Package ‘bayestestR’

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Type Package

Title Understand and Describe Bayesian Models and Posterior Distributions

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BugReports https://github.com/easystats/bayestestR/issues

Description Provides utilities to describe posterior distributions and Bayesian models. It includes point-estimates such as Maximum A Posteriori (MAP), measures of dispersion (Highest Density Interval - HDI; Kruschke, 2015 <doi:10.1016/C2012-0-00477-2>) and indices used for null-hypothesis testing (such as ROPE percentage, pd and Bayes factors).

License GPL-3

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Description

Based on the DescTools AUC function. It can calculate the area under the curve with a naive algorithm or a more elaborated spline approach. The curve must be given by vectors of xy-coordinates. This function can handle unsorted x values (by sorting x) and ties for the x values (by ignoring duplicates).

Usage

area_under_curve(x, y, method = c("trapezoid", "step", "spline"), ...)  
auc(x, y, method = c("trapezoid", "step", "spline"), ...)  

Arguments

x  Vector of x values.
y  Vector of y values.
method  Method to compute the Area Under the Curve (AUC). Can be "trapezoid" (default), "step" or "spline". If "trapezoid", the curve is formed by connecting all points by a direct line (composite trapezoid rule). If "step" is chosen then a stepwise connection of two points is used. For calculating the area under a spline interpolation the splinefun function is used in combination with integrate.

...  Arguments passed to or from other methods.

See Also

DescTools

Examples

library(bayestestR)
prior <- distribution_normal(1000)

dens <- estimate_density(prior)
dens <- dens[dens$x > 0, ]
x <- dens$x
y <- dens$y

area_under_curve(x, y, method = "trapezoid")
area_under_curve(x, y, method = "step")
area_under_curve(x, y, method = "spline")
as.data.frame.density  Coerce to a Data Frame

Description
Coerce to a Data Frame

Usage
## S3 method for class 'density'
as.data.frame(x, ...)

Arguments
x  any R object.
...  additional arguments to be passed to or from methods.

as.numeric.map_estimate  Convert to Numeric

Description
Convert to Numeric

Usage
## S3 method for class 'map_estimate'
as.numeric(x, ...)

## S3 method for class 'mhdior'
as.numeric(x, ...)

## S3 method for class 'p_direction'
as.numeric(x, ...)

## S3 method for class 'p_map'
as.numeric(x, ...)

## S3 method for class 'p_significance'
as.numeric(x, ...)

Arguments
x  object to be coerced or tested.
...  further arguments passed to or from other methods.
bayesfactor  Bayes Factors (BF)

Description

This function computes the Bayes factors (BFs) that are appropriate to the input. For vectors or single models, it will compute BFs for single parameters, or if hypothesis is specified, BFs for restricted models. For multiple models, it will return the BF corresponding to comparison between models and if a model comparison is passed, it will compute the inclusion BF.

For a complete overview of these functions, read the Bayes factor vignette.

Usage

```r
bayesfactor(
  ..., 
  prior = NULL,
  direction = "two-sided",
  null = 0,
  hypothesis = NULL,
  effects = c("fixed", "random", "all"),
  verbose = TRUE,
  denominator = 1,
  match_models = FALSE,
  prior_odds = NULL
)
```

Arguments

- `...`: A numeric vector, model object(s), or the output from `bayesfactor_models`.
- `prior`: An object representing a prior distribution (see 'Details').
- `direction`: Test type (see 'Details'). One of `0`, "two-sided" (default), -1, "left" (left tailed) or 1, "right" (right tailed).
- `null`: Value of the null, either a scaler (for point-null) or a range (for a interval-null).
- `hypothesis`: A character vector specifying the restrictions as logical conditions (see examples below).
- `effects`: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- `verbose`: Toggle off warnings.
- `denominator`: Either an integer indicating which of the models to use as the denominator, or a model to be used as a denominator. Ignored for `BFBayesFactor`.
- `match_models`: See details.
- `prior_odds`: Optional vector of prior odds for the models. See `BayesFactor::priorOdds<-`. 
bayesfactor_inclusion

