

Package ‘multinma’

March 6, 2024

Title Bayesian Network Meta-Analysis of Individual and Aggregate Data

Version 0.6.1

Description Network meta-analysis and network meta-regression models for aggregate data, individual patient data, and mixtures of both individual and aggregate data using multilevel network meta-regression as described by Phillipppo et al. (2020) <doi:10.1111/rssa.12579>. Models are estimated in a Bayesian framework using 'Stan'.

License GPL-3

Encoding UTF-8

LazyData true

Biarch true

Depends R (>= 3.4.0)

Imports methods, stats, graphics, survival, Rcpp (>= 0.12.0), RcppParallel (>= 5.0.1), rstan (>= 2.26.0), rstantools (>= 2.0.0), Rdpack (>= 0.7), tibble (>= 2.1.3), dplyr (>= 1.0.0), rlang, purrr, forcats, glue, randtoolbox, copula, tidyr (>= 1.0.0), stringr, Matrix, igraph, ggraph, ggplot2 (>= 3.3.0), ggdist (>= 2.1.1), truncdist, bayesplot

LinkingTo BH (>= 1.66.0), Rcpp (>= 0.12.0), RcppEigen (>= 0.3.3.3.0), RcppParallel (>= 5.0.1), rstan (>= 2.26.0), StanHeaders (>= 2.26.0)

SystemRequirements GNU make

RoxygenNote 7.2.3

Suggests testthat (>= 2.1.0), withr, knitr, rmarkdown, parallel, R.rsp, rprojroot, loo (>= 2.0.0), logitnorm, crayon, tidygraph, pkgdown, splines2 (>= 0.5.0), flexsurv, rstpm2

RdMacros Rdpack

URL <https://dmpillippo.github.io/multinma/>,
<https://github.com/dmpillippo/multinma>

BugReports <https://github.com/dmpillippo/multinma/issues>

VignetteBuilder knitr, R.rsp

NeedsCompilation yes

Author David M. Phillippo [aut, cre] (<<https://orcid.org/0000-0003-2672-7841>>)

Maintainer David M. Phillippo <david.phillippo@bristol.ac.uk>

Repository CRAN

Date/Publication 2024-03-06 01:00:05 UTC

R topics documented:

multinma-package	4
.default	5
adapt_delta	6
add_integration	6
as.array.stan_nma	10
as.igraph.nma_data	11
as.stanfit	12
atrial_fibrillation	13
bcg_vaccine	14
blocker	15
combine_network	15
dgent	18
diabetes	19
dic	19
dietary_fat	21
distr	22
dlogt	23
dmspline	24
example_ndmm	25
example_pso_mlnmr	26
example_smk_fe	28
example_smk_nodesplit	29
example_smk_re	30
example_smk_ume	30
geom_km	31
get_nodesplits	33
hta_psoriasis	35
is_network_connected	36
loo.stan_nma	37
make_knots	37
mcmc_array-class	39
multi	41
ndmm_ipd	43
nma	44
nma_data-class	53
nma_dic-class	54
nma_nodesplit-class	55

nma_prior-class	55
nma_summary-class	56
nodesplit_summary-class	56
pairs.stan_nma	57
parkinsons	58
plaque_psoriasis_ipd	59
plot.nma_data	61
plot.nma_dic	63
plot.nma_summary	65
plot.nodesplit_summary	67
plot_integration_error	69
plot_prior_posterior	72
posterior_ranks	73
predict.stan_nma	76
print.nma_data	83
print.nma_dic	84
print.nma_nodesplit_df	84
print.nma_summary	85
print.nodesplit_summary	86
print.stan_nma	87
priors	87
qbern	89
qgamma	90
qlogitnorm	91
relative_effects	91
RE_cor	93
set_agd_arm	94
set_agd_contrast	96
set_agd_surv	98
set_ipd	100
smoking	102
stan_nma-class	102
statins	103
summary.nma_nodesplit_df	104
summary.nma_prior	105
summary.stan_nma	106
theme_multinma	108
thrombolytics	108
transfusion	109

multinma-package	<i>multinma: A Package for Network Meta-Analysis of Individual and Aggregate Data in Stan</i>
------------------	---

Description

An R package for performing network meta-analysis and network meta-regression with aggregate data, individual patient data, or mixtures of both.

Details

Network meta-analysis (NMA) combines (aggregate) data from multiple studies on multiple treatments in order to produce consistent estimates of relative treatment effects between each pair of treatments in the network (Dias et al. 2011).

Network meta-regression (NMR) extends NMA to include covariates, allowing adjustment for differences in effect-modifying variables between studies (Dias et al. 2011). NMR is typically performed using aggregate data (AgD), which lacks power and is prone to ecological bias. NMR with individual patient data (IPD) is the gold standard, if data are available.

Multilevel network meta-regression (ML-NMR) allows IPD and AgD to be incorporated together in a network meta-regression (Phillippo et al. 2020; Phillippo 2019). As in IPD NMR, an individual-level regression model is defined. AgD studies are then fitted by integrating the individual-level model over the respective covariate distributions. This correctly links the two levels of the model (instead of "plugging in" mean covariate values), avoiding aggregation bias. Population-adjusted treatment effects (Phillippo et al. 2016) can be produced for any study population in the network, or for an external target population.

Models are estimated in a Bayesian framework using Stan (Carpenter et al. 2017). Quasi-Monte Carlo numerical integration based on Sobol' sequences is used for the integration in ML-NMR models, with a Gaussian copula to account for correlations between covariates (Phillippo et al. 2020; Phillippo 2019).

Getting Started

A good place to start is with the package vignettes which walk through example analyses, see `vignette("vignette_overview")` for an overview. The series of NICE Technical Support Documents on evidence synthesis gives a detailed introduction to network meta-analysis:

Dias S, Welton NJ, Sutton AJ, Caldwell DM, Lu G, Reken S, Ades AE (2011). "NICE DSU Technical Support Documents 1-7: Evidence Synthesis for Decision Making." National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Multilevel network meta-regression is set out in the following methods paper:

Phillippo DM, Dias S, Ades AE, Belger M, Brnabic A, Schacht A, Saure D, Kadziola Z, Welton NJ (2020). "Multilevel Network Meta-Regression for population-adjusted treatment comparisons." *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, **183**(3), 1189–1210. [doi:10.1111/rssa.12579](https://doi.org/10.1111/rssa.12579).

References

Carpenter B, Gelman A, Hoffman MD, Lee D, Goodrich B, Betancourt M, Brubaker M, Guo J, Li P, Riddell A (2017). “Stan: A Probabilistic Programming Language.” *Journal of Statistical Software*, **76**(1). doi:10.18637/jss.v076.i01.

Dias S, Sutton AJ, Welton NJ, Ades AE (2011). “NICE DSU Technical Support Document 3: Heterogeneity: subgroups, meta-regression, bias and bias-adjustment.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). “NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Phillippo DM (2019). *Calibration of Treatment Effects in Network Meta-Analysis using Individual Patient Data*. Ph.D. thesis, University of Bristol. Available from <https://research-information.bris.ac.uk/>.

Phillippo DM, Ades AE, Dias S, Palmer S, Abrams KR, Welton NJ (2016). “NICE DSU Technical Support Document 18: Methods for population-adjusted indirect comparisons in submission to NICE.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Phillippo DM, Dias S, Ades AE, Belger M, Brnabic A, Schacht A, Saure D, Kadziola Z, Welton NJ (2020). “Multilevel Network Meta-Regression for population-adjusted treatment comparisons.” *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, **183**(3), 1189–1210. doi:10.1111/rssa.12579.

.default

Set default values

Description

The `.default()` function is used internally to mark certain values as default, so that the user may be notified when default values are being used. For example, choosing a default reference treatment for a network, or using default prior distributions. The function `.is_default()` checks whether an argument/object is set to a default value. Neither of these functions are intended to be called by the user.

Usage

```
.default(x = list())
```

```
.is_default(x)
```

Arguments

x An object

Value

For `.default()`, an identical object with additional attribute `.default`. For `.is_default()`, a logical value (TRUE or FALSE).

<code>adapt_delta</code>	<i>Target average acceptance probability</i>
--------------------------	--

Description

The Stan control argument `adapt_delta` sets the target average acceptance probability for the No-U-Turn Sampler (NUTS) used by Stan.

Details

The default value of `adapt_delta` used by `nma()` is 0.8 for fixed effect models, and 0.95 for random effects models.

You should not need to change `adapt_delta` unless you see a warning message about divergent transitions. Increasing `adapt_delta` from the default to a value closer to 1 means that Stan will use a smaller step size, making sampling slower but more robust, and resulting in fewer divergent transitions.

For more details see the Stan documentation available from <https://mc-stan.org/users/documentation/>.

<code>add_integration</code>	<i>Add numerical integration points to aggregate data</i>
------------------------------	---

Description

The `add_integration()` generic creates Quasi-Monte Carlo numerical integration points using a Gaussian copula and Sobol' sequences, as described in Phillipppo et al. (2020). Methods are available for networks stored in `nma_data` objects, and for data frames. The function `unnest_integration()` unnests integration points stored in a data frame, to aid plotting or other exploration.

Usage

```
add_integration(x, ...)

## Default S3 method:
add_integration(x, ...)

## S3 method for class 'data.frame'
add_integration(
  x,
  ...,
  cor = NULL,
```

```

    cor_adjust = NULL,
    n_int = 64L,
    int_args = list()
  )

## S3 method for class 'nma_data'
add_integration(
  x,
  ...,
  cor = NULL,
  cor_adjust = NULL,
  n_int = 64L,
  int_args = list()
)

unnest_integration(data)

```

Arguments

x	An nma_data object, as created by the set_*() functions or combine_network(), or data frame
...	Distributions for covariates, see "Details"
cor	Correlation matrix to use for generating the integration points. By default, this takes a weighted correlation matrix from all IPD studies. Rows and columns should match the order of covariates specified in ...
cor_adjust	Adjustment to apply to the correlation matrix given by cor (or computed from the IPD if cor = NULL) to obtain the Gaussian copula correlations, either "spearman", "pearson", or "none", see "Details". The default when cor = NULL is "spearman", otherwise the default is "pearson".
n_int	Number of integration points to generate, default 64. Powers of 2 are recommended, as these are expected to be particularly efficient for QMC integration.
int_args	A named list of arguments to pass to sobol()
data	Data frame with nested integration points, stored in list columns as .int_<variable name>

Details

The arguments passed to ... specify distributions for the covariates. Argument names specify the name of the covariate, which should match a covariate name in the IPD (if IPD are present). The required marginal distribution is then specified using the function [distr\(\)](#).

The argument cor_adjust specifies how the correlation matrix given by cor (or computed from the IPD if cor = NULL) is adjusted to obtain the correlation matrix for the Gaussian copula, using the formulae in Xiao and Zhou (2018).

- cor_adjust = "spearman" should be used when the correlations cor have been computed using Spearman's rank correlation. Correlations between continuous covariates will be reproduced exactly by the integration points. Correlations between discrete covariates will be reproduced approximately. This is the default when cor = NULL and correlations are calculated from the IPD studies.

- `cor_adjust = "pearson"` should be used when the correlations `cor` have been computed using Pearson's product-moment correlation. Correlations between Normal covariates will be reproduced exactly by the integration points, all others will be reproduced approximately. Correlations between discrete covariates will be reproduced approximately (and identically to `cor_adjust = "spearman"`). This is the default when `cor` is provided by the user, since `cor()` defaults to `method = "pearson"` and Pearson correlations are most likely reported in published data. However, we recommend providing Spearman correlations (e.g. from `cor(, method = "spearman")`) and using `cor_adjust = "spearman"` where possible.
- `cor_adjust = "none"` allows the user to specify the correlation matrix for the Gaussian copula directly; no adjustment is applied.
- `cor_adjust = "legacy"` is also available, which reproduces exactly the behaviour from version 0.3.0 and earlier. This is similar to `cor_adjust = "none"`, but unadjusted Spearman correlations are used if `cor = NULL`.

When adding integration points to a network object the correlation matrix used is stored in `$int_cor`, and the copula correlation matrix and adjustment used are stored as attributes of `$int_cor`. If this correlation matrix is passed again to `add_integration()` (e.g. to reuse the correlations for an external target population) this will be detected, and the correct setting for `cor_adjust` will automatically be applied.

Value

For the `nma_data` method, an object of class `nma_data`. For the `data.frame` method, the input data frame is returned (as a `tibble`) with an added column for each covariate (prefixed with `".int_"`), containing the numerical integration points nested as `length-n_int` vectors within each row. For `unnest_integration()`, a data frame with integration points unnested.

References

Phillippo DM, Dias S, Ades AE, Belger M, Brnabic A, Schacht A, Saure D, Kadziola Z, Welton NJ (2020). "Multilevel Network Meta-Regression for population-adjusted treatment comparisons." *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, **183**(3), 1189–1210. doi:10.1111/rssa.12579.

Xiao Q, Zhou S (2018). "Matching a correlation coefficient by a Gaussian copula." *Communications in Statistics - Theory and Methods*, **48**(7), 1728–1747. doi:10.1080/03610926.2018.1439962.

Examples

```
## Plaque psoriasis ML-NMR - network setup and adding integration points
# Set up plaque psoriasis network combining IPD and AgD
library(dplyr)
pso_ipd <- filter(plaque_psoriasis_ipd,
                 studyc %in% c("UNCOVER-1", "UNCOVER-2", "UNCOVER-3"))

pso_agd <- filter(plaque_psoriasis_agd,
                 studyc == "FIXTURE")

head(pso_ipd)
head(pso_agd)
```



```
pso_ipd <- pso_ipd %>%
  mutate(# Variable transformations
    bsa = bsa / 100,
    prevsys = as.numeric(prevsys),
    psa = as.numeric(psa),
    weight = weight / 10,
    durnpso = durnpso / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker"),
    # Check complete cases for covariates of interest
    complete = complete.cases(durnpso, prevsys, bsa, weight, psa)
  )

pso_agd <- pso_agd %>%
  mutate(
    # Variable transformations
    bsa_mean = bsa_mean / 100,
    bsa_sd = bsa_sd / 100,
    prevsys = prevsys / 100,
    psa = psa / 100,
    weight_mean = weight_mean / 10,
    weight_sd = weight_sd / 10,
    durnpso_mean = durnpso_mean / 10,
    durnpso_sd = durnpso_sd / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker")
  )

# Exclude small number of individuals with missing covariates
pso_ipd <- filter(pso_ipd, complete)

pso_net <- combine_network(
  set_ipd(pso_ipd,
    study = studyc,
    trt = trtc,
    r = pasi75,
    trt_class = trtclass),
  set_agd_arm(pso_agd,
    study = studyc,
    trt = trtc,
    r = pasi75_r,
    n = pasi75_n,
    trt_class = trtclass)
)

# Print network details
pso_net
```

```

# Add integration points to the network
pso_net <- add_integration(pso_net,
  durnpso = distr(qgamma, mean = durnpso_mean, sd = durnpso_sd),
  prevsys = distr(qbern, prob = prevsys),
  bsa = distr(qlogitnorm, mean = bsa_mean, sd = bsa_sd),
  weight = distr(qgamma, mean = weight_mean, sd = weight_sd),
  psa = distr(qbern, prob = psa),
  n_int = 64)

## Adding integration points to a data frame, e.g. for prediction
# Define a data frame of covariate summaries
new_agd_int <- data.frame(
  bsa_mean = 0.6,
  bsa_sd = 0.3,
  prevsys = 0.1,
  psa = 0.2,
  weight_mean = 10,
  weight_sd = 1,
  durnpso_mean = 3,
  durnpso_sd = 1)

# Adding integration points, using the weighted average correlation matrix
# computed for the plaque psoriasis network
new_agd_int <- add_integration(new_agd_int,
  durnpso = distr(qgamma, mean = durnpso_mean, sd = durnpso_sd),
  prevsys = distr(qbern, prob = prevsys),
  bsa = distr(qlogitnorm, mean = bsa_mean, sd = bsa_sd),
  weight = distr(qgamma, mean = weight_mean, sd = weight_sd),
  psa = distr(qbern, prob = psa),
  cor = pso_net$int_cor,
  n_int = 64)

# Here, since we reused the correlation matrix pso_net$int_cor from the
# network, the correct setting of cor_adjust = "spearman" is automatically
# applied

new_agd_int

```

Description

Samples (post warm-up) from a stan_nma model object can be coerced into an array, matrix, or data frame.

Usage

```
## S3 method for class 'stan_nma'
as.array(x, ..., pars, include = TRUE)

## S3 method for class 'stan_nma'
as.data.frame(x, ..., pars, include = TRUE)

## S3 method for class 'stan_nma'
as_tibble(x, ..., pars, include = TRUE)

## S3 method for class 'stan_nma'
as.tibble(x, ..., pars, include = TRUE)

## S3 method for class 'stan_nma'
as.matrix(x, ..., pars, include = TRUE)
```

Arguments

x	A stan_nma object
...	Additional arguments passed to <code>as.array.stanfit()</code>
pars	Optional character vector of parameter names to include in output. If not specified, all parameters are used.
include	Logical, are parameters in pars to be included (TRUE, default) or excluded (FALSE)?

Value

The `as.array()` method produces a 3D array [Iteration, Chain, Parameter] containing posterior samples of each parameter (as class `mcmc_array`). This has the side effect of enabling `bayesplot` functions to seamlessly work on `stan_nma` objects.

The `as.data.frame()` method produces a data frame containing posterior samples of each parameter, combined over all chains.

The `as.matrix()` method produces a matrix containing posterior samples of each parameter, combined over all chains.

as.igraph.nma_data *Convert networks to graph objects*

Description

The method `as.igraph()` converts `nma_data` objects into the form used by the `igraph` package. The method `as_tbl_graph()` converts `nma_data` objects into the form used by the `ggraph` and `tidygraph` packages.

Usage

```
## S3 method for class 'nma_data'
as.igraph(x, ..., collapse = TRUE)
```

```
## S3 method for class 'nma_data'
as_tbl_graph(x, ...)
```

Arguments

x	An <code>nma_data</code> object to convert
...	Additional arguments
collapse	Logical, collapse edges over studies? Default TRUE, only one edge is produced for each comparison (by IPD or AgD study type) with a <code>.nstudy</code> attribute giving the number of studies making that comparison. If FALSE, repeated edges are added for each study making the comparison.

Value

An `igraph` object for `as.igraph()`, a `tbl_graph` object for `as_tbl_graph()`.

Examples

```
# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
                      study = studyn,
                      trt = trtc,
                      r = r,
                      n = n,
                      trt_ref = "No intervention")

# Print details
smk_net

# Convert to igraph object
igraph::as.igraph(smk_net) # Edges combined by default
igraph::as.igraph(smk_net, collapse = FALSE) # Without combining edges

# Convert to tbl_graph object
tidygraph::as_tbl_graph(smk_net) # Edges combined by default
tidygraph::as_tbl_graph(smk_net, collapse = FALSE) # Without combining edges
```

as.stanfit

as.stanfit

Description

Attempt to turn an object into a `stanfit` object.

Usage

```
as.stanfit(x, ...)  
  
## S3 method for class 'stan_nma'  
as.stanfit(x, ...)  
  
## Default S3 method:  
as.stanfit(x, ...)
```

Arguments

x	an object
...	additional arguments

Value

A `stanfit` object.

atrial_fibrillation	<i>Stroke prevention in atrial fibrillation patients</i>
---------------------	--

Description

Data frame containing the results of 26 trials comparing 17 treatments in 4 classes for the prevention of stroke in patients with atrial fibrillation (Cooper et al. 2009). The data are the corrected versions given by van Valkenhoef and Kuiper (2016).

Usage

```
atrial_fibrillation
```

Format

A data frame with 63 rows and 11 variables:

studyc study name
studyn numeric study ID
trtc treatment name
trtn numeric treatment code
trt_class treatment class
r number of events
n sample size
E person-years at risk
stroke proportion of individuals with prior stroke
year year of study publication
followup mean length of follow-up (years)

References

Cooper NJ, Sutton AJ, Morris D, Ades AE, Welton NJ (2009). “Addressing between-study heterogeneity and inconsistency in mixed treatment comparisons: Application to stroke prevention treatments in individuals with non-rheumatic atrial fibrillation.” *Statistics in Medicine*, **28**(14), 1861–1881. doi:10.1002/sim.3594.

van Valkenhoef G, Kuiper J (2016). *gemtc: Network Meta-Analysis Using Bayesian Methods*. R package version 0.8-2, <https://CRAN.R-project.org/package=gemtc>.

 bcg_vaccine

BCG vaccination

Description

Data frame containing the results of 13 trials comparing BCG vaccination to no vaccination for preventing tuberculosis (TB) (Dias et al. 2011; Berkey et al. 1995). The numbers of individuals diagnosed with TB in each arm during the study follow-up period are recorded. The absolute degrees latitude at which the study was conducted are also recorded.

Usage

```
bcg_vaccine
```

Format

A data frame with 26 rows and 6 variables:

studyn numeric study ID

trtn numeric treatment code

trtc treatment name

latitude absolute degrees latitude

r number diagnosed with TB

n sample size

References

Berkey CS, Hoaglin DC, Mosteller F, Colditz GA (1995). “A random-effects regression model for meta-analysis.” *Statistics in Medicine*, **14**(4), 395–411. doi:10.1002/sim.4780140406.

Dias S, Sutton AJ, Welton NJ, Ades AE (2011). “NICE DSU Technical Support Document 3: Heterogeneity: subgroups, meta-regression, bias and bias-adjustment.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

`blocker`*Beta blockers to prevent mortality after MI*

Description

Data frame containing the number of deaths in 22 trials comparing beta blockers vs. control for preventing mortality after myocardial infarction (Carlin 1992; Dias et al. 2011).

Usage`blocker`**Format**

A data frame with 44 rows and 5 variables:

studyn numeric study ID

trtn numeric treatment code

trtc treatment name

r total number of events

n total number of individuals

References

Carlin JB (1992). “Meta-analysis for 2 x 2 tables: A bayesian approach.” *Statistics in Medicine*, **11**(2), 141–158. doi:[10.1002/sim.4780110202](https://doi.org/10.1002/sim.4780110202).

