Package ‘metapack’

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Type Package

Title Bayesian Meta-Analysis and Network Meta-Analysis

Version 0.2.0

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Description Contains functions performing Bayesian inference for meta-analytic and network meta-analytic models through Markov chain Monte Carlo algorithm. Currently, the package implements Hui Yao, Sungduk Kim, Ming-Hui Chen, Joseph G. Ibrahim, Arvind K. Shah, and Jianxin Lin (2015) <doi:10.1080/01621459.2015.1006065> and Hao Li, Daeyoung Lim, Ming-Hui Chen, Joseph G. Ibrahim, Sungduk Kim, Arvind K. Shah, Jianxin Lin (2021) <doi:10.1002/sim.8983>. For maximal computational efficiency, the Markov chain Monte Carlo samplers for each model, written in C++, are fine-tuned. This software has been developed under the auspices of the National Institutes of Health and Merck & Co., Inc., Kenilworth, NJ, USA.

License GPL (>= 3)

Encoding UTF-8

LazyLoad yes

LazyData true

RoxygenNote 7.1.1

NeedsCompilation yes

Imports Rcpp, ggplot2, methods, gridExtra, Formula

Depends R (>= 3.4)

LinkingTo Rcpp, RcppArmadillo, RcppProgress, BH

Suggests knitr, rmarkdown

VignetteBuilder knitr

URL http://merlot.stat.uconn.edu/packages/metapack/

BugReports https://github.com/daeyounglim/metapack/issues

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**bayes_nmr**

**Fit Bayesian Network Meta-Regression Models**

**Description**

This is a function the fits the model introduced in *Bayesian Network Meta-Regression Models Using Heavy-Tailed Multivariate Random Effects with Covariate-Dependent Variances*. The first seven arguments are required except ZCovariate. If not provided, ZCovariate will be assigned a vector of ones, `rep(1, length(Outcome))`. ZCovariate is the centerpiece of the modeling of variances and the heavy-tailed random effects distribution.
Usage

bayes_nmr(
  Outcome, SD,
  XCovariate, ZCovariate,
  Treat, Trial,
  Npt,
  prior = list(),
  mcmc = list(),
  control = list(),
  init = list(),
  Treat_order = NULL,
  Trial_order = NULL,
  scale_x = FALSE,
  verbose = FALSE
)

Arguments

Outcome the aggregate mean of the responses for each arm of every study.
SD the standard deviation of the responses for each arm of every study.
XCovariate the aggregate covariates for the fixed effects.
ZCovariate the aggregate covariates associated with the variance of the random effects.
Treat the treatment identifiers for trial arm. This is equivalent to the arm labels in each study. The elements within will be coerced to consecutive integers.
Trial the study/trial identifiers. The elements within will be coerced to consecutive integers.
Npt the number of observations/participants for a unique (k, t), or each arm of every trial.
prior (Optional) a list of hyperparameters. The hyperparameters include \(d_0\), \(c_{01}\), \(c_{02}\), \(a_4\), \(b_4\), \(a_5\), and \(b_5\). \(d_0\) indicates the degrees of freedom whose value is 20. The hyperparameters \(a^*\) and \(b^*\) will take effect only if sample_df=TRUE. See control.
mcmc (Optional) a list of MCMC specification. ndiscard is the number of burn-in iterations. nskip configures the thinning of the MCMC. For instance, if nskip=5, bayes_nmr will save the posterior sample every 5 iterations. nkeep is the size of the posterior sample. The total number of iterations will be ndiscard + nskip * nkeep.
control (Optional) a list of parameters for the Metropolis-Hastings algorithm. lambda, phi, and Rho are sampled through the localized Metropolis algorithm. *_stepsize with the asterisk replaced with one of the names above specifies the stepsize for determining the sample evaluation points in the localized Metropolis algorithm. sample_Rho can be set to FALSE to suppress the sampling of Rho. When
sample_Rho is FALSE, Rho will be fixed using the value given by the init argument, which defaults to an equicorrelation matrix of $0.5 I + 0.5 \mathbf{1} \mathbf{1}'$ where $\mathbf{1}$ is the vector of ones. When sample_df is TRUE, df will be sampled.

init (Optional) a list of initial values for the parameters to be sampled: theta, phi, sig2, and Rho.

Treat_order (Optional) a vector of unique treatments to be used for renumbering the Treat vector. The first element will be assigned treatment zero, potentially indicating placebo. If not provided, the numbering will default to an alphabetical/numerical order.

Trial_order (Optional) a vector unique trials. The first element will be assigned trial zero. If not provided, the numbering will default to an alphabetical/numerical order.

scale_x (Optional) a logical variable indicating whether X Covariate should be scaled/standardized. The effect of setting this to TRUE is not limited to merely standardizing X Covariate. The following generic functions will scale the posterior sample of theta back to its original unit: plot, fitted, summary, and print. That is \( \text{theta}[j] <- \text{theta}[j] / \text{sd(X Covariate[,j])} \).

verbose (Optional) a logical value indicating whether to print the progress bar during the MCMC sampling.

Value

bayes_nmr returns an object of class "bayesnmr". The functions summary or print are used to obtain and print a summary of the results. The generic accessor function fitted extracts the posterior mean, posterior standard deviation, and the interval estimates of the value returned by bayes_nmr.

