In that case, $\sim 1 \mid \text{species}$ is used to specify the species and argument *R* is used to specify the phylogenetic correlation matrix of the species studied in the meta-analysis. The corresponding variance component then indicates how much variance/heterogeneity is attributable to the specified phylogeny. See Nakagawa and Santos (2012) for more details. As another example, in a genetic meta-analysis studying disease association for several single nucleotide polymorphisms (SNPs), linkage disequilibrium (LD) among the SNPs can induce an approximately known degree of correlation among the effects. In that case, $\sim 1 \mid \text{snp}$ could be used to specify the SNPs and *R* the corresponding LD correlation map for the SNPs included in the meta-analysis.

The *Rscale* argument controls how matrices specified via the *R* argument are scaled. With *Rscale*="none" (or *Rscale*=0 or *Rscale*=FALSE), no scaling is used. With *Rscale*="cor" (or *Rscale*=1 or *Rscale*=TRUE), the *cov2cor* function is used to ensure that the matrices are correlation matrices (assuming they were covariance matrices to begin with). With *Rscale*="cor0" (or *Rscale*=2), first *cov2cor* is used and then the elements of each correlation matrix are scaled with $(R - \min(R)) / (1 - \min(R))$ (this ensures that a correlation of zero in a phylogenetic correlation matrix corresponds to the split at the root node of the tree comprising the species that are actually analyzed). Finally, *Rscale*="cov0" (or *Rscale*=3) only rescales with $(R - \min(R))$ (which ensures that a phylogenetic covariance matrix is rooted at the lowest split).

Together with the variance-covariance matrix of the sampling errors (i.e., *V*), the random effects structure of the model implies a particular marginal variance-covariance matrix of the observed outcomes. Once estimates of the variance components (i.e., σ^2 , τ^2 , ρ , γ^2 , and/or ϕ , values) have been obtained, the estimated marginal variance-covariance matrix can be constructed (denoted by *M*). The model coefficients (i.e., β) are then estimated with $b = (X'WX')^{-1}X'Wy$, where $W = M^{-1}$ is the weight matrix. With the *W* argument, one can again specify user-defined weights (or a weight matrix).

Fixing Variance Components and/or Correlations

Arguments *sigma2*, *tau2*, *rho*, *gamma2*, and *phi* can be used to fix particular variance components and/or correlations at a given value. This is useful for sensitivity analyses (e.g., for plotting the regular/restricted log-likelihood as a function of a particular variance component or correlation) or for imposing a desired variance-covariance structure on the data.

For example, if $\text{random} = \text{list}(\sim 1 \mid \text{id1}, \sim 1 \mid \text{id2})$, then *sigma2* must be of length 2 (corresponding to σ_1^2 and σ_2^2) and a fixed value can be assigned to either or both variance components.

expect based on sampling variability (and the given covariances among the sampling errors) alone. A significant test suggests that the true effects or outcomes are heterogeneous. When moderators are included in the model, this is the Q_E -test for residual heterogeneity, which tests whether the variability in the observed effect sizes or outcomes that is not accounted for by the moderators included in the model is larger than one would expect based on sampling variability (and the given covariances among the sampling errors) alone.

Value

An object of class `c("rma.mv", "rma")`. The object is a list containing the following components:

<code>beta</code>	estimated coefficients of the model.
<code>se</code>	standard errors of the coefficients.
<code>zval</code>	test statistics of the coefficients.
<code>pval</code>	p-values for the test statistics.
<code>ci.lb</code>	lower bound of the confidence intervals for the coefficients.
<code>ci.ub</code>	upper bound of the confidence intervals for the coefficients.
<code>vb</code>	variance-covariance matrix of the estimated coefficients.
<code>sigma2</code>	estimated σ^2 value(s).
<code>tau2</code>	estimated τ^2 value(s).
<code>rho</code>	estimated ρ value(s).
<code>gamma2</code>	estimated γ^2 value(s).
<code>phi</code>	estimated ϕ value(s).
<code>k</code>	number of studies included in the model.
<code>p</code>	number of coefficients in the model (including the intercept).
<code>m</code>	number of coefficients included in the omnibus test of coefficients.
<code>QE</code>	test statistic for the test of (residual) heterogeneity.
<code>QEp</code>	p-value for the test of (residual) heterogeneity.
<code>QM</code>	test statistic for the omnibus test of coefficients.
<code>QMp</code>	p-value for the omnibus test of coefficients.
<code>int.only</code>	logical that indicates whether the model is an intercept-only model.
<code>yi, V, X</code>	the vector of outcomes, the corresponding variance-covariance matrix of the sampling errors, and the model matrix.
<code>M</code>	the estimated marginal variance-covariance matrix of the observed outcomes.
<code>fit.stats</code>	a list with the log-likelihood, deviance, AIC, BIC, and AICc values.
<code>...</code>	some additional elements/values.

Methods

The results of the fitted model are formatted and printed with the `print.rma.mv` function. If fit statistics should also be given, use `summary.rma` (or use the `fitstats.rma` function to extract them). Full versus reduced model comparisons in terms of fit statistics and likelihoods can be obtained with `anova.rma`. Wald-type tests for sets of model coefficients or linear combinations thereof can be obtained with the same function. Tests and confidence intervals based on (cluster) robust methods can be obtained with `robust.rma.mv`.

Predicted/fitted values can be obtained with `predict.rma` and `fitted.rma`. For best linear unbiased predictions, see `ranef.rma.mv`.

The `residuals.rma`, `rstandard.rma.mv`, and `rstudent.rma.mv` functions extract raw and standardized residuals. See `influence.rma.mv` for additional case diagnostics (e.g., to determine influential studies). For models with moderators, variance inflation factors can be obtained with `vif.rma`.

Confidence intervals for any variance/correlation parameters in the model can be obtained with `confint.rma.mv`.

For random/mixed-effects models, the `profile.rma.mv` function can be used to obtain a plot of the (restricted) log-likelihood as a function of a specific variance component or correlation parameter of the model.

Other extractor functions include `coef.rma`, `vcov.rma`, `logLik.rma`, `deviance.rma`, `AIC.rma`, `BIC.rma`, `hatvalues.rma.mv`, and `weights.rma.mv`.

Note

Argument `V` also accepts a list of variance-covariance matrices for the observed effects or outcomes. From the list elements, the full (block diagonal) variance-covariance matrix is then automatically constructed.

Model fitting is done via numerical optimization over the model parameters. By default, `nlm` is used for the optimization. One can also choose a different optimizer via the control argument (e.g., `control=list(optimizer="optim")`). Note that when using `optim`, one can set the particular method via the `optmethod` argument (e.g., `control=list(optimizer="optim", optmethod="BFGS")`). Besides `nlm` and `optim`, one can also choose one of the optimizers from the `minqa` package (i.e., `uobyqa`, `newuoa`, or `bobyqa`), one of the (derivative-free) algorithms from the `nloptr` package, the Newton-type algorithm implemented in `nlm`, the Hooke-Jeeves and Nelder-Mead algorithms as implemented in `hjk` and `nmk` from the `dfoptim` package, the quasi-Newton type optimizer `ucminf` from the package of the same name, or the parallelized version of the L-BFGS-B algorithm implemented in `optimParallel` from the package of the same name.

Note that the optimizer name must be given as a character string (i.e., in quotes). Additional control parameters can be specified via the control argument (e.g., `control=list(iter.max=500, rel.tol=1e-8)`). For `nloptr`, the default is to use the BOBYQA implementation from that package with a relative convergence criterion of $1e-8$ on the function value (i.e., log likelihood), but this can be changed via the `algorithm` and `f_top_rel` arguments (e.g., `control=list(optimizer="nloptr", algorithm="NLOPT_LN_SBPLX", f_top_rel=1e-8)`). For `optimParallel`, the control argument `ncpus` can be used to specify the number of cores to use for the parallelization (e.g., `control=list(optimizer="optimParallel", ncpus=2)`). With `parallel::detectCores()`, one can check on the number of available cores on the local machine.

At the moment, the starting values are not chosen in a terribly clever way and could be far off. As a result, the optimizer may be slow to converge or may even get stuck at a local maximum. One

can set the starting values manually for the various variance components and correlations in the model via the `control` argument by specifying the vectors `sigma2.init`, `tau2.init`, `rho.init`, `gamma2.init`, and/or `phi.init` as needed. Especially for complex models, it is a good idea to try out different starting values to make sure that the same estimates are obtained.

Information on the progress of the optimization algorithm can be obtained by setting `verbose=TRUE` (note that this won't work when using parallelization). Since fitting complex models with many random effects can be computationally expensive, this option is useful to determine how the model fitting is progressing. One can also set `verbose` to an integer (`verbose=2` yields even more information and `verbose=3` also sets `option(warn=1)` temporarily).

Whether particular variance components and/or correlations are actually identifiable needs to be carefully examined when fitting complex models. The function does some limited checking internally to fix variances and/or correlations at zero when it is clear that insufficient information is available to estimate a particular parameter (e.g., if a particular factor has only a single level, the corresponding variance component cannot be estimated). However, it is strongly advised in general to do post model fitting checks to make sure that the likelihood surface around the ML/REML estimates is not flat for some combination of the parameter estimates (which would imply that the estimates are essentially arbitrary). For example, one can plot the (restricted) log-likelihood as a function of each variance component and correlation in the model to make sure that each profile plot shows a clear peak at the corresponding ML/REML estimates. The `profile.rma.mv` function can be used for this purpose.

Finally, note that the model fitting is not done in a very efficient manner at the moment, which is partly a result of allowing for crossed random effects and correlations among the effect sizes or outcomes across the entire dataset (e.g., when using the `R` argument). As a result, the function works directly with the entire $k \times k$ (marginal) variance-covariance matrix of the effect sizes or outcomes (instead of working with smaller blocks in a block diagonal structure). As a result, model fitting can be slow for large k . However, when the variance-covariance structure is actually sparse, a lot of speed can be gained by setting `sparse=TRUE`, in which case sparse matrix objects are used (via the `Matrix` package). Also, when model fitting appears to be slow, setting `verbose=TRUE` is useful to obtain information on how the model fitting is progressing.

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See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), and [rma.glmm](#) for other model fitting functions.
[dat.konstantopoulos2011](#), [dat.hasselblad1998](#), [dat.begg1989](#), [dat.berkey1998](#), [dat.fine1993](#),
 and [dat.ishak2007](#) for further examples of the use of the `rma.mv` function.

Examples

```
### calculate log odds ratios and corresponding sampling variances
dat <- escalc(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model using rma.uni()
rma(yi, vi, data=dat)

### random-effects model using rma.mv()
### note: sigma^2 in this model is the same as tau^2 from the previous model
rma.mv(yi, vi, random = ~ 1 | trial, data=dat)

### change data into long format
dat.long <- to.long(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### set levels of group variable ("exp" = experimental/vaccinated; "con" = control/non-vaccinated)
levels(dat.long$group) <- c("exp", "con")

### set "con" to reference level
dat.long$group <- relevel(dat.long$group, ref="con")

### calculate log odds and corresponding sampling variances
dat.long <- escalc(measure="PLO", xi=out1, mi=out2, data=dat.long)

### bivariate random-effects model using rma.mv()
res <- rma.mv(yi, vi, mods = ~ group, random = ~ group | study, struct="UN", data=dat.long)
res
```


rma.peto

*Meta-Analysis via Peto's Method***Description**

Function to fit fixed-effects models to 2×2 table data via Peto's method. See below and the documentation of the [metafor-package](#) for more details on these models.

