Package ‘metaplus’

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Maintainer Ken Beath <ken.beath@mq.edu.au>
Contact Ken Beath <ken.beath@mq.edu.au>
Author Ken Beath [aut, cre], Ben Bolker [aut], R Development Core Team [aut]
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metaplus-package .......................................................... 2
AIC ........................................................................... 3
BIC ........................................................................... 3
cdp ........................................................................... 4
exercise ........................................................................ 5
Description

Allows fitting of random effects meta-analysis producing confidence intervals based on the profile likelihood (Hardy and Thompson, 1996). Two methods of robust meta-analysis are included, based on either the t-distribution (Baker and Jackson (2008) and Lee and Thompson (2008)) or normal-mixture distribution (Beath, 2014). Tests can be performed for the need for a robust model, using a parametric bootstrap, and for the normal-mixture the identity of the outliers using the posterior probability. Plots are produced allowing a comparison between the results of each method. Where possible use has been made of the metafor package.

The metaplus function

This is the main function that allows fitting the models. The metaplus objects may be plotted, using plot, and tested for outliers using testOutliers. The results of tests.outliers may also be plotted.

Author(s)

Ken Beath <ken.beath@mq.edu.au>

References


AIC

**Description**

Returns AIC for a metaplus object.

**Usage**

```r
## S3 method for class 'metaplus'
AIC(object, ...)
```

**Arguments**

- `object` metaplus object
- `...` additional argument; currently none are used.

**Value**

AIC of fitted model

**Author(s)**

Ken Beath

BIC

**Description**

Returns BIC for a metaplus object.

**Usage**

```r
## S3 method for class 'metaplus'
BIC(object, ...)
```

**Arguments**

- `object` metaplus object
- `...` additional argument; currently none are used.

**Value**

BIC of fitted model
Author(s)

Ken Beath

Description

Data for the meta-analysis by Fioravanti and Yanagi (2005) of cytidinediphosphocholine (CDP-choline) for cognitive and behavioural disturbances associated with chronic cerebral disorders in the elderly.

Usage

cdp

Format

A data frame with 10 observations on the following 3 variables.

    study  study authors and date
    yi     study effect estimate
    sei    study standard error

Source

Fioravanti and Yanagi (2005)

References


Examples

```R
## Not run:
cdp1 <- metaplus(cdp$yi, cdp$sei, plotci=TRUE, slab=cdp$study)

## End(Not run)
```
Description

Lawlor & Hopker (2001) performed a meta-analysis of trials of exercise in the management of depression, which was subsequently analysed using meta-regression (Higgins & Thompson 2004) with duration of treatment as a covariate. There is a possible outlier, the study by Reuter. While there are additional predictors, it seems excessive to use them given the small number of studies.

Usage

exercise

Format

A data frame with 10 observations on the following 9 variables.

- study: study author
- smd: study effect estimate
- varsmd: study effect variance
- sesmd: study effect standard error
- abstract: study available as abstract only?
- duration: length of study in weeks
- itt: intention to treat analysis?
- alloc: outcome assessor blinded
- phd: phd thesis?

Source


References


Examples

```r
## Not run:
exerciset <- metaplus(smd, sqrt(varsmd), mods=duration, slab=study, data=exercise)
exerciset <- metaplus(smd, sqrt(varsmd), mods=cbind(duration, itt), slab=study, data=exercise)
## End(Not run)
```
**Description**

Returns the log Likelihood for a metaplus object.

**Usage**

```r
## S3 method for class 'metaplus'
logLik(object, ...)
```

**Arguments**

- `object`: metaplus object
- `...`: additional argument; currently none are used.

**Value**

The loglikelihood of the fitted model.

**Author(s)**

Ken Beath

---

**mag**

*Magnesium meta-analysis data*

**Description**

Data for a meta-analysis of intravenous magnesium in acute myocardial infarction. An interesting question is whether the ISIS4 study is an outlier.

**Usage**

```r
mag
```

**Format**

A data frame with 16 observations on the following 3 variables.

- `study`: study author
- `yi`: study effect estimate
- `sei`: study standard error
Source

Sterne et al (2001)

References


Examples

```r
## Not run:
mag1 <- metaplus(yi, sei, plotci=TRUE, slab=study, data=mag)

## End(Not run)
```

marinho  

Marinho meta-analysis data

Description


Usage

marinho

Format

A data frame with 70 observations on the following 11 variables.