An object of class bayesnmr is a list containing the following components:

- Outcome - the aggregate response used in the function call.
- SD - the standard deviation used in the function call.
- Npt - the number of participants for (k, t) used in the function call.
- X Covariate - the aggregate design matrix for fixed effects used in the function call. Depending on scale_x, this may differ from the matrix provided at function call.
- Z Covariate - the aggregate design matrix for random effects. bayes_nmr will assign \( \text{rep}(1, \text{length(Outcome)}) \) if it was not provided at function call.
- Trial - the renumbered trial indicators. Depending on Trial_order, it may differ from the vector provided at function call.
- Treat - the renumbered treatment indicators. Depending on Treat_order, it may differ from the vector provided at function call.
- TrtLabels - the vector of treatment labels corresponding to the renumbered Treat. This is equivalent to Treat_order if it was given at function call.
- TrialLabels - the vector of trial labels corresponding to the renumbered Trial. This is equivalent to Trial_order if it was given at function call.
- K - the total number of trials.
- nT - the total number of treatments.
- scale_x - a Boolean indicating whether X Covariate has been scaled/standardized.
• *prior* - the list of hyperparameters used in the function call.
• *control* - the list of tuning parameters used for MCMC in the function call.
• *mcmc.time* - the elapsed time for the MCMC algorithm in the function call. This does not include all the other preprocessing and post-processing outside of MCMC.
• *mcmc* - the list of MCMC specification used in the function call.
• *mcmc.draws* - the list containing the MCMC draws. The posterior sample will be accessible here.

**Author(s)**

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**References**


**See Also**

*bmeta_analyze* for using the *Formula* interface

**Examples**

```r
library(metapack)
data(TNM)
groupInfo <- list(c("PBO"), c("R"))
.nz <- length(groupInfo)
.ns <- nrow(TNM)
XCovariate <- model.matrix(~ 0 + bldlc + bhdlc + btg + age +
                           white + male + bmi + potentymed + potencyhigh + durat, data = TNM)
XCovariate <- scale(XCovariate, center = TRUE, scale = FALSE)
ZCovariate <- matrix(0, ns, nz)
for (j in 1:length(groupInfo)) {
  for (i in 1:ns) {
    if (TNM$treat[i] %in% groupInfo[[j]]) {
      ZCovariate[i, j] <- 1
    }
  }
}
addz <- scale(cbind(TNM$bldlc, TNM$btg), center = TRUE, scale = TRUE)
ZCovariate <- cbind(1, ZCovariate, addz)
theta_init <- c(0.05113, -1.38866, 1.09817, -0.85855, -1.12056, -1.14133,
                -0.22435, 3.63453, -2.09322, 1.07858, 0.80566, -40.76753,
                -45.07127, -28.27232, -44.14054, -28.13203, -19.19989,
                -47.21824, -51.31234, -48.46266, -47.71443)
set.seed(2797542)
```
fit <- bayes_nmr(TNM$ptg, TNM$sdtg, XCovariate, ZCovariate, TNM$treat, 
TNM$trial, TNM$n, prior = list(c01 = 1.0e05, c02 = 4, df = 3),
mcmc = list(ndiscard = 1, nskip = 1, nkeep = 1),
init = list(theta = theta_init),
"AE", "LE", "PE"),
scale_x = TRUE, verbose = FALSE)

---

bayes_parobs

Fit Bayesian Inference for Meta-Regression

---

Description

This is a function for running the Markov chain Monte Carlo algorithm for the Bayesian inference for multivariate meta-regression with a partially observed within-study sample covariance matrix model. The first six arguments are required. fmodel can be one of 5 numbers: 1, 2, 3, 4, and 5. The first model, fmodel = 1 denoted by M1, indicates that the $\Sigma_{kt}$ are diagonal matrices with zero covariances. M2 indicates that $\Sigma_{kt}$ are all equivalent but allowed to be full symmetric positive definite. M3 is where $\Sigma_{kt}$ are allowed to differ across treatments, i.e., $\Sigma_{kt} = \Sigma_t$. M4 assumes that the correlation matrix, $\rho$, is identical for all trials/treatments, but the variances are allowed to vary. Finally, M5 assumes a hierarchical model where $(\Sigma_{kt} | \Sigma)$ follows an inverse-Wishart distribution with fixed degrees of freedom and scale matrix $\Sigma$. $\Sigma$ then follows another inverse-Wishart distribution with fixed parameters.

Usage

bayes_parobs(
    Outcome,
    SD, 
    XCovariate,
    WCovariate,
    Treat,
    Trial,
    Npt,
    fmodel = 1,
    prior = list(),
    mcmc = list(),
    control = list(),
    init = list(),
    Treat_order = NULL,
    Trial_order = NULL,
    group = NULL,
    group_order = NULL,
    scale_x = FALSE,
    verbose = FALSE
)
Arguments

**Outcome**
the aggregate mean of the responses for each arm of every study.

**SD**
the standard deviation of the responses for each arm of every study.

**XCovariate**
the aggregate covariates for the fixed effects.

**WCovariate**
the aggregate covariates for the random effects.

**Treat**
the treatment identifiers. This is equivalent to the arm number of each study. The number of unique treatments must be equal across trials. The elements within will be coerced to consecutive integers.