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). “NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

`combine_network`*Combine multiple data sources into one network*

Description

Multiple data sources created using `set_ipd()`, `set_agd_arm()`, or `set_agd_contrast()` can be combined into a single network for analysis.

Usage`combine_network(..., trt_ref)`

Arguments

... multiple data sources, as defined using the `set_*` functions

`trt_ref` reference treatment for the entire network, as a string (or coerced as such) referring to the levels of the treatment factor variable

Value

An object of class `nma_data`

See Also

`set_ipd()`, `set_agd_arm()`, and `set_agd_contrast()` for defining different data sources.

`print.nma_data()` for the print method displaying details of the network, and `plot.nma_data()` for network plots.

Examples

```
## Parkinson's - combining contrast- and arm-based data
studies <- parkinsons$studyn
(parkinsons_arm <- parkinsons[studies %in% 1:3, ])
(parkinsons_contr <- parkinsons[studies %in% 4:7, ])

park_arm_net <- set_agd_arm(parkinsons_arm,
                          study = studyn,
                          trt = trtn,
                          y = y,
                          se = se,
                          sample_size = n)

park_contr_net <- set_agd_contrast(parkinsons_contr,
                                  study = studyn,
                                  trt = trtn,
                                  y = diff,
                                  se = se_diff,
                                  sample_size = n)

park_net <- combine_network(park_arm_net, park_contr_net)

# Print network details
park_net

# Plot network
plot(park_net, weight_edges = TRUE, weight_nodes = TRUE)

## Plaque Psoriasis - combining IPD and AgD in a network
# Set up plaque psoriasis network combining IPD and AgD
library(dplyr)
pso_ipd <- filter(plaque_psoriasis_ipd,
                 studyc %in% c("UNCOVER-1", "UNCOVER-2", "UNCOVER-3"))

pso_agd <- filter(plaque_psoriasis_agd,
```



```
        studyc == "FIXTURE")

head(pso_ipd)
head(pso_agd)

pso_ipd <- pso_ipd %>%
  mutate(# Variable transformations
    bsa = bsa / 100,
    prevsys = as.numeric(prevsys),
    psa = as.numeric(psa),
    weight = weight / 10,
    durnpso = durnpso / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker"),
    # Check complete cases for covariates of interest
    complete = complete.cases(durnpso, prevsys, bsa, weight, psa)
  )

pso_agd <- pso_agd %>%
  mutate(
    # Variable transformations
    bsa_mean = bsa_mean / 100,
    bsa_sd = bsa_sd / 100,
    prevsys = prevsys / 100,
    psa = psa / 100,
    weight_mean = weight_mean / 10,
    weight_sd = weight_sd / 10,
    durnpso_mean = durnpso_mean / 10,
    durnpso_sd = durnpso_sd / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker")
  )

# Exclude small number of individuals with missing covariates
pso_ipd <- filter(pso_ipd, complete)

pso_net <- combine_network(
  set_ipd(pso_ipd,
    study = studyc,
    trt = trtc,
    r = pasi75,
    trt_class = trtclass),
  set_agd_arm(pso_agd,
    study = studyc,
    trt = trtc,
    r = pasi75_r,
    n = pasi75_n,
    trt_class = trtclass)
)
```

```
# Print network details
pso_net

# Plot network
plot(pso_net, weight_nodes = TRUE, weight_edges = TRUE, show_trt_class = TRUE)
```

dgent

Generalised Student's t distribution (with location and scale)

Description

Density, distribution, and quantile function for the generalised t distribution with degrees of freedom df , shifted by location and scaled by scale.

Usage

```
dgent(x, df, location = 0, scale = 1)
pgent(q, df, location = 0, scale = 1)
qgent(p, df, location = 0, scale = 1)
```

Arguments

<code>x, q</code>	Vector of quantiles
<code>df</code>	Degrees of freedom, greater than zero
<code>location</code>	Location parameter
<code>scale</code>	Scale parameter, greater than zero
<code>p</code>	Vector of probabilities

Value

`dgent()` gives the density, `pgent()` gives the distribution function, `qgent()` gives the quantile function.

diabetes	<i>Incidence of diabetes in trials of antihypertensive drugs</i>
----------	--

Description

Data frame containing the number of new cases of diabetes in 22 trials of 6 antihypertensive drugs (Elliott and Meyer 2007; Dias et al. 2011). The trial duration (in years) is also recorded.

Usage

```
diabetes
```

Format

A data frame with 48 rows and 7 variables:

studyn numeric study ID

studyc study name

trtn numeric treatment code

trtc treatment name

r total number of events

n total number of individuals

time trial follow-up (years)

References

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). “NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Elliott WJ, Meyer PM (2007). “Incident diabetes in clinical trials of antihypertensive drugs: a network meta-analysis.” *The Lancet*, **369**(9557), 201–207. doi:10.1016/s01406736(07)601081.

dic	<i>Deviance Information Criterion (DIC)</i>
-----	---

Description

Calculate the DIC for a model fitted using the `nma()` function.

Usage

```
dic(x, penalty = c("pD", "pV"), ...)
```

Arguments

x	A fitted model object, inheriting class <code>stan_nma</code>
penalty	The method for estimating the effective number of parameters, used to penalise model fit in the DIC. Either "pD" (the default), or "pV". For survival likelihoods only "pV" is currently available.
...	Other arguments (not used)

Value

A `nma_dic` object.

See Also

`print.nma_dic()` for printing details, `plot.nma_dic()` for producing plots of residual deviance contributions.

Examples

```
## Smoking cessation

# Run smoking FE NMA example if not already available
if (!exists("smk_fit_FE")) example("example_smk_fe", run.donttest = TRUE)

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Compare DIC of FE and RE models
(smk_dic_FE <- dic(smk_fit_FE))
(smk_dic_RE <- dic(smk_fit_RE)) # substantially better fit

# Plot residual deviance contributions under RE model
plot(smk_dic_RE)

# Check for inconsistency using UME model

# Run smoking UME NMA example if not already available
if (!exists("smk_fit_RE_UME")) example("example_smk_ume", run.donttest = TRUE)

# Compare DIC
smk_dic_RE
(smk_dic_RE_UME <- dic(smk_fit_RE_UME)) # no difference in fit

# Compare residual deviance contributions
plot(smk_dic_RE, smk_dic_RE_UME, show_uncertainty = FALSE)
```

dietary_fat	<i>Reduced dietary fat to prevent mortality</i>
-------------	---

Description

Data frame containing the number of deaths and person-years at risk in 10 trials comparing reduced fat diets vs. control (non-reduced fat diet) for preventing mortality (Hooper et al. 2000; Dias et al. 2011).

Usage

dietary_fat

Format

A data frame with 21 rows and 7 variables:

studyn numeric study ID

studyc study name

trtn numeric treatment code

trtc treatment name

r number of events

n number randomised

E person-years at risk

References

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). "NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials." National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Hooper L, Summerbell CD, Higgins JPT, Thompson RL, Clements G, Capps N, Davey Smith G, Riemersma R, Ebrahim S (2000). "Reduced or modified dietary fat for preventing cardiovascular disease." *Cochrane Database of Systematic Reviews*. ISSN 1465-1858, doi:10.1002/14651858.CD002137.

distr	<i>Specify a general marginal distribution</i>
-------	--

Description

`distr()` is used within the function `add_integration()` to specify marginal distributions for the covariates, via a corresponding inverse CDF. It is also used in `predict.stan_nma()` to specify a distribution for the baseline response (intercept) when predicting absolute outcomes.

Usage

```
distr(qfun, ...)
```

Arguments

<code>qfun</code>	an inverse CDF, either as a function name or a string
<code>...</code>	parameters of the distribution as arguments to <code>qfun</code> , these will be quoted and evaluated later in the context of the aggregate data sources

Details

The function `qfun` should have a formal argument called `p`. This restriction serves as a crude check for inverse CDFs (e.g. an error will be given if `dnorm` is used instead of `qnorm`). If a user-written CDF is supplied, it must have an argument `p` which takes a vector of probabilities.

Value

An object of class `distr`.

See Also

`add_integration()` where `distr()` is used to specify marginal distributions for covariates to integrate over, and `predict.stan_nma()` where `distr()` is used to specify a distribution on the baseline response.

Examples

```
## Specifying marginal distributions for integration

df <- data.frame(x1_mean = 2, x1_sd = 0.5, x2 = 0.8)

# Distribution parameters are evaluated in the context of the data frame
add_integration(df,
  x1 = distr(qnorm, mean = x1_mean, sd = x1_sd),
  x2 = distr(qbern, prob = x2),
  cor = diag(2))
```

dlogt	<i>Log Student's t distribution</i>
-------	-------------------------------------

Description

Density, distribution, and quantile function for the log t distribution, whose logarithm has degrees of freedom df , mean location, and standard deviation scale.

Usage

```
dlogt(x, df, location = 0, scale = 1)
```

```
plogt(q, df, location = 0, scale = 1)
```

```
qlogt(p, df, location = 0, scale = 1)
```

Arguments

<code>x, q</code>	Vector of quantiles
<code>df</code>	Degrees of freedom, greater than zero
<code>location</code>	Location parameter
<code>scale</code>	Scale parameter, greater than zero
<code>p</code>	Vector of probabilities

Details

If $\log(Y) \sim t_\nu(\mu, \sigma^2)$, then Y has a log t distribution with location μ , scale σ , and $df \nu$.

The mean and all higher moments of the log t distribution are undefined or infinite.

If $df = 1$ then the distribution is a log Cauchy distribution. As df tends to infinity, this approaches a log Normal distribution.

Value

`dlogt()` gives the density, `plogt()` gives the distribution function, `qlogt()` gives the quantile function.

dmspline *Distribution functions for M-spline baseline hazards*

Description

Density, distribution, quantile, hazard, cumulative hazard, and restricted mean survival time functions for the M-spline baseline hazards model.

Usage

```
dmspline(x, basis, scoef, rate, log = FALSE)

pmspline(q, basis, scoef, rate, lower.tail = TRUE, log.p = FALSE)

qmspline(p, basis, scoef, rate, lower.tail = TRUE, log.p = FALSE)

hmspline(x, basis, scoef, rate, log = FALSE)

Hmspline(x, basis, scoef, rate, log = FALSE)

rmst_mspline(t, basis, scoef, rate, start = 0)
```

Arguments

<code>x, q</code>	Vector of quantiles
<code>basis</code>	M-spline basis produced by <code>splines2::mSpline()</code>
<code>scoef</code>	Vector (or matrix) of spline coefficients with length (or number of columns) equal to the dimension of basis
<code>rate</code>	Vector of rate parameters
<code>log, log.p</code>	Logical; if TRUE, probabilities p are given as $\log(p)$
<code>lower.tail</code>	Logical; if TRUE (the default), probabilities are $P(X \leq x)$, otherwise $P(X > x)$
<code>p</code>	Vector of probabilities
<code>t</code>	Vector of times to which the restricted mean survival time is calculated
<code>start</code>	Optional left-truncation time or times. The returned restricted mean survival will be conditioned on survival up to this time

Details

Survival models with a flexible M-spline on the baseline hazard are described by Brilleman et al. (2020). Piecewise-exponential baseline hazards are a special case where the degree of the M-spline polynomial is 0.

The d/p/h/H functions are calculated from their definitions. `qmspline()` uses numerical inversion via `flexsurv::qgeneric()`. `rmst_mspline()` uses numerical integration via `flexsurv::rmst_generic()`, except for the special case of the piecewise-exponential hazard (i.e. degree 0 M-splines) which uses the explicit formula from Royston and Parmar (2013).

Beyond the boundary knots, the hazard is assumed to be constant. (This differs from the approach in `splines2::mSpline()` that extrapolates the polynomial basis functions, which is numerically unstable and highly dependent on the data just before the boundary knots.) As with all extrapolation, care should be taken when evaluating the splines at times beyond the boundary knots (either directly through the `d/p/h/H/rmst` functions, or indirectly by requesting quantiles with `qmspline()` that correspond to times beyond the boundary knots). For this reason evaluating the (unrestricted) mean survival time is not generally recommended as this requires integrating over an infinite time horizon (i.e. `rmst_mspline()` with `t = Inf`).

Value

`dmspline()` gives the density, `pmspline()` gives the distribution function (CDF), `qmspline()` gives the quantile function (inverse-CDF), `hmspline()` gives the hazard function, `Hmspline()` gives the cumulative hazard function, and `rmst_mspline()` gives restricted mean survival times.

References

Brilleman SL, Elci EM, Novik JB, Wolfe R (2020). “Bayesian Survival Analysis Using the rstanarm R Package.” *arXiv*. doi:10.48550/arXiv.2002.09633, 2002.09633.

Royston P, Parmar MKB (2013). “Restricted mean survival time: an alternative to the hazard ratio for the design and analysis of randomized trials with a time-to-event outcome.” *BMC Medical Research Methodology*, **13**(1). doi:10.1186/1471228813152.

example_ndmm

Example newly-diagnosed multiple myeloma

Description

Calling `example("example_ndmm")` will run a proportional hazards Weibull NMA model on the newly-diagnosed multiple myeloma data, using the code in the Examples section below. The resulting `stan_nma` object `ndmm_fit` will then be available in the global environment.

Examples

```
# Set up newly-diagnosed multiple myeloma network

head(ndmm_ipd)
head(ndmm_agd)

ndmm_net <- combine_network(
  set_ipd(ndmm_ipd,
    study, trt,
    Surv = Surv(eventtime / 12, status)),
  set_agd_surv(ndmm_agd,
    study, trt,
    Surv = Surv(eventtime / 12, status),
    covariates = ndmm_agd_covs))
```

```
# Fit Weibull (PH) model
ndmm_fit <- nma(ndmm_net,
               likelihood = "weibull",
               prior_intercept = normal(scale = 100),
               prior_trt = normal(scale = 10),
               prior_aux = half_normal(scale = 10))

ndmm_fit
```

example_pso_mlnmr *Example plaque psoriasis ML-NMR*

Description

Calling `example("example_pso_mlnmr")` will run a ML-NMR model with the plaque psoriasis IPD and AgD, using the code in the Examples section below. The resulting `stan_nma` object `pso_fit` will then be available in the global environment.

Details

Plaque psoriasis ML-NMR for use in examples.

Examples

```
# Set up plaque psoriasis network combining IPD and AgD
library(dplyr)
pso_ipd <- filter(plaque_psoriasis_ipd,
                 studyc %in% c("UNCOVER-1", "UNCOVER-2", "UNCOVER-3"))

pso_agd <- filter(plaque_psoriasis_agd,
                 studyc == "FIXTURE")

head(pso_ipd)
head(pso_agd)

pso_ipd <- pso_ipd %>%
  mutate(# Variable transformations
         bsa = bsa / 100,
         prevsys = as.numeric(prevsys),
         psa = as.numeric(psa),
         weight = weight / 10,
         durnpso = durnpso / 10,
         # Treatment classes
         trtclass = case_when(trtn == 1 ~ "Placebo",
                              trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                              trtn == 4 ~ "TNFa blocker"),
         # Check complete cases for covariates of interest
```

```

    complete = complete.cases(durnpso, prevsys, bsa, weight, psa)
  )

pso_agd <- pso_agd %>%
  mutate(
    # Variable transformations
    bsa_mean = bsa_mean / 100,
    bsa_sd = bsa_sd / 100,
    prevsys = prevsys / 100,
    psa = psa / 100,
    weight_mean = weight_mean / 10,
    weight_sd = weight_sd / 10,
    durnpso_mean = durnpso_mean / 10,
    durnpso_sd = durnpso_sd / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker")
  )

# Exclude small number of individuals with missing covariates
pso_ipd <- filter(pso_ipd, complete)

pso_net <- combine_network(
  set_ipd(pso_ipd,
    study = studyc,
    trt = trtc,
    r = pasi75,
    trt_class = trtclass),
  set_agd_arm(pso_agd,
    study = studyc,
    trt = trtc,
    r = pasi75_r,
    n = pasi75_n,
    trt_class = trtclass)
)

# Print network details
pso_net

# Add integration points to the network
pso_net <- add_integration(pso_net,
  durnpso = distr(qgamma, mean = durnpso_mean, sd = durnpso_sd),
  prevsys = distr(qbern, prob = prevsys),
  bsa = distr(qlogitnorm, mean = bsa_mean, sd = bsa_sd),
  weight = distr(qgamma, mean = weight_mean, sd = weight_sd),
  psa = distr(qbern, prob = psa),
  n_int = 64)

# Fitting a ML-NMR model.
# Specify a regression model to include effect modifier interactions for five
# covariates, along with main (prognostic) effects. We use a probit link and

```

```

# specify that the two-parameter Binomial approximation for the aggregate-level
# likelihood should be used. We set treatment-covariate interactions to be equal
# within each class. We narrow the possible range for random initial values with
# init_r = 0.1, since probit models in particular are often hard to initialise.
# Using the QR decomposition greatly improves sampling efficiency here, as is
# often the case for regression models.
pso_fit <- nma(pso_net,
  trt_effects = "fixed",
  link = "probit",
  likelihood = "bernoulli2",
  regression = ~(durnpso + prevsys + bsa + weight + psa)*.trt,
  class_interactions = "common",
  prior_intercept = normal(scale = 10),
  prior_trt = normal(scale = 10),
  prior_reg = normal(scale = 10),
  init_r = 0.1,
  QR = TRUE)

pso_fit

```

example_smk_fe

Example smoking FE NMA

Description

Calling `example("example_smk_fe")` will run a fixed effects NMA model with the smoking cessation data, using the code in the Examples section below. The resulting `stan_nma` object `smk_fit_FE` will then be available in the global environment.

Details

Smoking FE NMA for use in examples.

Examples

```

# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
  study = studyn,
  trt = trtc,
  r = r,
  n = n,
  trt_ref = "No intervention")

# Print details
smk_net

```

```
# Fitting a fixed effect model
smk_fit_FE <- nma(smk_net,
  trt_effects = "fixed",
  prior_intercept = normal(scale = 100),
  prior_trt = normal(scale = 100))

smk_fit_FE
```

example_smk_nodesplit *Example smoking node-splitting*

Description

Calling `example("example_smk_nodesplit")` will run node-splitting models with the smoking cessation data, using the code in the Examples section below. The resulting `nma_nodesplit_df` object `smk_fit_RE_nodesplit` will then be available in the global environment.

Details

Smoking node-splitting for use in examples.

Examples

```
# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
  study = studyn,
  trt = trtc,
  r = r,
  n = n,
  trt_ref = "No intervention")

# Print details
smk_net

# Fitting all possible node-splitting models
smk_fit_RE_nodesplit <- nma(smk_net,
  consistency = "nodesplit",
  trt_effects = "random",
  prior_intercept = normal(scale = 100),
  prior_trt = normal(scale = 100),
  prior_het = normal(scale = 5))
```

example_smk_re	<i>Example smoking RE NMA</i>
----------------	-------------------------------

Description

Calling `example("example_smk_re")` will run a random effects NMA model with the smoking cessation data, using the code in the Examples section below. The resulting `stan_nma` object `smk_fit_RE` will then be available in the global environment.

Details

Smoking RE NMA for use in examples.

Examples

```
# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
                      study = studyn,
                      trt = trtc,
                      r = r,
                      n = n,
                      trt_ref = "No intervention")

# Print details
smk_net

# Fitting a random effects model
smk_fit_RE <- nma(smk_net,
                 trt_effects = "random",
                 prior_intercept = normal(scale = 100),
                 prior_trt = normal(scale = 100),
                 prior_het = normal(scale = 5))

smk_fit_RE
```

example_smk_ume	<i>Example smoking UME NMA</i>
-----------------	--------------------------------

Description

Calling `example("example_smk_ume")` will run an unrelated mean effects (inconsistency) NMA model with the smoking cessation data, using the code in the Examples section below. The resulting `stan_nma` object `smk_fit_RE_UME` will then be available in the global environment.

Details

Smoking UME NMA for use in examples.

Examples

```
# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
                      study = studyn,
                      trt = trtc,
                      r = r,
                      n = n,
                      trt_ref = "No intervention")

# Print details
smk_net

# Fitting an unrelated mean effects (inconsistency) model
smk_fit_RE_UME <- nma(smk_net,
                     consistency = "ume",
                     trt_effects = "random",
                     prior_intercept = normal(scale = 100),
                     prior_trt = normal(scale = 100),
                     prior_het = normal(scale = 5))

smk_fit_RE_UME
```

 geom_km

Kaplan-Meier curves of survival data

Description

This helper function constructs a ggplot2 geom to plot Kaplan-Meier curves from a network containing survival or time-to-event outcomes. This is useful for overlaying the "raw" survival data on the estimated survival functions created with plotted with `plot.surv_nma_summary()`, but can also be used standalone to plot Kaplan-Meier curves before fitting a model.