**Value**

Some type of Bayes factor, depending on the input. See `bayesfactor_parameters`, `bayesfactor_models` or `bayesfactor_inclusion`

**Examples**

```r
library(bayestestR)

# Vectors
prior <- distribution_normal(1000, mean = 0, sd = 1)
posterior <- distribution_normal(1000, mean = .5, sd = .3)

bayesfactor(posterior, prior = prior)
## Not run:
# rstanarm models
# ---------------
if (require("rstanarm")) {
  model <- stan_lmer(extra ~ group + (1 | ID), data = sleep)
  bayesfactor(model)
}
## End(Not run)

# Frequentist models
# ---------------
m0 <- lm(extra ~ 1, data = sleep)
m1 <- lm(extra ~ group, data = sleep)
m2 <- lm(extra ~ group + ID, data = sleep)

comparison <- bayesfactor(m0, m1, m2)
comparison
bayesfactor(comparison)
```

---

**bayesfactor_inclusion**  
*Inclusion Bayes Factors for testing predictors across Bayesian models*

**Description**

The `bf_*` function is an alias of the main function.

For more info, see the Bayes factors vignette.

**Usage**

```r
bayesfactor_inclusion(models, match_models = FALSE, prior_odds = NULL, ...)
```

```r
bf_inclusion(models, match_models = FALSE, prior_odds = NULL, ...)
```
Arguments

models: An object of class `bayesfactor_models` or `BFBayesFactor`.
match_models: See details.
prior_odds: Optional vector of prior odds for the models. See `BayesFactor::priorOdds<-`.
...: Arguments passed to or from other methods.

Details

Inclusion Bayes factors answer the question: Are the observed data more probable under models with a particular effect, than they are under models without that particular effect? In other words, on average - are models with effect $X$ more likely to have produced the observed data than models without effect $X$?

**Match Models:** If `match_models=FALSE` (default), Inclusion BFs are computed by comparing all models with a predictor against all models without that predictor. If `TRUE`, comparison is restricted to models that (1) do not include any interactions with the predictor of interest; (2) for interaction predictors, averaging is done only across models that contain the main effect from which the interaction predictor is comprised.

Value

a data frame containing the prior and posterior probabilities, and BF for each effect.

Note

Random effects in the `lme` style will be displayed as interactions: i.e., $(X \mid G)$ will become $1 \cdot G$ and $X:G$.

Author(s)

Mattan S. Ben-Shachar

References


See Also

`weighted_posteriors` for Bayesian parameter averaging.
### Examples

```r
library(bayestestR)

# Using bayesfactor_models:
# ------------------------------
mo0 <- lm(Sepal.Length ~ 1, data = iris)
mo1 <- lm(Sepal.Length ~ Species, data = iris)
mo2 <- lm(Sepal.Length ~ Species + Petal.Length, data = iris)
mo3 <- lm(Sepal.Length ~ Species * Petal.Length, data = iris)

BFmodels <- bayesfactor_models(mo1, mo2, mo3, denominator = mo0)
bayesfactor_inclusion(BFmodels)

# Not run:
# BayesFactor
# -------------------------------
library(BayesFactor)

BF <- generalTestBF(len ~ supp * dose, ToothGrowth, progress = FALSE)
bayesfactor_inclusion(BF)

# compare only matched models:
bayesfactor_inclusion(BF, match_models = TRUE)

## End(Not run)
```

---

### bayesfactor_models

*Bayes Factors (BF) for model comparison*

#### Description

This function computes or extracts Bayes factors from fitted models.

The `bf_*` function is an alias of the main function.