**Trial**
the trial identifiers. This is equivalent to the arm labels in each study. The elements within will be coerced to consecutive integers.

**Npt**
the number of observations/participants for a unique \((k,t)\), or each arm of every trial.

**fmodel**
the model number. The possible values for fmodel are 1 to 5, each indicating a different prior specification for \(\Sigma_{kt}\). It will default to M1, fmodel=1 if not specified at function call. See the following model descriptions. The objects enclosed in parentheses at the end of every bullet point are the hyperparameters associated with each model.

- **fmodel=1** - \(\Sigma_{kt} = \text{diag}(\sigma^2_{kt,11}, \ldots, \sigma^2_{kt,JJ})\) where \(\sigma^2_{kt,jj} \sim IG(a_0, b_0)\) and \(IG(a, b)\) is the inverse-gamma distribution. This specification is useful if the user does not care about the correlation recovery. (c0, dj0, a0, b0, Omega0)

- **fmodel=2** - \(\Sigma_{kt} = \Sigma\) for every combination of \((k, t)\) and \(\Sigma^{-1} \sim \text{Wish}_{s_0}(\Sigma_0)\). This specification assumes that the user has prior knowledge that the correlation structure does not change across the arms included. (c0, dj0, s0, Omega0, Sigma0)

- **fmodel=3** - \(\Sigma_{kt} = \Sigma_t\) and \(\Sigma_t^{-1} \sim \text{Wish}_{s_0}(\Sigma_0)\). This is a relaxed version of fmodel=2, allowing the correlation structure to differ across trials but forcing it to stay identical within a trial. (c0, dj0, s0, Omega0, Sigma0)

- **fmodel=4** - \(\Sigma_{kt} = \delta_{kt} \rho \delta_{kt}\) where \(\delta_{kt} = \text{diag}(\Sigma^{1/2}_{kt,11}, \ldots, \Sigma^{1/2}_{kt,JJ})\), and \(\rho\) is the correlation matrix. This specification allows the variances to vary across arms but requires that the correlations be the same. This is due to the lack of correlation information in the data, which would in turn lead to the nonidentifiability of the correlations if they were allowed to vary. However, this still is an ambitious model which permits maximal degrees of freedom in terms of variance and correlation estimation. (c0, dj0, a0, b0, Omega0)

- **fmodel=5** - The fifth model is hierarchical and thus may require more data than the others: \((\Sigma^{-1}_{kt} | \Sigma) \sim \text{Wish}_{nu_0}((\nu_0 - J - 1)^{-1} \Sigma^{-1})\) and \(\Sigma \sim \text{Wish}_{d_0}(\Sigma_0)\). \(\Sigma_{kt}\) encodes the within-treatment-arm variation while \(\Sigma\) captures the between-treatment-arm variation. The hierarchical structure allows the "borrowing of strength" across treatment arms. (c0, dj0, d0, nu0, Sigma0, Omega0)

**Prior**
(Optional) a list of hyperparameters. Despite the ta in every model, each fmodel, along with the group argument, requires a different set of hyperparameters. See fmodel for the model specifications.
mcmc (Optional) a list for MCMC specification. ndiscard is the number of burn-in iterations. nskip configures the thinning of the MCMC. For instance, if nskip=5, bayes_parobs will save the posterior sample every 5 iterations. nkeep is the size of the posterior sample. The total number of iterations will be ndiscard + nskip * nkeep.

control (Optional) a list of tuning parameters for the Metropolis-Hastings algorithm. Rho, R, and delta are sampled through either localized Metropolis algorithm or delayed rejection robust adaptive Metropolis algorithm. {*_stepsize with the asterisk replaced with one of the names above specifies the stepsize for determining the sample evaluation points in the localized Metropolis algorithm. sample_Rho can be set to FALSE to suppress the sampling of Rho for fmodel=4. When sample_Rho is FALSE, ρ will be fixed using the value given by the init argument, which defaults to 0.5I + 0.5I′ where I is the vector of ones.

init (Optional) a list of initial values for the parameters to be sampled: theta, gamR, Omega, and Rho. The initial value for Rho will be effective only if fmodel=4.

Treat_order (Optional) a vector of unique treatments to be used for renumbering the Treat vector. The first element will be assigned treatment zero, potentially indicating placebo. If not provided, the numbering will default to an alphabetical/numerical order.

Trial_order (Optional) a vector of unique trials. The first element will be assigned zero. If not provided, the numbering will default to an alphabetical/numerical order.

group (Optional) a vector containing binary variables for ukt. If not provided, bayes_parobs will assume that there is no grouping and set ut = 0 for all (k, t).

group_order (Optional) a vector of unique group labels. The first element will be assigned zero. If not provided, the numbering will default to an alphabetical/numerical order. group_order will take effect only if group is provided by the user.

scale_x (Optional) a logical variable indicating whether XCovariate should be scaled/standardized. The effect of setting this to TRUE is not limited to merely standardizing XCovariate. The following generic functions will scale the posterior sample of theta back to its original unit: plot, fitted, summary, and print.

verbose (Optional) a logical variable indicating whether to print the progress bar during the MCMC sampling.