Usage

```
geom_km(
  network,
  ...,
  transform = c("identity", "cloglog", "log", "cumhaz"),
  curve_args = list(),
```

```
cens_args = list()
)
```

Arguments

network	A nma_data network object containing survival outcomes
...	Additional arguments passed to <code>survival::survfit()</code>
transform	Character string giving the transformation to apply to the KM curves before plotting. The default is "identity" for no transformation; other options are "cloglog" for $\log(-\log(S))$, "log" for $\log(S)$, or "cumhaz" for the cumulative hazard $-\log(S)$.
curve_args	Optional list of arguments to customise the curves plotted with <code>ggplot2::geom_step()</code>
cens_args	Optional list of arguments to customise the censoring marks plotted with <code>ggplot2::geom_point()</code>

Value

A ggplot2 geom list that can be added to a ggplot2 plot object

Examples

```
# Set up newly-diagnosed multiple myeloma network

head(ndmm_ipd)
head(ndmm_agd)

ndmm_net <- combine_network(
  set_ipd(ndmm_ipd,
    study, trt,
    Surv = Surv(eventtime / 12, status)),
  set_agd_surv(ndmm_agd,
    study, trt,
    Surv = Surv(eventtime / 12, status),
    covariates = ndmm_agd_covs))

# Plot KM curves using ggplot2
library(ggplot2)

# We need to create an empty ggplot object to add the curves to
ggplot() + geom_km(ndmm_net)

# Adding plotting options, facets, axis labels, and a plot theme
ggplot() +
  geom_km(ndmm_net,
    curve_args = list(linewidth = 0.5),
    cens_args = list(size = 3, shape = 124)) +
  facet_wrap(vars(Study)) +
  labs(xlab = "Time", ylab = "Survival Probability") +
  theme_multinma()

# Using the transform argument to produce log-log plots (e.g. to assess the
# proportional hazards assumption)
ggplot() +
```



```

geom_km(ndmm_net, transform = "cloglog") +
facet_wrap(vars(Study)) +
theme_multinma()

# Using the transform argument to produce cumulative hazard plots
ggplot() +
  geom_km(ndmm_net, transform = "cumhaz") +
  facet_wrap(vars(Study)) +
  theme_multinma()

# This function can also be used to add KM data to plots of estimated survival
# curves from a fitted model, in a similar manner

# Run newly-diagnosed multiple myeloma example if not already available
if (!exists("ndmm_fit")) example("example_ndmm", run.donttest = TRUE)

# Plot estimated survival curves, and overlay the KM data

plot(predict(ndmm_fit, type = "survival")) + geom_km(ndmm_net)

```

get_nodesplits

Direct and indirect evidence

Description

Determine whether two treatments in a network are connected by direct and/or indirect evidence, and generate a list of comparisons with both direct and indirect evidence (i.e. potential inconsistency) for node-splitting.

Usage

```
get_nodesplits(network, include_consistency = FALSE)
```

```
has_direct(network, trt1, trt2)
```

```
has_indirect(network, trt1, trt2)
```

Arguments

network	An <code>nma_data</code> object, as created by the functions <code>set_*</code> () or <code>combine_network()</code> .
include_consistency	Logical, whether to include a row of NAs to indicate that a consistency model (i.e. a model with no node-splitting) should also be fitted by the <code>nma()</code> function. Default is FALSE when calling <code>get_nodesplits()</code> by hand, and <code>nma()</code> sets this to TRUE by default.
trt1, trt2	Treatments, each as a single integer, string, or factor

Details

The list of comparisons for node-splitting is generated following the algorithm of van Valkenhoef et al. (2016). A comparison between two treatments has the potential for inconsistency, and is thus considered for node-splitting, if the comparison has both direct evidence and *independent* indirect evidence.

The notion of independent indirect evidence is necessary when multi-arm trials are present, since by design these trials are internally consistent. A comparison between two treatments has independent indirect evidence if, after removing all studies comparing the two treatments from the network, the two treatments are still connected by a path of evidence. This is the criterion considered by the `has_indirect()` function.

Value

For `has_direct()` and `has_indirect()`, a single logical value. For `get_nodesplits()`, a data frame with two columns giving the comparisons for node-splitting.

References

van Valkenhoef G, Dias S, Ades AE, Welton NJ (2016). “Automated generation of node-splitting models for assessment of inconsistency in network meta-analysis.” *Research Synthesis Methods*, 7(1), 80–93. doi:10.1002/jrsm.1167.

Examples

```
# Parkinsons example
park_net <- set_agd_arm(parkinsons,
                      study = studyn,
                      trt = trtn,
                      y = y,
                      se = se,
                      trt_ref = 1)

# View the network plot
plot(park_net)

# The 4 vs. 5 comparison is a spur on the network
has_direct(park_net, 4, 5)
has_indirect(park_net, 4, 5)

# 1 and 5 are not directly connected
has_direct(park_net, 1, 5)
has_indirect(park_net, 1, 5)

# The 1 vs. 2 comparison does not have independent indirect evidence, since
# the 1-2-4 loop is a multi-arm study
has_indirect(park_net, 1, 2)

# Get a list of comparisons with potential inconsistency for node-splitting
get_nodesplits(park_net)

# See van Valkenhoef (2016) for a discussion of this example
```

hta_psoriasis	<i>HTA Plaque Psoriasis</i>
---------------	-----------------------------

Description

Data frame containing the results of 16 trials comparing 8 treatments for moderate-to-severe plaque psoriasis from an HTA report (Woolacott et al. 2006), analysed in TSD2 (Dias et al. 2011). Outcomes are success/failure to achieve 50%, 75%, or 90% reduction in symptoms on the Psoriasis Area and Severity Index (PASI) scale. Some studies report all three ordered outcomes, others only one or two. The latter are coded as missing values (see details).

Usage

```
hta_psoriasis
```

Format

A data frame with 36 rows and 9 variables:

studyn numeric study ID

studyc study name

year year of publication

trtn numeric treatment code

trtc treatment name

sample_size sample size in each arm

PASI50, PASI75, PASI90 ordered multinomial outcome counts (exclusive, see details)

Details

Outcome counts are "exclusive"; that is, for a study reporting all outcomes, the counts represent the categories $50 < \text{PASI} < 75$, $75 < \text{PASI} < 90$, and $90 < \text{PASI} < 100$, and are named by the lower end of the interval. (As opposed to "inclusive" counts, which would represent the overlapping categories $\text{PASI} > 50$, $\text{PASI} > 70$, and $\text{PASI} > 90$.) The count for the fourth category (the lowest), $0 < \text{PASI} < 50$, is equal to $\text{sample_size} - \text{PASI50} - \text{PASI75} - \text{PASI90}$.

Missing values are used where studies only report a subset of the outcomes. For a study reporting only two outcomes, say 50 and 75, the counts represent $50 < \text{PASI} < 75$ and $75 < \text{PASI} < 100$. For a study reporting only one outcome, say PASI 75, the count represents $75 < \text{PASI} < 100$.

References

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). "NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials." National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Woolacott N, Hawkins N, Mason A, Kainth A, Khadjesari Z, Bravo Vergel Y, Misso K, Light K, Chalmers R, Sculpher M, Riemsma R (2006). "Etanercept and efalizumab for the treatment of psoriasis: a systematic review." *Health Technology Assessment*, **10**(46). doi:10.3310/hta10460.

is_network_connected *Check network connectedness*

Description

Check whether a network is connected - whether there is a path of study evidence linking every pair of treatments in the network.

Usage

```
is_network_connected(network)
```

Arguments

network An nma_data object, as created by the functions set_*(*)* or combine_network(*)*.

Details

Models will still run with disconnected networks. However, estimated relative effects between treatments across disconnected parts of the network will be entirely based on the prior distribution (typically very uncertain), as there is no information to update the prior distribution. Relative effects within each connected sub-network will be estimated as if each sub-network had been analysed separately.

Value

Logical TRUE or FALSE

Examples

```
## Smoking cessation
# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
                      study = studyn,
                      trt = trtc,
                      r = r,
                      n = n,
                      trt_ref = "No intervention")

# Print details
smk_net

is_network_connected(smk_net) # TRUE, network is connected
```

```
## A disconnected network
disc_net <- set_agd_arm(smoking[smoking$studyn %in% c(15, 21), ],
                      study = studyn,
                      trt = trtc,
                      r = r,
                      n = n)
is_network_connected(disc_net) # FALSE, network is disconnected
disc_net
plot(disc_net)
```

loo.stan_nma	<i>Model comparison using the loo package</i>
--------------	---

Description

The `loo()` and `waic()` functions from the loo package may be called directly on `stan_nma` and `stan_mlnmr` objects.

Usage

```
## S3 method for class 'stan_nma'
loo(x, ...)

## S3 method for class 'stan_nma'
waic(x, ...)
```

Arguments

<code>x</code>	An object of class <code>stan_nma</code> or <code>stan_mlnmr</code>
<code>...</code>	Further arguments to <code>loo()</code> or <code>waic()</code>

make_knots	<i>Knot locations for M-spline baseline hazard models</i>
------------	---

Description

Several different algorithms are provided to calculate knot locations for M-spline baseline hazard models. This function is called internally within the `nma()` function, but may be called directly by the user for more control.

Usage

```
make_knots(
  network,
  n_knots = 7,
  type = c("quantile", "quantile_common", "quantile_lumped", "quantile_longest", "equal",
           "equal_common")
)
```

Arguments

network	A network object, containing survival outcomes
n_knots	Non-negative integer giving the number of internal knots (default 7)
type	String specifying the knot location algorithm to use (see details). The default used by <code>nma()</code> is "quantile", except when a regression model is specified (using <code>aux_regression</code>) in which case the default is "quantile_common".

Details

The type argument can be used to choose between different algorithms for placing the knots:

"quantile" Creates separate knot locations for each study, internal knots are placed at evenly-spaced quantiles of the observed event times within each study.

"quantile_lumped" Creates a common set of knots for all studies, calculated as evenly-spaced quantiles of the observed event times from all studies lumped together.

"quantile_common" Creates a common set of knots for all studies, taking quantiles of the quantiles of the observed event times within each study. This often seems to result in a more even knot spacing than "quantile_lumped", particularly when follow-up is uneven across studies, and may handle differing behaviour in the baseline hazard across studies better than "quantile_longest".

"quantile_longest" Creates a common set of knots for all studies, using evenly-spaced quantiles of the observed event times in the longest study.

"equal" Creates separate knot locations for each study, at evenly-spaced times between the boundary knots in each study.

"equal_common" Creates a common set of knots for all studies, at evenly-spaced times between the earliest entry time and last event/censoring time in the network.

Boundary knots are calculated as follows:

- For separate knot locations in each study, boundary knots are placed at the earliest entry time and last event/censoring time in each study.
- For a common set of knots across all studies, boundary knots are placed at the earliest entry time and last event/censoring time across all studies.

Models with regression on the spline coefficients (i.e. with `aux_regression` specified) require a common set of knots across all studies.

Provided that a sufficient number of knots are used, model fit should be largely unaffected by the knot locations. However, sampling difficulties can sometimes occur if knot placement is poor, for example if a knot is placed just before the last follow-up time in a study.

Value

A named list of vectors giving the knot locations in each study.

Examples

```

# Set up newly-diagnosed multiple myeloma network

head(ndmm_ipd)
head(ndmm_agd)

ndmm_net <- combine_network(
  set_ipd(ndmm_ipd,
    study, trt,
    Surv = Surv(eventtime / 12, status)),
  set_agd_surv(ndmm_agd,
    study, trt,
    Surv = Surv(eventtime / 12, status),
    covariates = ndmm_agd_covs))

# The default knot locations
make_knots(ndmm_net, type = "quantile")

# Increasing the number of knots
make_knots(ndmm_net, n_knots = 10)

# Comparing alternative knot positioning algorithms
# Visualise these with a quick function
plot_knots <- function(network, knots) {
  ggplot2::ggplot() +
    geom_km(network) +
    ggplot2::geom_vline(ggplot2::aes(xintercept = .data$knot),
      data = tidyr::pivot_longer(as.data.frame(knots), cols = dplyr::everything(),
        names_to = "Study", values_to = "knot"),
      linetype = 2, colour = "grey60") +
    ggplot2::facet_wrap(~Study) +
    theme_multinma()
}

plot_knots(ndmm_net, make_knots(ndmm_net, type = "quantile"))
plot_knots(ndmm_net, make_knots(ndmm_net, type = "quantile_common"))
plot_knots(ndmm_net, make_knots(ndmm_net, type = "quantile_lumped"))
plot_knots(ndmm_net, make_knots(ndmm_net, type = "quantile_longest"))
plot_knots(ndmm_net, make_knots(ndmm_net, type = "equal"))
plot_knots(ndmm_net, make_knots(ndmm_net, type = "equal_common"))

```

Description

3D MCMC arrays (Iterations, Chains, Parameters) are produced by `as.array()` methods applied to `stan_nma` or `nma_summary` objects.

Usage

```
## S3 method for class 'mcmc_array'
summary(object, ..., probs = c(0.025, 0.25, 0.5, 0.75, 0.975))

## S3 method for class 'mcmc_array'
print(x, ...)

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

## S3 method for class 'mcmc_array'
names(x)

## S3 replacement method for class 'mcmc_array'
names(x) <- value
```

Arguments

...	Further arguments passed to other methods
probs	Numeric vector of quantiles of interest
x, object	A 3D MCMC array of class mcmc_array
value	Character vector of replacement parameter names

Value

The `summary()` method returns a `nma_summary` object, the `print()` method returns `x` invisibly. The `names()` method returns a character vector of parameter names, and `names()<-` returns the object with updated parameter names. The `plot()` method is a shortcut for `plot(summary(x), ...)`, passing all arguments on to `plot.nma_summary()`.

Examples

```
## Smoking cessation

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Working with arrays of posterior draws (as mcmc_array objects) is
# convenient when transforming parameters

# Transforming log odds ratios to odds ratios
LOR_array <- as.array(relative_effects(smk_fit_RE))
OR_array <- exp(LOR_array)

# mcmc_array objects can be summarised to produce a nma_summary object
smk_OR_RE <- summary(OR_array)

# This can then be printed or plotted
```



```

smk_OR_RE
plot(smk_OR_RE, ref_line = 1)

# Transforming heterogeneity SD to variance
tau_array <- as.array(smk_fit_RE, pars = "tau")
tausq_array <- tau_array^2

# Correct parameter names
names(tausq_array) <- "tausq"

# Summarise
summary(tausq_array)

```

multi

Multinomial outcome data

Description

This function aids the specification of multinomial outcome data when setting up a network with [set_agd_arm\(\)](#) or [set_ipd\(\)](#). It takes a set of columns (or, more generally, numeric vectors of the same length) of outcome counts in each category, and binds these together to produce a matrix.

Usage

```
multi(..., inclusive = FALSE, type = c("ordered", "competing"))
```

Arguments

...	Two or more numeric columns (or vectors) of category counts. Argument names (optional) will be used to label the categories.
inclusive	Logical, are ordered category counts inclusive (TRUE) or exclusive (FALSE)? Default FALSE. Only used when type = "ordered". See details.
type	String, indicating whether categories are "ordered" or "competing". Currently only ordered categorical outcomes are supported by the modelling functions in this package.

Details

When specifying ordered categorical counts, these can either be given as *exclusive* counts (`inclusive = FALSE`, the default) where individuals are only counted in the highest category they achieve, or *inclusive* counts (`inclusive = TRUE`) where individuals are counted in every category up to and including the highest category achieved. (Competing outcomes, by nature, are always specified as exclusive counts.)

NA values can be used to indicate categories/cutpoints that were not measured.

Value

A matrix of (exclusive) category counts

ndmm_ipd

*Newly diagnosed multiple myeloma***Description**

Three data frames, `ndmm_ipd`, `ndmm_agd`, and `ndmm_agd_covs` containing (simulated) individual patient data (IPD) from three studies and aggregate data (AgD) from two studies on newly diagnosed multiple myeloma. The outcome of interest is progression-free survival after autologous stem cell transplant. The IPD studies in `ndmm_ipd` provide event/censoring times and covariate values for each individual. The AgD studies provide reconstructed event/censoring times from digitized Kaplan-Meier curves in `ndmm_agd` and covariate summaries in `ndmm_agd_covs`, obtained from published trial reports. The data are constructed to resemble those used by Leahy and Walsh (2019).

Usage`ndmm_ipd``ndmm_agd``ndmm_agd_covs`**Format**

The individual patient data are contained in a data frame `ndmm_ipd` with 1325 rows, one per individual, and 10 variables:

study, studyf study name**trt, trtf** treatment name**eventtime** event/censoring time**status** censoring indicator (0 = censored, 1 = event)**age** age (years)**iss_stage3** ISS stage 3 (0 = no, 1 = yes)**response_cr_vgpr** complete or very good partial response (0 = no, 1 = yes)**male** male sex (0 = no, 1 = yes)

The reconstructed Kaplan-Meier data for the aggregate studies are contained in a data frame `ndmm_agd` with 2819 rows and 6 variables:

study, studyf study name**trt, trtf** treatment name**eventtime** event/censoring time**status** censoring indicator (0 = censored, 1 = event)

The covariate summaries extracted from published reports for the aggregate studies are contained in a data frame `ndmm_agd_covs` with 4 rows, one per study arm, and 15 columns:

study, studyf study name
trt, trtf treatment name
sample_size sample size in each arm
age_min, age_iqr_l, age_median, age_iqr_h, age_max, age_mean, age_sd summary statistics for age (years)
iss_stage3 proportion of participants with ISS stage 3
response_cr_vgpr proportion of participants with complete or very good partial response
male proportion of male participants

References

Leahy J, Walsh C (2019). “Assessing the impact of a matching-adjusted indirect comparison in a Bayesian network meta-analysis.” *Research Synthesis Methods*, **10**(4), 546–568. doi:10.1002/jrsm.1372.

nma

Network meta-analysis models

Description

The `nma` function fits network meta-analysis and (multilevel) network meta-regression models in Stan.

Usage

```
nma(
  network,
  consistency = c("consistency", "ume", "nodesplit"),
  trt_effects = c("fixed", "random"),
  regression = NULL,
  class_interactions = c("common", "exchangeable", "independent"),
  likelihood = NULL,
  link = NULL,
  ...,
  nodesplit = get_nodesplits(network, include_consistency = TRUE),
  prior_intercept = .default(normal(scale = 100)),
  prior_trt = .default(normal(scale = 10)),
  prior_het = .default(half_normal(scale = 5)),
  prior_het_type = c("sd", "var", "prec"),
  prior_reg = .default(normal(scale = 10)),
  prior_aux = .default(),
  prior_aux_reg = .default(),
  aux_by = NULL,
  aux_regression = NULL,
  QR = FALSE,
```

```

center = TRUE,
adapt_delta = NULL,
int_thin = 0,
int_check = TRUE,
mspline_degree = 3,
n_knots = 7,
knots = NULL,
mspline_basis = NULL
)

```

Arguments

network	An nma_data object, as created by the functions <code>set_*</code> (<code>combine_network()</code>), or <code>add_integration()</code>
consistency	Character string specifying the type of (in)consistency model to fit, either "consistency", "ume", or "nodesplit"
trt_effects	Character string specifying either "fixed" or "random" effects
regression	A one-sided model formula, specifying the prognostic and effect-modifying terms for a regression model. Any references to treatment should use the <code>.trt</code> special variable, for example specifying effect modifier interactions as <code>variable:.trt</code> (see details).
class_interactions	Character string specifying whether effect modifier interactions are specified as "common", "exchangeable", or "independent".
likelihood	Character string specifying a likelihood, if unspecified will be inferred from the data (see details)
link	Character string specifying a link function, if unspecified will default to the canonical link (see details)
...	Further arguments passed to <code>sampling()</code> , such as <code>iter</code> , <code>chains</code> , <code>cores</code> , etc.
nodesplit	For consistency = "nodesplit", the comparison(s) to split in the node-splitting model(s). Either a length 2 vector giving the treatments in a single comparison, or a 2 column data frame listing multiple treatment comparisons to split in turn. By default, all possible comparisons will be chosen (see <code>get_nodesplits()</code>).
prior_intercept	Specification of prior distribution for the intercept
prior_trt	Specification of prior distribution for the treatment effects
prior_het	Specification of prior distribution for the heterogeneity (if <code>trt_effects = "random"</code>)
prior_het_type	Character string specifying whether the prior distribution <code>prior_het</code> is placed on the heterogeneity standard deviation τ ("sd", the default), variance τ^2 ("var"), or precision $1/\tau^2$ ("prec").
prior_reg	Specification of prior distribution for the regression coefficients (if regression formula specified)
prior_aux	Specification of prior distribution for the auxiliary parameter, if applicable (see details). For <code>likelihood = "gengamma"</code> this should be a list of prior distributions with elements <code>sigma</code> and <code>k</code> .

prior_aux_reg	Specification of prior distribution for the auxiliary regression parameters, if <code>aux_regression</code> is specified (see details).
aux_by	Vector of variable names listing the variables to stratify the auxiliary parameters by. Currently only used for survival models, see details. Cannot be used with <code>aux_regression</code> .
aux_regression	A one-sided model formula giving a regression model for the auxiliary parameters. Currently only used for survival models, see details. Cannot be used with <code>aux_by</code> .
QR	Logical scalar (default FALSE), whether to apply a QR decomposition to the model design matrix
center	Logical scalar (default TRUE), whether to center the (numeric) regression terms about the overall means
adapt_delta	See adapt_delta for details
int_thin	A single integer value, the thinning factor for returning cumulative estimates of integration error. Saving cumulative estimates is disabled by <code>int_thin = 0</code> , which is the default.
int_check	Logical, check sufficient accuracy of numerical integration by fitting half of the chains with <code>n_int/2</code> ? When TRUE, <code>Rhat</code> and <code>n_eff</code> diagnostic warnings will be given if numerical integration has not sufficiently converged (suggesting increasing <code>n_int</code> in add_integration()). Default TRUE, but disabled (FALSE) when <code>int_thin > 0</code> .
mspline_degree	Non-negative integer giving the degree of the M-spline polynomial for likelihood = "mspline". Piecewise exponential hazards (likelihood = "pexp") are a special case with <code>mspline_degree = 0</code> .
n_knots	For <code>mspline</code> and <code>pexp</code> likelihoods, a non-negative integer giving the number of internal knots for partitioning the baseline hazard into intervals. The knot locations within each study will be determined by the corresponding quantiles of the observed event times, plus boundary knots at the earliest entry time (0 with no delayed entry) and the maximum event/censoring time. For example, with <code>n_knots = 3</code> , the internal knot locations will be at the 25%, 50%, and 75% quantiles of the observed event times. The default is <code>n_knots = 7</code> ; overfitting is avoided by shrinking towards a constant hazard with a random walk prior (see details). If <code>aux_regression</code> is specified then a single set of knot locations will be calculated across all studies in the network. See make_knots() for more details on the knot positioning algorithms. Ignored when <code>knots</code> is specified.
knots	For <code>mspline</code> and <code>pexp</code> likelihoods, a named list of numeric vectors of knot locations (including boundary knots) for each of the studies in the network. Currently, each vector must have the same length (i.e. each study must use the same number of knots). Alternatively, a single numeric vector of knot locations can be provided which will be shared across all studies in the network. If unspecified (the default), the knots will be chosen based on <code>n_knots</code> as described above. If <code>aux_regression</code> is specified then <code>knots</code> should be a single numeric vector of knot locations which will be shared across all studies in the network. make_knots() can be used to help specify <code>knots</code> directly, or to investigate knot placement prior to model fitting.