Usage

```
rma.peto(ai, bi, ci, di, n1i, n2i,
         data, slab, subset,
         add=1/2, to="only0", drop00=TRUE,
         level=95, digits, verbose=FALSE, ...)
```

Arguments

ai	vector to specify the 2×2 table frequencies (upper left cell). See below and the documentation of the escalc function for more details.
bi	vector to specify the 2×2 table frequencies (upper right cell). See below and the documentation of the escalc function for more details.
ci	vector to specify the 2×2 table frequencies (lower left cell). See below and the documentation of the escalc function for more details.
di	vector to specify the 2×2 table frequencies (lower right cell). See below and the documentation of the escalc function for more details.
n1i	vector to specify the group sizes or row totals (first group). See below and the documentation of the escalc function for more details.
n2i	vector to specify the group sizes or row totals (second group). See below and the documentation of the escalc function for more details.
data	optional data frame containing the data supplied to the function.
slab	optional vector with labels for the k studies.
subset	optional (logical or numeric) vector indicating the subset of studies that should be used for the analysis.
add	non-negative number indicating the amount to add to zero cells, counts, or frequencies when calculating the observed outcomes of the individual studies. Can also be a vector of two numbers, where the first number is used in the calculation of the observed outcomes and the second number is used when applying Peto's method. See below and the documentation of the escalc function for more details.
to	character string indicating when the values under add should be added (either "only0", "all", "if0all", or "none"). Can also be a character vector, where the first string again applies when calculating the observed outcomes and the second string when applying Peto's method. See below and the documentation of the escalc function for more details.

drop00	logical indicating whether studies with no cases (or only cases) in both groups should be dropped when calculating the observed outcomes (the outcomes for such studies are set to NA). Can also be a vector of two logicals, where the first applies to the calculation of the observed outcomes and the second when applying Peto's method. See below and the documentation of the <code>escalc</code> function for more details.
level	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is 4).
verbose	logical indicating whether output should be generated on the progress of the model fitting (the default is FALSE).
...	additional arguments.

Details

Specifying the Data

The studies are assumed to provide data in terms of 2×2 tables of the form:

	outcome 1	outcome 2	total
group 1	ai	bi	n1i
group 2	ci	di	n2i

where ai, bi, ci, and di denote the cell frequencies and n1i and n2i the row totals. For example, in a set of randomized clinical trials (RCTs) or cohort studies, group 1 and group 2 may refer to the treatment (exposed) and placebo/control (not exposed) group, with outcome 1 denoting some event of interest (e.g., death) and outcome 2 its complement. In a set of case-control studies, group 1 and group 2 may refer to the group of cases and the group of controls, with outcome 1 denoting, for example, exposure to some risk factor and outcome 2 non-exposure.

Peto's Method

An approach for aggregating 2×2 table data of this type was suggested by Peto (see Yusuf et al., 1985). The method provides a weighted estimate of the (log) odds ratio under a fixed-effects model. The method is particularly advantageous when the event of interest is rare, but it should only be used when the group sizes within the individual studies are not too dissimilar and effect sizes are generally small (Greenland & Salvan, 1990; Sweeting et al., 2004; Bradburn et al., 2007). Note that the printed results are given both in terms of the log and the raw units (for easier interpretation).

Observed Outcomes of the Individual Studies

Peto's method itself does not require the calculation of the observed (log) odds ratios of the individual studies and directly makes use of the 2×2 table counts. Zero cells are not a problem (except in extreme cases, such as when one of the two outcomes never occurs in any of the tables). Therefore, it is unnecessary to add some constant to the cell counts when there are zero cells.

However, for plotting and various other functions, it is necessary to calculate the observed (log) odds ratios for the k studies. Here, zero cells can be problematic, so adding a constant value to the cell counts ensures that all k values can be calculated. The `add` and `to` arguments are used to specify what value should be added to the cell frequencies and under what circumstances when calculating

the observed (log) odds ratios and when applying Peto's method. Similarly, the `drop00` argument is used to specify how studies with no cases (or only cases) in both groups should be handled. The documentation of the `escalc` function explains how the `add`, `to`, and `drop00` arguments work. If only a single value for these arguments is specified (as per default), then these values are used when calculating the observed (log) odds ratios and no adjustment to the cell counts is made when applying Peto's method. Alternatively, when specifying two values for these arguments, the first value applies when calculating the observed (log) odds ratios and the second value when applying Peto's method.

Note that `drop00` is set to `TRUE` by default. Therefore, the observed (log) odds ratios for studies where $a_i=c_i=0$ or $b_i=d_i=0$ are set to `NA`. When applying Peto's method, such studies are not explicitly dropped (unless the second value of `drop00` argument is also set to `TRUE`), but this is practically not necessary, as they do not actually influence the results (assuming no adjustment to the cell/event counts are made when applying Peto's method).

Value

An object of class `c("rma.peto", "rma")`. The object is a list containing the following components:

<code>beta</code>	aggregated log odds ratio.
<code>se</code>	standard error of the aggregated value.
<code>zval</code>	test statistics of the aggregated value.
<code>pval</code>	p-value for the test statistic.
<code>ci.lb</code>	lower bound of the confidence interval.
<code>ci.ub</code>	upper bound of the confidence interval.
<code>QE</code>	test statistic for the test of heterogeneity.
<code>QEp</code>	p-value for the test of heterogeneity.
<code>k</code>	number of tables included in the analysis.
<code>yi, vi</code>	the vector of individual log odds ratios and corresponding sampling variances.
<code>fit.stats</code>	a list with the log-likelihood, deviance, AIC, BIC, and AICc values under the unrestricted and restricted likelihood.
<code>...</code>	some additional elements/values.

Methods

The results of the fitted model are formatted and printed with the `print.rma.peto` function. If fit statistics should also be given, use `summary.rma` (or use the `fitstats.rma` function to extract them).

The `residuals.rma`, `rstandard.rma.peto`, and `rstudent.rma.peto` functions extract raw and standardized residuals. Leave-one-out diagnostics can be obtained with `leave1out.rma.peto`.

Forest, funnel, radial, L'Abbé, and Baujat plots can be obtained with `forest.rma`, `funnel.rma`, `radial.rma`, `labbe.rma`, and `baujat`. The `qqnorm.rma.peto` function provides normal QQ plots of the standardized residuals. One can also just call `plot.rma.peto` on the fitted model object to obtain various plots at once.

A cumulative meta-analysis (i.e., adding one observation at a time) can be obtained with `cumul.rma.peto`.

Other extractor functions include `coef.rma`, `vcov.rma`, `logLik.rma`, `deviance.rma`, `AIC.rma`, and `BIC.rma`.

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See Also

[rma.uni](#), [rma.glmm](#), [rma.mh](#), and [rma.mv](#) for other model fitting functions.
[dat.collins1985a](#), [dat.collins1985b](#), and [dat.yusuf1985](#) for further examples of the use of the `rma.peto` function.

Examples

```
### meta-analysis of the (log) odds ratios using Peto's method
rma.peto(ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
```

rma.uni

Meta-Analysis via Linear (Mixed-Effects) Models

Description

Function to fit the meta-analytic fixed- and random/mixed-effects models with or without moderators via linear (mixed-effects) models. See the documentation of the [metafor-package](#) for more details on these models.

Usage

```
rma.uni(yi, vi, sei, weights, ai, bi, ci, di, n1i, n2i, x1i, x2i, t1i, t2i,
        m1i, m2i, sd1i, sd2i, xi, mi, ri, ti, sdi, r2i, ni, mods,
        measure="GEN", intercept=TRUE, data, slab, subset,
        add=1/2, to="only0", drop00=FALSE, vtype="LS",
        method="REML", weighted=TRUE, test="z",
        level=95, digits, btt, tau2, verbose=FALSE, control, ...)
```

```
rma(yi, vi, sei, weights, ai, bi, ci, di, n1i, n2i, x1i, x2i, t1i, t2i,
    m1i, m2i, sd1i, sd2i, xi, mi, ri, ti, sdi, r2i, ni, mods,
    measure="GEN", intercept=TRUE, data, slab, subset,
    add=1/2, to="only0", drop00=FALSE, vtype="LS",
    method="REML", weighted=TRUE, test="z",
    level=95, digits, btt, tau2, verbose=FALSE, control, ...)
```

Arguments

<code>yi</code>	vector of length k with the observed effect sizes or outcomes. See ‘Details’.
<code>vi</code>	vector of length k with the corresponding sampling variances. See ‘Details’.
<code>sei</code>	vector of length k with the corresponding standard errors (only relevant when not using <code>vi</code>). See ‘Details’.
<code>weights</code>	optional argument to specify a vector of length k with user-defined weights. See ‘Details’.
<code>ai</code>	see below and the documentation of the escalc function for more details.
<code>bi</code>	see below and the documentation of the escalc function for more details.
<code>ci</code>	see below and the documentation of the escalc function for more details.
<code>di</code>	see below and the documentation of the escalc function for more details.
<code>n1i</code>	see below and the documentation of the escalc function for more details.
<code>n2i</code>	see below and the documentation of the escalc function for more details.
<code>x1i</code>	see below and the documentation of the escalc function for more details.
<code>x2i</code>	see below and the documentation of the escalc function for more details.
<code>t1i</code>	see below and the documentation of the escalc function for more details.
<code>t2i</code>	see below and the documentation of the escalc function for more details.
<code>m1i</code>	see below and the documentation of the escalc function for more details.
<code>m2i</code>	see below and the documentation of the escalc function for more details.
<code>sd1i</code>	see below and the documentation of the escalc function for more details.
<code>sd2i</code>	see below and the documentation of the escalc function for more details.
<code>xi</code>	see below and the documentation of the escalc function for more details.
<code>mi</code>	see below and the documentation of the escalc function for more details.
<code>ri</code>	see below and the documentation of the escalc function for more details.
<code>ti</code>	see below and the documentation of the escalc function for more details.
<code>sdi</code>	see below and the documentation of the escalc function for more details.
<code>r2i</code>	see below and the documentation of the escalc function for more details.
<code>ni</code>	see below and the documentation of the escalc function for more details.
<code>mods</code>	optional argument to include one or more moderators in the model. A single moderator can be given as a vector of length k specifying the values of the moderator. Multiple moderators are specified by giving a matrix with k rows and as many columns as there are moderator variables. Alternatively, a model formula can be used to specify the model. See ‘Details’.

measure	character string indicating the type of data supplied to the function. When <code>measure="GEN"</code> (default), the observed effect sizes or outcomes and corresponding sampling variances (or standard errors) should be supplied to the function via the <code>yi</code> , <code>vi</code> , and <code>sei</code> arguments (only one of the two, <code>vi</code> or <code>sei</code> , needs to be specified). Alternatively, one can set <code>measure</code> to one of the effect size or outcome measures described under the documentation for the <code>escalc</code> function and specify the needed data via the appropriate arguments.
intercept	logical indicating whether an intercept should be added to the model (the default is TRUE). Ignored when <code>mods</code> is a formula.
data	optional data frame containing the data supplied to the function.
slab	optional vector with labels for the k studies.
subset	optional (logical or numeric) vector indicating the subset of studies that should be used for the analysis.
add	see the documentation of the <code>escalc</code> function.
to	see the documentation of the <code>escalc</code> function.
drop00	see the documentation of the <code>escalc</code> function.
vtype	see the documentation of the <code>escalc</code> function.
method	character string specifying whether a fixed- or a random/mixed-effects model should be fitted. A fixed-effects model (with or without moderators) is fitted when using <code>method="FE"</code> . Random/mixed-effects models are fitted by setting <code>method</code> equal to one of the following: "DL", "HE", "SJ", "ML", "REML", "EB", "HS", or "GENQ". Default is "REML". See 'Details'.
weighted	logical indicating whether weighted (default) or unweighted estimation should be used to fit the model.
test	character string specifying how test statistics and confidence intervals for the fixed effects should be computed. By default (<code>test="z"</code>), Wald-type tests and CIs are obtained, which are based on a standard normal distribution. When <code>test="knha"</code> , the method by Knapp and Hartung (2003) is used for adjusting test statistics and confidence intervals. See 'Details'.
level	numerical value between 0 and 100 specifying the confidence interval level (the default is 95).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is 4).
btt	optional vector of indices specifying which coefficients to include in the omnibus test of moderators. Can also be a string to grep for. See 'Details'.
tau2	optional numerical value to specify the amount of (residual) heterogeneity in a random- or mixed-effects model (instead of estimating it). Useful for sensitivity analyses (e.g., for plotting results as a function of τ^2). When unspecified, the value of τ^2 is estimated from the data.
verbose	logical indicating whether output should be generated on the progress of the model fitting (the default is FALSE). Can also be an integer. Values > 1 generate more verbose output. See 'Note'.
control	optional list of control values for the iterative estimation algorithms. If unspecified, default values are defined inside the function. See 'Note'.
...	additional arguments.