#### Usage

```r
bayesfactor_models(..., denominator = 1, verbose = TRUE)
```

```r
bf_models(..., denominator = 1, verbose = TRUE)
```

#### Arguments

- `...`: Fitted models (see details), all fit on the same data, or a single `BFBayesFactor` object (see 'Details').
- `denominator`: Either an integer indicating which of the models to use as the denominator, or a model to be used as a denominator. Ignored for `BFBayesFactor`.
- `verbose`: Toggle off warnings.
bayesfactor_models

Details

If the passed models are supported by insight the DV of all models will be tested for equality (else this is assumed to be true), and the models’ terms will be extracted (allowing for follow-up analysis with bayesfactor_inclusion).

- For brmsfit or stanreg models, Bayes factors are computed using the bridgesampling package.
  - brmsfit models must have been fitted with save_all_pars = TRUE.
  - stanreg models must have been fitted with a defined diagnostic_file.
- For BFBayesFactor, bayesfactor_models() is mostly a wraparound BayesFactor::extractBF().
- For all other model types (supported by insight), BIC approximations are used to compute Bayes factors.

In order to correctly and precisely estimate Bayes factors, a rule of thumb are the 4 P’s: Proper Priors and Plentiful Posterior (i.e. probably at least 40,000 samples instead of the default of 4,000).

A Bayes factor greater than 1 can be interpreted as evidence against the compared-to model (the denominator). One convention is that a Bayes factor greater than 3 can be considered as “substantial” evidence against the denominator model (and vice versa, a Bayes factor smaller than 1/3 indicates substantial evidence in favor of the denominator model) (Wetzels et al. 2011).

See also the Bayes factors vignette.

Value

A data frame containing the models’ formulas (reconstructed fixed and random effects) and their BFs, that prints nicely.

Author(s)

Mattan S. Ben-Shachar

References

Examples

# With lm objects:
# ----------------
lm1 <- lm(Sepal.Length ~ 1, data = iris)
lm2 <- lm(Sepal.Length ~ Species, data = iris)
lm3 <- lm(Sepal.Length ~ Species + Petal.Length, data = iris)
lm4 <- lm(Sepal.Length ~ Species * Petal.Length, data = iris)
bayesfactor_models(lm1, lm2, lm3, lm4, denominator = 1)
bayesfactor_models(lm2, lm3, lm4, denominator = lm1) # same result
bayesfactor_models(lm1, lm2, lm3, lm4, denominator = lm1) # same result

## Not run:
# With lmerMod objects:
# ---------------------
if (require("lme4")) {
lmer1 <- lmer(Sepal.Length ~ Petal.Length + (1 | Species), data = iris)
lmer2 <- lmer(Sepal.Length ~ Petal.Length + (Petal.Length | Species), data = iris)
lmer3 <- lmer(
  Sepal.Length ~ Petal.Length + (Petal.Length | Species) + (1 | Petal.Width),
  data = iris
)
bayesfactor_models(lmer1, lmer2, lmer3, denominator = 1)
bayesfactor_models(lmer1, lmer2, lmer3, denominator = lmer1)
}

# rstanarm models
# ---------------------
# (note that a unique diagnostic_file MUST be specified in order to work)
if (require("rstanarm")) {
  stan_m0 <- stan_glm(Sepal.Length ~ 1,
    data = iris,
    family = gaussian(),
    diagnostic_file = file.path(tempdir(), "df0.csv")
  )
  stan_m1 <- stan_glm(Sepal.Length ~ Species,
    data = iris,
    family = gaussian(),
    diagnostic_file = file.path(tempdir(), "df1.csv")
  )
  stan_m2 <- stan_glm(Sepal.Length ~ Species + Petal.Length,
    data = iris,
    family = gaussian(),
    diagnostic_file = file.path(tempdir(), "df2.csv")
  )
bayesfactor_models(stan_m1, stan_m2, denominator = stan_m0)
}

# brms models
# ---------------------
# (note the save_all_pars MUST be set to TRUE in order to work)
if (require("brms")) {

```
bayesfactor_parameters