`mspline_basis` Instead of specifying `mspline_degree` and `n_knots` or `knots`, a named list of M-spline bases (one for each study) can be provided with `mspline_basis` which will be used directly. In this case, all other M-spline options will be ignored.

Details

When specifying a model formula in the regression argument, the usual formula syntax is available (as interpreted by `model.matrix()`). The only additional requirement here is that the special variable `.trt` should be used to refer to treatment. For example, effect modifier interactions should be specified as `variable:.trt`. Prognostic (main) effects and interactions can be included together compactly as `variable*.trt`, which expands to `variable + variable:.trt` (plus `.trt`, which is already in the NMA model).

For the advanced user, the additional specials `.study` and `.trtclass` are also available, and refer to studies and (if specified) treatment classes respectively. When node-splitting models are fitted (`consistency = "nodesplit"`) the special `.omega` is available, indicating the arms to which the node-splitting inconsistency factor is added.

See [?priors](#) for details on prior specification. Default prior distributions are available, but may not be appropriate for the particular setting and will raise a warning if used. No attempt is made to tailor these defaults to the data provided. Please consider appropriate prior distributions for the particular setting, accounting for the scales of outcomes and covariates, etc. The function `plot_prior_posterior()` may be useful in examining the influence of the chosen prior distributions on the posterior distributions, and the `summary()` method for `nma_prior` objects prints prior intervals.

Value

`nma()` returns a `stan_nma` object, except when `consistency = "nodesplit"` when a `nma_nodesplit` or `nma_nodesplit_df` object is returned. `nma.fit()` returns a `stanfit` object.

Likelihoods and link functions

Currently, the following likelihoods and link functions are supported for each data type:

Data type	Likelihood
Binary	bernoulli, bernoulli2
Count	binomial, binomial2
Rate	poisson
Continuous	normal
Ordered	ordered
Survival	exponential, weibull, gompertz, exponential-aft, weibull-aft, lognormal, loglogistic, gamma, geng

The `bernoulli2` and `binomial2` likelihoods correspond to a two-parameter Binomial likelihood for arm-based AgD, which more closely matches the underlying Poisson Binomial distribution for the summarised aggregate outcomes in a ML-NMR model than the typical (one parameter) Binomial distribution (see Phillippo et al. 2020).

When a `cloglog` link is used, including an offset for log follow-up time (i.e. `regression = ~offset(log(time))`) results in a model on the log hazard (see Dias et al. 2011).

For survival data, all accelerated failure time models (exponential-aft, weibull-aft, lognormal, loglogistic, gamma, gengamma) are parameterised so that the treatment effects and any regression parameters are log Survival Time Ratios (i.e. a coefficient of $\log(2)$ means that the treatment or covariate is associated with a doubling of expected survival time). These can be converted to log Acceleration Factors using the relation $\log(\text{AF}) = -\log(\text{STR})$ (or equivalently $\text{AF} = 1/\text{STR}$).

Further details on each likelihood and link function are given by Dias et al. (2011).

Auxiliary parameters

Auxiliary parameters are only present in the following models.

Normal likelihood with IPD:

When a Normal likelihood is fitted to IPD, the auxiliary parameters are the arm-level standard deviations σ_{jk} on treatment k in study j .

Ordered multinomial likelihood:

When fitting a model to M ordered outcomes, the auxiliary parameters are the latent cutoffs between each category, $c_0 < c_1 < \dots < c_M$. Only c_2 to c_{M-1} are estimated; we fix $c_0 = -\infty$, $c_1 = 0$, and $c_M = \infty$. When specifying priors for these latent cutoffs, we choose to specify priors on the *differences* $c_{m+1} - c_m$. Stan automatically truncates any priors so that the ordering constraints are satisfied.

Survival (time-to-event) likelihoods:

All survival likelihoods except the exponential and exponential-aft likelihoods have auxiliary parameters. These are typically study-specific shape parameters $\gamma_j > 0$, except for the lognormal likelihood where the auxiliary parameters are study-specific standard deviations on the log scale $\sigma_j > 0$.

The gengamma likelihood has two sets of auxiliary parameters, study-specific scale parameters $\sigma_j > 0$ and shape parameters k_j , following the parameterisation of Lawless (1980), which permits a range of behaviours for the baseline hazard including increasing, decreasing, bathtub and arc-shaped hazards. This parameterisation is related to that discussed by Cox et al. (2007) and implemented in the flexsurv package with $Q = k^{-0.5}$. The parameterisation used here effectively bounds the shape parameter k away from numerical instabilities as $k \rightarrow \infty$ (i.e. away from $Q \rightarrow 0$, the log-Normal distribution) via the prior distribution. Implicitly, this parameterisation is restricted to $Q > 0$ and so certain survival distributions like the inverse-Gamma and inverse-Weibull are not part of the parameter space; however, $Q > 0$ still encompasses the other survival distributions implemented in this package.

For the mspline and pexp likelihoods, the auxiliary parameters are the spline coefficients for each study. These form a unit simplex (i.e. lie between 0 and 1, and sum to 1), and are given a random walk prior distribution. prior_aux specifies the hyperprior on the random walk standard deviation σ which controls the level of smoothing of the baseline hazard, with $\sigma = 0$ corresponding to a constant baseline hazard.

The auxiliary parameters can be stratified by additional factors through the aux_by argument. For example, to allow the shape of the baseline hazard to vary between treatment arms as well as studies, use `aux_by = c(".study", ".trt")`. (Technically, `.study` is always included in the stratification even if omitted from `aux_by`, but we choose here to make the stratification explicit.) This is a common way of relaxing the proportional hazards assumption. The default is equivalent to `aux_by = ".study"` which stratifies the auxiliary parameters by study, as described above.

A regression model may be specified on the auxiliary parameters using `aux_regression`. This is useful if we wish to model departures from non-proportionality, rather than allowing the baseline hazards to be completely independent using `aux_by`. This is necessary if absolute predictions (e.g. survival curves) are required in a population for unobserved combinations of covariates; for example, if `aux_by = . trt` then absolute predictions may only be produced for the observed treatment arms in each study population, whereas if `aux_regression = ~ . trt` then absolute predictions can be produced for all treatments in any population. For `mspline` and `pexp` likelihoods, the regression coefficients are smoothed over time using a random walk prior to avoid overfitting: `prior_aux_reg` specifies the hyperprior for the random walk standard deviation. For other parametric likelihoods, `prior_aux_reg` specifies the prior for the auxiliary regression coefficients.

References

Cox C, Chu H, Schneider MF, Muñoz A (2007). “Parametric survival analysis and taxonomy of hazard functions for the generalized gamma distribution.” *Statistics in Medicine*, **26**(23), 4352–4374. doi:10.1002/sim.2836.

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). “NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Lawless JF (1980). “Inference in the Generalized Gamma and Log Gamma Distributions.” *Technometrics*, **22**(3), 409–419. doi:10.1080/00401706.1980.10486173.

Phillippo DM, Dias S, Ades AE, Belger M, Brnabic A, Schacht A, Saure D, Kadziola Z, Welton NJ (2020). “Multilevel Network Meta-Regression for population-adjusted treatment comparisons.” *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, **183**(3), 1189–1210. doi:10.1111/rssa.12579.

Examples

```
## Smoking cessation NMA
# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
                      study = studyn,
                      trt = trtc,
                      r = r,
                      n = n,
                      trt_ref = "No intervention")

# Print details
smk_net

# Fitting a fixed effect model
smk_fit_FE <- nma(smk_net,
                 trt_effects = "fixed",
```

```
prior_intercept = normal(scale = 100),
prior_trt = normal(scale = 100))

smk_fit_FE

# Fitting a random effects model
smk_fit_RE <- nma(smk_net,
  trt_effects = "random",
  prior_intercept = normal(scale = 100),
  prior_trt = normal(scale = 100),
  prior_het = normal(scale = 5))

smk_fit_RE

# Fitting an unrelated mean effects (inconsistency) model
smk_fit_RE_UME <- nma(smk_net,
  consistency = "ume",
  trt_effects = "random",
  prior_intercept = normal(scale = 100),
  prior_trt = normal(scale = 100),
  prior_het = normal(scale = 5))

smk_fit_RE_UME

# Fitting all possible node-splitting models
smk_fit_RE_nodesplit <- nma(smk_net,
  consistency = "nodesplit",
  trt_effects = "random",
  prior_intercept = normal(scale = 100),
  prior_trt = normal(scale = 100),
  prior_het = normal(scale = 5))

# Summarise the node-splitting results
summary(smk_fit_RE_nodesplit)

## Plaque psoriasis ML-NMR
# Set up plaque psoriasis network combining IPD and AgD
library(dplyr)
pso_ipd <- filter(plaque_psoriasis_ipd,
  studyc %in% c("UNCOVER-1", "UNCOVER-2", "UNCOVER-3"))

pso_agd <- filter(plaque_psoriasis_agd,
  studyc == "FIXTURE")
```

```

head(pso_ipd)
head(pso_agd)

pso_ipd <- pso_ipd %>%
  mutate(# Variable transformations
    bsa = bsa / 100,
    prevsys = as.numeric(prevsys),
    psa = as.numeric(psa),
    weight = weight / 10,
    durnpso = durnpso / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker"),
    # Check complete cases for covariates of interest
    complete = complete.cases(durnpso, prevsys, bsa, weight, psa)
  )

pso_agd <- pso_agd %>%
  mutate(
    # Variable transformations
    bsa_mean = bsa_mean / 100,
    bsa_sd = bsa_sd / 100,
    prevsys = prevsys / 100,
    psa = psa / 100,
    weight_mean = weight_mean / 10,
    weight_sd = weight_sd / 10,
    durnpso_mean = durnpso_mean / 10,
    durnpso_sd = durnpso_sd / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker")
  )

# Exclude small number of individuals with missing covariates
pso_ipd <- filter(pso_ipd, complete)

pso_net <- combine_network(
  set_ipd(pso_ipd,
    study = studyc,
    trt = trtc,
    r = pasi75,
    trt_class = trtclass),
  set_agd_arm(pso_agd,
    study = studyc,
    trt = trtc,
    r = pasi75_r,
    n = pasi75_n,
    trt_class = trtclass)
)

# Print network details

```

```

pso_net

# Add integration points to the network
pso_net <- add_integration(pso_net,
  durnpso = distr(qgamma, mean = durnpso_mean, sd = durnpso_sd),
  prevsys = distr(qbern, prob = prevsys),
  bsa = distr(qlogitnorm, mean = bsa_mean, sd = bsa_sd),
  weight = distr(qgamma, mean = weight_mean, sd = weight_sd),
  psa = distr(qbern, prob = psa),
  n_int = 64)

# Fitting a ML-NMR model.
# Specify a regression model to include effect modifier interactions for five
# covariates, along with main (prognostic) effects. We use a probit link and
# specify that the two-parameter Binomial approximation for the aggregate-level
# likelihood should be used. We set treatment-covariate interactions to be equal
# within each class. We narrow the possible range for random initial values with
# init_r = 0.1, since probit models in particular are often hard to initialise.
# Using the QR decomposition greatly improves sampling efficiency here, as is
# often the case for regression models.
pso_fit <- nma(pso_net,
  trt_effects = "fixed",
  link = "probit",
  likelihood = "bernoulli2",
  regression = ~(durnpso + prevsys + bsa + weight + psa)*.trt,
  class_interactions = "common",
  prior_intercept = normal(scale = 10),
  prior_trt = normal(scale = 10),
  prior_reg = normal(scale = 10),
  init_r = 0.1,
  QR = TRUE)

pso_fit

## Newly-diagnosed multiple myeloma NMA
# Set up newly-diagnosed multiple myeloma network

head(ndmm_ipd)
head(ndmm_agd)

ndmm_net <- combine_network(
  set_ipd(ndmm_ipd,
    study, trt,
    Surv = Surv(eventtime / 12, status)),
  set_agd_surv(ndmm_agd,
    study, trt,
    Surv = Surv(eventtime / 12, status),
    covariates = ndmm_agd_covs))

# Fit Weibull (PH) model
ndmm_fit <- nma(ndmm_net,
  likelihood = "weibull",

```

```

prior_intercept = normal(scale = 100),
prior_trt = normal(scale = 10),
prior_aux = half_normal(scale = 10))

ndmm_fit

```

nma_data-class

The nma_data class

Description

The `nma_data` class contains the data for a NMA in a standard format, created using the functions `set_ipd()`, `set_agd_arm()`, `set_agd_contrast()`, `set_agd_surv()`, or `combine_network()`. The sub-class `mlnmr_data` is created by the function `add_integration()`, and further contains numerical integration points for the aggregate data.

Details

Objects of class `nma_data` have the following components:

`agd_arm` data from studies with aggregate data (arm format)
`agd_contrast` data from studies with aggregate data (contrast format)
`ipd` data from studies with individual patient data
`treatments` treatment coding factor for entire network
`classes` treatment class coding factor (same length as `treatments` for entire network)
`studies` study coding factor for entire network
`outcome` outcome type for each data source, named list

The `agd_arm`, `agd_contrast`, and `ipd` components are tibbles with the following columns:

- `.study` study (as factor)
- `.trt` treatment (as factor)
- `.trtclass` treatment class (as factor), if specified
- `.y` continuous outcome
- `.se` standard error (continuous)
- `.r` event count (discrete)
- `.n` event count denominator (discrete, `agd_arm` only)
- `.E` time at risk (discrete)
- `.Surv` survival outcome of type `Surv` (time-to-event), nested by study arm
- `.sample_size` sample size (`agd_*` only)
- `...` other columns (typically covariates) from the original data frame

Objects of class `mlnmr_data` additionally have components:

n_int number of numerical integration points

int_names names of covariates with numerical integration points

int_cor correlation matrix for covariates used to generate numerical integration points

The `agd_arm` and `agd_contrast` tibbles have additional list columns with prefix `.int_`, one for each covariate, which contain the numerical integration points nested as length-`n_int` vectors within each row.

See Also

[print.nma_data\(\)](#) for the print method displaying details of the network, and [plot.nma_data\(\)](#) for network plots.

nma_dic-class

The nma_dic class

Description

The `nma_dic` class contains details of the Deviance Information Criterion (DIC), produced using the [dic\(\)](#) function.

Details

Objects of class `nma_dic` have the following components:

`dic` The DIC value

`pd, pv` The effective number of parameters

`resdev` The total residual deviance

`pointwise` A list of data frames containing the pointwise contributions for the IPD and AgD.

`resdev_array` A 3D MCMC array [Iterations, Chains, Parameters] of posterior residual deviance samples.

See Also

[dic\(\)](#), [print.nma_dic\(\)](#), [plot.nma_dic\(\)](#).

nma_nodesplit-class *The nma_nodesplit class*

Description

The `nma_nodesplit` and `nma_nodesplit_df` classes contains the results from running a node-splitting model with the function `nma()`.

Details

Objects of class `nma_nodesplit` inherit from the `stan_nma` class, and contain the results of fitting a single node-split model. They have one additional component, `nodesplit`, which gives the comparison that was node-split as a length 2 vector.

Objects of class `nma_nodesplit_df` are tibble data frames with one row for each node-split comparison and columns:

`trt1, trt2` Treatments forming the comparison

`model` A list column containing the results of each model as a `nma_nodesplit` object

Optionally, there will be an additional row for the consistency model if this was fitted (e.g. by `get_nodesplits(., include_consistency = TRUE)`) with `trt1` and `trt2` both NA.

nma_prior-class *The nma_prior class*

Description

The `nma_prior` class is used to specify prior distributions.

Details

Objects of class `nma_prior` have the following components:

`dist` Distribution name

`fun` Name of constructor function, as string (e.g. "normal")

`...` Parameters of the distribution

The distribution parameters, specified as named components in `...`, match those in the constructor functions (see [priors](#)).

mma_summary-class *The mma_summary class*

Description

The `mma_summary` class contains posterior summary statistics of model parameters or other quantities of interest, and the draws used to obtain these statistics.

Details

Objects of class `mma_summary` have the following components:

summary A data frame containing the computed summary statistics. Column `.trt` indicates the corresponding treatment, or columns `.trta` and `.trtb` indicate the corresponding contrast (`.trtb` vs. `.trta`). If a regression model was fitted with effect modifier interactions with treatment, these summaries will be study-specific. In this case, the corresponding study population is indicated in the `.study` column. If a multinomial model was fitted, the `.category` column indicates the corresponding category.

sims A 3D array [Iteration, Chain, Parameter] of MCMC simulations

studies (Optional) A data frame containing study information, printed along with the corresponding summary statistics if `summary` contains a `.study` column. Should have a matching `.study` column.

The following attributes may also be set:

xlab Label for x axis in plots, usually either "Treatment" or "Contrast".

ylab Label for y axis in plots, usually used for the scale e.g. "log Odds Ratio".

The subclass `mma_rank_probs` is used by the function `posterior_rank_probs()`, and contains posterior rank probabilities. This subclass does not have a `sims` component, as the rank probabilities are themselves posterior summaries of the ranks (i.e. they do not have a posterior distribution). The posterior ranks from which the rank probabilities are calculated may be obtained from `posterior_ranks()`.

nodesplit_summary-class *The nodesplit_summary class*

Description

The `nodesplit_summary` class contains posterior summary statistics for node-splitting models, as a result of calling `summary()` on a `mma_nodesplit` or `mma_nodesplit_df` object.

Details

Objects of class `nodesplit_summary` are tibble data frames, with one row for each node-split comparison and columns:

`trt1`, `trt2` Treatments forming the comparison

`summary` A list column containing `nma_summary` objects with the posterior summaries and draws for each of the node-splitting parameters

`p_value` Bayesian p-value for inconsistency

`dic` A list column containing `nma_dic` objects, giving the model fit statistics

The parameters included in `summary` are:

`d_net` Network estimate from the corresponding consistency model, if available

`d_dir` Direct estimate from the node-splitting model

`d_ind` Indirect estimate from the node-splitting model

`omega` Inconsistency factor $\omega = d_{\text{dir}} - d_{\text{ind}}$

`tau` Heterogeneity standard deviation from the node-splitting model, if a random effects model was fitted

`tau_consistency` Heterogeneity standard deviation from the corresponding consistency model, if available and if a random effects model was fitted

<code>pairs.stan_nma</code>	<i>Matrix of plots for a stan_nma object</i>
-----------------------------	--

Description

A `pairs()` method for `stan_nma` objects, which calls `bayesplot::mcmc_pairs()` on the underlying `stanfit` object.

Usage

```
## S3 method for class 'stan_nma'
pairs(x, ..., pars, include = TRUE)
```

Arguments

<code>x</code>	An object of class <code>stan_nma</code>
<code>...</code>	Other arguments passed to <code>bayesplot::mcmc_pairs()</code>
<code>pars</code>	Optional character vector of parameter names to include in output. If not specified, all parameters are used.
<code>include</code>	Logical, are parameters in <code>pars</code> to be included (TRUE, default) or excluded (FALSE)?

Value

A grid of ggplot objects produced by `bayesplot::mcmc_pairs()`.

Examples

```
## Not run:
## Parkinson's mean off time reduction
park_net <- set_agd_arm(parkinsons,
                      study = studyn,
                      trt = trtn,
                      y = y,
                      se = se,
                      sample_size = n)

# Fitting a RE model
park_fit_RE <- nma(park_net,
                  trt_effects = "random",
                  prior_intercept = normal(scale = 100),
                  prior_trt = normal(scale = 100),
                  prior_het = half_normal(scale = 5))

# We see a small number of divergent transition errors
# These do not go away entirely when adapt_delta is increased

# Try to diagnose with a pairs plot
pairs(park_fit_RE, pars = c("mu[4]", "d[3]", "delta[4: 3]", "tau"))

# Transforming tau onto log scale
pairs(park_fit_RE, pars = c("mu[4]", "d[3]", "delta[4: 3]", "tau"),
      transformations = list(tau = "log"))

# The divergent transitions occur in the upper tail of the heterogeneity
# standard deviation. In this case, with only a small number of studies, there
# is not very much information to estimate the heterogeneity standard deviation
# and the prior distribution may be too heavy-tailed. We could consider a more
# informative prior distribution for the heterogeneity variance to aid
# estimation.

## End(Not run)
```

parkinsons

Mean off-time reduction in Parkinson's disease

Description

Data frame containing the mean off-time reduction in patients given dopamine agonists as adjunct therapy in Parkinson's disease, from 7 trials comparing four active drugs and placebo (Dias et al. 2011).

Usage

parkinsons

Format

A data frame with 15 rows and 7 variables:

studyn numeric study ID

trtn numeric treatment code (placebo = 1)

y mean off-time reduction

se standard error

n sample size

diff mean difference vs. treatment in reference arm

se_diff standard error of mean difference, see details

Details

This dataset may be analysed using either an arm-based likelihood using `y` and `se`, or a contrast-based likelihood using `diff` and `se_diff` (or a combination of the two across different studies).

The contrast-based data is formatted as described in `set_agd_contrast()`. That is, for the chosen reference arm in each study, the mean difference `diff` is set to `NA`, and `se_diff` is set to the standard error `se` of the outcome on the reference arm.

References

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). “NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

plaque_psoriasis_ipd *Plaque psoriasis data*

Description

Two data frames, `plaque_psoriasis_ipd` and `plaque_psoriasis_agd`, containing (simulated) individual patient data from four studies and aggregate data from five studies (Phillippo 2019). Outcomes are binary success/failure to achieve 75%, 90%, or 100% reduction in symptoms on the Psoriasis Area and Severity Index (PASI) scale.