Details

Specifying the Data

The function can be used in conjunction with any of the usual effect size or outcome measures used in meta-analyses (e.g., log risk ratios, log odds ratios, risk differences, mean differences, standardized mean differences, raw correlation coefficients, correlation coefficients transformed with Fisher's r-to-z transformation, and so on). Simply specify the observed outcomes via the `yi` argument and the corresponding sampling variances via the `vi` argument. Instead of specifying `vi`, one can specify the standard errors (the square root of the sampling variances) via the `sei` argument. The `escalc` function can be used to compute a wide variety of effect size and outcome measures (and the corresponding sampling variances) based on summary statistics.

Alternatively, the function can automatically calculate the values of a chosen effect size or outcome measure (and the corresponding sampling variances) when supplied with the necessary data. The `escalc` function describes which effect size or outcome measures are currently implemented and what data/arguments should then be specified/used. The `measure` argument should then be set to the desired effect size or outcome measure.

Specifying the Model

The function can be used to fit fixed- and random/mixed-effects models, as well as meta-regression models including moderators (the difference between the various models is described in detail in the introductory [metafor-package](#) help file).

Assuming the observed outcomes and corresponding sampling variances are supplied via `yi` and `vi`, a *fixed-effects model* can be fitted with `rma(yi, vi, method="FE")`. Weighted estimation (with inverse-variance weights) is used by default. User-defined weights can be supplied via the `weights` argument. Unweighted estimation can be used by setting `weighted=FALSE` (same as setting the weights equal to a constant).

A *random-effects model* can be fitted with the same code but setting `method` to one of the various estimators for the amount of heterogeneity:

- `method="DL"` = DerSimonian-Laird estimator
- `method="HE"` = Hedges estimator
- `method="HS"` = Hunter-Schmidt estimator
- `method="SJ"` = Sidik-Jonkman estimator
- `method="ML"` = maximum-likelihood estimator
- `method="REML"` = restricted maximum-likelihood estimator
- `method="EB"` = empirical Bayes estimator
- `method="PM"` = Paule-Mandel estimator
- `method="GENQ"` = generalized Q-statistic estimator

For a description of the various estimators, see DerSimonian and Kacker (2007), Raudenbush (2009), Viechtbauer (2005), and Viechtbauer et al. (2015). Note that the Hedges estimator is also called the 'variance component estimator' or 'Cochran estimator', the Sidik-Jonkman estimator is also called the 'model error variance estimator', and the empirical Bayes estimator is actually identical to the Paule-Mandel estimator (Paule & Mandel, 1982). Finally, the generalized Q-statistic estimator is a general method-of-moments estimator (DerSimonian & Kacker, 2007) requiring the specification of weights (the HE and DL estimators are just special cases with equal and inverse variance weights, respectively).

One or more moderators can be included in these models via the `mods` argument. A single moderator can be given as a (row or column) vector of length k specifying the values of the moderator. Multiple moderators are specified by giving an appropriate model matrix (i.e., X) with k rows and as many columns as there are moderator variables (e.g., `mods = cbind(mod1, mod2, mod3)`, where `mod1`, `mod2`, and `mod3` correspond to the names of the variables for three moderator variables). The intercept is added to the model matrix by default unless `intercept=FALSE`.

Alternatively, one can use the standard `formula` syntax to specify the model. In this case, the `mods` argument should be set equal to a one-sided formula of the form `mods = ~ model` (e.g., `mods = ~ mod1 + mod2 + mod3`). Interactions, polynomial terms, and factors can be easily added to the model in this manner. When specifying a model formula via the `mods` argument, the `intercept` argument is ignored. Instead, the inclusion/exclusion of the intercept is controlled by the specified formula (e.g., `mods = ~ mod1 + mod2 + mod3 - 1` would lead to the removal of the intercept).

A *fixed-effects with moderators model* is then fitted by setting `method="FE"`, while a *mixed-effects model* is fitted by specifying one of the estimators for the amount of (residual) heterogeneity given earlier.

When the observed outcomes and corresponding sampling variances are supplied via the `yi` and `vi` (or `sei`) arguments, one can also specify moderators via the `yi` argument (e.g., `rma(yi ~ mod1 + mod2 + mod3, vi)`). In that case, the `mods` argument is ignored and the inclusion/exclusion of the intercept again is controlled by the specified formula.

Omnibus Test of Parameters

For models including moderators, an omnibus test of all the model coefficients is conducted that excludes the intercept (the first coefficient) if it is included in the model. If no intercept is included in the model, then the omnibus test includes all of the coefficients in the model including the first. Alternatively, one can manually specify the indices of the coefficients to test via the `btt` argument. For example, with `btt=c(3,4)`, only the third and fourth coefficient from the model would be included in the test (if an intercept is included in the model, then it corresponds to the first coefficient in the model). Instead of specifying the coefficient numbers, one can specify a string for `btt`. In that case, `grep` will be used to search for all coefficient names that match the string.

Categorical Moderators

Categorical moderator variables can be included in the model via the `mods` argument in the same way that appropriately (dummy) coded categorical independent variables can be included in linear models. One can either do the dummy coding manually or use a model formula together with the `factor` function to let R handle the coding automatically. An example to illustrate these different approaches is provided below.

Knapp & Hartung Adjustment

By default, the test statistics of the individual coefficients in the model (and the corresponding confidence intervals) are based on a standard normal distribution, while the omnibus test is based on a chi-square distribution with m degrees of freedom (m being the number of coefficients tested). The Knapp and Hartung (2003) method (`test="knha"`) is an adjustment to the standard errors of the estimated coefficients, which helps to account for the uncertainty in the estimate of the amount of (residual) heterogeneity and leads to different reference distributions. Tests of individual coefficients and confidence intervals are then based on the t-distribution with $k - p$ degrees of freedom, while the omnibus test statistic then uses an F-distribution with m and $k - p$ degrees of freedom (p being the total number of model coefficients including the intercept if it is present). The Knapp and Hartung (2003) adjustment is only meant to be used in the context of random- or mixed-effects models.

Test for (Residual) Heterogeneity

A test for (residual) heterogeneity is automatically carried out by the function. Without moderators in the model, this is simply Cochran's Q -test (Cochran, 1954), which tests whether the variability in the observed effect sizes or outcomes is larger than would be expected based on sampling variability alone. A significant test suggests that the true effects or outcomes are heterogeneous. When moderators are included in the model, this is the Q_E -test for residual heterogeneity, which tests whether the variability in the observed effect sizes or outcomes not accounted for by the moderators included in the model is larger than would be expected based on sampling variability alone.

Value

An object of class `c("rma.uni", "rma")`. The object is a list containing the following components:

<code>beta</code>	estimated coefficients of the model.
<code>se</code>	standard errors of the coefficients.
<code>zval</code>	test statistics of the coefficients.
<code>pval</code>	p-values for the test statistics.
<code>ci.lb</code>	lower bound of the confidence intervals for the coefficients.
<code>ci.ub</code>	upper bound of the confidence intervals for the coefficients.
<code>vb</code>	variance-covariance matrix of the estimated coefficients.
<code>tau2</code>	estimated amount of (residual) heterogeneity. Always \emptyset when <code>method="FE"</code> .
<code>se.tau2</code>	estimated standard error of the estimated amount of (residual) heterogeneity.
<code>k</code>	number of outcomes included in the model fitting.
<code>p</code>	number of coefficients in the model (including the intercept).
<code>m</code>	number of coefficients included in the omnibus test of coefficients.
<code>QE</code>	test statistic for the test of (residual) heterogeneity.
<code>QEp</code>	p-value for the test of (residual) heterogeneity.
<code>QM</code>	test statistic for the omnibus test of coefficients.
<code>QMp</code>	p-value for the omnibus test of coefficients.
<code>I2</code>	value of I^2 . See print.rma.uni for more details.
<code>H2</code>	value of H^2 . See print.rma.uni for more details.
<code>R2</code>	value of R^2 . See print.rma.uni for more details.
<code>int.only</code>	logical that indicates whether the model is an intercept-only model.
<code>yi, vi, X</code>	the vector of outcomes, the corresponding sampling variances, and the model matrix.
<code>fit.stats</code>	a list with the log-likelihood, deviance, AIC, BIC, and AICc values under the unrestricted and restricted likelihood.
<code>...</code>	some additional elements/values.

Methods

The results of the fitted model are formatted and printed with the `print.rma.uni` function. If fit statistics should also be given, use `summary.rma` (or use the `fitstats.rma` function to extract them). Full versus reduced model comparisons in terms of fit statistics and likelihoods can be obtained with `anova.rma`. Wald-type tests for sets of model coefficients or linear combinations thereof can be obtained with the same function. Permutation tests for the model coefficient(s) can be obtained with `permutest.rma.uni`. Tests and confidence intervals based on (cluster) robust methods can be obtained with `robust.rma.uni`.

Predicted/fitted values can be obtained with `predict.rma` and `fitted.rma`. For best linear unbiased predictions, see `blup.rma.uni` and `ranef.rma.uni`.

The `residuals.rma`, `rstandard.rma.uni`, and `rstudent.rma.uni` functions extract raw and standardized residuals. Additional case diagnostics (e.g., to determine influential studies) can be obtained with the `influence.rma.uni` function. For models without moderators, leave-one-out diagnostics can also be obtained with `leave1out.rma.uni`. For models with moderators, variance inflation factors can be obtained with `vif.rma`.

A confidence interval for the amount of (residual) heterogeneity in the random/mixed-effects model can be obtained with `confint.rma.uni`.

Forest, funnel, radial, L'Abbé, and Baujat plots can be obtained with `forest.rma`, `funnel.rma`, `radial.rma`, `labbe.rma`, and `baujat` (radial and L'Abbé plots only for models without moderators). The `qqnorm.rma.uni` function provides normal QQ plots of the standardized residuals. One can also just call `plot.rma.uni` on the fitted model object to obtain various plots at once. For random/mixed-effects models, the `profile.rma.uni` function can be used to obtain a plot of the (restricted) log-likelihood as a function of τ^2 .

Tests for funnel plot asymmetry (which may be indicative of publication bias) can be obtained with `ranktest.rma` and `regtest.rma`. For models without moderators, the `trimfill.rma.uni` method can be used to carry out a trim and fill analysis and `hc.rma.uni` provides a random-effects model analysis that is more robust to publication bias (based on the method by Henmi & Copas, 2010).

For models without moderators, a cumulative meta-analysis (i.e., adding one observation at a time) can be obtained with `cumul.rma.uni`.

Other extractor functions include `coef.rma`, `vcov.rma`, `logLik.rma`, `deviance.rma`, `AIC.rma`, `BIC.rma`, `hatvalues.rma.uni`, and `weights.rma.uni`.