Value
bayes_parobs returns an object of class “bayesparobs”. The functions summary or print are used to obtain and print a summary of the results. The generic accessor function fitted extracts the posterior mean, posterior standard deviation, and the interval estimates of the value returned by bayes_parobs.

An object of class bayesparobs is a list containing the following components:

• Outcome - the aggregate response used in the function call.
• SD - the standard deviation used in the function call.
• Npt - the number of participants for (k, t) used in the function call.
• XCovariate - the aggregate design matrix for fixed effects used in the function call. Depending on scale_x, this may differ from the matrix provided at function call.
• WCovariate - the aggregate design matrix for random effects.
• Treat - the renumbered treatment indicators. Depending on Treat_order, it may differ from the vector provided at function call.
• Trial - the renumbered trial indicators. Depending on Trial_order, it may differ from the vector provided at function call.
• group - the renumbered grouping indicators in the function call. Depending on group_order, it may differ from the vector provided at function call. If group was missing at function call, bayes_parobs will assign NULL for group.
• TrtLabels - the vector of treatment labels corresponding to the renumbered Treat. This is equivalent to Treat_order if it was given at function call.
• TrialLabels - the vector of trial labels corresponding to the renumbered Trial. This is equivalent to Trial_order if it was given at function call.
• GroupLabels - the vector of group labels corresponding to the renumbered group. This is equivalent to group_order if it was given at function call. If group was missing at function call, bayes_parobs will assign NULL for GroupLabels.
• K - the total number of trials.
• T - the total number of treatments.
• fmodel - the model number as described here.
• scale_x - a Boolean indicating whether XCovariate has been scaled/standardized.
• prior - the list of hyperparameters used in the function call.
• control - the list of tuning parameters used for MCMC in the function call.
• mcmctime - the elapsed time for the MCMC algorithm in the function call. This does not include all the other preprocessing and post-processing outside of MCMC.
• mcmc - the list of MCMC specification used in the function call.
• mcmc.draws - the list containing the MCMC draws. The posterior sample will be accessible here.

Author(s)
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References

See Also
bmeta_analyze for using the Formula interface
bmeta_analyze supersedes the previous two functions: bayes_parobs, bayes_nmr

Description

All other worker functions are superseded by this function, so that users can forget about the implementation details and focus on modeling. Meta-analytic data can be either aggregate or individual participant data (IPD). Aggregate data implies that the response consists of estimated effect sizes and their corresponding standard errors, whereas IPD is raw data. Data sets to be used for metapack should be formatted as follows:

<table>
<thead>
<tr>
<th>Outcome</th>
<th>SD</th>
<th>DesignM1</th>
<th>DesignM2</th>
<th>Trial indicator (k)</th>
<th>Treatment indicator (t)</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>y_{13}</td>
<td>S_{13}</td>
<td>x_{13}</td>
<td>w_{13}</td>
<td>1</td>
<td>3</td>
<td>1000</td>
</tr>
<tr>
<td>y_{10}</td>
<td>S_{10}</td>
<td>x_{10}</td>
<td>w_{10}</td>
<td>1</td>
<td>0</td>
<td>545</td>
</tr>
<tr>
<td>y_{20}</td>
<td>S_{20}</td>
<td>x_{20}</td>
<td>w_{20}</td>
<td>2</td>
<td>0</td>
<td>1200</td>
</tr>
</tbody>
</table>

The first treatment indicator is intentionally selected to be 3, a number greater than 1, to indicate that this data format works for both meta-regression and network meta-regression. Meta-regression refers to when trials included have 2 treatments (i.e., \( t = 0, 1 \) for all \( k \)), and the treatments are compared head to head. On the other hand, network meta-regression includes more than two treatments, where each trial can have a different set of treatments, allowing indirect comparison between treatments that are not compared head to head as long as consistency holds (see Higgins et al. (2012) for consistency).

bmeta_analyze() and bmeta_analyse() are synonyms.
Usage

bmeta_analyze(
  formula, 
  data, 
  prior = list(), 
  mcmc = list(), 
  control = list(), 
  init = list()
)

bmeta_analyse(
  formula, 
  data, 
  prior = list(), 
  mcmc = list(), 
  control = list(), 
  init = list()
)

Arguments

formula an object of class Formula: a symbolic description of the meta-analytic model to fit. For aggregate models, the vector of arm sample sizes must be provided using the function ns(). For example, y1 + y2 | sd1 + sd2 ~ x1 + x2 + ns(n)—an incomplete formula only for illustration purposes. If no ns() is found, individual participant data (IPD) model is assumed.

data a data frame, list, or environment (or an object coercible by as.data.frame to a data frame) containing the variables in the model. If not found in data, the variables are taken from environment(formula), typically the environment from which bmeta_analyze is called.

prior an optional object that contains the hyperparameter values for the model. To see the complete list of hyperparameters for a specific model, refer to the corresponding worker function’s help page, e.g., help(bayes_parobs) or help(bayes_nmr). For meta-analysis, model is required in the prior argument, which is passed to fmodel as an integer. If the response is univariate, NoRecovery is the only valid option.