Usage

plaque_psoriasis_ipd

plaque_psoriasis_agd

Format

The individual patient data are contained in a data frame `plaque_psoriasis_ipd` with 4118 rows, one per individual, and 16 variables:

studyc study name
trtc_long treatment name (long format)
trtc treatment name
trtn numeric treatment code
pasi75 binary PASI 75 outcome
pasi90 binary PASI 90 outcome
pasi100 binary PASI 100 outcome
age age (years)
bmi body mass index (BMI)
pasi_w0 PASI score at week 0
male male sex (TRUE or FALSE)
bsa body surface area (percent)
weight weight (kilograms)
durnpso duration of psoriasis (years)
prevsys previous systemic treatment (TRUE or FALSE)
psa psoriatic arthritis (TRUE or FALSE)

The aggregate data are contained in a data frame `plaque_psoriasis_agd` with 15 rows, one per study arm, and 26 variables:

studyc study name
trtc_long treatment name (long format)
trtc treatment name
trtn numeric treatment code
pasi75_r, pasi75_n PASI 75 outcome count and denominator
pasi90_r, pasi90_n PASI 90 outcome count and denominator
pasi100_r, pasi100_n PASI 100 outcome count and denominator
sample_size_w0 sample size at week zero
age_mean, age_sd mean and standard deviation of age (years)
bmi_mean, bmi_sd mean and standard deviation of BMI
pasi_w0_mean, pasi_w0_sd mean and standard deviation of PASI score at week 0
male percentage of males
bsa_mean, bsa_sd mean and standard deviation of body surface area (percent)
weight_mean, weight_sd mean and standard deviation of weight (kilograms)
durnpso_mean, durnpso_sd mean and standard deviation of duration of psoriasis (years)
prevsys percentage of individuals with previous systemic treatment
psa percentage of individuals with psoriatic arthritis

An object of class `data.frame` with 15 rows and 26 columns.

References

Phillippo DM (2019). *Calibration of Treatment Effects in Network Meta-Analysis using Individual Patient Data*. Ph.D. thesis, University of Bristol. Available from <https://research-information.bris.ac.uk/>.

plot.nma_data	<i>Network plots</i>
---------------	----------------------

Description

Create a network plot from a nma_data network object.

Usage

```
## S3 method for class 'nma_data'
plot(
  x,
  ...,
  layout,
  circular,
  weight_edges = TRUE,
  weight_nodes = FALSE,
  show_trt_class = FALSE,
  nudge = 0
)
```

Arguments

x	A nma_data object to plot
...	Additional arguments passed to ggraph() and on to the layout function
layout	The type of layout to create. Any layout accepted by ggraph() may be used, including all of the layout functions provided by igraph .
circular	Whether to use a circular representation. See ggraph() .
weight_edges	Weight edges by the number of studies? Default is TRUE.
weight_nodes	Weight nodes by the total sample size? Default is FALSE.
show_trt_class	Colour treatment nodes by class, if trt_class is set? Default is FALSE.
nudge	Numeric value to nudge the treatment labels away from the nodes when weight_nodes = TRUE. Default is 0 (no adjustment to label position). A small value like 0.1 is usually sufficient.

Details

The default is equivalent to `layout = "linear"` and `circular = TRUE`, which places the treatment nodes on a circle in the order defined by the treatment factor variable. An alternative layout which may give good results for simple networks is `"sugiyama"`, which attempts to minimise the number of edge crossings.

`weight_nodes = TRUE` requires that sample sizes have been specified for any aggregate data in the network, using the `sample_size` option of `set_agd_*()`.

Value

A ggplot object, as produced by `ggraph()`.

Examples

```
## Stroke prevention in atrial fibrillation
# Setting up the network
af_net <- set_agd_arm(atrial_fibrillation,
                     study = studyc,
                     trt = abbreviate(trtc, minlength = 3),
                     r = r,
                     n = n,
                     trt_class = trt_class)

af_net

# Basic plot
plot(af_net)

# Turn off weighting edges by number of studies
plot(af_net, weight_edges = FALSE)

# Turn on weighting nodes by sample size
plot(af_net, weight_nodes = TRUE)

# Colour treatment nodes by class
plot(af_net, weight_nodes = TRUE, show_trt_class = TRUE)

# Nudge the treatment labels away from the nodes
plot(af_net, weight_nodes = TRUE, show_trt_class = TRUE, nudge = 0.1)

# Output may be customised using standard ggplot commands
# For example, to display the legends below the plot:
plot(af_net, weight_nodes = TRUE, show_trt_class = TRUE) +
  ggplot2::theme(legend.position = "bottom",
                legend.box = "vertical",
                legend.margin = ggplot2::margin(0, 0, 0, 0),
                legend.spacing = ggplot2::unit(0.5, "lines"))

# Choosing a different ggraph layout, hiding some legends
plot(af_net, weight_nodes = TRUE, show_trt_class = TRUE,
     layout = "star") +
  ggplot2::guides(edge_width = "none", size = "none")
```

plot.nma_dic *Plots of model fit diagnostics*

Description

The `plot()` method for `nma_dic` objects produced by `dic()` produces several useful diagnostic plots for checking model fit and model comparison. Further detail on these plots and their interpretation is given by Dias et al. (2011).

Usage

```
## S3 method for class 'nma_dic'
plot(
  x,
  y,
  ...,
  show_uncertainty = TRUE,
  stat = "pointinterval",
  orientation = c("vertical", "horizontal", "x", "y")
)
```

Arguments

<code>x</code>	A <code>nma_dic</code> object
<code>y</code>	(Optional) A second <code>nma_dic</code> object, to produce "dev-dev" plots for model comparison.
<code>...</code>	Additional arguments passed on to other methods
<code>show_uncertainty</code>	Logical, show uncertainty with a <code>ggdist</code> plot stat? Default <code>TRUE</code> .
<code>stat</code>	Character string specifying the <code>ggdist</code> plot stat to use if <code>show_uncertainty = TRUE</code> , default "pointinterval". If <code>y</code> is provided, currently only "pointinterval" is supported.
<code>orientation</code>	Whether the <code>ggdist</code> geom is drawn horizontally ("horizontal") or vertically ("vertical"). Only used for residual deviance plots, default "vertical".

Details

When a single `nma_dic` object is given, a plot of the residual deviance contribution for each data point is produced. For a good fitting model, each data point is expected to have a residual deviance of 1; larger values indicate data points that are fit poorly by the model.

When two `nma_dic` objects are given, a "dev-dev" plot comparing the residual deviance contributions under each model is produced. Data points with residual deviance contributions lying on the line of equality are fit equally well under either model. Data points lying below the line of equality indicate better fit under the second model (`y`); conversely, data points lying above the line

of equality indicate better fit under the first model (x). A common use case is to compare a standard consistency model (fitted using `nma()` with `consistency = "consistency"`) with an unrelated mean effects (UME) inconsistency model (fitted using `nma()` with `consistency = "ume"`), to check for potential inconsistency.

See Dias et al. (2011) for further details.

Value

A ggplot object.

References

Dias S, Welton NJ, Sutton AJ, Ades AE (2011). "NICE DSU Technical Support Document 2: A generalised linear modelling framework for pair-wise and network meta-analysis of randomised controlled trials." National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Examples

```
## Smoking cessation

# Run smoking FE NMA example if not already available
if (!exists("smk_fit_FE")) example("example_smk_fe", run.donttest = TRUE)

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Compare DIC of FE and RE models
(smk_dic_FE <- dic(smk_fit_FE))
(smk_dic_RE <- dic(smk_fit_RE)) # substantially better fit

# Plot residual deviance contributions under RE model
plot(smk_dic_RE)

# Further customisation is possible using ggplot commands
# For example, highlighting data points with residual deviance above a certain threshold
plot(smk_dic_RE) +
  ggplot2::aes(colour = ggplot2::after_stat(ifelse(y > 1.5, "darkorange", "black"))) +
  ggplot2::scale_colour_identity()

# Or by posterior probability, for example here a central probability of 0.6
# corresponds to a lower tail probability of (1 - 0.6)/2 = 0.2
plot(smk_dic_RE, .width = c(0.6, 0.95)) +
  ggplot2::aes(colour = ggplot2::after_stat(ifelse(ymin > 1, "darkorange", "black"))) +
  ggplot2::scale_colour_identity()

# Check for inconsistency using UME model

# Run smoking UME NMA example if not already available
```



```

if (!exists("smk_fit_RE_UME")) example("example_smk_ume", run.donttest = TRUE)

# Compare DIC
smk_dic_RE
(smk_dic_RE_UME <- dic(smk_fit_RE_UME)) # no difference in fit

# Compare residual deviance contributions with a "dev-dev" plot
plot(smk_dic_RE, smk_dic_RE_UME)

# By default the dev-dev plot can be a little cluttered
# Hiding the credible intervals
plot(smk_dic_RE, smk_dic_RE_UME, show_uncertainty = FALSE)

# Changing transparency
plot(smk_dic_RE, smk_dic_RE_UME, point_alpha = 0.5, interval_alpha = 0.1)

```

plot.nma_summary *Plots of summary results*

Description

The plot method for `nma_summary` objects is used to produce plots of parameter estimates (when called on a `stan_nma` object or its summary), relative effects (when called on the output of `relative_effects()`), absolute predictions (when called on the output of `predict.stan_nma()`), posterior ranks and rank probabilities (when called on the output of `posterior_ranks()` or `posterior_rank_probs()`).

Usage

```

## S3 method for class 'nma_summary'
plot(
  x,
  ...,
  stat = "pointinterval",
  orientation = c("horizontal", "vertical", "y", "x"),
  ref_line = NA_real_
)

## S3 method for class 'nma_parameter_summary'
plot(
  x,
  ...,
  stat = "pointinterval",
  orientation = c("horizontal", "vertical", "y", "x"),
  ref_line = NA_real_
)

```

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

## S3 method for class 'surv_nma_summary'
plot(x, ..., stat = "lineribbon")
```

Arguments

x	A nma_summary object
...	Additional arguments passed on to the underlying ggdist plot stat, see Details
stat	Character string specifying the ggdist plot stat to use, default "pointinterval", except when plotting estimated survival/hazard/cumulative hazard curves from survival models where the default is "lineribbon"
orientation	Whether the ggdist geom is drawn horizontally ("horizontal") or vertically ("vertical"), default "horizontal"
ref_line	Numeric vector of positions for reference lines, by default no reference lines are drawn

Details

Plotting is handled by [ggplot2](#) and the stats and geoms provided in the [ggdist](#) package. As a result, the output is very flexible. Any plotting stats provided by ggdist may be used, via the argument stat.

The default uses [ggdist::stat_pointinterval\(\)](#), to produce medians and 95% Credible Intervals with 66% inner bands. Additional arguments in ... are passed to the ggdist stat, to customise the output. For example, to produce means and Credible Intervals, specify point_interval = "mean_qi". To produce an 80% Credible Interval with no inner band, specify .width = c(0, 0.8).

Alternative stats can be specified to produce different summaries. For example, specify stat = "[half]eye" to produce (half) eye plots, or stat = "histinterval" to produce histograms with intervals.

A full list of options and examples is found in the ggdist vignette `vignette("slabinterval", package = "ggdist")`.

For survival/hazard/cumulative hazard curves estimated from survival models, the default uses [ggdist::stat_lineribbon\(\)](#) which produces curves of posterior medians with 50%, 80%, and 95% Credible Interval bands. Again, additional arguments in ... are passed to the ggdist stat. For example, to produce posterior means and 95% Credible bands, specify point_interval = "mean_qi" and .width = 0.95.

A ggplot object is returned which can be further modified through the usual [ggplot2](#) functions to add further aesthetics, geoms, themes, etc.

Value

A ggplot object.

Examples

```
## Smoking cessation

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Produce relative effects
smk_releff_RE <- relative_effects(smk_fit_RE)
plot(smk_releff_RE, ref_line = 0)

# Customise plot options
plot(smk_releff_RE, ref_line = 0, stat = "halfeye")

# Further customisation is possible with ggplot commands
plot(smk_releff_RE, ref_line = 0, stat = "halfeye", slab_alpha = 0.6) +
  ggplot2::aes(slab_fill = ggplot2::after_stat(ifelse(x < 0, "darkred", "grey60")))

# Produce posterior ranks
smk_rank_RE <- posterior_ranks(smk_fit_RE, lower_better = FALSE)
plot(smk_rank_RE)

# Produce rank probabilities
smk_rankprob_RE <- posterior_rank_probs(smk_fit_RE, lower_better = FALSE)
plot(smk_rankprob_RE)

# Produce cumulative rank probabilities
smk_cumrankprob_RE <- posterior_rank_probs(smk_fit_RE, lower_better = FALSE,
                                          cumulative = TRUE)
plot(smk_cumrankprob_RE)

# Further customisation is possible with ggplot commands
plot(smk_cumrankprob_RE) +
  ggplot2::facet_null() +
  ggplot2::aes(colour = Treatment)
```

plot.nodesplit_summary

Plots of node-splitting models

Description

Produce summary plots of node-splitting models

Usage

```
## S3 method for class 'nodesplit_summary'
plot(
```

```

x,
...,
pars = "d",
stat = "dens_overlay",
orientation = c("horizontal", "vertical", "y", "x"),
ref_line = NA_real_
)

```

Arguments

x	A nodesplit_summary object.
...	Additional arguments passed on to the underlying ggdist plot stat, see Details.
pars	Character vector specifying the parameters to include in the plot, choices include "d" for the direct, indirect, and network estimates of relative effects, "omega" for the inconsistency factor, and "tau" for heterogeneity standard deviation in random effects models. Default is "d".
stat	Character string specifying the ggdist plot stat to use. The default "dens_overlay" is a special case, producing an overlaid density plot.
orientation	Whether the ggdist geom is drawn horizontally ("horizontal") or vertically ("vertical"), default "horizontal".
ref_line	Numeric vector of positions for reference lines, by default no reference lines are drawn.

Details

Plotting is handled by [ggplot2](#) and the stats and geoms provided in the [ggdist](#) package. As a result, the output is very flexible. Any plotting stats provided by [ggdist](#) may be used, via the argument `stat`. The default "dens_overlay" is a special exception, which uses [ggplot2::geom_density\(\)](#), to plot overlaid densities. Additional arguments in ... are passed to the [ggdist](#) stat, to customise the output.

Alternative stats can be specified to produce different summaries. For example, specify `stat = "[half]eye"` to produce (half) eye plots, or `stat = "pointinterval"` to produce point estimates and credible intervals.

A full list of options and examples is found in the [ggdist](#) vignette `vignette("slabinterval", package = "ggdist")`.

A [ggplot](#) object is returned which can be further modified through the usual [ggplot2](#) functions to add further aesthetics, geoms, themes, etc.

Value

A [ggplot](#) object.

See Also

[summary.nma.nodesplit_df\(\)](#)

Examples

```

# Run smoking node-splitting example if not already available
if (!exists("smk_fit_RE_nodesplit")) example("example_smk_nodesplit", run.donttest = TRUE)

# Summarise the node-splitting results
(smk_nodesplit_summary <- summary(smk_fit_RE_nodesplit))

# Plot the node-splitting results
plot(smk_nodesplit_summary)

# Plot the inconsistency factors instead, change the plot stat to half-eye,
# and add a reference line at 0
plot(smk_nodesplit_summary, pars = "omega", stat = "halfeye", ref_line = 0)

# Plot a comparison of the heterogeneity under the node-split models vs.
# the consistency model
plot(smk_nodesplit_summary, pars = "tau")

```

plot_integration_error

Plot numerical integration error

Description

For ML-NMR models, plot the estimated numerical integration error over the entire posterior distribution, as the number of integration points increases. See (Phillippo et al. 2020; Phillippo 2019) for details.

Usage

```

plot_integration_error(
  x,
  ...,
  stat = "violin",
  orientation = c("vertical", "horizontal", "x", "y"),
  show_expected_rate = TRUE
)

```

Arguments

x	An object of type <code>stan_mlnmr</code>
...	Additional arguments passed to the <code>ggdist</code> plot stat.
stat	Character string specifying the <code>ggdist</code> plot stat used to summarise the integration error over the posterior. Default is "violin", which is equivalent to "eye" with some cosmetic tweaks.

orientation Whether the ggdist geom is drawn horizontally ("horizontal") or vertically ("vertical"), default "vertical"

show_expected_rate Logical, show typical convergence rate $1/N$? Default TRUE.

Details

The total number of integration points is set by the `n_int` argument to `add_integration()`, and the intervals at which integration error is estimated are set by the `int_thin` argument to `nma()`. The typical convergence rate of Quasi-Monte Carlo integration (as used here) is $1/N$, which by default is displayed on the plot output.

The integration error at each thinning interval N_{thin} is estimated for each point in the posterior distribution by subtracting the final estimate (using all `n_int` points) from the estimate using only the first N_{thin} points.

Value

A ggplot object.

Note for survival models

This function is not supported for survival/time-to-event models. These do not save cumulative integration points for efficiency reasons (both time and memory).

Examples

```
## Plaque psoriasis ML-NMR
# Set up plaque psoriasis network combining IPD and AgD
library(dplyr)
pso_ipd <- filter(plaque_psoriasis_ipd,
                 studyc %in% c("UNCOVER-1", "UNCOVER-2", "UNCOVER-3"))

pso_agd <- filter(plaque_psoriasis_agd,
                 studyc == "FIXTURE")

head(pso_ipd)
head(pso_agd)

pso_ipd <- pso_ipd %>%
  mutate(# Variable transformations
         bsa = bsa / 100,
         prevsys = as.numeric(prevsys),
         psa = as.numeric(psa),
         weight = weight / 10,
         durnpso = durnpso / 10,
         # Treatment classes
         trtclass = case_when(trtn == 1 ~ "Placebo",
                              trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                              trtn == 4 ~ "TNFa blocker"),
         # Check complete cases for covariates of interest
         complete = complete.cases(durnpso, prevsys, bsa, weight, psa))
```

```

)

pso_agd <- pso_agd %>%
  mutate(
    # Variable transformations
    bsa_mean = bsa_mean / 100,
    bsa_sd = bsa_sd / 100,
    prevsys = prevsys / 100,
    psa = psa / 100,
    weight_mean = weight_mean / 10,
    weight_sd = weight_sd / 10,
    durnpso_mean = durnpso_mean / 10,
    durnpso_sd = durnpso_sd / 10,
    # Treatment classes
    trtclass = case_when(trtn == 1 ~ "Placebo",
                        trtn %in% c(2, 3, 5, 6) ~ "IL blocker",
                        trtn == 4 ~ "TNFa blocker")
  )

# Exclude small number of individuals with missing covariates
pso_ipd <- filter(pso_ipd, complete)

pso_net <- combine_network(
  set_ipd(pso_ipd,
    study = studyc,
    trt = trtc,
    r = pasi75,
    trt_class = trtclass),
  set_agd_arm(pso_agd,
    study = studyc,
    trt = trtc,
    r = pasi75_r,
    n = pasi75_n,
    trt_class = trtclass)
)

# Print network details
pso_net

# Add integration points to the network
pso_net <- add_integration(pso_net,
  durnpso = distr(qgamma, mean = durnpso_mean, sd = durnpso_sd),
  prevsys = distr(qbern, prob = prevsys),
  bsa = distr(qlogitnorm, mean = bsa_mean, sd = bsa_sd),
  weight = distr(qgamma, mean = weight_mean, sd = weight_sd),
  psa = distr(qbern, prob = psa),
  n_int = 64)

# Fit the ML-NMR model
pso_fit <- nma(pso_net,
  trt_effects = "fixed",
  link = "probit",

```

```

likelihood = "bernoulli2",
regression = ~(durnpso + prevsys + bsa + weight + psa)*.trt,
class_interactions = "common",
prior_intercept = normal(scale = 10),
prior_trt = normal(scale = 10),
prior_reg = normal(scale = 10),
init_r = 0.1,
QR = TRUE,
# Set the thinning factor for saving the cumulative results
# (This also sets int_check = FALSE)
int_thin = 8)

pso_fit

# Plot numerical integration error
plot_integration_error(pso_fit)

```

plot_prior_posterior *Plot prior vs posterior distribution*

Description

Produce plots comparing the prior and posterior distributions of model parameters.

Usage

```

plot_prior_posterior(
  x,
  ...,
  prior = NULL,
  post_args = list(),
  prior_args = list(),
  overlay = c("prior", "posterior"),
  ref_line = NA_real_
)

```

Arguments

x	A stan_nma object
...	Additional arguments passed on to methods
prior	Character vector selecting the prior and posterior distribution(s) to plot. May include "intercept", "trt", "het", "reg", or "aux", as appropriate.
post_args	List of arguments passed on to ggplot2::geom_histogram to control plot output for the posterior distribution
prior_args	List of arguments passed on to ggplot2::geom_path to control plot output for the prior distribution. Additionally, n controls the number of points the density curve is evaluated at (default 500), and p_limits controls the endpoints of the curve as quantiles (default c(.001, .999)).

overlay	String, should prior or posterior be shown on top? Default "prior".
ref_line	Numeric vector of positions for reference lines, by default no reference lines are drawn

Details

Prior distributions are displayed as lines, posterior distributions are displayed as histograms.

Value

A ggplot object.

Examples

```
## Smoking cessation NMA

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Plot prior vs. posterior, by default all parameters are plotted
plot_prior_posterior(smk_fit_RE)

# Plot prior vs. posterior for heterogeneity SD only
plot_prior_posterior(smk_fit_RE, prior = "het")

# Customise plot
plot_prior_posterior(smk_fit_RE, prior = "het",
  prior_args = list(colour = "darkred", size = 2),
  post_args = list(alpha = 0.6))
```

posterior_ranks *Treatment rankings and rank probabilities*

Description

Produce posterior treatment rankings and rank probabilities from a fitted NMA model. When a meta-regression is fitted with effect modifier interactions with treatment, these will differ by study population.

Usage