- study: study authors and date
- nfluor: number in fluoride group
- meanfluor: mean effect in fluoride group
- sdfluor: standard deviation of effect in fluoride group
- nplacebo: number in placebo group
- meanplacebo: mean effect in placebo group
- sdpplacebo: standard deviation of effect in placebo group
- meaneffect: mean effect difference
- seeffect: standard error of effect difference

Source

Marinho et al (2009)
References


Examples

```r
## Not run:
marinho1 <- metaplus(meaneffect, seffect, plotci=TRUE, slab=study, data=marinho)

## End(Not run)
```

```r
metaplus  Fits random effects meta-analysis models, using either a standard normal distribution, a t-distribution or a mixture of normals for the random effect.
```

Description

Allows fitting of random effects meta-analysis producing confidence intervals based on profile likelihood. Two methods of robust meta-analysis are included, based on either the t-distribution or normal-mixture distribution.

Usage

```r
metaplus(yi, sei, mods=NULL, random="normal", label=switch(random, "normal"="Random Normal","t-dist"="Random t-distribution","mixture"="Random mixture"), plotci=FALSE, justfit=FALSE, slab=1:length(yi), useAGQ=FALSE, quadpoints=21, data)
```

Arguments

- `yi` vector of observed effect size
- `sei` vector of observed standard errors
- `mods` data frame of covariates corresponding to each study
- `random` The type of random effects distribution. One of "normal","t-dist","mixture", for standard normal, t-distribution or mixture of normals respectively.
- `label` The label to be used for this model when plotting
- `plotci` Should profile be plotted for each confidence interval?
- `justfit` Should model only be fitted? If justfit=TRUE then profiling and likelihood ratio statistics are not calculated. Useful for when bootstrapping.
- `slab` Vector of character strings corresponding to each study.
- `useAGQ` Use adaptive Gauss-Hermite quadrature when performing integration for t-distribution random-effects. Useful when standard errors for studies are relatively small.
- `quadpoints` Number of quadrature points to use in adaptive Gauss-Hermite quadrature.
- `data` Optional data frame containing some or all other data.
Details

As well as standard normal random effects meta-analysis, fitting of robust models incorporating either a $t$-distribution random effect (Lee and Thompson, 2008 or Baker and Jackson, 2008) or a mixture of normals (Beath, 2014) may be fitted. For all models the profile log-likelihood (Hardy and Thompson, 1996) is used to determine the confidence intervals for the parameters, with corresponding p values calculated using the likelihood ratio test, to give consistency between the confidence intervals and p values. The profile log-likelihood produces confidence intervals with better properties than REML or Der Simonian-Laird method (Brockwell and Gordon 2001, Jackson et al 2010).

For the mixture normal model, multiple starting values are used. This is achieved by starting with the no outlier model, then all possible single outlier models and choosing the model with the maximum likelihood. The process is repeated by adding all possible outliers to obtain the two outlier models and the maximum likelihood chosen. The process is repeated until the likelihood is not further maximised by adding outliers. This method gives a faster fitting time and is more reliable than using random assignments, as we have usually only a small number of outliers.

Value

results Matrix containing columns for estimate, lower 95%, upper 95% and p value, or if justfit=TRUE then only the parameter estimates

yi Effect sizes

sei Standard error of effect sizes

mods Modifiers for meta-regression

slab Study labels

justfit Value of justfit passed to the method.

fittedmodel final model returned by mle2

profile profile likelihood returned as described in bbmle

random Type of random effect

outlier.prob Outlier probabilities for robust mixture model only

Author(s)

Ken Beath <ken.beath@mq.edu.au>

References


Examples

```r
## Not run:
library(metaplus)

# perform meta-analysis for mag studies, which have no outliers
# fit standard normal random-effect model and print summary
mag.meta <- metaplus(yi, sei, slab = study, data = mag)
summary(mag.meta)
# repeat, but this time plot the profile likelihood diagnostic plot using plotci
mag.meta <- metaplus(mag$yi, mag$sei, slab = mag$study, plotci = TRUE)
# plot a forest plot with exponential transform, so that the odds ratios are plotted
plot(mag.meta, atransf = exp, at = log(c(.01, .1, 1, 10, 100)), xlab = "Odds Ratio", cex = 0.75)
# repeat for t-distribution random effects
mag.tdist <- metaplus(yi, sei, slab = study,
   random = "t-dist", data = mag)
summary(mag.tdist)
# use parametric bootstrap to test for presence of outliers
summary(testoutliers(mag.tdist))
# repeat for robust mixture random effects
mag.mix <- metaplus(yi, sei, slab = study,
   random = "mixture", data = mag)
summary(mag.mix)
# use parametric bootstrap to test for presence of outliers
summary(testoutliers(mag.mix))

# perform meta-analysis for CDP studies
# where there is one outlier
cdp.meta <- metaplus(yi, sei, slab = study, data = cdp)
summary(cdp.meta)
# where there is one outlier
cdp.tdist <- metaplus(yi, sei, slab = study,
   random = "t-dist", data = cdp)
summary(cdp.tdist)
summary(testoutliers(cdp.tdist))
cdp.mix <- metaplus(yi, sei, slab = study,
   random = "mixture", data = cdp)
summary(cdp.mix)
summary(testoutliers(cdp.mix))

# extract and plot outlier probabilities
cdp.mix.outlierProbs <- outlierProbs(cdp.mix)
plot(cdp.mix.outlierProbs)

# produce forest plot with summary for all 3 models, showing narrower confidence
```
outlierProbs