Note

While the HS, HE, DL, SJ, and GENQ estimators of τ^2 are based on closed-form solutions, the ML, REML, and EB estimators must be obtained numerically. For this, the function makes use of the Fisher scoring algorithm, which is robust to poor starting values and usually converges quickly (Harville, 1977; Jennrich & Sampson, 1976). By default, the starting value is set equal to the value of the Hedges (HE) estimator and the algorithm terminates when the change in the estimated value of τ^2 is smaller than 10^{-5} from one iteration to the next. The maximum number of iterations is 100 by default (which should be sufficient in most cases). Information on the progress of the algorithm can be obtained by setting `verbose=TRUE`. One can also set `verbose` to an integer (`verbose=2` yields even more information and `verbose=3` also sets `option(warn=1)` temporarily).

A different starting value, threshold, and maximum number of iterations can be specified via the control argument by setting `control=list(tau2.init=value, threshold=value, maxiter=value)`.

The step length of the Fisher scoring algorithm can also be manually adjusted by a desired factor with `control=list(stepadj=value)` (values below 1 will reduce the step length). If using `verbose=TRUE` shows the estimate jumping around erratically (or cycling through a few values), decreasing the step length (and increasing the maximum number of iterations) can often help with convergence (e.g., `control=list(stepadj=0.5,maxiter=1000)`).

The PM estimator also involves an iterative algorithm, which makes use of the `uniroot` function. By default, the desired accuracy (`tol`) is set equal to `.Machine$double.eps^0.25` and the maximum number of iterations (`maxiter`) to 100 (as above). The upper bound of the interval searched (`tau2.max`) is set to 100 (which should be large enough for most cases). These values can be adjusted with `control=list(tol=value,maxiter=value,tau2.max=value)`.

All of the heterogeneity estimators except SJ can in principle yield negative estimates for the amount of (residual) heterogeneity. However, negative estimates of τ^2 are outside of the parameter space. For the HS, HE, DL, and GENQ estimators, negative estimates are therefore truncated to zero. For the ML, REML, and EB estimators, the Fisher scoring algorithm makes use of step halving (Jennrich & Sampson, 1976) to guarantee a non-negative estimate. Finally, for the PM estimator, the lower bound of the interval searched is set by default to zero. For those brave enough to step into risky territory, there is the option to set the lower bound for all these estimators equal to some other value besides zero (even a negative one) with `control=list(tau2.min=value)`, but the lowest value permitted is `-min(vi)` (to ensure that the marginal variances are always non-negative).

The Hunter-Schmidt estimator for the amount of heterogeneity is defined in Hunter and Schmidt (1990) only in the context of the random-effects model when analyzing correlation coefficients. A general version of this estimator for random- and mixed-effects models not specific to any particular outcome measure is described in Viechtbauer (2005) and Viechtbauer et al. (2015) and is implemented here.

The Sidik-Jonkman estimator starts with a crude estimate of τ^2 , which is then updated as described in Sidik and Jonkman (2005b, 2007). If, instead of the crude estimate, one wants to use a better a priori estimate, one can do so by passing this value via `control=list(tau2.init=value)`.

Outcomes with non-positive sampling variances are problematic. If a sampling variance is equal to zero, then its weight will be $1/0$ for fixed-effects models when using weighted estimation. Switching to unweighted estimation is a possible solution then. For random/mixed-effects model, some estimators of τ^2 are undefined when there is at least one sampling variance equal to zero. Other estimators may work, but it may still be necessary to switch to unweighted model fitting, especially when the estimate of τ^2 turns out to be zero.

When including moderators in the model, it is possible that the model matrix is not of full rank (i.e., there is a linear relationship between the moderator variables included in the model). The function automatically tries to reduce the model matrix to full rank by removing redundant predictors, but if this fails the model cannot be fitted and an error will be issued. Deleting (redundant) moderator variables from the model as needed should solve this problem.

Finally, some general words of caution about the assumptions underlying the models:

- The sampling variances (i.e., the v_i values) are treated as if they are known constants. This (usually) implies that the distributions of the test statistics and corresponding confidence intervals are only exact and have nominal coverage when the within-study sample sizes are large (i.e., when the error in the sampling variance estimates is small). Certain outcome measures (e.g., the arcsine square root transformed risk difference and Fisher's r -to- z transformed correlation coefficient) are based on variance stabilizing transformations that also help to make the assumption of known sampling variances much more reasonable.

- When fitting a mixed/random-effects model, τ^2 is estimated and then treated as a known constant thereafter. This ignores the uncertainty in the estimate of τ^2 . As a consequence, the standard errors of the parameter estimates tend to be too small, yielding test statistics that are too large and confidence intervals that are not wide enough. The Knapp and Hartung (2003) adjustment can be used to counter this problem, yielding test statistics and confidence intervals whose properties are closer to nominal.
- Most effect size measures are not exactly normally distributed as assumed under the various models. However, the normal approximation usually becomes more accurate for most effect size or outcome measures as the within-study sample sizes increase. Therefore, sufficiently large within-study sample sizes are (usually) needed to be certain that the tests and confidence intervals have nominal levels/coverage. Again, certain outcome measures (e.g., Fisher's r-to-z transformed correlation coefficient) may be preferable from this perspective as well.

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See Also

[rma.mh](#), [rma.peto](#), [rma.glmm](#), and [rma.mv](#) for other model fitting functions.

Examples

```
### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model, using log risk ratios and variances as input
### note: method="REML" is the default, so one could leave this out
rma(yi, vi, data=dat, method="REML")

### random-effects model, using log risk ratios and standard errors as input
### note: the second argument of rma() is for the *variances*, so we use the
### named argument 'sei' to supply the standard errors to the function
dat$sei <- sqrt(dat$vi)
rma(yi, sei=sei, data=dat)

### supplying the 2x2 table cell frequencies directly to the rma() function
rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat)

### mixed-effects model with two moderators (absolute latitude and publication year)
rma(yi, vi, mods=cbind(ablat, year), data=dat)

### using a model formula to specify the same model
rma(yi, vi, mods = ~ ablat + year, data=dat)

### using a model formula as part of the yi argument
rma(yi ~ ablat + year, vi, data=dat)

### manual dummy coding of the allocation factor
```

```

alloc.random    <- ifelse(dat$alloc == "random",    1, 0)
alloc.alternate <- ifelse(dat$alloc == "alternate", 1, 0)
alloc.systematic <- ifelse(dat$alloc == "systematic", 1, 0)

### test the allocation factor (in the presence of the other moderators)
### note: 'alternate' is the reference level of the allocation factor,
###       since this is the dummy/level we leave out of the model
### note: the intercept is the first coefficient, so with btt=2:3 we test
###       coefficients 2 and 3, corresponding to the coefficients for the
###       allocation factor
rma(yi, vi, mods = ~ alloc.random + alloc.systematic + year + ablat, data=dat, btt=2:3)

### using a model formula to specify the same model
rma(yi, vi, mods = ~ factor(alloc) + year + ablat, data=dat, btt=2:3)

### test all pairwise differences with Holm's method (using the 'multcomp' package if installed)
res <- rma(yi, vi, mods = ~ factor(alloc) - 1, data=dat)
res
if (require(multcomp))
  summary(glht(res, linfct=contrMat(c("alternate"=1,"random"=1,"systematic"=1),
    type="Tukey")), test=adjusted("holm"))

### subgrouping versus using a single model with a factor (subgrouping provides
### an estimate of tau^2 within each subgroup, but the number of studies in each
### subgroup is quite small; the model with the allocation factor provides a
### single estimate of tau^2 based on a larger number of studies, but assumes
### that tau^2 is the same within each subgroup)
res.a <- rma(yi, vi, data=dat, subset=(alloc=="alternate"))
res.r <- rma(yi, vi, data=dat, subset=(alloc=="random"))
res.s <- rma(yi, vi, data=dat, subset=(alloc=="systematic"))
res.a
res.r
res.s
res <- rma(yi, vi, mods = ~ factor(alloc) - 1, data=dat)
res

### demonstrating that Q_E + Q_M = Q_Total for fixed-effects models
### note: this does not work for random/mixed-effects models, since Q_E and
### Q_Total are calculated under the assumption that tau^2 = 0, while the
### calculation of Q_M incorporates the estimate of tau^2
res <- rma(yi, vi, data=dat, method="FE")
res ### this gives Q_Total
res <- rma(yi, vi, mods = ~ ablat + year, data=dat, method="FE")
res ### this gives Q_E and Q_M
res$QE + res$QM

### decomposition of Q_E into subgroup Q-values
res <- rma(yi, vi, mods = ~ factor(alloc), data=dat)
res

res.a <- rma(yi, vi, data=dat, subset=(alloc=="alternate"))
res.r <- rma(yi, vi, data=dat, subset=(alloc=="random"))
res.s <- rma(yi, vi, data=dat, subset=(alloc=="systematic"))

```

```

res.a$QE ### Q-value within subgroup "alternate"
res.r$QE ### Q-value within subgroup "random"
res.s$QE ### Q-value within subgroup "systematic"

res$QE
res.a$QE + res.r$QE + res.s$QE

```

robust

(Cluster) Robust Tests and Confidence Intervals for 'rma' Objects

Description

The function provides (cluster) robust tests and confidence intervals of the model coefficients for objects of class "rma".

Usage

```

robust(x, cluster, ...)

## S3 method for class 'rma.uni'
robust(x, cluster, adjust=TRUE, digits, ...)
## S3 method for class 'rma.mv'
robust(x, cluster, adjust=TRUE, digits, ...)

```

Arguments

<code>x</code>	an object of class "rma.uni" or "rma.mv".
<code>cluster</code>	a vector specifying a clustering variable to use for constructing the sandwich estimator of the variance-covariance matrix.
<code>adjust</code>	logical indicating whether a small-sample correction should be applied to the variance-covariance matrix.
<code>digits</code>	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
<code>...</code>	other arguments.

Details

The function constructs a (cluster) robust estimate of the variance-covariance matrix of the model coefficients based on a sandwich-type estimator and then computes tests and confidence intervals of the model coefficients.

Tests of individual coefficients and confidence intervals are based on a t-distribution with $n - p$ degrees of freedom is used, while the omnibus test statistic uses an F-distribution with m and $n - p$ degrees of freedom, where n is the number of clusters, p denotes the total number of model coefficients (including the intercept if it is present), and m denotes the number of coefficients tested (in the omnibus test).

When `adjust=TRUE` (the default), the (cluster) robust estimate of the variance-covariance matrix is multiplied by the factor $n/(n-p)$, which serves as a small-sample adjustment that tends to improve the performance of the method when the number of clusters is small.

Value

An object of class "robust.rma". The object is a list containing the following components:

<code>beta</code>	estimated coefficients of the model.
<code>se</code>	robust standard errors of the coefficients.
<code>zval</code>	test statistics of the coefficients.
<code>pval</code>	p-values for the test statistics.
<code>ci.lb</code>	lower bound of the confidence intervals for the coefficients.
<code>ci.ub</code>	upper bound of the confidence intervals for the coefficients.
<code>vb</code>	robust variance-covariance matrix of the estimated coefficients.
<code>QM</code>	test statistic for the omnibus test of coefficients.
<code>QMp</code>	p-value for the omnibus test of coefficients.
<code>...</code>	some additional elements/values.

The results are formatted and printed with the `print.robust.rma` function.

Note

The variable specified via `cluster` is assumed to be of the same length as the data originally passed to the `rma.uni` or `rma.mv` function. Any subsetting and removal of studies with missing values as done when fitting the original model is also automatically applied to the variable specified via `cluster`.

The idea of the robust (sandwich-type) estimator for models with unspecified heteroscedasticity can be traced back to Eicker (1967), Huber (1967), and White (1980). Hence, the method in general is often referred to as the Eicker-Huber-White method. Some small-sample improvements to the method are described by MacKinnon and White (1985). The extension to the cluster robust estimator can be found in Froot (1989) and Williams (2000). Cameron and Miller (2015) provide an extensive overview of cluster robust methods. Sidik and Jonkman (2005, 2006) introduced robust methods in the meta-analytic context for standard random/mixed-effects models. The use of the cluster robust estimator for multivariate/multilevel meta-analytic models is described in Hedges, Tipton, and Johnson (2010).