```
posterior_ranks(
  x,
  newdata = NULL,
  study = NULL,
  lower_better = TRUE,
```

```

probs = c(0.025, 0.25, 0.5, 0.75, 0.975),
sucra = FALSE,
summary = TRUE
)

posterior_rank_probs(
  x,
  newdata = NULL,
  study = NULL,
  lower_better = TRUE,
  cumulative = FALSE,
  sucra = FALSE
)

```

Arguments

x	A <code>stan_nma</code> object created by <code>nma()</code>
newdata	Only used if a regression model is fitted. A data frame of study details, one row per study, giving the covariate values at which to produce relative effects. Column names must match variables in the regression model. If <code>NULL</code> , relative effects are produced for all studies in the network.
study	Column of <code>newdata</code> which specifies study names, otherwise studies will be labelled by row number.
lower_better	Logical, are lower treatment effects better (<code>TRUE</code> ; default) or higher better (<code>FALSE</code>)? See details.
probs	Numeric vector of quantiles of interest to present in computed summary, default <code>c(0.025, 0.25, 0.5, 0.75, 0.975)</code>
sucra	Logical, calculate the surface under the cumulative ranking curve (SUCRA) for each treatment? Default <code>FALSE</code> .
summary	Logical, calculate posterior summaries? Default <code>TRUE</code> .
cumulative	Logical, return cumulative rank probabilities? Default is <code>FALSE</code> , return posterior probabilities of each treatment having a given rank. If <code>TRUE</code> , cumulative posterior rank probabilities are returned for each treatment having a given rank or better.

Details

The function `posterior_ranks()` produces posterior rankings, which have a distribution (e.g. mean/median rank and 95% Credible Interval). The function `posterior_rank_probs()` produces rank probabilities, which give the posterior probabilities of being ranked first, second, etc. out of all treatments.

The argument `lower_better` specifies whether lower treatment effects or higher treatment effects are preferred. For example, with a negative binary outcome lower (more negative) log odds ratios are preferred, so `lower_better = TRUE`. Conversely, for example, if treatments aim to increase the rate of a positive outcome then `lower_better = FALSE`.

Value

A `nma_summary` object if `summary = TRUE`, otherwise a list containing a 3D MCMC array of samples and (for regression models) a data frame of study information.

See Also

`plot.nma_summary()` for plotting the ranks and rank probabilities.

Examples

```
## Smoking cessation

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Produce posterior ranks
smk_rank_RE <- posterior_ranks(smk_fit_RE, lower_better = FALSE)
smk_rank_RE
plot(smk_rank_RE)

# Produce rank probabilities
smk_rankprob_RE <- posterior_rank_probs(smk_fit_RE, lower_better = FALSE)
smk_rankprob_RE
plot(smk_rankprob_RE)

# Produce cumulative rank probabilities
smk_cumrankprob_RE <- posterior_rank_probs(smk_fit_RE, lower_better = FALSE,
                                           cumulative = TRUE)
smk_cumrankprob_RE
plot(smk_cumrankprob_RE)

# Further customisation is possible with ggplot commands
plot(smk_cumrankprob_RE) +
  ggplot2::facet_null() +
  ggplot2::aes(colour = Treatment)

## Plaque psoriasis ML-NMR

# Run plaque psoriasis ML-NMR example if not already available
if (!exists("pso_fit")) example("example_pso_mlnmr", run.donttest = TRUE)

# Produce population-adjusted rankings for all study populations in
# the network

# Ranks
pso_rank <- posterior_ranks(pso_fit)
pso_rank
plot(pso_rank)
```

```

# Rank probabilities
pso_rankprobs <- posterior_rank_probs(pso_fit)
pso_rankprobs
plot(pso_rankprobs)

# Cumulative rank probabilities
pso_cumrankprobs <- posterior_rank_probs(pso_fit, cumulative = TRUE)
pso_cumrankprobs
plot(pso_cumrankprobs)

# Produce population-adjusted rankings for a different target
# population
new_agd_means <- data.frame(
  bsa = 0.6,
  prevsys = 0.1,
  psa = 0.2,
  weight = 10,
  durnpso = 3)

# Ranks
posterior_ranks(pso_fit, newdata = new_agd_means)

# Rank probabilities
posterior_rank_probs(pso_fit, newdata = new_agd_means)

# Cumulative rank probabilities
posterior_rank_probs(pso_fit, newdata = new_agd_means,
  cumulative = TRUE)

```

predict.stan_nma

Predictions of absolute effects from NMA models

Description

Obtain predictions of absolute effects from NMA models fitted with `nma()`. For example, if a model is fitted to binary data with a logit link, predicted outcome probabilities or log odds can be produced. For survival models, predictions can be made for survival probabilities, (cumulative) hazards, (restricted) mean survival times, and quantiles including median survival times. When an IPD NMA or ML-NMR model has been fitted, predictions can be produced either at an individual level or at an aggregate level. Aggregate-level predictions are population-average absolute effects; these are marginalised or standardised over a population. For example, average event probabilities from a logistic regression, or marginal (standardised) survival probabilities from a survival model.

Usage

```

## S3 method for class 'stan_nma'
predict(
  object,

```

```

    ...,
    baseline = NULL,
    newdata = NULL,
    study = NULL,
    trt_ref = NULL,
    type = c("link", "response"),
    level = c("aggregate", "individual"),
    baseline_type = c("link", "response"),
    baseline_level = c("individual", "aggregate"),
    probs = c(0.025, 0.25, 0.5, 0.75, 0.975),
    predictive_distribution = FALSE,
    summary = TRUE
)

## S3 method for class 'stan_nma_surv'
predict(
  object,
  times = NULL,
  ...,
  baseline = NULL,
  aux = NULL,
  newdata = NULL,
  study = NULL,
  trt_ref = NULL,
  type = c("survival", "hazard", "cumhaz", "mean", "median", "quantile", "rmst", "link"),
  quantiles = c(0.25, 0.5, 0.75),
  level = c("aggregate", "individual"),
  times_seq = NULL,
  probs = c(0.025, 0.25, 0.5, 0.75, 0.975),
  predictive_distribution = FALSE,
  summary = TRUE
)

```

Arguments

object	A <code>stan_nma</code> object created by <code>nma()</code> .
...	Additional arguments, passed to <code>uniroot()</code> for regression models if <code>baseline_level = "aggregate"</code> .
baseline	<p>An optional <code>distr()</code> distribution for the baseline response (i.e. intercept), about which to produce absolute effects. Can also be a character string naming a study in the network to take the estimated baseline response distribution from. If <code>NULL</code>, predictions are produced using the baseline response for each study in the network with IPD or arm-based AgD.</p> <p>For regression models, this may be a list of <code>distr()</code> distributions (or study names in the network to use the baseline distributions from) of the same length as the number of studies in <code>newdata</code>, possibly named by the studies in <code>newdata</code> or otherwise in order of appearance in <code>newdata</code>.</p> <p>Use the <code>baseline_type</code> and <code>baseline_level</code> arguments to specify whether</p>

this distribution is on the response or linear predictor scale, and (for ML-NMR or models including IPD) whether this applies to an individual at the reference level of the covariates or over the entire newdata population, respectively. For example, in a model with a logit link with `baseline_type = "link"`, this would be a distribution for the baseline log odds of an event. For survival models, `baseline` always corresponds to the intercept parameters in the linear predictor (i.e. `baseline_type` is always "link", and `baseline_level` is "individual" for IPD NMA or ML-NMR, and "aggregate" for AgD NMA).

Use the `trt_ref` argument to specify which treatment this distribution applies to.

<code>newdata</code>	<p>Only required if a regression model is fitted and <code>baseline</code> is specified. A data frame of covariate details, for which to produce predictions. Column names must match variables in the regression model.</p> <p>If <code>level = "aggregate"</code> this should either be a data frame with integration points as produced by <code>add_integration()</code> (one row per study), or a data frame with individual covariate values (one row per individual) which are summarised over.</p> <p>If <code>level = "individual"</code> this should be a data frame of individual covariate values, one row per individual.</p> <p>If <code>NULL</code>, predictions are produced for all studies with IPD and/or arm-based AgD in the network, depending on the value of <code>level</code>.</p>
<code>study</code>	<p>Column of <code>newdata</code> which specifies study names or IDs. When not specified: if <code>newdata</code> contains integration points produced by <code>add_integration()</code>, studies will be labelled sequentially by row; otherwise data will be assumed to come from a single study.</p>
<code>trt_ref</code>	<p>Treatment to which the baseline response distribution refers, if <code>baseline</code> is specified. By default, the baseline response distribution will refer to the network reference treatment. Coerced to character string.</p>
<code>type</code>	<p>Whether to produce predictions on the "link" scale (the default, e.g. log odds) or "response" scale (e.g. probabilities).</p> <p>For survival models, the options are "survival" for survival probabilities (the default), "hazard" for hazards, "cumhaz" for cumulative hazards, "mean" for mean survival times, "quantile" for quantiles of the survival time distribution, "median" for median survival times (equivalent to <code>type = "quantile"</code> with <code>quantiles = 0.5</code>), "rmst" for restricted mean survival times, or "link" for the linear predictor. For <code>type = "survival"</code>, "hazard" or "cumhaz", predictions are given at the times specified by <code>times</code> or at the event/censoring times in the network if <code>times = NULL</code>. For <code>type = "rmst"</code>, the restricted time horizon is specified by <code>times</code>, or if <code>times = NULL</code> the earliest last follow-up time amongst the studies in the network is used. When <code>level = "aggregate"</code>, these all correspond to the standardised survival function (see details).</p>
<code>level</code>	<p>The level at which predictions are produced, either "aggregate" (the default), or "individual". If <code>baseline</code> is not specified, predictions are produced for all IPD studies in the network if <code>level</code> is "individual" or "aggregate", and for all arm-based AgD studies in the network if <code>level</code> is "aggregate".</p>

baseline_type	When a baseline distribution is given, specifies whether this corresponds to the "link" scale (the default, e.g. log odds) or "response" scale (e.g. probabilities). For survival models, baseline always corresponds to the intercept parameters in the linear predictor (i.e. baseline_type is always "link").
baseline_level	When a baseline distribution is given, specifies whether this corresponds to an individual at the reference level of the covariates ("individual", the default), or from an (unadjusted) average outcome on the reference treatment in the newdata population ("aggregate"). Ignored for AgD NMA, since the only option is "aggregate" in this instance. For survival models, baseline always corresponds to the intercept parameters in the linear predictor (i.e. baseline_level is "individual" for IPD NMA or ML-NMR, and "aggregate" for AgD NMA).
probs	Numeric vector of quantiles of interest to present in computed summary, default <code>c(0.025, 0.25, 0.5, 0.75, 0.975)</code>
predictive_distribution	Logical, when a random effects model has been fitted, should the predictive distribution for absolute effects in a new study be returned? Default FALSE.
summary	Logical, calculate posterior summaries? Default TRUE.
times	A numeric vector of times to evaluate predictions at. Alternatively, if newdata is specified, times can be the name of a column in newdata which contains the times. If NULL (the default) then predictions are made at the event/censoring times from the studies included in the network (or according to times_seq). Only used if type is "survival", "hazard", "cumhaz" or "rmst".
aux	An optional <code>distr()</code> distribution for the auxiliary parameter(s) in the baseline hazard (e.g. shapes). Can also be a character string naming a study in the network to take the estimated auxiliary parameter distribution from. If NULL, predictions are produced using the parameter estimates for each study in the network with IPD or arm-based AgD. For regression models, this may be a list of <code>distr()</code> distributions (or study names in the network to use the auxiliary parameters from) of the same length as the number of studies in newdata, possibly named by the study names or otherwise in order of appearance in newdata.
quantiles	A numeric vector of quantiles of the survival time distribution to produce estimates for when type = "quantile".
times_seq	A positive integer, when specified evaluate predictions at this many evenly-spaced event times between 0 and the latest follow-up time in each study, instead of every observed event/censoring time. Only used if newdata = NULL and type is "survival", "hazard" or "cumhaz". This can be useful for plotting survival or (cumulative) hazard curves, where prediction at every observed even/censoring time is unnecessary and can be slow. When a call from within plot() is detected, e.g. like <code>plot(predict(fit, type = "survival"))</code> , times_seq will default to 50.

Value

A `nma_summary` object if summary = TRUE, otherwise a list containing a 3D MCMC array of samples and (for regression models) a data frame of study information.

Aggregate-level predictions from IPD NMA and ML-NMR models

Population-average absolute effects can be produced from IPD NMA and ML-NMR models with `level = "aggregate"`. Predictions are averaged over the target population (i.e. standardised/marginalised), either by (numerical) integration over the joint covariate distribution (for AgD studies in the network for ML-NMR, or AgD newdata with integration points created by `add_integration()`), or by averaging predictions for a sample of individuals (for IPD studies in the network for IPD NMA/ML-NMR, or IPD newdata).

For example, with a binary outcome, the population-average event probabilities on treatment k in study/population j are

$$\bar{p}_{jk} = \int_{\mathfrak{X}} p_{jk}(\mathbf{x}) f_{jk}(\mathbf{x}) d\mathbf{x}$$

for a joint covariate distribution $f_{jk}(\mathbf{x})$ with support \mathfrak{X} or

$$\bar{p}_{jk} = \sum_i p_{jk}(\mathbf{x}_i)$$

for a sample of individuals with covariates \mathbf{x}_i .

Population-average absolute predictions follow similarly for other types of outcomes, however for survival outcomes there are specific considerations.

Standardised survival predictions:

Different types of population-average survival predictions, often called standardised survival predictions, follow from the **standardised survival function** created by integrating (or equivalently averaging) the individual-level survival functions at each time t :

$$\bar{S}_{jk}(t) = \int_{\mathfrak{X}} S_{jk}(t|\mathbf{x}) f_{jk}(\mathbf{x}) d\mathbf{x}$$

which is itself produced using `type = "survival"`.

The **standardised hazard function** corresponding to this standardised survival function is a weighted average of the individual-level hazard functions

$$\bar{h}_{jk}(t) = \frac{\int_{\mathfrak{X}} S_{jk}(t|\mathbf{x}) h_{jk}(t|\mathbf{x}) f_{jk}(\mathbf{x}) d\mathbf{x}}{\bar{S}_{jk}(t)}$$

weighted by the probability of surviving to time t . This is produced using `type = "hazard"`.

The corresponding **standardised cumulative hazard function** is

$$\bar{H}_{jk}(t) = -\log(\bar{S}_{jk}(t))$$

and is produced using `type = "cumhaz"`.

Quantiles and medians of the standardised survival times are found by solving

$$\bar{S}_{jk}(t) = 1 - \alpha$$

for the $\alpha\%$ quantile, using numerical root finding. These are produced using `type = "quantile"` or `"median"`.

(Restricted) means of the standardised survival times are found by integrating

$$\text{RMST}_{jk}(t^*) = \int_0^{t^*} \bar{S}_{jk}(t) dt$$

up to the restricted time horizon t^* , with $t^* = \infty$ for mean standardised survival time. These are produced using `type = "rmst"` or `"mean"`.

See Also

[plot.nma_summary\(\)](#) for plotting the predictions.

Examples

```
## Smoking cessation

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Predicted log odds of success in each study in the network
predict(smk_fit_RE)

# Predicted probabilities of success in each study in the network
predict(smk_fit_RE, type = "response")

# Predicted probabilities in a population with 67 observed events out of 566
# individuals on No Intervention, corresponding to a Beta(67, 566 - 67)
# distribution on the baseline probability of response, using
# `baseline_type = "response"`
(smk_pred_RE <- predict(smk_fit_RE,
  baseline = distr(qbeta, 67, 566 - 67),
  baseline_type = "response",
  type = "response"))
plot(smk_pred_RE, ref_line = c(0, 1))

# Predicted probabilities in a population with a baseline log odds of
# response on No Intervention given a Normal distribution with mean -2
# and SD 0.13, using `baseline_type = "link"` (the default)
# Note: this is approximately equivalent to the above Beta distribution on
# the baseline probability
(smk_pred_RE2 <- predict(smk_fit_RE,
  baseline = distr(qnorm, mean = -2, sd = 0.13),
  type = "response"))
plot(smk_pred_RE2, ref_line = c(0, 1))

## Plaque psoriasis ML-NMR

# Run plaque psoriasis ML-NMR example if not already available
if (!exists("pso_fit")) example("example_pso_mlnmr", run.donttest = TRUE)

# Predicted probabilities of response in each study in the network
(pso_pred <- predict(pso_fit, type = "response"))
plot(pso_pred, ref_line = c(0, 1))

# Predicted probabilities of response in a new target population, with means
# and SDs or proportions given by
new_agd_int <- data.frame(
  bsa_mean = 0.6,
```

```

    bsa_sd = 0.3,
    prevsys = 0.1,
    psa = 0.2,
    weight_mean = 10,
    weight_sd = 1,
    durnpso_mean = 3,
    durnpso_sd = 1
  )

# We need to add integration points to this data frame of new data
# We use the weighted mean correlation matrix computed from the IPD studies
new_agd_int <- add_integration(new_agd_int,
                             durnpso = distr(qgamma, mean = durnpso_mean, sd = durnpso_sd),
                             prevsys = distr(qbern, prob = prevsys),
                             bsa = distr(qlogitnorm, mean = bsa_mean, sd = bsa_sd),
                             weight = distr(qgamma, mean = weight_mean, sd = weight_sd),
                             psa = distr(qbern, prob = psa),
                             cor = pso_net$int_cor,
                             n_int = 64)

# Predicted probabilities of achieving PASI 75 in this target population, given
# a Normal(-1.75, 0.08^2) distribution on the baseline probit-probability of
# response on Placebo (at the reference levels of the covariates), are given by
(pso_pred_new <- predict(pso_fit,
                        type = "response",
                        newdata = new_agd_int,
                        baseline = distr(qnorm, -1.75, 0.08)))
plot(pso_pred_new, ref_line = c(0, 1))

## Progression free survival with newly-diagnosed multiple myeloma

# Run newly-diagnosed multiple myeloma example if not already available
if (!exists("ndmm_fit")) example("example_ndmm", run.donttest = TRUE)

# We can produce a range of predictions from models with survival outcomes,
# chosen with the type argument to predict

# Predicted survival probabilities at 5 years
predict(ndmm_fit, type = "survival", times = 5)

# Survival curves
plot(predict(ndmm_fit, type = "survival"))

# Hazard curves
# Here we specify a vector of times to avoid attempting to plot infinite
# hazards for some studies at t=0
plot(predict(ndmm_fit, type = "hazard", times = seq(0.001, 6, length.out = 50)))

# Cumulative hazard curves
plot(predict(ndmm_fit, type = "cumhaz"))

```

```

# Survival time quantiles and median survival
predict(ndmm_fit, type = "quantile", quantiles = c(0.2, 0.5, 0.8))
plot(predict(ndmm_fit, type = "median"))

# Mean survival time
predict(ndmm_fit, type = "mean")

# Restricted mean survival time
# By default, the time horizon is the shortest follow-up time in the network
predict(ndmm_fit, type = "rmst")

# An alternative restriction time can be set using the times argument
predict(ndmm_fit, type = "rmst", times = 5) # 5-year RMST

```

```
print.nma_data      Print nma_data objects
```

Description

Print details of networks stored as `nma_data` objects, as created by `set_ipd()`, `set_agd_arm()`, `set_agd_contrast()`, `set_agd_surv()`, or `combine_network()`.

Usage

```

## S3 method for class 'nma_data'
print(x, ..., n = 10)

## S3 method for class 'mInmr_data'
print(x, ..., n = 10)

```

Arguments

<code>x</code>	<code>nma_data</code> object
<code>...</code>	other options (not used)
<code>n</code>	number of studies of each type to print

Value

`x` is returned invisibly.

```
print.nma_dic          Print DIC details
```

Description

Print details of DIC model fit statistics, computed by `dic()` function.

Usage

```
## S3 method for class 'nma_dic'
print(x, digits = 1, ...)
```

Arguments

<code>x</code>	An object of class <code>nma_dic</code>
<code>digits</code>	An integer passed to <code>round()</code>
<code>...</code>	Ignored

Value

`x` is returned invisibly.

```
print.nma_nodesplit_df          Print nma_nodesplit_df objects
```

Description

Print `nma_nodesplit_df` objects

Usage

```
## S3 method for class 'nma_nodesplit_df'
print(x, ...)