• model="NoRecovery" - $\Sigma_{tk} = diag(\sigma^2_{tk,11}, \ldots, \sigma^2_{tk,JJ})$ where $\sigma^2_{tk,ij} \sim IG(a_0, b_0)$ and $IG(a, b)$ is the inverse-gamma distribution. This specification is useful if the user does not care about the correlation recovery. (c0, dj0, a0, b0, Omega0)

• model="EquiCovariance" - $\Sigma_{tk} = \Sigma$ for every combination of $(t,k)$ and $\Sigma^{-1} \sim Wish_{s_0}(\Sigma_0)$. This specification assumes that the user has prior knowledge that the correlation structure does not change across the arms included. (c0, dj0, s0, Omega0, Sigma0)

• model="EquiWithinTreat" - $\Sigma_{tk} = \Sigma_t$ and $\Sigma_t^{-1} \sim Wish_{s_0}(\Sigma_0)$. This is a relaxed version of model=2, allowing the correlation structure to differ
across trials but forcing it to stay identical within a trial. \((\phi, \delta_0, \sigma_0, \Omega_0, \Sigma_0)\)

- **model="EquiCorrelation"** - \(\Sigma_{tk} = \delta_{tk} \rho \delta_{tk}\) where \(\delta_{tk} = \text{diag}(\Sigma_{tk,11}^{1/2}, \ldots, \Sigma_{tk,JJ}^{1/2})\), and \(\rho\) is the correlation matrix. This specification allows the variances to vary across arms but requires that the correlations be the same. This is due to the lack of correlation information in the data, which would in turn lead to the nonidentifiability of the correlations if they were allowed to vary. However, this still is an ambitious model which permits maximal degrees of freedom in terms of variance and correlation estimation. \((\phi, \delta_0, \sigma_0, \Omega_0, \Sigma_0)\)

- **model="Hierarchical"** - The fifth model is hierarchical and thus may require more data than the others: \((\Sigma_{tk}^{-1} | \Sigma) \sim \text{Wish}(\nu_0 - J - 1, -1 \Sigma^{-1})\) and \(\Sigma \sim \text{Wish}_{d_0}(\Sigma_0)\). \(\Sigma_{tk}\) encodes the within-treatment-arm variation while \(\Sigma\) captures the between-treatment-arm variation. The hierarchical structure allows the "borrowing of strength" across treatment arms. \((\phi, \delta_0, \sigma_0, \nu_0, \Sigma_0, \Omega_0)\)

For network meta-analysis,

- **df** - the degrees of freedom of the multivariate t-distribution for the random effects. Any positive value can be assigned; if \(df=\text{Inf}\), multivariate normal random effects will be assumed.
- **c01** - the variance of the fixed-effect coefficients’ prior distribution, a multivariate normal distribution, i.e., \(\theta \sim \mathcal{N}(0, c_1 I)\).
- **c02** - the variance of the random-effects’ variance-related coefficients’ prior distribution, a multivariate normal distribution, i.e., \(\phi \sim \mathcal{N}(0, c_2 I)\).
- **a4, b4, a5, b5** - the hyperparameters related to when the degrees of freedom for the random effects are treated as unknown/random. \(\text{df}\) is then considered to follow \(\text{Ga}(\nu_a, \nu_a/\nu_b)\), \(\nu_a \sim \text{Ga}(a_4, b_4)\), and \(\nu_b \sim \text{IG}(a_5, b_5)\). All gamma and inverse-gamma distributions are rate-parameterized.

**mcmc**

- an optional object containing MCMC specification. \(\text{ndiscard}\) is the number of burn-in iterations. \(\text{nskip}\) configures the thinning of the MCMC. For instance, if \(\text{nskip}=5\), parameters will be saved every 5 iterations. \(\text{nkeep}\) is the size of the posterior sample. The total number of iterations will be \(\text{ndiscard} + \text{nskip} \times \text{nkeep}\).

**control**

- an optional object that contains the control tuning parameters for the Metropolis-Hastings algorithm. Similar to \(\text{prior}\), the complete list of control parameters for a specific model is given in the corresponding worker function’s help page (see \texttt{bayes_parobs}\) or \texttt{bayes_nmr}). These are the lists of available tuning parameters in control for meta-analysis and network meta-analysis. Keep in mind that \(\text{model}\) will render some irrelevant tuning parameters ineffective.

- **Meta-analysis** - model (string), sample_Rho (logical), Rho_stepsize (double), R_stepsize (double), delta_stepsize (double), sample_Rho (logical)

- **Network meta-analysis** - sample_df (logical), sample_Rho (logical), lambda_stepsize (double), phi_stepsize (double), Rho_stepsize (double)

**init**

- (Optional) a list of initial values for the parameters to be sampled. The following is the list of available parameters for meta-analysis and network meta-analysis.
bmeta_analyze

- Meta-analysis - theta (vector), gamR (matrix), Omega (matrix), Rho (matrix)
- Network meta-analysis - theta (vector), phi (vector), sig2 (vector), Rho (matrix)

The dimensions of the initial values must be conformable for matrix operations.
If dimensions don’t agree, bmeta_analyze will tell you the correct dimension.