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See Also

[rma.uni](#), [rma.mv](#)

Examples

```
### copy data from Konstantopoulos (2011) into 'dat'
dat <- dat.konstantopoulos2011

### multilevel random-effects model
res <- rma.mv(yi, vi, random = ~ 1 | district/school, data=dat)
res

### results based on sandwich method
robust(res, cluster=dat$district)

### copy data from Berkey et al. (1998) into 'dat'
dat <- dat.berkey1998

### construct list of the variance-covariance matrices of the observed outcomes for the studies
V <- lapply(split(dat[c("v1i", "v2i")], dat$trial), as.matrix)

### construct block diagonal matrix
V <- bldiag(V)
```

```
### fit multivariate model
res <- rma.mv(yi, V, mods = ~ outcome - 1, random = ~ outcome | trial, struct="UN", data=dat)
res

### results based on sandwich method
robust(res, cluster=dat$trial)
```

simulate.rma

Simulate Method for 'rma' Objects

Description

The function simulates observed outcomes based on "rma" model object.

Usage

```
## S3 method for class 'rma'
simulate(object, nsim = 1, seed = NULL, ...)
```

Arguments

object	an object of class "rma".
nsim	number of response vectors to simulate (defaults to 1).
seed	an object specifying if and how the random number generator should be initialized ('seeded'). Either NULL or an integer that will be used in a call to <code>set.seed</code> before simulating the response vectors. If set, the value is saved as the "seed" attribute of the returned value. The default, NULL will not change the random generator state, and return <code>.Random.seed</code> as the "seed" attribute; see 'Value'.
...	other arguments.

Details

The model specified via `object` must be a model fitted with either the `rma.uni` or `rma.mv` function.

Value

A data frame with `nsim` columns with the simulated outcomes.

The data frame comes with an attribute "seed". If argument `seed` is NULL, the attribute is the value of `.Random.seed` before the simulation was started; otherwise it is the value of the argument with a "kind" attribute with value `as.list(RNGkind())`.

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References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mv](#)

Examples

```
### copy BCG vaccine data into 'dat'
dat <- dat.bcg

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat)
dat

### random-effects model
res <- rma(yi, vi, data=dat)
res

### simulate 10 sets of new outcomes based on the fitted model
newdat <- simulate(res, nsim=10, seed=1234)
newdat
```

to.long

Convert Data from Vector to Long Format

Description

The function converts summary data in vector format to the corresponding long format.

Usage

```
to.long(measure, ai, bi, ci, di, n1i, n2i, x1i, x2i, t1i, t2i,
        m1i, m2i, sd1i, sd2i, xi, mi, ri, ti, sdi, ni, data, slab, subset,
        add=1/2, to="none", drop00=FALSE, vlong=FALSE, append=TRUE, var.names)
```

Arguments

measure	a character string indicating the effect size or outcome measure corresponding to the summary data supplied. See below and the documentation of the escalc function for more details.
ai	vector to specify the 2×2 table frequencies (upper left cell).
bi	vector to specify the 2×2 table frequencies (upper right cell).
ci	vector to specify the 2×2 table frequencies (lower left cell).
di	vector to specify the 2×2 table frequencies (lower right cell).

n1i	vector to specify the group sizes or row totals (first group/row).
n2i	vector to specify the group sizes or row totals (second group/row).
x1i	vector to specify the number of events (first group).
x2i	vector to specify the number of events (second group).
t1i	vector to specify the total person-times (first group).
t2i	vector to specify the total person-times (second group).
m1i	vector to specify the means (first group or time point).
m2i	vector to specify the means (second group or time point).
sd1i	vector to specify the standard deviations (first group or time point).
sd2i	vector to specify the standard deviations (second group or time point).
xi	vector to specify the frequencies of the event of interest.
mi	vector to specify the frequencies of the complement of the event of interest or the group means.
ri	vector to specify the raw correlation coefficients.
ti	vector to specify the total person-times.
sdi	vector to specify the standard deviations.
ni	vector to specify the sample/group sizes.
data	optional data frame containing the variables given to the arguments above.
slab	optional vector with labels for the studies.
subset	optional (logical or numeric) vector indicating the subset of studies that should included in the data frame returned by the function.
add	see the documentation of the escalc function.
to	see the documentation of the escalc function.
drop00	see the documentation of the escalc function.
vlong	optional logical whether a very long format should be used (only relevant for 2×2 or 1×2 table data).
append	logical indicating whether the data frame specified via the data argument (if one has been specified) should be returned together with the long format data (the default is TRUE).
var.names	optional vector with variable names (length depends on the data type). If unspecified, the function sets appropriate variable names by default.

Details

The [escalc](#) function describes a wide variety of effect size and outcome measures that can be computed for a meta-analysis. The summary data used to compute those measures are typically contained in vectors, each element corresponding to a study. The `to.long` function takes this information and constructs a long format dataset from these data.

For example, in various fields (such as the health and medical sciences), the response variable measured is often dichotomous (binary), so that the data from a study comparing two different groups can be expressed in terms of a 2×2 table, such as:

	outcome 1	outcome 2	total
group 1	ai	bi	n1i
group 2	ci	di	n2i

where a_i , b_i , c_i , and d_i denote the cell frequencies (i.e., the number of people falling into a particular category) and n_{1i} and n_{2i} the row totals (i.e., the group sizes).

The cell frequencies in k such 2×2 tables can be specified via the a_i , b_i , c_i , and d_i arguments (or alternatively, via the a_i , c_i , n_{1i} , and n_{2i} arguments). The function then creates the corresponding long format dataset. The `measure` argument should then be set equal to one of the outcome measures that can be computed based on this type of data, such as "RR", "OR", "RD" (it is not relevant which specific measure is chosen, as long as it corresponds to the specified summary data). See the documentation of the `escalc` function for more details on the types of data formats available.

The long format for data of this type consists of two rows per study, a factor indicating the study (default name `study`), a dummy variable indicating the group (default name `group`, coded as 1 and 2), and two variables indicating the number of individuals experiencing outcome 1 or outcome 2 (default names `out1` and `out2`). Alternatively, if `vlong=TRUE`, then the long format consists of four rows per study, a factor indicating the study (default name `study`), a dummy variable indicating the group (default name `group`, coded as 1 and 2), a dummy variable indicating the outcome (default name `outcome`, coded as 1 and 2), and a variable indicating the frequency of the respective outcome (default name `freq`).

The default variable names can be changed via the `var.names` argument (must be of the appropriate length, depending on the data type).

The examples below illustrate the use of this function.

Value

A data frame with either k , $2k$, or $4k$ rows and an appropriate number of columns (depending on the data type) with the data in long format. If `append=TRUE` and a data frame was specified via the `data` argument, then the data in long format are appended to the original data frame (with rows repeated an appropriate number of times).

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References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[escalc](#), [to.table](#)

Examples

```

### convert data to long format
dat <- to.long(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
dat

### extra long format
dat <- to.long(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg, vlong=TRUE)
dat

### convert data to long format
dat <- to.long(measure="IRR", x1i=x1i, x2i=x2i, t1i=t1i, t2i=t2i,
              data=dat.hart1999, var.names=c("id", "group", "events", "ptime"))
dat

### convert data to long format
dat <- to.long(measure="MD", m1i=m1i, sd1i=sd1i, n1i=n1i,
              m2i=m2i, sd2i=sd2i, n2i=n2i, data=dat.normand1999,
              var.names=c("id", "group", "mean", "sd", "n"))
dat

```

to.table

*Convert Data from Vector to Table Format***Description**

The function converts summary data in vector format to the corresponding table format.

Usage

```

to.table(measure, ai, bi, ci, di, n1i, n2i, x1i, x2i, t1i, t2i,
        m1i, m2i, sd1i, sd2i, xi, mi, ri, ti, sdi, ni, data, slab, subset,
        add=1/2, to="none", drop00=FALSE, rows, cols)

```

Arguments

measure	a character string indicating the effect size or outcome measure corresponding to the summary data supplied. See below and the documentation of the escalc function for more details.
ai	vector to specify the 2×2 table frequencies (upper left cell).
bi	vector to specify the 2×2 table frequencies (upper right cell).
ci	vector to specify the 2×2 table frequencies (lower left cell).
di	vector to specify the 2×2 table frequencies (lower right cell).
n1i	vector to specify the group sizes or row totals (first group/row).
n2i	vector to specify the group sizes or row totals (second group/row).
x1i	vector to specify the number of events (first group).
x2i	vector to specify the number of events (second group).

t1i	vector to specify the total person-times (first group).
t2i	vector to specify the total person-times (second group).
m1i	vector to specify the means (first group or time point).
m2i	vector to specify the means (second group or time point).
sd1i	vector to specify the standard deviations (first group or time point).
sd2i	vector to specify the standard deviations (second group or time point).
xi	vector to specify the frequencies of the event of interest.
mi	vector to specify the frequencies of the complement of the event of interest or the group means.
ri	vector to specify the raw correlation coefficients.
ti	vector to specify the total person-times.
sdi	vector to specify the standard deviations.
ni	vector to specify the sample/group sizes.
data	optional data frame containing the variables given to the arguments above.
slab	optional vector with labels for the studies.
subset	optional (logical or numeric) vector indicating the subset of studies that should be included in the array returned by the function.
add	see the documentation of the escalc function.
to	see the documentation of the escalc function.
drop00	see the documentation of the escalc function.
rows	optional vector with row/group names.
cols	optional vector with column/outcome names.

Details

The [escalc](#) function describes a wide variety of effect size and outcome measures that can be computed for a meta-analysis. The summary data used to compute those measures are typically contained in vectors, each element corresponding to a study. The `to.table` function takes this information and constructs an array of k tables from these data.

For example, in various fields (such as the health and medical sciences), the response variable measured is often dichotomous (binary), so that the data from a study comparing two different groups can be expressed in terms of a 2×2 table, such as:

	outcome 1	outcome 2	total
group 1	ai	bi	n1i
group 2	ci	di	n2i

where ai, bi, ci, and di denote the cell frequencies (i.e., the number of people falling into a particular category) and n1i and n2i the row totals (i.e., the group sizes).

The cell frequencies in k such 2×2 tables can be specified via the ai, bi, ci, and di arguments (or alternatively, via the ai, ci, n1i, and n2i arguments). The function then creates the corresponding $2 \times 2 \times k$ array of tables. The measure argument should then be set equal to one of the outcome

measures that can be computed based on this type of data, such as "RR", "OR", "RD" (it is not relevant which specific measure is chosen, as long as it corresponds to the specified summary data). See the documentation of the `escalc` function for more details on the types of data formats available.

The examples below illustrate the use of this function.

Value

An array with k elements each consisting of either 1 or 2 rows and an appropriate number of columns.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[escalc](#), [to.long](#)

Examples

```
### create tables
dat <- to.table(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
               data=dat.bcg, slab=paste(author, year, sep=", "),
               rows=c("Vaccinated", "Not Vaccinated"), cols=c("TB+", "TB-"))
dat

### create tables
dat <- to.table(measure="IRR", x1i=x1i, x2i=x2i, t1i=t1i, t2i=t2i,
               data=dat.hart1999, slab=paste(study, year, sep=", "),
               rows=c("Warfarin Group", "Placebo/Control Group"))
dat

### create tables
dat <- to.table(measure="MD", m1i=m1i, sd1i=sd1i, n1i=n1i,
               m2i=m2i, sd2i=sd2i, n2i=n2i, data=dat.normand1999,
               slab=source, rows=c("Specialized Care", "Routine Care"))
dat
```

to.wide	<i>Convert Data from a Long to a Wide Format</i>
---------	--------------------------------------------------

Description

The function converts data given in long format to a wide format.