# intervals for robust models
plot(cdp.meta, extrameta = list(cdp.tdist, cdp.mix), xlab = "Standardised Mean Difference")

# effect of exercise on depression with covariate of length of study
# fit the 3 models
exercise.meta <- metaplus(smd, sqrt(var.smd),
  mods = duration, slab = study, data = exercise)
summary(exercise.meta)
exercise.mix <- metaplus(smd, sqrt(var.smd),
  mods = duration, slab = study, random = "mixture",
  data = exercise)
summary(exercise.mix)
exercise.testOutliers <- testOutliers(exercise.mix)
summary(exercise.testOutliers)

# identify possible outliers
exercise.outlierProbs <- outlierProbs(exercise.mix)
plot(exercise.outlierProbs)

# centre duration at different values to obtain predictions at 4, 8 and 12 weeks
exercise$duration4 <- exercise$duration-4
exercise$duration8 <- exercise$duration-8
exercise$duration12 <- exercise$duration-12

# fit the different models, giving each an appropriate label
exercise.nodurn <- metaplus(smd, sqrt(var.smd),
  label = "Random Mixture (No Duration)", slab = study,
  random = "mixture", data = exercise)
exercise.wk4 <- metaplus(smd, sqrt(var.smd),
  mods = duration4, label = "Random Mixture (Week 4)",
  slab = study, random = "mixture", data = exercise)
exercise.wk8 <- metaplus(smd, sqrt(var.smd),
  mods = duration8, label = "Random Mixture (Week 8)",
  slab = study, random = "mixture", data = exercise)
exercise.wk12 <- metaplus(smd, sqrt(var.smd),
  mods = duration12, label = "Random Mixture (Week 12)",
  slab = study, random = "mixture", data = exercise)

# produce forest plot with summary for each model with robust mixture model at different weeks
plot(exercise.nodurn, extrameta = list(exercise.wk4, exercise.wk8, exercise.wk12), xlab = "Standardised mean difference")

## End(Not run)
**Description**

For the normal mixture random effect calculates the probability that each study is an outlier based on the posterior probability of it being an outlier.

**Usage**

```r
## S3 method for class 'metaplus'
outlierProbs(object)
```

**Arguments**

- `object` A metaplus object with a mixture (robust) random effects distribution.

**Details**

The outlier probabilities are obtained as the posterior probabilities of each study being an outlier based on the fitted mixture model.

**Value**

- `outlier.prob` Posterior probability that each study is an outlier
- `slab` Labels corresponding to each study

**Author(s)**

Ken Beath <ken.beath@mq.edu.au>

**Examples**

```r
## Not run:
cdp3 <- metaplus(cdp$yi, cdp$sei, plotci=TRUE, slab=cdp$study, random="mixture")
outlierProbs(cdp3)
plot(outlierProbs(cdp3))
## End(Not run)
```

---

**plot.metaplus**

Produces forest plot for the studies together with the meta-analysis results.

**Description**

Produces a forest plot for the studies in the meta-analysis and the result of the meta-analysis. Allows the inclusion of extra results of alternative meta-analyses, to allow, for example comparison between standard and robust methods of meta-analysis. Makes extensive use of the metafor package to produce the forest plot.
plot.metaplus

Usage

## S3 method for class 'metaplus'
plot(x, ..., extrameta = NULL)

Arguments

x  metaplus object to be plotted

... additional parameters to plot

extrameta  Additional metaplus objects to be plotted. Only the summary statistic is plotted at the end of the plot. This is useful for comparing standard and robust methods, or meta-regressions for various values of the predictor.

Value

Plot

Note

On some systems the alignment of characters in the CI may be poor when saving the plots to pdf. A solution is to use the extrafont package and a fixed width font, for example Courier New. Then if creating the plot using pdf() the parameter family="Courier New" will use this font and fonts="Courier New" will add it to the pdf.

An alternative is to use pdf.options() with the same parameters before the plot, and pdf.options(reset=TRUE) will produce the same effect.