Details

bmeta_analyze currently subsumes two worker functions: bayes_parobs and bayes_nmr. bmeta_analyze offers a formula interface. All formulas are parsed using Formula. Formulas for bmeta_analyze are constrained to have a strict structure: one or two LHS, and two or three RHS. That is, \( \text{lhs}_1 \sim \text{rhs}_1 | \text{rhs}_2 | \text{rhs}_3 \) or \( \text{lhs}_1 | \text{lhs}_2 \sim \text{rhs}_1 | \text{rhs}_2 | \text{rhs}_3 \) (see Examples for more). The tilde (\( \sim \)) separates the LHS’s and RHS’s, each side further separated into parts by vertical bars (\( | \)). The meaning of each part is syntactically determined by its location inside the formula, like an English sentence. Therefore, all parts must come in the exact order as prescribed for bmeta_analyze to correctly configure your model.

- The first LHS, the responses, is required for all models.
- The second LHS is only required for aggregate models, corresponding to the standard deviations of the responses.
- The first RHS corresponds to fixed-effects covariates.
- The second RHS corresponds to the variables in either the random-effects matrix (\( w_{ik}' \cdot \gamma_k \)) for multivariate meta-analysis or modeling the variances (\( \log \tau_{ik} = z_{ik}' \cdot \phi \)) for univariate network meta-analysis.
- The third RHS corresponds to the treatment and trial indicators, and optionally the grouping variable if it exists. The order must be \text{treat} + \text{trial} + \text{group}, or \text{treat} + \text{trial} if no grouping exists. Variables here must be supplied in the exact order described; otherwise, model will not be correctly identified.

Internally, bmeta_analyze looks for three things: multivariate/univariate, meta-analysis/network meta-analysis, and aggregate/IPD.

- multivariate/univariate: the dimension of the response is explicit in the formula, and determines univariate versus multivariate.
- meta-analysis/network meta-analysis: the number of levels (\text{nlevels}) of treatments determines this. If treat is not already a factor variable, it is coerced to one.
- aggregate/IPD: bmeta_analyze looks for \text{ns()} in the first RHS. Aggregate models must provide the arm sample sizes using the function \text{ns()} (e.g., if \text{n} is the sample sizes, \( y_1 + y_2 \mid s_{d1} + s_{d2} \sim x_1 + x_2 + \text{ns(n)} \)). If there is no \text{ns()}, IPD is assumed. Currently, IPD models are a work in progress and not supported yet.

Currently, only univariate/multivariate + meta-analysis and univariate + network meta-analysis are allowed. More models will be added in the future.

Value

bmeta_analyze returns a classed object of bsynthesis for Bayesian synthesis
cholesterol

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References


See Also
bayes_parobs for multivariate meta-analysis, and bayes_nmr for univariate network meta-analysis.

Examples
```r
set.seed(2797542)
data("cholesterol")
f_1 <- 'pldlc + phdlc + ptg | sdldl + sdhdl + sdtg ~ 0 + bldlc + bhdlc + btg + age + durat + white + male + dm + ns(n) | treat | treat + trial + onstat'
out_1 <- bmeta_analyze(as.formula(f_1), data = cholesterol,
prior = list(model="NoRecovery"),
mcmc = list(ndiscard = 3, nskip = 1, nkeep = 1),
control=list(scale_x = TRUE, verbose=FALSE))

set.seed(2797542)
data("TNM")
TNM$group <- factor(match(TNM$treat, c("PBO", "R"), nomatch = 0))
f_2 <- 'ptg | sdtg ~ 0 + bldlc + bhdlc + btg + age + white + male + bmi + potencymed + potencyhigh + durat + ns(n) | scale(bldlc) + scale(btg) + group | treat + trial'
out_2 <- bmeta_analyze(as.formula(f_2), data = TNM,
mcmc = list(ndiscard = 1, nskip = 1, nkeep = 1),
control=list(scale_x = TRUE, verbose=FALSE))
```

cholesterol
26 double-blind, randomized, active, or placebo-controlled clinical trials on patients with primary hypercholesterolemia sponsored by *Merck & Co., Inc., Kenilworth, NJ, USA.*
Description

A data set containing clinical trial on hypercholesterolemia including 26 trials and 2 treatment arms each, and other attributes of the participants

Usage

data(cholesterol)

Format

A data frame with 52 rows and 19 variables

study  study identifier
trial   trial identifier
treat   treatment indicator for Statin or Statin+Ezetimibe
n       the number of participants in the study arms corresponding to the trial and treatment
pldlc  aggregate percentage change in LDL-C
phdlc  aggregate percentage change from baseline in HDL-C
ptg    aggregate percentage change from baseline in triglycerides (TG)
sddl   sample standard deviation of percentage change in LDL-C
sddh   sample standard deviation of percentage change in HDL-C
sdtg   sample standard deviation of percentage change in triglycerides (TG)
onstat whether the participants were on Statin prior to the trial
bdlc   baseline LDL-C
bhdh   baseline HDL-C
bttg   baseline triglycerides (TG)
age    age in years
white  the proportion of white participants
male   the proportion of male participants
dm     the proportion of participants with diabetes mellitus
durat  duration in weeks

Examples

data(cholesterol)
coef.bsynthesis  get the posterior mean of fixed-effect coefficients

Description
get the posterior mean of fixed-effect coefficients

Usage
## S3 method for class 'bsynthesis'
coef(object, ...)