Usage

```
to.wide(data, study, grp, ref, grpvars, postfix=c(".1", ".2"),
        addid=TRUE, addcomp=TRUE, adddesign=TRUE, minlen=2,
        var.names=c("id", "comp", "design"))
```

Arguments

data	a data frame in long format.
study	either the name (given as a character string) or the position (given as a single number) of the study variable in the data frame.
grp	either the name (given as a character string) or the position (given as a single number) of the group variable in the data frame.
ref	optional character string to specify the reference group (must be one of the groups in the group variable). If not given, the most frequently occurring group is used as the reference group.
grpvars	either the names (given as a character vector) or the positions (given as a numeric vector) of the group-level variables.
postfix	a character string of length 2 giving the affix that is placed after the names of the group-level variables for the first and second group.
addid	logical indicating whether a row id variable should be added to the data frame (TRUE by default).
addcomp	logical indicating whether a comparison id variable should be added to the data frame (TRUE by default).
adddesign	logical indicating whether a design id variable should be added to the data frame (TRUE by default).
minlen	integer indicating the minimum length of the shortened group names for the comparison and design id variables (2 by default).
var.names	a character string with three elements, specifying the name of the id, comparison, and design variables (the default is <code>c("id", "comp", "design")</code>), respectively).

Details

A meta-analytic dataset may be structured in a ‘long’ format, where each row in the dataset corresponds to a particular study group (e.g., treatment arm). Using this function, such a dataset can be restructured into a ‘wide’ format, where each group within a study is contrasted against a particular reference group.

The `study` and `group` arguments are used to specify the study and group variables in the dataset (either as character strings or as numbers indicating the column positions of these variables in the dataset). Optional argument `ref` is used to specify the reference group (this must be one of the groups in the `group` variable). Argument `grpvars` is used to specify (either as a character vector or by giving the column positions) of those variables in the dataset that correspond to group-level outcomes (the remaining variables are treated as study-level outcomes).

The dataset is restructured so that a two-group study will yield a single row in the restructured dataset, contrasting the first group against the second group (either the specified reference group if the study actually includes that group or the other group that was included in the study). For studies with more than two groups (often called ‘multiarm’ studies in the medical literature), the reference group is repeated as many times as needed (so a three-group study would yield two rows in the restructured dataset, contrasting two groups against a common reference group).

To distinguish the names of the group-level outcome variables for the two first and second group in the restructured dataset, the strings given for the `postfix` argument are placed after the respective variable names.

If requested, `row id`, `comparison id`, and `design id` variables are added to the restructured dataset. The `row id` is simply a unique number for each row in the dataset. The `comparison id` variable indicates which two groups have been compared against each other). The `design id` variable indicates which groups were included in a particular study. The group names are shortened for the comparison and design variables (to at least `minlen`; the actual length might be longer to ensure uniqueness of the group names).

The examples below illustrate the use of this function.

Value

A data frame with rows contrasting groups against a reference group and an appropriate number of columns (depending on the number of group-level outcome variables).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[to.long](#), [to.table](#), [dat.senn2013](#), [dat.hasselblad1998](#)

Examples

```

### data in long format
dat <- dat.senn2013
dat <- dat[c(1,4,3,2,5,6)]
dat

### restructure to wide format
dat <- to.wide(dat, study="study", grp="treatment", ref="placebo", grpvars=4:6)
dat

### data in long format
dat <- dat.hasselblad1998
dat

### restructure to wide format
dat <- to.wide(dat, study="study", grp="trt", ref="no_contact", grpvars=6:7)
dat

```

transf

Transformation Function

Description

A set of transformation functions useful for meta-analyses.

Usage

```

transf.rtoz(xi, ...)
transf.ztor(xi, ...)
transf.logit(xi, ...)
transf.ilogit(xi, ...)
transf.arcsin(xi, ...)
transf.iarcsin(xi, ...)
transf.pft(xi, ni, ...)
transf.ipft(xi, ni, ...)
transf.ipft.hm(xi, targs, ...)
transf.isqrt(xi, ...)
transf.irft(xi, ti, ...)
transf.iirft(xi, ti, ...)
transf.ahw(xi, ...)
transf.iahw(xi, ...)
transf.abt(xi, ...)
transf.iabt(xi, ...)
transf.ztor.int(xi, targs, ...)
transf.exp.int(xi, targs, ...)
transf.ilogit.int(xi, targs, ...)

```

Arguments

<code>xi</code>	vector of values to be transformed.
<code>ni</code>	vector of sample sizes.
<code>ti</code>	vector of person-times at risk.
<code>targs</code>	list with additional arguments for the transformation function. See ‘Details’.
<code>...</code>	other arguments.

Details

The following transformation functions are currently implemented:

- `transf.rtoz`: Fisher’s r-to-z transformation for correlations.
- `transf.ztor`: inverse of the Fisher’s r-to-z transformation.
- `transf.logit`: logit (log odds) transformation for proportions.
- `transf.ilogit`: inverse of the logit transformation.
- `transf.arcsin`: arcsine square root transformation for proportions.
- `transf.iarcsin`: inverse of the arcsine transformation.
- `transf.pft`: Freeman-Tukey (double arcsine) transformation for proportions. See Freeman & Tukey (1950). The `xi` argument is used to specify the proportions and the `ni` argument the corresponding sample sizes.
- `transf.ipft`: inverse of the Freeman-Tukey (double arcsine) transformation for proportions. See Miller (1978).
- `transf.ipft.hm`: inverse of the Freeman-Tukey (double arcsine) transformation for proportions using the harmonic mean of the sample sizes for the back-transformation. See Miller (1978). The sample sizes are specified via the `targs` argument (the list element should be called `ni`).
- `transf.isqrt`: inverse of the square root transformation (i.e., function to square a number).
- `transf.irft`: Freeman-Tukey transformation for incidence rates. See Freeman & Tukey (1950). The `xi` argument is used to specify the incidence rates and the `ti` argument the corresponding person-times at risk.
- `transf.iirft`: inverse of the Freeman-Tukey transformation for incidence rates.
- `transf.ahw`: Transformation of coefficient alpha as suggested by Hakstian & Whalen (1976).
- `transf.iahw`: Inverse of the transformation of coefficient alpha as suggested by Hakstian & Whalen (1976).
- `transf.abt`: Transformation of coefficient alpha as suggested by Bonett (2002).
- `transf.iabt`: Inverse of the transformation of coefficient alpha as suggested by Bonett (2002).
- `transf.ztor.int`: integral transformation method for the z-to-r transformation.
- `transf.exp.int`: integral transformation method for the exponential transformation.
- `transf.ilogit.int`: integral transformation method for the inverse of the logit transformation.

The integral transformation method for a transformation function $h(z)$ integrates $h(z)f(z)$ over z using the limits `targs$lower` and `targs$upper`, where $f(z)$ is the density of a normal distribution with mean equal to `xi` and variance equal to `targs$tau2`. An example is provided below.

Value

A vector with the transformed values.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Bonett, D. G. (2002). Sample size requirements for testing and estimating coefficient alpha. *Journal of Educational and Behavioral Statistics*, **27**, 335–340.
- Fisher, R. A. (1921). On the “probable error” of a coefficient of correlation deduced from a small sample. *Metron*, **1**, 1–32.
- Freeman, M. F., & Tukey, J. W. (1950). Transformations related to the angular and the square root. *Annals of Mathematical Statistics*, **21**, 607–611.
- Hakstian, A. R., & Whalen, T. E. (1976). A k-sample significance test for independent alpha coefficients. *Psychometrika*, **41**, 219–231.
- Miller, J. J. (1978). The inverse of the Freeman-Tukey double arcsine transformation. *American Statistician*, **32**, 138.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

Examples

```
### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### average risk ratio with 95% CI (but technically, this provides an
### estimate of the median risk ratio, not the mean risk ratio!)
predict(res, transf=exp)

### average risk ratio with 95% CI using the integral transformation
predict(res, transf=transf.exp.int, targ= list(tau2=res$tau2, lower=-4, upper=4))
```

trimfill

Trim and Fill Analysis for 'rma.uni' Objects

Description

Carry out a trim and fill analysis for objects of class "rma.uni".

Usage

```
trimfill(x, ...)

## S3 method for class 'rma.uni'
trimfill(x, side, estimator="L0", maxiter=100, verbose=FALSE, ilim, ...)
```

Arguments

<code>x</code>	an object of class <code>"rma.uni"</code> .
<code>side</code>	either <code>"left"</code> or <code>"right"</code> , indicating on which side of the funnel plot the missing studies should be imputed. If left undefined, the side is chosen within the function depending on the results of Egger's regression test (see <code>regtest</code> for details on this test).
<code>estimator</code>	either <code>"L0"</code> , <code>"R0"</code> , or <code>"Q0"</code> , indicating the estimator to use for estimating the number of missing studies (the default is <code>"L0"</code>).
<code>maxiter</code>	integer indicating the maximum number of iterations to use for the trim and fill method (the default is 100).
<code>verbose</code>	logical indicating whether output should be generated on the progress of the iterative algorithm used as part of the trim and fill method (the default is <code>FALSE</code>).
<code>ilim</code>	limits for the imputed values. If unspecified, no limits are used.
<code>...</code>	other arguments.

Details

The trim and fill method is a nonparametric (rank-based) data augmentation technique proposed by Duval and Tweedie (2000a, 2000b; see also Duval, 2005). The method can be used to estimate the number of studies missing from a meta-analysis due to the suppression of the most extreme results on one side of the funnel plot. The method then augments the observed data so that the funnel plot is more symmetric and recomputes the summary estimate based on the complete data. The trim and fill method can only be used in the context of a fixed- or random-effects model (i.e., in models without moderators). The method should not be regarded as a way of yielding a more "valid" estimate of the overall effect or outcome, but as a way of examining the sensitivity of the results to one particular selection mechanism (i.e., one particular form of publication bias).

Value

An object of class `c("rma.uni.trimfill", "rma.uni", "rma")`. The object is a list containing the same components as objects created by `rma.uni`, except that the data are augmented by the trim and fill method. The following components are also added:

<code>k0</code>	estimated number of missing studies.
<code>side</code>	either <code>"left"</code> or <code>"right"</code> , indicating on which side of the funnel plot the missing studies (if any) were imputed.
<code>se.k0</code>	estimated standard error of <code>k0</code> .
<code>p.k0</code>	p-value for the test of H_0 : no missing studies on the chosen side (only when <code>estimator="R0"</code> ; NA otherwise).
<code>fill</code>	a logical vector, indicating which of the data are the observed (<code>FALSE</code>) and the augmented (<code>TRUE</code>) data.

The results of the fitted model after the data augmentation are printed with the `print.rma.uni` function. Calling `funnel.rma` on the object provides a funnel plot of the observed and augmented data.

Note

Three different estimators for the number of missing studies were proposed by Duval and Tweedie (2000a, 2000b). Based on these articles and Duval (2005), "R0" and "L0" are recommended. An advantage of estimator "R0" is that it provides a test of the null hypothesis that the number of missing studies (on the chosen side) is zero.

If the outcome measure used for the analysis is bounded (e.g., correlations are bounded between -1 and 1, proportions are bounded between 0 and 1), one can use the `ilim` argument to enforce those limits when imputing values (imputed values cannot exceed those bounds then).