```r
brm1 <- brm(Sepal.Length ~ 1, data = iris, save_all_pars = TRUE)
brm2 <- brm(Sepal.Length ~ Species, data = iris, save_all_pars = TRUE)
brm3 <- brm(
  Sepal.Length ~ Species + Petal.Length,
  data = iris,
  save_all_pars = TRUE
)

bayesfactor_models(brm1, brm2, brm3, denominator = 1)
}

# BayesFactor
# --------------
if (require("BayesFactor")) {
  data(puzzles)
  BF <- anovaBF(RT ~ shape * color + ID,
                data = puzzles,
                whichRandom = "ID", progress = FALSE)
  BF

  bayesfactor_models(BF) # basically the same
}

## End(Not run)
```

bayesfactor_parameters

Bayes Factors (BF) for a Single Parameter

**Description**

This method computes Bayes factors against the null (either a point or an interval), based on prior and posterior samples of a single parameter. This Bayes factor indicates the degree by which the mass of the posterior distribution has shifted further away from or closer to the null value(s) (relative to the prior distribution), thus indicating if the null value has become less or more likely given the observed data.

When the null is an interval, the Bayes factor is computed by comparing the prior and posterior odds of the parameter falling within or outside the null interval (Morey & Rouder, 2011; Liao et al., 2020); When the null is a point, a Savage-Dickey density ratio is computed, which is also an approximation of a Bayes factor comparing the marginal likelihoods of the model against a model in which the tested parameter has been restricted to the point null (Wagenmakers et al., 2010; Heck, 2019).

Note that the logspline package is used for estimating densities and probabilities, and must be installed for the function to work.

bayesfactor_pointnull() and bayesfactor_rope() are wrappers around bayesfactor_parameters
with different defaults for the null to be tested against (a point and a range, respectively). Aliases of the main functions are prefixed with bf_*; like bf_parameters() or bf_pointnull()

For more info, in particular on specifying correct priors for factors with more than 2 levels, see the Bayes factors vignette.

Usage

bayesfactor_parameters(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = 0,
    verbose = TRUE,
    ...
)

bayesfactor_pointnull(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = 0,
    verbose = TRUE,
    ...
)

bayesfactor_rope(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = rope_range(posterior),
    verbose = TRUE,
    ...
)

bf_parameters(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = 0,
    verbose = TRUE,
    ...
)

bf_pointnull(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = 0,
bayesfactor_parameters

    verbose = TRUE,
    ...
  }

bf_rope(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = rope_range(posterior),
    verbose = TRUE,
    ...
  }

## S3 method for class 'numeric'
bayesfactor_parameters(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = 0,
    verbose = TRUE,
    ...
  }

## S3 method for class 'stanreg'
bayesfactor_parameters(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = 0,
    verbose = TRUE,
    effects = c("fixed", "random", "all"),
    component = c("conditional", "zi", "zero_inflated", "all"),
    parameters = NULL,
    ...
  }

## S3 method for class 'brmsfit'
bayesfactor_parameters(
    posterior,
    prior = NULL,
    direction = "two-sided",
    null = 0,
    verbose = TRUE,
    effects = c("fixed", "random", "all"),
    component = c("conditional", "zi", "zero_inflated", "all"),
    parameters = NULL,
    ...
  )
bayesfactor_parameters

## S3 method for class 'emmGrid'
bayesfactor_parameters(
  posterior,
  prior = NULL,
  direction = "two-sided",
  null = 0,
  verbose = TRUE,
  ...
)

## S3 method for class 'data.frame'
bayesfactor_parameters(
  posterior,
  prior = NULL,
  direction = "two-sided",
  null = 0,
  verbose = TRUE,
  ...
)

### Arguments

- **posterior**: A numerical vector, stanreg / brmsfit object, emmGrid or a data frame - representing a posterior distribution(s) from (see 'Details').
- **prior**: An object representing a prior distribution (see 'Details').
- **direction**: Test type (see 'Details'). One of 0, "two-sided" (default, two tailed), -1, "left" (left tailed) or 1, "right" (right tailed).