Arguments
object  a class of bsynthesize
...
other arguments

Value
Coefficients extracted from the model object object

fitted.bayesnmr  get fitted values

Description
get fitted values

Usage
## S3 method for class 'bayesnmr'
fitted(object, level = 0.95, HPD = TRUE, ...)

Arguments
object  the output model from fitting a meta analysis/regression model
level  credible level for interval estimation; set to 0.95 by default
HPD  a logical argument indicating whether HPD intervals should be computed; if FALSE, equal-tail credible intervals are computed
...
additional arguments for fitted

Value
a list of fitted values
fitted.bayesparobs  

**Description**

get fitted values

**Usage**

```r
## S3 method for class 'bayesparobs'
fitted(object, level = 0.95, HPD = TRUE, ...)
```

**Arguments**

- `object`: the output model from fitting a meta analysis/regression model
- `level`: credible level for interval estimation; set to 0.95 by default
- `HPD`: a logical argument indicating whether HPD intervals should be computed; if FALSE, equal-tail credible intervals are computed
- `...`: additional arguments for fitted

**Value**

a list of fitted values

---

**hpd**  

**Description**

get the highest posterior density (HPD) interval

**Usage**

```r
hpd(object, parm, level = 0.95, HPD = TRUE)
```

**Arguments**

- `object`: the output model from fitting a (network) meta analysis/regression model
- `parm`: a specification of which parameters are to be given confidence intervals, either a vector of numbers or a vector of names. If missing, all parameters are considered.
- `level`: the probability which the HPD interval will cover
- `HPD`: a logical value indicating whether HPD or equal-tailed credible interval should be computed; by default, TRUE
Details

A 100(1 − α)% HPD interval for θ is given by

\[ R(\pi_\alpha) = \theta : \pi(\theta|D) \geq \pi_\alpha, \]

where \( \pi_\alpha \) is the largest constant that satisfies \( P(\theta \in R(\pi_\alpha)) \geq 1 - \alpha \). hpd computes the HPD interval from an MCMC sample by letting \( \theta(j) \) be the jth smallest of the MCMC sample, \( \theta_i \) and denoting

\[ R_j(n) = (\theta(j), \theta(j+[(1-\alpha)n])), \]

for \( j = 1, 2, \ldots, n - [(1-\alpha)n] \). Once \( \theta_i \)'s are sorted, the appropriate \( j \) is chosen so that

\[ \theta(j+[(1-\alpha)n]) - \theta(j) = \min_{1 \leq j \leq n - [(1-\alpha)n]} (\theta(j+[(1-\alpha)n]) - \theta(j)). \]

Value

dataframe containing HPD intervals for the parameters

References


hpd.bayesnmr

get the highest posterior density (HPD) interval

Description

get the highest posterior density (HPD) interval

Usage

```r
## S3 method for class 'bayesnmr'
hpd(object, parm, level = 0.95, HPD = TRUE)
```

Arguments

- `object`: the output model from fitting a (network) meta analysis/regression model
- `parm`: a specification of which parameters are to be given confidence intervals, either a vector of numbers or a vector of names. If missing, all parameters are considered.
- `level`: the probability which the HPD interval will cover
- `HPD`: a logical value indicating whether HPD or equal-tailed credible interval should be computed; by default, TRUE

Value

dataframe containing HPD intervals for the parameters
**Description**

get the highest posterior density (HPD) interval or equal-tailed credible interval

**Usage**

```r
## S3 method for class 'bayesparobs'
hpd(object, parm, level = 0.95, HPD = TRUE)
```

**Arguments**

- `object`: the output model from fitting a (network) meta analysis/regression model
- `parm`: a specification of which parameters are to be given confidence intervals, either a vector of numbers or a vector of names. If missing, all parameters are considered.
- `level`: the probability which the HPD interval will cover
- `HPD`: a logical value indicating whether HPD or equal-tailed credible interval should be computed; by default, TRUE

**Value**

dataframe containing HPD intervals for the parameters

---

**metapack**

*metapack: a package for Bayesian meta-analysis and network meta-analysis*

**Description**

The metapack package provides one category of functions: `bayes.parobs` and `bayes.nmr`

**Multivariate Meta-Regression function**

The `bayes.parobs` function fits the multivariate meta-regression model with partially observed sample covariance matrix to the given data.

**Network Meta-Regression function**

The `bayes.nmr` function fits the network meta-regression model with heavy-tailed random effects distribution to the given data.
model_comp is a generic function that computes the model comparison measures (DIC and LPML) or the Pearson’s residuals. Note that the Pearson’s residuals are not available for bayes.nmr when df is either random or fixed but smaller than 2 since the variance of the random effects is not finite.

Usage

```r
model_comp(object, type = "lpml", verbose = FALSE, ncores = NULL)
```

Arguments

- `object`: the output model from fitting a meta analysis/regression model
- `type`: the type of model comparison measure to compute; DIC or LPML
- `verbose`: FALSE by default; If TRUE, then progress bar will appear
- `ncores`: the number of CPU cores to use for parallel processing. It must not exceed the number of existing cores. If unspecified, it will default to 2 cores or the number of existing cores, whichever is smaller.