## S3 method for class 'nma_nodesplit'
print(x, ...)
```

Arguments

<code>x</code>	A <code>nma_nodesplit_df</code> object
<code>...</code>	Further arguments passed to <code>print.stanfit()</code>

Value

`x` is returned invisibly.

See Also

The summary method `summary.nma_nodesplit_df()` summarises the node-splitting results.

print.nma_summary *Methods for nma_summary objects*

Description

The `as.data.frame()`, `as_tibble()`, and `as.tibble()` methods return the posterior summary statistics in a data frame or tibble. The `as.matrix()` method returns a matrix of posterior draws. The `as.array()` method returns a 3D array [Iteration, Chain, Parameter] of posterior draws (as class `mcmc_array`).

Usage

```
## S3 method for class 'nma_summary'
print(x, ..., digits = 2, pars, include = TRUE)
```

```
## S3 method for class 'nma_summary'
as.data.frame(x, ...)
```

```
## S3 method for class 'nma_summary'
as.tibble(x, ...)
```

```
## S3 method for class 'nma_summary'
as_tibble(x, ...)
```

```
## S3 method for class 'nma_summary'
as.array(x, ...)
```

```
## S3 method for class 'nma_summary'
as.matrix(x, ...)
```

```
## S3 method for class 'nma_rank_probs'
as.array(x, ...)
```

```
## S3 method for class 'nma_rank_probs'
as.matrix(x, ...)
```

Arguments

<code>x</code>	A <code>nma_summary</code> object
<code>...</code>	Additional arguments passed on to other methods
<code>digits</code>	Integer number of digits to display
<code>pars</code>	Character vector of parameters to display in the printed summary
<code>include</code>	Logical, are parameters named in <code>pars</code> included (TRUE) or excluded (FALSE)

Value

A `data.frame` for `as.data.frame()`, a `tbl_df` for `as.tibble()` and `as_tibble()`, a `matrix` for `as.matrix()`, and an `mcmc_array` for `as.array()`.

The `print()` method returns `x` invisibly.

See Also

[plot.nma_summary\(\)](#)

print.nodesplit_summary

Methods for nodesplit_summary objects

Description

The `as.data.frame()`, `as_tibble()`, and `as.tibble()` methods return the node-splitting summaries in a data frame or tibble.

Usage

```
## S3 method for class 'nodesplit_summary'
print(x, ..., digits = 2)

## S3 method for class 'nodesplit_summary'
as_tibble(x, ..., nest = FALSE)

as.tibble.nodesplit_summary(x, ..., nest = FALSE)

## S3 method for class 'nodesplit_summary'
as.data.frame(x, ...)
```

Arguments

<code>x</code>	A <code>nodesplit_summary</code> object
<code>...</code>	Additional arguments passed on to other methods
<code>digits</code>	Integer number of digits to display
<code>nest</code>	Whether to return a nested tibble, with the full nma_summary and nma_dic objects, or to unnest their summaries, default <code>FALSE</code>

Value

A `data.frame` for `as.data.frame()`, a `tbl_df` for `as.tibble()` and `as_tibble()`.

The `print()` method returns `x` invisibly.

See Also

[plot.nodesplit_summary\(\)](#)

print.stan_nma	<i>Print stan_nma objects</i>
----------------	-------------------------------

Description

Print stan_nma objects

Usage

```
## S3 method for class 'stan_nma'  
print(x, ...)
```

Arguments

x	A stan_nma object
...	Further arguments passed to print.stanfit()

Value

x is returned invisibly.

priors	<i>Prior distributions</i>
--------	----------------------------

Description

These functions are used to specify prior distributions for the model parameters.

Usage

```
normal(location = 0, scale)
```

```
half_normal(scale)
```

```
log_normal(location, scale)
```

```
cauchy(location = 0, scale)
```

```
half_cauchy(scale)
```

```
student_t(location = 0, scale, df)
```

```
half_student_t(scale, df)
```

```
log_student_t(location, scale, df)
```

```
exponential(scale = 1/rate, rate = 1/scale)
```

```
flat()
```

Arguments

location	Prior location. Typically prior mean (see details).
scale	Prior scale. Typically prior standard deviation (see details).
df	Prior degrees of freedom.
rate	Prior rate.

Details

The location and scale parameters are typically the prior mean and standard deviation, with the following exceptions:

- For the Cauchy distribution location is the prior median and scale is the prior scale.
- For the log-Normal distribution, location and scale are the prior mean and standard deviation of the logarithm.

Compatibility with model parameters:

The following table summarises which prior distributions may be used with which model parameters. Essentially, priors that take only non-negative values (e.g. half-Normal) may only be used for non-negative parameters (heterogeneity SD/variance/precision, and any auxiliary parameter). If a real-valued prior distribution is specified for a non-negative parameter, it will be truncated at 0 to be non-negative.

	Intercept prior_intercept	Treatment effects prior_trt	Heterogeneity prior_
Normal normal()	Yes	Yes	Yes
half-Normal half_normal()	-	-	Yes
log-Normal log_normal()	-	-	Yes
Cauchy cauchy()	Yes	Yes	Yes
half-Cauchy half_cauchy()	-	-	Yes
Student t student_t()	Yes	Yes	Yes
half-Student t half_student_t()	-	-	Yes
log-Student t log_student_t()	-	-	Yes
Exponential exponential()	-	-	Yes
Flat flat()	Yes	Yes	Yes

The flat() prior is a special case where no prior information is added to the model, resulting in an implicit flat uniform prior distribution over the entire support for a parameter. This will be an improper prior if the parameter is unbounded, and is not generally advised. See the [Stan user's guide](#) for more details.

Value

Object of class `nma_prior`.

See Also

`summary.nma_prior()` for summarising details of prior distributions. `plot_prior_posterior()` for plots comparing the prior and posterior distributions of model parameters.

qbern

The Bernoulli Distribution

Description

The density function `dbern()`, distribution function `pbern()`, and quantile function `qbern()` for a Bernoulli distribution, with success probability `prob`. These are equivalent to `dbinom(p, 1, prob)`, `pbinom(p, 1, prob)` and `qbinom(p, 1, prob)`.

Usage

```
qbern(p, prob, lower.tail = TRUE, log.p = FALSE)
```

```
pbern(q, prob, lower.tail = TRUE, log.p = FALSE)
```

```
dbern(x, prob, log = FALSE)
```

Arguments

`p` vector of probabilities

`prob` probability of success

`lower.tail`, `log.p`, `log`
see [stats::Binomial](#)

`x`, `q` vector of quantiles

Value

Numeric vector of length equal to the maximum of the lengths of the input arguments.

qgamma

The Gamma distribution

Description

We provide convenient extensions of the [dpq]gamma functions, which allow the distribution to be specified in terms of its mean and standard deviation, instead of shape and rate/scale.

Usage

```
qgamma(  
  p,  
  shape,  
  rate = 1,  
  scale = 1/rate,  
  lower.tail = TRUE,  
  log.p = FALSE,  
  mean,  
  sd  
)
```

```
dgamma(x, shape, rate = 1, scale = 1/rate, log = FALSE, mean, sd)
```

```
pgamma(  
  q,  
  shape,  
  rate = 1,  
  scale = 1/rate,  
  lower.tail = TRUE,  
  log.p = FALSE,  
  mean,  
  sd  
)
```

Arguments

p	vector of probabilities
shape, rate, scale, log, lower.tail, log.p	see stats::GammaDist
mean, sd	mean and standard deviation, overriding shape and rate or scale if specified
x, q	vector of quantiles

Value

Numeric vector of length equal to the maximum of the lengths of the input arguments.

qlogitnorm	<i>The logit Normal distribution</i>
------------	--------------------------------------

Description

We provide convenient extensions of the [dpq]logitnorm functions in the package [logitnorm](#), which allow the distribution to be specified in terms of its mean and standard deviation, instead of its logit-mean and logit-sd.

Usage

```
qlogitnorm(p, mu = 0, sigma = 1, ..., mean, sd)
```

```
dlogitnorm(x, mu = 0, sigma = 1, ..., mean, sd)
```

```
plogitnorm(q, mu = 0, sigma = 1, ..., mean, sd)
```

Arguments

p, x	vector of quantiles
mu, sigma, ...	see logitnorm
mean, sd	mean and standard deviation, overriding mu and sigma if specified
q	vector of probabilities

Value

Numeric vector of length equal to the maximum of the lengths of the input arguments.

relative_effects	<i>Relative treatment effects</i>
------------------	-----------------------------------

Description

Generate (population-average) relative treatment effects. If a ML-NMR or meta-regression model was fitted, these are specific to each study population.

Usage

```
relative_effects(  
  x,  
  newdata = NULL,  
  study = NULL,  
  all_contrasts = FALSE,  
  trt_ref = NULL,  
  probs = c(0.025, 0.25, 0.5, 0.75, 0.975),
```

```

    predictive_distribution = FALSE,
    summary = TRUE
  )

```

Arguments

x	A stan_nma object created by nma()
newdata	Only used if a regression model is fitted. A data frame of study details, one row per study, giving the covariate values at which to produce relative effects. Column names must match variables in the regression model. If NULL, relative effects are produced for all studies in the network.
study	Column of newdata which specifies study names, otherwise studies will be labelled by row number.
all_contrasts	Logical, generate estimates for all contrasts (TRUE), or just the "basic" contrasts against the network reference treatment (FALSE)? Default FALSE.
trt_ref	Reference treatment to construct relative effects against, if all_contrasts = FALSE. By default, relative effects will be against the network reference treatment. Coerced to character string.
probs	Numeric vector of quantiles of interest to present in computed summary, default <code>c(0.025, 0.25, 0.5, 0.75, 0.975)</code>
predictive_distribution	Logical, when a random effects model has been fitted, should the predictive distribution for relative effects in a new study be returned? Default FALSE.
summary	Logical, calculate posterior summaries? Default TRUE.

Value

A [nma_summary](#) object if `summary = TRUE`, otherwise a list containing a 3D MCMC array of samples and (for regression models) a data frame of study information.

See Also

[plot.nma_summary\(\)](#) for plotting the relative effects.

Examples

```

## Smoking cessation

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Produce relative effects
smk_releff_RE <- relative_effects(smk_fit_RE)
smk_releff_RE
plot(smk_releff_RE, ref_line = 0)

# Relative effects for all pairwise comparisons

```

```

relative_effects(smkn_fit_RE, all_contrasts = TRUE)

# Relative effects against a different reference treatment
relative_effects(smkn_fit_RE, trt_ref = "Self-help")

# Transforming to odds ratios
# We work with the array of relative effects samples
LOR_array <- as.array(smkn_releff_RE)
OR_array <- exp(LOR_array)

# mcmc_array objects can be summarised to produce a nma_summary object
smkn_OR_RE <- summary(OR_array)

# This can then be printed or plotted
smkn_OR_RE
plot(smkn_OR_RE, ref_line = 1)

## Plaque psoriasis ML-NMR

# Run plaque psoriasis ML-NMR example if not already available
if (!exists("pso_fit")) example("example_pso_mlnmr", run.donttest = TRUE)

# Produce population-adjusted relative effects for all study populations in
# the network
pso_releff <- relative_effects(pso_fit)
pso_releff
plot(pso_releff, ref_line = 0)

# Produce population-adjusted relative effects for a different target
# population
new_agd_means <- data.frame(
  bsa = 0.6,
  prevsys = 0.1,
  psa = 0.2,
  weight = 10,
  durnpso = 3)

relative_effects(pso_fit, newdata = new_agd_means)

```

RE_cor

Random effects structure

Description

Use RE_cor to generate the random effects correlation matrix, under the assumption of common heterogeneity variance (i.e. all within-study correlations are 0.5). Use which_RE to return a vector of IDs for the RE deltas (0 means no RE delta on this arm).

Usage

```
RE_cor(study, trt, contrast, type = c("reftrt", "blshift"))

which_RE(study, trt, contrast, type = c("reftrt", "blshift"))
```

Arguments

study	A vector of study IDs (integer, character, or factor)
trt	A factor vector of treatment codes (or coercible as such), with first level indicating the reference treatment
contrast	A logical vector, of the same length as study and trt, indicating whether the corresponding data are in contrast rather than arm format.
type	Character string, whether to generate RE structure under the "reference treatment" parameterisation, or the "baseline shift" parameterisation.

Value

For `RE_cor()`, a correlation matrix of dimension equal to the number of random effects deltas (excluding those that are set equal to zero).

For `which_RE()`, an integer vector of IDs indexing the rows and columns of the correlation matrix returned by `RE_cor()`.

Examples

```
RE_cor(smoking$studyn, smoking$trtn, contrast = rep(FALSE, nrow(smoking)))
RE_cor(smoking$studyn, smoking$trtn, contrast = rep(FALSE, nrow(smoking)), type = "blshift")
which_RE(smoking$studyn, smoking$trtn, contrast = rep(FALSE, nrow(smoking)))
which_RE(smoking$studyn, smoking$trtn, contrast = rep(FALSE, nrow(smoking)), type = "blshift")
```

set_agd_arm	<i>Set up arm-based aggregate data</i>
-------------	--

Description

Set up a network containing arm-based aggregate data (AgD), such as event counts or mean outcomes on each arm. Multiple data sources may be combined once created using `combine_network()`.

Usage

```
set_agd_arm(
  data,
  study,
  trt,
  y = NULL,
  se = NULL,
  r = NULL,
```

```

n = NULL,
E = NULL,
sample_size = NULL,
trt_ref = NULL,
trt_class = NULL
)

```

Arguments

data	a data frame
study	column of data specifying the studies, coded using integers, strings, or factors
trt	column of data specifying treatments, coded using integers, strings, or factors
y	column of data specifying a continuous outcome
se	column of data specifying the standard error for a continuous outcome
r	column of data specifying a binary or Binomial outcome count
n	column of data specifying Binomial outcome numerator
E	column of data specifying the total time at risk for Poisson outcomes
sample_size	column of data giving the sample size in each arm. Optional, see details.
trt_ref	reference treatment for the network, as a single integer, string, or factor. If not specified, a reasonable well-connected default will be chosen (see details).
trt_class	column of data specifying treatment classes, coded using integers, strings, or factors. By default, no classes are specified.

Details

By default, `trt_ref = NULL` and a network reference treatment will be chosen that attempts to maximise computational efficiency and stability. If an alternative reference treatment is chosen and the model runs slowly or has low effective sample size (ESS) this may be the cause - try letting the default reference treatment be used instead. Regardless of which treatment is used as the network reference at the model fitting stage, results can be transformed afterwards: see the `trt_ref` argument of [relative_effects\(\)](#) and [predict.stan_nma\(\)](#).

The `sample_size` argument is optional, but when specified:

- Enables automatic centering of predictors (`center = TRUE`) in [nma\(\)](#) when a regression model is given for a network combining IPD and AgD
- Enables production of study-specific relative effects, rank probabilities, etc. for studies in the network when a regression model is given
- Nodes in [plot.nma_data\(\)](#) may be weighted by sample size

If a Binomial outcome is specified and `sample_size` is omitted, `n` will be used as the sample size by default. If a Multinomial outcome is specified and `sample_size` is omitted, the sample size will be determined automatically from the supplied counts by default.

All arguments specifying columns of data accept the following:

- A column name as a character string, e.g. `study = "studyc"`
- A bare column name, e.g. `study = studyc`
- `dplyr::mutate()` style semantics for inline variable transformations, e.g. `study = paste(author, year)`

Value

An object of class `nma_data`

See Also

`set_ipd()` for individual patient data, `set_agd_contrast()` for contrast-based aggregate data, and `combine_network()` for combining several data sources in one network.

`print.nma_data()` for the print method displaying details of the network, and `plot.nma_data()` for network plots.

Examples

```
# Set up network of smoking cessation data
head(smoking)

smk_net <- set_agd_arm(smoking,
                      study = studyn,
                      trt = trtc,
                      r = r,
                      n = n,
                      trt_ref = "No intervention")

# Print details
smk_net

# Plot network
plot(smk_net)
```

<code>set_agd_contrast</code>	<i>Set up contrast-based aggregate data</i>
-------------------------------	---

Description

Set up a network containing contrast-based aggregate data (AgD), i.e. summaries of relative effects between treatments such as log Odds Ratios. Multiple data sources may be combined once created using `combine_network()`.

Usage

```
set_agd_contrast(
  data,
  study,
  trt,
  y = NULL,
  se = NULL,
  sample_size = NULL,
  trt_ref = NULL,
```



```

    trt_class = NULL
  )

```

Arguments

<code>data</code>	a data frame
<code>study</code>	column of data specifying the studies, coded using integers, strings, or factors
<code>trt</code>	column of data specifying treatments, coded using integers, strings, or factors
<code>y</code>	column of data specifying a continuous outcome
<code>se</code>	column of data specifying the standard error for a continuous outcome
<code>sample_size</code>	column of data giving the sample size in each arm. Optional, see details.
<code>trt_ref</code>	reference treatment for the network, as a single integer, string, or factor. If not specified, a reasonable well-connected default will be chosen (see details).
<code>trt_class</code>	column of data specifying treatment classes, coded using integers, strings, or factors. By default, no classes are specified.

Details

Each study should have a single reference/baseline treatment, against which relative effects in the other arm(s) are given. For the reference arm, include a data row with continuous outcome `y` equal to NA. If a study has three or more arms (so two or more relative effects), set the standard error `se` for the reference arm data row equal to the standard error of the mean outcome on the reference arm (this determines the covariance of the relative effects, when expressed as differences in mean outcomes between arms).

All arguments specifying columns of data accept the following:

- A column name as a character string, e.g. `study = "studyc"`
- A bare column name, e.g. `study = studyc`
- `dplyr::mutate()` style semantics for inline variable transformations, e.g. `study = paste(author, year)`

By default, `trt_ref = NULL` and a network reference treatment will be chosen that attempts to maximise computational efficiency and stability. If an alternative reference treatment is chosen and the model runs slowly or has low effective sample size (ESS) this may be the cause - try letting the default reference treatment be used instead. Regardless of which treatment is used as the network reference at the model fitting stage, results can be transformed afterwards: see the `trt_ref` argument of [relative_effects\(\)](#) and [predict.stan_nma\(\)](#).

The `sample_size` argument is optional, but when specified:

- Enables automatic centering of predictors (`center = TRUE`) in [nma\(\)](#) when a regression model is given for a network combining IPD and AgD
- Enables production of study-specific relative effects, rank probabilities, etc. for studies in the network when a regression model is given
- Nodes in [plot.nma_data\(\)](#) may be weighted by sample size

Value

An object of class `nma_data`

See Also

`set_ipd()` for individual patient data, `set_agd_arm()` for arm-based aggregate data, and `combine_network()` for combining several data sources in one network.

`print.nma_data()` for the print method displaying details of the network, and `plot.nma_data()` for network plots.

Examples

```
# Set up network of Parkinson's contrast data
head(parkinsons)

park_net <- set_agd_contrast(parkinsons,
                            study = studyn,
                            trt = trtn,
                            y = diff,
                            se = se_diff,
                            sample_size = n)

# Print details
park_net

# Plot network
plot(park_net)
```

<code>set_agd_surv</code>	<i>Set up aggregate survival data</i>
---------------------------	---------------------------------------

Description

Set up a network containing aggregate survival data (AgD) in the form of event/censoring times (e.g. reconstructed from digitized Kaplan-Meier curves) and covariate summary statistics from each study. Multiple data sources may be combined once created using `combine_network()`.

Usage

```
set_agd_surv(
  data,
  study,
  trt,
  Surv,
  covariates = NULL,
  trt_ref = NULL,
  trt_class = NULL
)
```

Arguments

data	a data frame
study	column of data specifying the studies, coded using integers, strings, or factors
trt	column of data specifying treatments, coded using integers, strings, or factors
Surv	column of data specifying a survival or time-to-event outcome, using the Surv() function. Right/left/interval censoring and left truncation (delayed entry) are supported.
covariates	data frame of covariate summary statistics for each study or study arm, with corresponding study and trt columns to match to those in data
trt_ref	reference treatment for the network, as a single integer, string, or factor. If not specified, a reasonable well-connected default will be chosen (see details).
trt_class	column of data specifying treatment classes, coded using integers, strings, or factors. By default, no classes are specified.

Details

By default, `trt_ref = NULL` and a network reference treatment will be chosen that attempts to maximise computational efficiency and stability. If an alternative reference treatment is chosen and the model runs slowly or has low effective sample size (ESS) this may be the cause - try letting the default reference treatment be used instead. Regardless of which treatment is used as the network reference at the model fitting stage, results can be transformed afterwards: see the `trt_ref` argument of [relative_effects\(\)](#) and [predict.stan_nma\(\)](#).

All arguments specifying columns of data accept the following:

- A column name as a character string, e.g. `study = "studyc"`
- A bare column name, e.g. `study = studyc`
- `dplyr::mutate()` style semantics for inline variable transformations, e.g. `study = paste(author, year)`

Value

An object of class [nma_data](#)

See Also

[set_ipd\(\)](#) for individual patient data, [set_agd_contrast\(\)](#) for contrast-based aggregate data, and [combine_network\(\)](#) for combining several data sources in one network.

[print.nma_data\(\)](#) for the print method displaying details of the network, and [plot.nma_data\(\)](#) for network plots.

Examples

```
## Newly diagnosed multiple myeloma

head(ndmm_agd) # Reconstructed Kaplan-Meier data
ndmm_agd_covs # Summary covariate information on each arm
```

```

set_agd_surv(ndmm_agd,
             study = studyf,
             trt = trtf,
             Surv = Surv(eventtime, status),
             covariates = ndmm_agd_covs)

```

set_ipd

Set up individual patient data

Description

Set up a network containing individual patient data (IPD). Multiple data sources may be combined once created using [combine_network\(\)](#).

Usage

```

set_ipd(
  data,
  study,
  trt,
  y = NULL,
  r = NULL,
  E = NULL,
  Surv = NULL,
  trt_ref = NULL,
  trt_class = NULL
)

```

Arguments

data	a data frame
study	column of data specifying the studies, coded using integers, strings, or factors
trt	column of data specifying treatments, coded using integers, strings, or factors
y	column of data specifying a continuous outcome
r	column of data specifying a binary outcome or Poisson outcome count
E	column of data specifying the total time at risk for Poisson outcomes
Surv	column of data specifying a survival or time-to-event outcome, using the Surv() function. Right/left/interval censoring and left truncation (delayed entry) are supported.
trt_ref	reference treatment for the network, as a single integer, string, or factor. If not specified, a reasonable well-connected default will be chosen (see details).
trt_class	column of data specifying treatment classes, coded using integers, strings, or factors. By default, no classes are specified.

Details

By default, `trt_ref = NULL` and a network reference treatment will be chosen that attempts to maximise computational efficiency and stability. If an alternative reference treatment is chosen and the model runs slowly or has low effective sample size (ESS) this may be the cause - try letting the default reference treatment be used instead. Regardless of which treatment is used as the network reference at the model fitting stage, results can be transformed afterwards: see the `trt_ref` argument of [relative_effects\(\)](#) and [predict.stan_nma\(\)](#).

All arguments specifying columns of data accept the following:

- A column name as a character string, e.g. `study = "studyc"`
- A bare column name, e.g. `study = studyc`
- `dplyr::mutate()` style semantics for inline variable transformations, e.g. `study = paste(author, year)`

Value

An object of class `nma_data`

See Also

[set_agd_arm\(\)](#) for arm-based aggregate data, [set_agd_contrast\(\)](#) for contrast-based aggregate data, and [combine_network\(\)](#) for combining several data sources in one network.

[print.nma_data\(\)](#) for the print method displaying details of the network, and [plot.nma_data\(\)](#) for network plots.

Examples