- **null**: Value of the null, either a scaler (for point-null) or a a range (for a interval-null).
- **verbose**: Toggle off warnings.
- **...**: Currently not used.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior__) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.

### Details

This method is used to compute Bayes factors based on prior and posterior distributions.

For the computation of Bayes factors, the model priors must be proper priors (at the very least
they should be not flat, and it is preferable that they be informative); As the priors for the alternative get wider, the likelihood of the null value(s) increases, to the extreme that for completely flat priors the null is infinitely more favorable than the alternative (this is called the Jeffreys-Lindley-Bartlett paradox). Thus, you should only ever try (or want) to compute a Bayes factor when you have an informed prior.

(Note that by default, brms::brm() uses flat priors for fixed-effects; See example below.)

**Setting the correct prior:** It is important to provide the correct prior for meaningful results.

- When posterior is a numerical vector, prior should also be a numerical vector.
- When posterior is a data.frame, prior should also be a data.frame, with matching column order.
- When posterior is a stanreg or brmsfit model:
  - prior can be set to NULL, in which case prior samples are drawn internally.
  - prior can also be a model equivalent to posterior but with samples from the priors only.
- When posterior is an emmGrid object:
  - prior should be the stanreg or brmsfit model used to create the emmGrid objects.
  - prior can also be an emmGrid object equivalent to posterior but created with a model of priors samples only.

**One-sided Tests (setting an order restriction):** One sided tests (controlled by direction) are conducted by restricting the prior and posterior of the non-null values (the "alternative") to one side of the null only (Morey & Wagenmakers, 2014). For example, if we have a prior hypothesis that the parameter should be positive, the alternative will be restricted to the region to the right of the null (point or interval).

**Interpreting Bayes Factors:** A Bayes factor greater than 1 can be interpreted as evidence against the null, at which one convention is that a Bayes factor greater than 3 can be considered as "substantial" evidence against the null (and vice versa, a Bayes factor smaller than 1/3 indicates substantial evidence in favor of the null-model) (Wetzels et al. 2011).

**Value**

A data frame containing the Bayes factor representing evidence against the null.

**Author(s)**

Mattan S. Ben-Shachar

**References**


Examples

library(bayestestR)

prior <- distribution_normal(1000, mean = 0, sd = 1)
posterior <- distribution_normal(1000, mean = .5, sd = .3)

bayesfactor_parameters(posterior, prior)
## Not run:
# rstanarm models
# ---------------
if (require("rstanarm") & require("emmeans")) {
  contrasts(sleep$group) <- contr.bayes # see vignette
  stan_model <- stan_lmer(extra ~ group + (1 | ID), data = sleep)
  bayesfactor_parameters(stan_model)
  bayesfactor_parameters(stan_model, null = rope_range(stan_model))
}

# emmGrid objects
# ---------------
group_diff <- pairs(emmeans(stan_model, ~group))
bayesfactor_parameters(group_diff, prior = stan_model)
}

# brms models
# -----------
if (require("brms")) {
  contrasts(sleep$group) <- contr.bayes # see vignette
  my_custom_priors <-
  set_prior("student_t(3, 0, 1)", class = "b") +
  set_prior("student_t(3, 0, 1)", class = "sd", group = "ID")

  brms_model <- brm(extra ~ group + (1 | ID),
    data = sleep,
    prior = my_custom_priors
  )
  bayesfactor_parameters(brms_model)
}

## End(Not run)
Bayes Factors (BF) for Order Restricted Models

Description

This method computes Bayes factors for comparing a model with an order restrictions on its parameters with the fully unrestricted model. *Note that this method should only be used for confirmatory analyses.*

The `bf_*` function is an alias of the main function.

For more info, in particular on specifying correct priors for factors with more than 2 levels, see the Bayes factors vignette.

Usage

```r
bayesfactor_restricted(
  posterior,
  hypothesis,
  prior = NULL,
  verbose = TRUE,
  ...
)
```