Author(s)

Ken Beath <ken.beath@mq.edu.au>

Examples

## Not run:
# produce all 3 models for the CDP data and plot them all
cdp1 <- metaplus(yi,sei,plotci=TRUE,slab=study,data=cdp)
cdp2 <- metaplus(yi,sei,plotci=TRUE,slab=study,random="t-dist",data=cdp)
cdp3 <- metaplus(yi,sei,plotci=TRUE,slab=study,random="mixture",data=cdp)
plot(cdp1,extrameta=list(cdp2,cdp3))

# plot effect of exercise on depression at 4, 8 and 12 weeks
eexercise$duration4 <- exercise$duration-4
eexercise$duration8 <- exercise$duration-8
eexercise$duration12 <- exercise$duration-12
eexercise.wk4 <- metaplus(smd,sqrt(varsmd),mods=duration4,
  label="Random Mixture (Week 4)",slab=study,random="mixture",data=exercise)
eexercise.wk8 <- metaplus(smd,sqrt(varsmd),mods=duration8,
  label="Random Mixture (Week 8)",slab=study,random="mixture",data=exercise)
eexercise.wk12 <- metaplus(smd,sqrt(varsmd),mods=duration12,
  label="Random Mixture (Week 12)",slab=study,random="mixture",data=exercise)
exercise.nodurn <- metaplus(smd,sqrt(var.smd),plotci=TRUE,
   label="Random Mixture (No Duration)",slab=study,random="mixture",data=exercise)

plot(exercise.nodurn,extrameta=list(exercise.wk4,exercise.wk8,exercise.wk12))

## End(Not run)

---

### Description

Plots the outlier probability for each study, from an outlierProbs object.

### Usage

```r
## S3 method for class 'outlierProbs'
plot(x, ...)
```

### Arguments

- `x` outlierProbs object to be plotted
- `...` additional parameters to plot

### Value

Plot

### Author(s)

Ken Beath <ken.beath@mq.edu.au>

### Examples

```r
## Not run:

cdp.mix <- metaplus(yi,sei,plotci=TRUE,slab=study,random="mixture",data=cdp)
cdp.mix.outlierProbs <- outlierProbs(cdp.mix)
plot(cdp.mix.outlierProbs)

## End(Not run)
**summary**

Summary of a metaplus object.

**Description**

Summarises the meta-analysis, giving the parameter estimates and goodness of fit statistics. For the robust methods this includes the values of the parameters relating to robustness. In the summary the 95

**Usage**

```r
## S3 method for class 'metaplus'
summary(object,...)
```

**Arguments**

- `object` metaplus object to summarise.
- `...` Additional parameters to summary.

**Value**

- `results` Matrix containing parameter estimates, confidence intervals and p values
- `fitstats` List containing logLikelihood, AIC and BIC

**Author(s)**

Ken Beath <ken.beath@mq.edu.au>

**Examples**

```r
cdp1 <- metaplus(yi,sei,plotci=TRUE,slab=study,data=cdp)
summary(cdp1)
```

---

**testOutliers**

Tests for the presence of outliers.

**Description**

For the $t$-distribution models this is a test that the degrees of freedom is infinitite, or equivalently that it’s inverse is zero. For the mixture-normal model it is a test that the proportion of outliers is zero. As both tests involve a parameter on the boundary of the parameter space, asymptotic theory does not apply, so a parametric bootstrap is performed to determine the empirical distribution of the test statistic under the null hypothesis. The observed likelihood ratio statistic is then compared to this distribution to determine the p value.
Usage

```r
## S3 method for class 'metaplus'
testOutliers(object, R = 999)
```

Arguments

- **object**: The meta-analysis for which the presence of outliers is to be tested.
- **R**: Number of simulations (parametric bootstraps) used in testing the hypothesis. Initially, it may be useful to set this to a smaller value, to allow faster execution time.

Value

- **pvalue**: p value obtained from parametric bootstrap
- **observed**: Observed value of the likelihood ratio test statistic
- **sims**: Simulated values of the test statistic under the null hypothesis

Note

Running the default number of bootstrap samples may take considerable time, of the order of hours. Use of the parallel options will improve these times. For a preliminary guide to whether there are outliers, this is indicated by a reduction in AIC or BIC with the robust model, and a change in the estimated mean effect.

Author(s)

Ken Beath <ken.beath@mq.edu.au>

Examples

```r
## Not run:
cdp3 <- metaplus(cdp$yi, cdp$sei, plotci=TRUE, slab=cdp$study, random="mixture")
summary(testOutliers(cdp3))
```

```r
## End(Not run)
```
Index

*Topic datasets
  cdp, 4
  exercise, 5
  mag, 6
  marinho, 7

*Topic methods
  AIC, 3
  BIC, 3
  logLik, 6
  testOutliers, 15

*Topic method
  outlierProbs, 11
  plot.metaplus, 12
  plot.outlierProbs, 14
  summary, 15

*Topic models
  metaplus, 8

  AIC, 3
  BIC, 3
  cdp, 4
  exercise, 5
  logLik, 6
  mag, 6
  marinho, 7
  metaplus, 8
  metaplus-package, 2
  outlierProbs, 11
  plot.metaplus, 12
  plot.outlierProbs, 14
  summary, 15
  testOutliers, 15