```
# Set up network of plaque psoriasis IPD
head(plaque_psoriasis_ipd)

pso_net <- set_ipd(plaque_psoriasis_ipd,
                  study = studyc,
                  trt = trtc,
                  r = pasi75)

# Print network details
pso_net

# Plot network
plot(pso_net)

# Setting a different reference treatment
set_ipd(plaque_psoriasis_ipd,
        study = studyc,
        trt = trtc,
        r = pasi75,
        trt_ref = "PBO")
```

smoking

Smoking cessation data

Description

Data frame containing the results of 24 trials of 4 smoking cessation treatments (Hasselblad 1998; Dias et al. 2011).

Usage

```
smoking
```

Format

A data frame with 50 rows and 5 variables:

studyn numeric study ID

trtn numeric treatment code

trtc treatment name

r total number of events

n total number of individuals

References

Dias S, Welton NJ, Sutton AJ, Caldwell DM, Lu G, Ades AE (2011). “NICE DSU Technical Support Document 4: Inconsistency in networks of evidence based on randomised controlled trials.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Hasselblad V (1998). “Meta-analysis of Multitreatment Studies.” *Medical Decision Making*, **18**(1), 37–43. doi:10.1177/0272989x9801800110.

stan_nma-class*The stan_nma class*

Description

The `stan_nma` and `stan_mlnmr` classes contains the results from running a model with the function `nma()`.

Details

Objects of class `stan_nma` and `stan_mlnmr` have the following components:

`network` The network data from which the model was run (class `nma_data` for `stan_nma`, or class `mlnmr_data` for `stan_mlnmr`)

`stanfit` The `stanfit` object returned by calling `sampling()` for the model

`trt_effects` Whether fixed or random effects were used (character string)

`consistency` The consistency/inconsistency model used (character string)

`regression` The regression model used (formula)

`class_interactions` If treatment classes and a regression model are specified, the model used for interactions within each class (common, exchangeable, or independent)

`xbar` A named vector of values used for centering

`likelihood` The likelihood used (character string)

`link` The link function used (character string)

`priors` A list containing the priors used (as `nma_prior` objects)

`basis` For `mspline` and `pexp` models, a named list of spline bases for each study

The `stan_mlnmr` sub-class inherits from `stan_nma`, and differs only in the class of the network object.

statins

Statins for cholesterol lowering

Description

Data frame containing the results of 19 trials comparing statins to placebo or usual care (Dias et al. 2011). The number of deaths (all-cause mortality) are recorded. In some studies the aim was primary prevention (patients had no previous heart disease), and in others the aim was secondary prevention (patients had previous heart disease).

Usage

`statins`

Format

A data frame with 38 rows and 7 variables:

studyn numeric study ID

studyc study name

trtn numeric treatment code

trtc treatment name

prevention primary or secondary prevention study

r number of deaths

n sample size

References

Dias S, Sutton AJ, Welton NJ, Ades AE (2011). “NICE DSU Technical Support Document 3: Heterogeneity: subgroups, meta-regression, bias and bias-adjustment.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

```
summary.nma_nodesplit_df
```

Summarise the results of node-splitting models

Description

Posterior summaries of node-splitting models (`nma_nodesplit` and `nma_nodesplit_df` objects) can be produced using the `summary()` method, and plotted using the `plot()` method.

Usage

```
## S3 method for class 'nma_nodesplit_df'
summary(
  object,
  consistency = NULL,
  ...,
  probs = c(0.025, 0.25, 0.5, 0.75, 0.975)
)

## S3 method for class 'nma_nodesplit'
summary(
  object,
  consistency = NULL,
  ...,
  probs = c(0.025, 0.25, 0.5, 0.75, 0.975)
)

## S3 method for class 'nma_nodesplit'
plot(x, consistency = NULL, ...)

## S3 method for class 'nma_nodesplit_df'
plot(x, consistency = NULL, ...)
```

Arguments

<code>consistency</code>	Optional, a <code>stan_nma</code> object for the corresponding fitted consistency model, to display the network estimates alongside the direct and indirect estimates. The fitted consistency model present in the <code>nma_nodesplit_df</code> object will be used if this is present (see <code>get_nodesplits()</code>).
<code>...</code>	Additional arguments passed on to other methods

probs	Numeric vector of specifying quantiles of interest, default <code>c(0.025, 0.25, 0.5, 0.75, 0.975)</code>
x, object	A <code>nma_nodesplit</code> or <code>nma_nodesplit_df</code> object

Details

The `plot()` method is a shortcut for `plot(summary(nma_nodesplit))`. For details of plotting options, see [plot.nodesplit_summary\(\)](#).

Value

A `nodesplit_summary` object

See Also

[plot.nodesplit_summary\(\)](#)

Examples

```
# Run smoking node-splitting example if not already available
if (!exists("smk_fit_RE_nodesplit")) example("example_smk_nodesplit", run.donttest = TRUE)

# Summarise the node-splitting results
summary(smk_fit_RE_nodesplit)

# Plot the node-splitting results
plot(smk_fit_RE_nodesplit)
```

summary.nma_prior	<i>Summary of prior distributions</i>
-------------------	---------------------------------------

Description

Print a summary of prior distribution details.

Usage

```
## S3 method for class 'nma_prior'
summary(object, ..., probs = c(0.5, 0.95), digits = 2, trunc = NULL)
```

Arguments

object	Prior distribution as a nma_prior object
...	Additional arguments, not used
probs	Numeric vector of probabilities to calculate prior intervals
digits	Number of digits to display
trunc	Optional numeric vector of length 2, giving the truncation limits of the prior distribution. Useful if a real-valued prior is assigned to a positive-valued parameter, then trunc = c(0, Inf) will give the correct prior intervals. By default, truncation is not used.

Value

A data frame is returned invisibly, giving the prior intervals

Examples

```
summary(normal(location = 0, scale = 1))
summary(half_normal(scale = 1))
summary(log_normal(location = -3.93, scale = 1.51))

# Truncation limits may be set, for example to restrict a prior to positive values
summary(normal(location = 0.5, scale = 1), trunc = c(0, Inf))
```

summary.stan_nma *Posterior summaries from stan_nma objects*

Description

Posterior summaries of model parameters in stan_nma objects may be produced using the summary() method and plotted with the plot() method. NOTE: To produce relative effects, absolute predictions, or posterior ranks, see [relative_effects\(\)](#), [predict.stan_nma\(\)](#), [posterior_ranks\(\)](#), [posterior_rank_probs\(\)](#).

Usage

```
## S3 method for class 'stan_nma'
summary(object, ..., pars, include, probs = c(0.025, 0.25, 0.5, 0.75, 0.975))

## S3 method for class 'stan_nma'
plot(
  x,
  ...,
  pars,
  include,
  stat = "pointinterval",
```

```
orientation = c("horizontal", "vertical", "y", "x"),
ref_line = NA_real_
)
```

Arguments

...	Additional arguments passed on to other methods
pars, include	See rstan::extract()
probs	Numeric vector of specifying quantiles of interest, default <code>c(0.025, 0.25, 0.5, 0.75, 0.975)</code>
x, object	A <code>stan_nma</code> object
stat	Character string specifying the <code>ggdist</code> plot stat to use, default <code>"pointinterval"</code>
orientation	Whether the <code>ggdist</code> geom is drawn horizontally (<code>"horizontal"</code>) or vertically (<code>"vertical"</code>), default <code>"horizontal"</code>
ref_line	Numeric vector of positions for reference lines, by default no reference lines are drawn
summary	Logical, calculate posterior summaries? Default <code>TRUE</code> .

Details

The `plot()` method is a shortcut for `plot(summary(stan_nma))`. For details of plotting options, see [plot.nma_summary\(\)](#).

Value

A `nma_summary` object

See Also

[plot.nma_summary\(\)](#), [relative_effects\(\)](#), [predict.stan_nma\(\)](#), [posterior_ranks\(\)](#), [posterior_rank_probs\(\)](#)

Examples

```
## Smoking cessation

# Run smoking RE NMA example if not already available
if (!exists("smk_fit_RE")) example("example_smk_re", run.donttest = TRUE)

# Summary and plot of all model parameters
summary(smk_fit_RE)
plot(smk_fit_RE)

# Summary and plot of heterogeneity tau only
summary(smk_fit_RE, pars = "tau")
plot(smk_fit_RE, pars = "tau")

# Customising plot output
plot(smk_fit_RE,
```

```
pars = c("d", "tau"),
stat = "halfeye",
ref_line = 0)
```

theme_multinma	<i>Plot theme for multinma plots</i>
----------------	--------------------------------------

Description

A simple ggplot2 theme for plots in the multinma package.

Usage

```
theme_multinma(...)
```

Arguments

... Arguments passed to `ggplot2::theme_light()`

Value

A ggplot2 theme

See Also

`ggplot2::theme()`, `ggplot2::theme_set()`

Examples

```
library(ggplot2)
theme_set(theme_multinma())
```

thrombolytics	<i>Thrombolytic treatments data</i>
---------------	-------------------------------------

Description

Data frame containing the results of 50 trials of 8 thrombolytic drugs (streptokinase, SK; alteplase, t-PA; accelerated alteplase, Acc t-PA; streptokinase plus alteplase, SK+tPA; reteplase, r-PA; tenecteplase, TNK; urokinase, UK; anistreplase, ASPAC) plus per-cutaneous transluminal coronary angioplasty (PTCA) (Boland et al. 2003; Lu and Ades 2006; Dias et al. 2011). The number of deaths in 30 or 35 days following acute myocardial infarction are recorded.

Usage

thrombolytics

Format

A data frame with 102 rows and 5 variables:

studyn numeric study ID

trtn numeric treatment code

trtc treatment name

r total number of events

n total number of individuals

References

Boland A, Dunder Y, Bagust A, Haycox A, Hill R, Mota RM, Walley T, Dickson R (2003). “Early thrombolysis for the treatment of acute myocardial infarction: a systematic review and economic evaluation.” *Health Technology Assessment*, **7**(15). doi:10.3310/hta7150.

Dias S, Welton NJ, Sutton AJ, Caldwell DM, Lu G, Ades AE (2011). “NICE DSU Technical Support Document 4: Inconsistency in networks of evidence based on randomised controlled trials.” National Institute for Health and Care Excellence. <https://www.sheffield.ac.uk/nice-dsu>.

Lu GB, Ades AE (2006). “Assessing evidence inconsistency in mixed treatment comparisons.” *Journal of the American Statistical Association*, **101**(474), 447–459. doi:10.1198/016214505000001302.

transfusion

Granulocyte transfusion in patients with neutropenia or neutrophil dysfunction

Description

Data frame containing the number of deaths in 6 trials comparing transfusion of granulocytes (white blood cells) to control (Stanworth et al. 2005). Previously used to demonstrate informative prior distributions for the heterogeneity variance by Turner et al. (2012).

Usage

transfusion

Format

A data frame with 12 rows and 4 variables:

studyc study name

trtc treatment name

r total number of deaths

n total number of individuals

References

Stanworth S, Massey E, Hyde C, Brunskill SJ, Navarette C, Lucas G, Marks D, Paulus U (2005). “Granulocyte transfusions for treating infections in patients with neutropenia or neutrophil dysfunction.” *Cochrane Database of Systematic Reviews*. ISSN 1465-1858, doi:10.1002/14651858.CD005339.

Turner RM, Davey J, Clarke MJ, Thompson SG, Higgins JPT (2012). “Predicting the extent of heterogeneity in meta-analysis, using empirical data from the Cochrane Database of Systematic Reviews.” *International Journal of Epidemiology*, **41**(3), 818–827. doi:10.1093/ije/dys041.

Index

- * **datasets**
 - atrial_fibrillation, 13
 - bcg_vaccine, 14
 - blocker, 15
 - diabetes, 19
 - dietary_fat, 21
 - hta_psoriasis, 35
 - ndmm_ipd, 43
 - parkinsons, 58
 - plaque_psoriasis_ipd, 59
 - smoking, 102
 - statins, 103
 - thrombolytics, 108
 - transfusion, 109
- * **examples**
 - example_ndmm, 25
 - example_pso_mlnmr, 26
 - example_smk_fe, 28
 - example_smk_nodesplit, 29
 - example_smk_re, 30
 - example_smk_ume, 30
 - .default, 5
 - .is_default(.default), 5
 - ?priors, 47
- adapt_delta, 6, 46
- add_integration, 6
- add_integration(), 22, 46, 53, 70, 78, 80
- as.array.nma_rank_probs
 - (print.nma_summary), 85
- as.array.nma_summary
 - (print.nma_summary), 85
- as.array.stan_nma, 10
- as.array.stanfit(), 11
- as.data.frame.nma_summary
 - (print.nma_summary), 85
- as.data.frame.nodesplit_summary
 - (print.nodesplit_summary), 86
- as.data.frame.stan_nma
 - (as.array.stan_nma), 10
- as.igraph.nma_data, 11
- as.matrix.nma_rank_probs
 - (print.nma_summary), 85
- as.matrix.nma_summary
 - (print.nma_summary), 85
- as.matrix.stan_nma (as.array.stan_nma), 10
- as.stanfit, 12
- as.tibble.nma_summary
 - (print.nma_summary), 85
- as.tibble.nodesplit_summary
 - (print.nodesplit_summary), 86
- as.tibble.stan_nma (as.array.stan_nma), 10
- as_ttbl_graph.nma_data
 - (as.igraph.nma_data), 11
- as_tibble.nma_summary
 - (print.nma_summary), 85
- as_tibble.nodesplit_summary
 - (print.nodesplit_summary), 86
- as_tibble.stan_nma (as.array.stan_nma), 10
- atrial_fibrillation, 13
- bayesplot, 11
- bayesplot::mcmc_pairs(), 57, 58
- bcg_vaccine, 14
- blocker, 15
- cauchy (priors), 87
- combine_network, 15
- combine_network(), 53, 83, 94, 96, 98–101
- cor(), 8
- dbern (qbern), 89
- dgamma (qgamma), 90
- dgent, 18
- diabetes, 19
- dic, 19
- dic(), 54, 63, 84

- dietary_fat, 21
- distr, 22, 22
- distr(), 7, 77, 79
- dlogitnorm (qlogitnorm), 91
- dlogt, 23
- dmspline, 24

- example_ndmm, 25
- example_pso mlnmr, 26
- example_smk_fe, 28
- example_smk_nodesplit, 29
- example_smk_re, 30
- example_smk_ume, 30
- exponential (priors), 87

- flat (priors), 87
- flexsurv::qgeneric(), 24
- flexsurv::rmst_generic(), 24

- geom_km, 31
- get_nodesplits, 33
- get_nodesplits(), 45, 104
- ggdist, 66, 68
- ggdist::stat_lineribbon(), 66
- ggdist::stat_pointinterval(), 66
- ggplot2, 66, 68
- ggplot2::geom_density(), 68
- ggplot2::geom_histogram, 72
- ggplot2::geom_path, 72
- ggplot2::geom_point(), 32
- ggplot2::geom_step(), 32
- ggplot2::theme(), 108
- ggplot2::theme_light(), 108
- ggplot2::theme_set(), 108
- ggraph, 11
- ggraph(), 61, 62

- half_cauchy (priors), 87
- half_normal (priors), 87
- half_student_t (priors), 87
- has_direct (get_nodesplits), 33
- has_indirect (get_nodesplits), 33
- Hmspline (dmspline), 24
- hmspline (dmspline), 24
- hta_psoriasis, 35

- igraph, 11, 61
- is_network_connected, 36

- log_normal (priors), 87

- log_student_t (priors), 87
- logitnorm, 91
- loo (loo.stan_nma), 37
- loo(), 37
- loo.stan_nma, 37

- make_knots, 37
- make_knots(), 46
- mcmc_array, 11, 85
- mcmc_array (mcmc_array-class), 39
- mcmc_array-class, 39
- mlnmr_data, 103
- mlnmr_data (nma_data-class), 53
- mlnmr_data-class (nma_data-class), 53
- model.matrix(), 47
- multi, 41
- multinma (multinma-package), 4
- multinma-package, 4

- names.mcmc_array (mcmc_array-class), 39
- names<- .mcmc_array (mcmc_array-class), 39
- ndmm_agd (ndmm_ipd), 43
- ndmm_agd_covs (ndmm_ipd), 43
- ndmm_ipd, 43
- nma, 44
- nma(), 6, 19, 33, 37, 38, 55, 64, 70, 74, 76, 77, 92, 95, 97, 102
- nma_data, 8, 12, 16, 61, 83, 96, 98, 99, 101, 103
- nma_data (nma_data-class), 53
- nma_data-class, 53
- nma_dic, 20, 57, 63, 84, 86
- nma_dic (nma_dic-class), 54
- nma_dic-class, 54
- nma_nodesplit, 47
- nma_nodesplit (nma_nodesplit-class), 55
- nma_nodesplit-class, 55
- nma_nodesplit_df, 47, 84
- nma_nodesplit_df (nma_nodesplit-class), 55
- nma_nodesplit_df-class (nma_nodesplit-class), 55
- nma_prior, 89, 103
- nma_prior (nma_prior-class), 55
- nma_prior-class, 55
- nma_rank_probs (nma_summary-class), 56
- nma_summary, 40, 57, 75, 79, 86, 92, 107
- nma_summary (nma_summary-class), 56

- nma_summary-class, 56
- nodesplit_summary, 105
- nodesplit_summary
 - (nodesplit_summary-class), 56
- nodesplit_summary-class, 56
- normal (priors), 87
- pairs(), 57
- pairs.stan_nma, 57
- parkinsons, 58
- pbern (qbern), 89
- pgamma (qgamma), 90
- pgent (dgent), 18
- plaque_psoriasis
 - (plaque_psoriasis_ipd), 59
- plaque_psoriasis_agd
 - (plaque_psoriasis_ipd), 59
- plaque_psoriasis_ipd, 59
- plogitnorm (qlogitnorm), 91
- plot (dlogt), 23
- plot.mcmc_array (mcmc_array-class), 39
- plot.nma_data, 61
- plot.nma_data(), 16, 54, 95–99, 101
- plot.nma_dic, 63
- plot.nma_dic(), 20, 54
- plot.nma_nodesplit
 - (summary.nma_nodesplit_df), 104
- plot.nma_nodesplit_df
 - (summary.nma_nodesplit_df), 104
- plot.nma_parameter_summary
 - (plot.nma_summary), 65
- plot.nma_rank_probs (plot.nma_summary), 65
- plot.nma_summary, 65
- plot.nma_summary(), 40, 75, 81, 86, 92, 107
- plot.nodesplit_summary, 67
- plot.nodesplit_summary(), 86, 105
- plot.stan_nma (summary.stan_nma), 106
- plot.surv_nma_summary
 - (plot.nma_summary), 65
- plot.surv_nma_summary(), 31
- plot_integration_error, 69
- plot_prior_posterior, 72
- plot_prior_posterior(), 47, 89
- pmspline (dmspline), 24
- posterior_rank_probs (posterior_ranks), 73
- posterior_rank_probs(), 56, 65, 106, 107
- posterior_ranks, 73
- posterior_ranks(), 56, 65, 106, 107
- predict.stan_nma, 76
- predict.stan_nma(), 22, 65, 95, 97, 99, 101, 106, 107
- predict.stan_nma_surv
 - (predict.stan_nma), 76
- print.mcmc_array (mcmc_array-class), 39
- print.mlnmr_data (print.nma_data), 83
- print.nma_data, 83
- print.nma_data(), 16, 54, 96, 98, 99, 101
- print.nma_dic, 84
- print.nma_dic(), 20, 54
- print.nma_nodesplit
 - (print.nma_nodesplit_df), 84
- print.nma_nodesplit_df, 84
- print.nma_summary, 85
- print.nodesplit_summary, 86
- print.stan_nma, 87
- print.stanfit(), 84, 87
- priors, 55, 87
- qbern, 89
- qgamma, 90
- qgent (dgent), 18
- qlogitnorm, 91
- qlogt (dlogt), 23
- qmspline (dmspline), 24
- RE_cor, 93
- relative_effects, 91
- relative_effects(), 65, 95, 97, 99, 101, 106, 107
- rmst_mspline (dmspline), 24
- round(), 84
- rstan::extract(), 107
- sampling(), 45, 103
- set_agd_arm, 94
- set_agd_arm(), 15, 16, 41, 53, 83, 98, 101
- set_agd_contrast, 96
- set_agd_contrast(), 15, 16, 53, 59, 83, 96, 99, 101
- set_agd_surv, 98
- set_agd_surv(), 53, 83
- set_ipd, 100
- set_ipd(), 15, 16, 41, 53, 83, 96, 98, 99
- smoking, 102
- sobol(), 7
- splines2::mSpline(), 24, 25

stan_mlnmr, [37](#)
stan_mlnmr (stan_nma-class), [102](#)
stan_nma, [20](#), [37](#), [47](#), [55](#), [87](#)
stan_nma (stan_nma-class), [102](#)
stan_nma-class, [102](#)
stanfit, [12](#), [13](#), [47](#)
statins, [103](#)
stats::Binomial, [89](#)
stats::GammaDist, [90](#)
student_t (priors), [87](#)
summary(), [47](#)
summary.mcmc_array (mcmc_array-class),
[39](#)
summary.nma_nodesplit
(summary.nma_nodesplit_df), [104](#)
summary.nma_nodesplit_df, [104](#)
summary.nma_nodesplit_df(), [68](#), [85](#)
summary.nma_prior, [105](#)
summary.nma_prior(), [89](#)
summary.stan_nma, [106](#)
Surv, [53](#)
Surv(), [99](#), [100](#)
survival::survfit(), [32](#)

theme_multinma, [108](#)
thrombolytics, [108](#)
tibble, [8](#)
tidygraph, [11](#)
transfusion, [109](#)

uniroot(), [77](#)
unnest_integration (add_integration), [6](#)

waic (loo.stan_nma), [37](#)
waic(), [37](#)
which_RE (RE_cor), [93](#)