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

- Duval, S. J., & Tweedie, R. L. (2000a). Trim and fill: A simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis. *Biometrics*, **56**, 455–463.
- Duval, S. J., & Tweedie, R. L. (2000b). A nonparametric "trim and fill" method of accounting for publication bias in meta-analysis. *Journal of the American Statistical Association*, **95**, 89–98.
- Duval, S. J. (2005). The trim and fill method. In H. R. Rothstein, A. J. Sutton, & M. Borenstein (Eds.) *Publication bias in meta-analysis: Prevention, assessment, and adjustments* (pp. 127–144). Chichester, England: Wiley.
- Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[funnel.rma](#)

Examples

```
### meta-analysis of the log risk ratios using a fixed-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg, method="FE")
res.tf <- trimfill(res)
res.tf
funnel(res.tf, legend=TRUE, cex=1.2)

### estimator "R0" also provides test
res.tf <- trimfill(res, estimator="R0")
res.tf

### meta-analysis of the log risk ratios using a random-effects model
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)
res.tf <- trimfill(res)
res.tf
funnel(res.tf, legend=TRUE, cex=1.2)
```

`update.rma`*Model Updating for 'rma' Objects*

Description

The function can be used to update and (by default) re-fit "rma" models. It does this by extracting the call stored in the object, updating the call and (by default) evaluating that call.

Usage

```
## S3 method for class 'rma'  
update(object, formula., ..., evaluate = TRUE)
```

Arguments

<code>object</code>	an object of class "rma".
<code>formula.</code>	changes to the formula. See 'Details'.
<code>...</code>	additional arguments to the call, or arguments with changed values.
<code>evaluate</code>	logical indicating whether to evaluate the new call or just return the call.

Details

For objects of class "rma.uni", "rma.glmm", and "rma.mv", the `formula.` argument can be used to update the set of moderators included in the model (see 'Examples').

Value

If `evaluate=TRUE` the fitted object, otherwise the updated call.

Author(s)

The present function is based on `update.default`, with changes made by Wolfgang Viechtbauer (<wvb@metafor-project.org>) so that the formula updating works with the (somewhat non-standard) interface of the `rma.uni`, `rma.glmm`, and `rma.mv` functions.

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

`rma.uni`, `rma.mh`, `rma.peto`, `rma.glmm`, `rma.mv`

Examples

```

### calculate log risk ratios and corresponding sampling variances
dat <- escalc(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg)

### random-effects model (method="REML" is default)
res <- rma(yi, vi, data=dat, digits=3)
res

### mixed-effects model with two moderators (absolute latitude and publication year)
res <- update(res, ~ ablat + year)
res

### remove 'year' moderator
res <- update(res, ~ . - year)
res

### fit model with ML estimation
update(res, method="ML")

### example with rma.glm()
res <- rma.glm(measure="OR", ai=tpos, bi=tneg, ci=cpos, di=cneg, data=dat.bcg, digits=3)
res <- update(res, mods = ~ ablat)
res

### conditional model with approximate likelihood
update(res, model="CM.AL")

```

vcov.rma

Extract Various Types of Variance-Covariance Matrices from 'rma' Objects

Description

The function extracts various types of variance-covariance matrices from objects of class "rma". By default, the variance-covariance matrix of the parameter estimates (fixed effects) is returned.

Usage

```

## S3 method for class 'rma'
vcov(object, type="fixed", ...)

```

Arguments

object	an object of class "rma".
type	character string indicating the type of variance-covariance matrix to return; type="fixed" returns the variance-covariance matrix of the fixed effects (the default), type="obs" returns the marginal variance-covariance matrix of the observed effect sizes or outcomes, type="fitted" returns the variance-covariance matrix of the fitted values, type="resid" returns the variance-covariance matrix of the residuals.
...	other arguments.

Details

Note that `type="obs"` currently only works for object of class `"rma.uni"` and `"rma.mv"`.

For objects of class `"rma.uni"`, the marginal variance-covariance matrix is just a diagonal matrix with $\tau^2 + v_i$ along the diagonal, where τ^2 is the estimated amount of (residual) heterogeneity (set to 0 in fixed-effects models) and v_i is the sampling variance of the i th study.

For objects of class `"rma.mv"`, the structure can be more complex and depends on the types of random effects included in the model.

Value

A matrix corresponding to the requested variance-covariance matrix.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.glmm](#), [rma.mv](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects model
### with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)
vcov(res)

### marginal var-cov matrix of the observed log risk ratios
vcov(res, type="obs")

### var-cov matrix of the fitted values
vcov(res, type="fitted")

### var-cov matrix of the residuals
vcov(res, type="resid")
```

vif *Variance Inflation Factors for 'rma' Objects*

Description

Compute variance inflation factors (VIFs) for objects of class "rma".

Usage

```
vif(x, ...)
```

```
## S3 method for class 'rma'
```

```
vif(x, intercept=FALSE, table=FALSE, digits, ...)
```

Arguments

x	an object of class "rma".
intercept	logical indicating whether to include the intercept (if the model includes one) in the computation of the VIFs (the default is FALSE). See 'Note'.
table	logical indicating whether the VIFs should be added to the model coefficient table (the default is FALSE).
digits	integer specifying the number of decimal places to which the printed results should be rounded (if unspecified, the default is to take the value from the object).
...	other arguments.

Details

The function computes variance inflation factors (VIFs) for meta-regression models. Hence, the model specified via `x` must include moderator variables. VIFs indicate the inflation in the variance of a model coefficient due to collinearity among the predictor variables.

Value

Either a vector (if `table=FALSE`) with the VIFs or a data frame (if `table=TRUE`) with the following elements:

estimate	estimated model coefficients.
se	corresponding standard errors.
zval	corresponding test statistics.
pval	corresponding p-values.
ci.lb	corresponding lower bound of the confidence intervals.
ci.ub	corresponding upper bound of the confidence intervals.
vif	corresponding variance inflation factors.

Note

The values of the VIFs are invariant to the scaling of the predictor variables if the model includes an intercept that is removed when inverting the correlation matrix of the model coefficients to compute the VIFs. This is the default behavior. See ‘Examples’.

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Davis, C. E., Hyde, J. E., Bangdiwala, S. I., & Nelson, J. J. (1986). An example of dependencies among variables in a conditional logistic regression. In S. H. Moolgavkar & R. L. Prentice (Eds.), *Modern statistical methods in chronic disease epidemiology* (pp. 140–147). New York: Wiley.

Wax, Y. (1992). Collinearity diagnosis for a relative risk regression-analysis: An application to assessment of diet cancer relationship in epidemiologic studies. *Statistics in Medicine*, **11**, 1273–1287.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mv](#), [rma.glmm](#)

Examples

```
### copy data from Bangert-Drowns et al. (2004) into 'dat'
dat <- dat.bangertdrowns2004

### fit mixed-effects meta-regression model
res <- rma(yi, vi, mods = ~ length + wic + feedback + info + pers + imag + meta, data=dat)

### get variance inflation factors
vif(res)

### show that VIFs are not influenced by scaling of the predictors
u <- scale # to standardize the predictors
res <- rma(yi, vi, mods = ~ u(length) + u(wic) + u(feedback) + u(info) +
          u(pers) + u(imag) + u(meta), data=dat)
vif(res)

### get full table
vif(res, table=TRUE)
```

weights.rma.uni *Compute Weights for 'rma' Objects*

Description

The function computes the weights given to the observed effects or outcomes during the model fitting for objects of class "rma.uni", "rma.mh", "rma.peto", and "rma.mv".

Usage

```
## S3 method for class 'rma.uni'  
weights(object, type="diagonal", ...)  
## S3 method for class 'rma.mh'  
weights(object, type="diagonal", ...)  
## S3 method for class 'rma.peto'  
weights(object, type="diagonal", ...)  
## S3 method for class 'rma.glmm'  
weights(object, ...)  
## S3 method for class 'rma.mv'  
weights(object, type="diagonal", ...)
```

Arguments

object	an object of class "rma.uni", "rma.mh", "rma.peto", or "rma.mv". The method is not yet implemented for objects of class "rma.glmm".
type	character string indicating whether to return only the diagonal of the weight matrix ("diagonal") or the entire weight matrix ("matrix").
...	other arguments.

Value

Either a vector with the diagonal elements of the weight matrix or the entire weight matrix. When only the diagonal elements are returned, they are given in % (and they add up to 100%). When the entire weight matrix is requested, this is always a diagonal matrix for objects of class "rma.uni", "rma.mh", "rma.peto".

Author(s)

Wolfgang Viechtbauer <wvb@metafor-project.org> <http://www.metafor-project.org/>

References

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, **36**(3), 1–48. <https://www.jstatsoft.org/v036/i03>.

See Also

[rma.uni](#), [rma.mh](#), [rma.peto](#), [rma.mv](#), [influence.rma.uni](#)

Examples