```r
bf_restricted(posterior, hypothesis, prior = NULL, verbose = TRUE, ...)
```

```r
## S3 method for class 'stanreg'
bayesfactor_restricted(
  posterior,
  hypothesis,
  prior = NULL,
  verbose = TRUE,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  ...
)
```

```r
## S3 method for class 'brmsfit'
bayesfactor_restricted(
  posterior,
  hypothesis,
  prior = NULL,
  verbose = TRUE,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  ...
)
```
bayesfactor_restricted

## S3 method for class 'emmGrid'
bayesfactor_restricted(
  posterior,
  hypothesis,
  prior = NULL,
  verbose = TRUE,
  ...
)

### Arguments

- **posterior**: A `stanreg` or `brmsfit` object, `emmGrid` or a data frame - representing a posterior distribution(s) from (see Details).
- **hypothesis**: A character vector specifying the restrictions as logical conditions (see examples below).
- **prior**: An object representing a prior distribution (see Details).
- **verbose**: Toggle off warnings.
- **...**: Currently not used.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

### Details

This method is used to compute Bayes factors for order-restricted models vs un-restricted models by setting an order restriction on the prior and posterior distributions (Morey & Wagenmakers, 2013).

(Though it is possible to use `bayesfactor_restricted()` to test interval restrictions, it is more suitable for testing order restrictions; see examples).

For the computation of Bayes factors, the model priors must be proper priors (at the very least they should be *not flat*, and it is preferable that they be *informative*); As the priors for the alternative get wider, the likelihood of the null value(s) increases, to the extreme that for completely flat priors the null is infinitely more favorable than the alternative (this is called the *Jeffreys-Lindley-Bartlett paradox*). Thus, you should only ever try (or want) to compute a Bayes factor when you have an informed prior.

(Note that by default, `brms::brm()` uses flat priors for fixed-effects.)

**Setting the correct prior**: It is important to provide the correct prior for meaningful results.

- When `posterior` is a `data.frame`, `prior` should also be a `data.frame`, with matching column order.
- When `posterior` is a `stanreg` or `brmsfit` model:
prior can be set to NULL, in which case prior samples are drawn internally.

– prior can also be a model equivalent to posterior but with samples from the priors only.

• When posterior is an `emmGrid` object:
  – prior should be the `stanreg` or `brmsfit` model used to create the `emmGrid` objects.
  – prior can also be an `emmGrid` object equivalent to posterior but created with a model of priors samples only.

**Interpreting Bayes Factors:** A Bayes factor greater than 1 can be interpreted as evidence against the null, at which one convention is that a Bayes factor greater than 3 can be considered as "substantial" evidence against the null (and vice versa, a Bayes factor smaller than 1/3 indicates substantial evidence in favor of the null-hypothesis) (Wetzels et al. 2011). 

**Value**

A data frame containing the Bayes factor representing evidence against the un-restricted model.

**References**


**Examples**

```r
library(bayestestR)
prior <- data.frame(
  X = rnorm(100),
  X1 = rnorm(100),
  X3 = rnorm(100)
)

posterior <- data.frame(
  X = rnorm(100, .4),
  X1 = rnorm(100, -.2),
  X3 = rnorm(100)
)

hyps <- c(
  "X > X1 & X1 > X3",
  "X > X1"
)