Value

dataframe containing the compute the model comparison measures
model_comp.bayesparobs

Value
dataframe containing the compute the model comparison measures

model_comp.bayesparobs

compute the model comparison measures

Description
compute the model comparison measures

Usage

## S3 method for class 'bayesparobs'
model_comp(object, type = "lpml", verbose = FALSE, ncores = NULL)

Arguments

object the output model from fitting a meta analysis/regression model
type the type of model comparison measures; DIC or LPML
verbose FALSE by default; If TRUE, then progress bar will appear
ncores the number of CPU cores to use for parallel processing. It must not exceed the number of existing cores. If unspecified, it will default to 2 cores or the number of existing cores, whichever is smaller.

Value
dataframe containing the compute the model comparison measures

ns

helper function encoding trial sample sizes in formulas

Description
helper function encoding trial sample sizes in formulas

Usage

ns(x)

Arguments

x the name of the variable containing trial sample sizes
plot.bayesnmr  get goodness of fit

Description
get goodness of fit

Usage
## S3 method for class 'bayesnmr'
plot(x, ...)

Arguments

x the output model from fitting a meta analysis/regression model
...
additional parameters for plot

Value
No return value

plot.bayesparobs  get goodness of fit

Description
get goodness of fit

Usage
## S3 method for class 'bayesparobs'
plot(x, ...)

Arguments

x the output model from fitting a meta analysis/regression model
...
additional parameters for plot

Value
No return value
plot.sucra

Description
plot the surface under the cumulative ranking curve (SUCRA)

Usage
## S3 method for class 'sucra'
plot(x, legend.position = "none", ...)

Arguments
x the output model from fitting a network meta analysis/regression model
legend.position the position of the legend that will be passed onto ggplot
... additional arguments for plot

Value
No return value

print.bayesnmr

Description
Print results

Usage
## S3 method for class 'bayesnmr'
print(x, level = 0.95, HPD = TRUE, ...)

Arguments
x the output model from fitting a network meta analysis/regression model
level credible level for interval estimation; set to 0.95 by default
HPD a logical argument indicating whether HPD intervals should be computed; if FALSE, equal-tail credible intervals are computed
... additional arguments for print

Value
No return value; print a summary of the output
Description

Print results

Usage

## S3 method for class 'bayesparobs'
print(x, level = 0.95, HPD = TRUE, ...)

Arguments

x the output model from fitting a meta analysis/regression model
level credible level for interval estimation; set to 0.95 by default
HPD a logical argument indicating whether HPD intervals should be computed; if
FALSE, equal-tail credible intervals are computed
... additional arguments for print

Value

No return value; print a summary of the output

sucra

get surface under the cumulative ranking curve (SUCRA)

Description

get surface under the cumulative ranking curve (SUCRA)

Usage

sucra(object)

Arguments

object the output model from fitting a network meta analysis/regression model

Value

a list containing SUCRA and the discrete rank probability matrix of size T by T
sucra.bayesnmr

Description
get surface under the cumulative ranking curve (SUCRA)

Usage

## S3 method for class 'bayesnmr'
sucra(object)

Arguments

object the output model from fitting a network meta analysis/regression model

Value

a list containing SUCRA and the discrete rank probability matrix of size T by T

summary.bayesnmr

'summary' method for class "bayesnmr"

Description

'summary' method for class "bayesnmr"

Usage

## S3 method for class 'bayesnmr'
summary(object, level = 0.95, HPD = TRUE, ...)

Arguments

object the output model from fitting a network meta analysis/regression model
level credible level for interval estimation; set to 0.95 by default
HPD a logical argument indicating whether HPD intervals should be computed; if FALSE, equal-tail credible intervals are computed
... additional arguments for print

Value
does not return anything; print a summary of the output
TNM

Triglycerides Network Meta (TNM) data

Description

A systemically reviewed network meta data set on tryglyceride (TG) lowering drugs

Usage

data(TNM)

Format

A data frame with 73 rows and 15 variables

- **trial** trial identifier
- **treat** treatment indicator for placebo (PBO), simvastatin (S), atorvastatin (A), lovastatin (L), rosuvastatin (R), pravastatin (P), ezetimibe (E), simvastatin+ezetimibe (SE), atorvastatin+ezetimibe (AE), lovastatin+ezetimibe (LE), or pravastatin+ezetimibe (PE)
- **n** the number of participants in the study corresponding to the trial and treatment

---

summary.bayesparobs summary method for class "bayesparobs"

**Description**

summary method for class "bayesparobs"

**Usage**

```r
## S3 method for class 'bayesparobs'
summary(object, level = 0.95, HPD = TRUE, ...)
```

**Arguments**

- **object** the output model from fitting a meta analysis/regression model
- **level** credible level for interval estimation; set to 0.95 by default
- **HPD** a logical argument indicating whether HPD intervals should be computed; if FALSE, equal-tail credible intervals are computed
- **...** additional arguments for summary

**Value**

print summary for the model fit
ptg  percentage change from baseline in triglycerides (TG)
sdtg  sample standard deviation of percentage change in triglycerides (TG)
bldlc  baseline LDL-C
bhdlc  baseline HDL-C
btg  baseline triglycerides (TG)
age  age in years
white  the proportion of white participants
male  the proportion of male participants
bmi  body fat index
potencymed  the proportion of medium statin potency
potencyhigh  the proportion of high statin potency
durat  duration in weeks

Examples

data(TNM)
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