```
### meta-analysis of the log risk ratios using a mixed-effects model
### with two moderators (absolute latitude and publication year)
res <- rma(measure="RR", ai=tpos, bi=tneg, ci=cpos, di=cneg,
          mods = ~ ablat + year, data=dat.bcg)
weights(res)
```

Index

*Topic **aplot**

addpoly.default, 11
addpoly.rma, 13

*Topic **datagen**

escalc, 93
simulate.rma, 250

*Topic **datasets**

dat.bangertdrowns2004, 35
dat.begg1989, 37
dat.berkey1998, 38
dat.bonett2010, 40
dat.bourassa1996, 41
dat.colditz1994, 43
dat.collins1985a, 45
dat.collins1985b, 46
dat.curtis1998, 48
dat.debruin2009, 50
dat.egger2001, 51
dat.fine1993, 53
dat.gibson2002, 56
dat.graves2010, 58
dat.hackshaw1998, 59
dat.hart1999, 60
dat.hasselblad1998, 61
dat.hine1989, 64
dat.ishak2007, 65
dat.konstantopoulos2011, 67
dat.laopaiboon2015, 69
dat.lee2004, 70
dat.li2007, 71
dat.linde2005, 72
dat.mcdaniel1994, 74
dat.molloy2014, 75
dat.nielweise2007, 77
dat.nielweise2008, 78
dat.normand1999, 80
dat.pagliaro1992, 81
dat.pignon2000, 82
dat.pritz1997, 84

dat.raudenbush1985, 85
dat.riley2003, 87
dat.senn2013, 89
dat.yusuf1985, 92

*Topic **hplot**

baujat, 19
forest, 112
forest.cumul.rma, 113
forest.default, 116
forest.rma, 120
funnel, 130
labbe, 145
llplot, 150
plot.cumul.rma, 158
plot.gosh.rma, 160
plot.infl.rma.uni, 162
plot.rma, 164
profile.rma.uni, 186
qqnorm.rma.uni, 189
radial, 192

*Topic **htest**

fsn, 128
hc, 138
ranktest, 197
regtest, 198
robust, 247

*Topic **manip**

bldiag, 21
contrmat, 31
replmiss, 202
to.long, 251
to.table, 254
to.wide, 257
transf, 259

*Topic **methods**

addpoly, 10
cumul, 33
gosh, 135
leave1out, 148

- reporter, 203
- *Topic **models**
 - anova.rma, 15
 - blup, 22
 - coef.permutest.rma.uni, 24
 - coef.rma, 25
 - confint.rma, 26
 - fitstats, 109
 - fitted.rma, 111
 - formula.rma, 127
 - influence.rma.mv, 140
 - influence.rma.uni, 142
 - model.matrix.rma, 153
 - permutest, 154
 - predict.rma, 165
 - ranef, 194
 - residuals.rma, 205
 - rma.glmm, 209
 - rma.mh, 217
 - rma.mv, 221
 - rma.peto, 233
 - rma.uni, 236
 - trimfill, 261
 - update.rma, 264
 - vcov.rma, 265
 - vif, 267
 - weights.rma.uni, 269
- *Topic **package**
 - metafor-package, 4
- *Topic **print**
 - print.anova.rma, 169
 - print.confint.rma, 171
 - print.escalc, 172
 - print.fsn, 174
 - print.gosh.rma, 175
 - print.hc.rma.uni, 176
 - print.list.rma, 177
 - print.permutest.rma.uni, 177
 - print.ranktest.rma, 179
 - print.regtest.rma, 180
 - print.rma, 181
 - print.robust.rma, 184
- *Topic **utilities**
 - metafor.news, 152
 - .Random.seed, 250
- addpoly, 10, 119, 120, 124, 125
- addpoly.default, 10, 11
- addpoly.rma, 10, 13
- AIC, 109
- AIC.rma, 220, 230, 235, 242
- AIC.rma (fitstats), 109
- anova.rma, 15, 110, 170, 184, 230, 242
- baujat, 19, 220, 235, 242
- BIC.rma, 220, 230, 235, 242
- BIC.rma (fitstats), 109
- bldiag, 21
- blup, 22, 195
- blup.rma.uni, 111, 168, 196, 207, 242
- bobyqa, 230
- coef.permutest.rma.uni, 24, 156
- coef.rma, 25, 220, 230, 235, 242
- coef.summary.rma (coef.rma), 25
- confint, 27
- confint.rma, 26
- confint.rma.mv, 171, 230
- confint.rma.uni, 171, 242
- contrmat, 31
- cooks.distance.rma.mv
 - (influence.rma.mv), 140
- cooks.distance.rma.uni
 - (influence.rma.uni), 142
- cor.test, 198
- cov2cor, 227
- cumul, 33, 116
- cumul.rma.mh, 112, 220
- cumul.rma.peto, 112, 235
- cumul.rma.uni, 112, 159, 242
- dat.bangertdrowns2004, 35
- dat.bcg, 97
- dat.bcg (dat.colditz1994), 43
- dat.begg1989, 37, 232
- dat.berkey1998, 38, 225, 232
- dat.bonett2010, 40, 104
- dat.bourassa1996, 41, 100
- dat.colditz1994, 43
- dat.collins1985a, 45, 97, 216, 236
- dat.collins1985b, 46, 97, 236
- dat.curtis1998, 48, 99
- dat.debruin2009, 50, 101
- dat.egger2001, 51, 71, 72, 97
- dat.fine1993, 53, 226, 232
- dat.gibson2002, 56, 97, 99
- dat.graves2010, 58
- dat.hackshaw1998, 59

- dat.hart1999, 60, 98
 dat.hasselblad1998, 32, 61, 225, 232, 258
 dat.hine1989, 64, 97
 dat.ishak2007, 65, 226, 232
 dat.konstantopoulos2011, 67, 225, 232
 dat.laopaiboon2015, 69, 97
 dat.lee2004, 70, 97
 dat.li2007, 52, 71, 97
 dat.linde2005, 72, 97
 dat.mcdaniel1994, 74, 100
 dat.molloy2014, 75, 100
 dat.nielweise2007, 77, 97, 216
 dat.nielweise2008, 78, 98, 216
 dat.normand1999, 80, 99
 dat.pagliari1992, 81
 dat.pignon2000, 82
 dat.pritz1997, 84, 101, 216
 dat.raudenbush1985, 85
 dat.riley2003, 87
 dat.senn2013, 32, 89, 225, 258
 dat.yusuf1985, 92, 97, 236
 density, 161
 deviance.rma, 220, 230, 235, 242
 deviance.rma (fitstats), 109
 df.residual.rma (fitstats), 109
 dfbetas.rma.mv (influence.rma.mv), 140
 dfbetas.rma.uni (influence.rma.uni), 142
 escalc, 5, 9, 93, 129, 146, 147, 151, 173,
 209–211, 213, 217–219, 224,
 233–235, 237–239, 251–256
 factor, 212, 228, 240
 fitstats, 109
 fitstats.rma, 214, 220, 230, 235, 242
 fitted.rma, 23, 111, 153, 168, 195, 196, 230,
 242
 forest, 12, 14, 112, 116, 120, 125, 165
 forest.cumul.rma, 34, 35, 112, 113
 forest.default, 10, 12, 14, 112, 116, 125
 forest.rma, 10, 12, 14, 112, 120, 120, 203,
 220, 235, 242
 formula, 209, 212, 222, 224, 237, 240
 formula.rma, 127
 fsn, 128, 174
 funnel, 130, 165
 funnel.rma, 204, 220, 235, 242, 262, 263
 galbraith (radial), 192
 glm, 214, 215
 glmer, 214, 215
 gosh, 135
 gosh.rma, 161, 175
 grep, 16, 212, 228, 240
 hatvalues.rma.mv, 230
 hatvalues.rma.mv (influence.rma.mv), 140
 hatvalues.rma.uni, 242
 hatvalues.rma.uni (influence.rma.uni),
 142
 hc, 138
 hc.rma.uni, 176, 242
 hessian, 214, 215
 hist, 161
 hjk, 230
 influence.rma.mv, 140, 207, 208, 230
 influence.rma.uni, 20, 134, 137, 142, 164,
 207, 208, 242, 269
 integrate, 214, 215
 labbe, 145
 labbe.rma, 220, 235, 242
 leave1out, 148
 leave1out.rma.mh, 220
 leave1out.rma.peto, 235
 leave1out.rma.uni, 242
 legend, 132
 llplot, 150
 logLik.rma, 220, 230, 235, 242
 logLik.rma (fitstats), 109
 makePSOCKcluster, 137, 141, 188, 208
 mclapply, 137, 141, 188, 208
 metafor (metafor-package), 4
 metafor-package, 4, 152, 209, 217, 221, 233,
 236, 239
 metafor.news, 152
 model.matrix.rma, 153
 newuoa, 230
 nlm, 230
 nlminb, 230
 nloptr, 230
 nmk, 230
 nobs.rma (fitstats), 109
 optim, 214, 230
 optimParallel, 230

- options, *178, 182, 185*
- pairs, *161*
- par, *163*
- parallel, *137, 141, 188, 208*
- parLapply, *137, 141, 188, 208*
- permutest, *154*
- permutest.rma.uni, *25, 178, 242*
- plot.cumul.rma, *34, 35, 158*
- plot.gosh.rma, *137, 160*
- plot.infl.rma.uni, *144, 145, 162*
- plot.profile.rma (profile.rma.uni), *186*
- plot.rma, *164*
- plot.rma.mh, *220*
- plot.rma.peto, *235*
- plot.rma.uni, *242*
- points, *20, 114, 118, 122, 132, 146, 159, 160, 163, 187, 190, 193*
- predict.rma, *23, 111, 165, 195, 196, 230, 242*
- print.anova.rma, *17, 18, 169*
- print.confint.rma, *29, 171*
- print.escalc, *105, 108, 172*
- print.fsn, *129, 174*
- print.gosh.rma, *137, 175*
- print.hc.rma.uni, *139, 176*
- print.infl.rma.uni (influence.rma.uni), *142*
- print.list.confint.rma, *29*
- print.list.confint.rma (print.confint.rma), *171*
- print.list.rma, *22, 34, 149, 168, 177, 195, 207*
- print.permutest.rma.uni, *156, 157, 177*
- print.profile.rma (profile.rma.uni), *186*
- print.ranktest.rma, *179, 197*
- print.regtest.rma, *180, 200*
- print.rma, *181*
- print.rma.glmm, *214*
- print.rma.mh, *220*
- print.rma.mv, *230*
- print.rma.peto, *235*
- print.rma.uni, *28, 241, 242, 262*
- print.robust.rma, *184, 248*
- print.summary.rma (print.rma), *181*
- profile.rma.mv, *28, 230, 231*
- profile.rma.mv (profile.rma.uni), *186*
- profile.rma.uni, *186, 242*
- qqnorm.rma.glmm (qqnorm.rma.uni), *189*
- qqnorm.rma.mh, *220*
- qqnorm.rma.mh (qqnorm.rma.uni), *189*
- qqnorm.rma.mv (qqnorm.rma.uni), *189*
- qqnorm.rma.peto, *235*
- qqnorm.rma.peto (qqnorm.rma.uni), *189*
- qqnorm.rma.uni, *165, 189, 242*
- radial, *20, 165, 192*
- radial.rma, *220, 235, 242*
- ranef, *23, 194*
- ranef.rma.mv, *230*
- ranef.rma.uni, *23, 242*
- ranktest, *130, 197, 201*
- ranktest.rma, *179, 242*
- regtest, *130, 198, 198, 262*
- regtest.rma, *180, 242*
- replmiss, *202*
- reporter, *203*
- residuals.rma, *132, 191, 205, 220, 230, 235, 242*
- rma, *5*
- rma (rma.uni), *236*
- rma.glmm, *8–10, 26, 30, 45, 108, 110, 134, 146, 147, 152, 168, 183, 184, 192, 194, 208, 209, 221, 232, 236, 245, 264, 266, 268*
- rma.mh, *7, 9, 10, 20, 26, 30, 108, 110, 112, 134, 136, 137, 146, 147, 149, 184, 192, 194, 205, 208, 216, 217, 232, 236, 245, 264, 266, 269*
- rma.mv, *8, 9, 21, 26, 28, 30, 108, 110, 123, 127, 134, 141, 166–168, 184, 187, 189, 192, 194, 205, 207, 208, 216, 221, 221, 236, 245, 249–251, 264, 266, 268, 269*
- rma.peto, *7, 9, 10, 20, 26, 30, 45, 92, 108, 110, 112, 134, 136, 137, 146, 147, 149, 184, 192, 194, 205, 208, 216, 221, 232, 233, 245, 264, 266, 269*
- rma.uni, *5, 9, 10, 18, 20, 23–26, 28, 30, 108, 110, 112, 127, 134, 136, 137, 139, 146, 147, 149, 152, 157, 168, 184, 187, 189, 192, 194, 196, 205, 207, 208, 213, 216, 221, 228, 232, 236, 236, 249–251, 262, 264, 266, 268, 269*
- RNGkind, *250*
- robust, *247*
- robust.rma.mv, *185, 230*

robust.rma.uni, [185](#), [242](#)
rstandard.rma.mh, [220](#)
rstandard.rma.mh (residuals.rma), [205](#)
rstandard.rma.mv, [230](#)
rstandard.rma.mv (residuals.rma), [205](#)
rstandard.rma.peto, [235](#)
rstandard.rma.peto (residuals.rma), [205](#)
rstandard.rma.uni, [242](#)
rstandard.rma.uni (residuals.rma), [205](#)
rstudent.rma.mh, [220](#)
rstudent.rma.mh (residuals.rma), [205](#)
rstudent.rma.mv, [142](#), [230](#)
rstudent.rma.mv (residuals.rma), [205](#)
rstudent.rma.peto, [235](#)
rstudent.rma.peto (residuals.rma), [205](#)
rstudent.rma.uni, [143](#), [145](#), [242](#)
rstudent.rma.uni (residuals.rma), [205](#)

simulate.rma, [250](#)
summary.escalc, [105](#), [108](#)
summary.escalc (print.escalc), [172](#)
summary.rma, [214](#), [220](#), [230](#), [235](#), [242](#)
summary.rma (print.rma), [181](#)
supsmu, [191](#)

tempdir, [203](#)
to.long, [251](#), [256](#), [258](#)
to.table, [253](#), [254](#), [258](#)
to.wide, [32](#), [257](#)
transf, [11](#), [12](#), [14](#), [22](#), [27](#), [34](#), [114](#), [118](#), [119](#),
[122](#), [124](#), [131](#), [132](#), [138](#), [146–148](#),
[158](#), [166](#), [172](#), [193](#), [195](#), [259](#)
trimfill, [130](#), [132–134](#), [261](#)
trimfill.rma.uni, [242](#)

ucminf, [230](#)
uniroot, [28](#), [139](#), [156](#), [243](#)
uobyqa, [230](#)
update.default, [264](#)
update.rma, [264](#)

vcov.rma, [220](#), [230](#), [235](#), [242](#), [265](#)
vif, [267](#)
vif.rma, [230](#), [242](#)

weights.rma.glm (weights.rma.uni), [269](#)
weights.rma.mh (weights.rma.uni), [269](#)
weights.rma.mv, [142](#), [230](#)
weights.rma.mv (weights.rma.uni), [269](#)