bayesfactor_restricted(posterior, hypothesis = hyps, prior = prior)
```
check_prior <- stan_glm(mpg ~ wt + cyl + am, 
  data = mtcars)

hyps <- c("am > 0 & cyl < 0",
  "cyl < 0",
  "wt - cyl > 0"
)
bayesfactor_restricted(fit_stan, hypothesis = hyps)

# emmGrid objects
# ---------------

disgust_data <- read.table(url("http://www.learnbayes.org/disgust_example.txt"), header = TRUE)

contrasts(disgust_data$condition) <- contr.bayes # see vignette
fit_model <- stan_glm(score ~ condition, data = disgust_data, family = gaussian())

em_condition <- emmeans(fit_model, ~condition)

hyps <- c("lemon < control & control < sulfur")
bayesfactor_restricted(em_condition, prior = fit_model, hypothesis = hyps)

# Bayes Factor (Order-Restriction)
# Hypothesis P(Prior) P(Posterior) Bayes Factor
# lemon < control & control < sulfur 0.17 0.75 4.49
# ---
# Bayes factors for the restricted model vs. the un-restricted model.

check_prior

---

check_prior  
Check if Prior is Informative

Description

Performs a simple test to check whether the prior is informative to the posterior. This idea, and the accompanying heuristics, were discussed in this blogpost.

Usage

check_prior(model, method = "gelman", simulate_priors = TRUE, ...)

Arguments

model  
A stanreg, stanfit, or brmsfit object.
method Can be "gelman" or "lakeland". For the "gelman" method, if the SD of the posterior is more than 0.1 times the SD of the prior, then the prior is considered as informative. For the "lakeland" method, the prior is considered as informative if the posterior falls within the 95% HDI of the prior.

simulate_priors Should prior distributions be simulated using simulate_prior (default; faster) or sampled (slower, more accurate).

... Currently not used.

References

https://statmodeling.stat.columbia.edu/2019/08/10/

Examples

```r
## Not run:
library(bayestestR)
if (require("rstanarm")) {
  model <- stan_glm(mpg ~ wt + am, data = mtcars, chains = 1, refresh = 0)
  check_prior(model, method = "gelman")
  check_prior(model, method = "lakeland")

  # An extreme example where both methods diverge:
  model <- stan_glm(mpg ~ wt, data = mtcars[1:3,],
        prior = normal(-3.3, 1, FALSE),
        prior_intercept = normal(0, 1000, FALSE),
        refresh = 0)
  check_prior(model, method = "gelman")
  check_prior(model, method = "lakeland")
  plot(si(model)) # can provide visual confirmation to the Lakeland method
}
## End(Not run)
```

---

**ci**

Confidence/Credible/Compatibility Interval (CI)

Description

Compute Confidence/Credible/Compatibility Intervals (CI) or Support Intervals (SI) for Bayesian and frequentist models. The Documentation is accessible for:

Usage

```r
ci(x, ...)
```

## S3 method for class 'numeric'
```r
ci(x, ci = 0.89, method = "ETI", verbose = TRUE, BF = 1, ...)
```
## S3 method for class 'data.frame'
\texttt{ci}(x, \texttt{ci} = 0.89, \texttt{method} = "ETI", \texttt{verbose} = \texttt{TRUE}, \texttt{BF} = 1, \ldots)

## S3 method for class 'emmGrid'
\texttt{ci}(x, \texttt{ci} = 0.89, \texttt{method} = "ETI", \texttt{verbose} = \texttt{TRUE}, \texttt{BF} = 1, \ldots)

## S3 method for class 'sim.merMod'
\texttt{ci}(x, \texttt{ci} = 0.89, \texttt{method} = "ETI", \texttt{verbose} = \texttt{TRUE}, \texttt{BF} = 1, \ldots)

## S3 method for class 'sim'
\texttt{ci}(x, \texttt{ci} = 0.89, \texttt{method} = "ETI", \texttt{parameters} = \texttt{NULL}, \texttt{verbose} = \texttt{TRUE}, \ldots)

## S3 method for class 'stanreg'
\texttt{ci}(x, \texttt{ci} = 0.89, \texttt{method} = "ETI", \texttt{effects} = \texttt{c("fixed", "random", "all")}, \texttt{parameters} = \texttt{NULL}, \texttt{verbose} = \texttt{TRUE}, \texttt{BF} = 1, \ldots)

## S3 method for class 'brmsfit'
\texttt{ci}(x, \texttt{ci} = 0.89, \texttt{method} = "ETI", \texttt{effects} = \texttt{c("fixed", "random", "all")}, \texttt{component} = \texttt{c("conditional", "zi", "zero_inflated", "all")}, \texttt{parameters} = \texttt{NULL}, \texttt{verbose} = \texttt{TRUE}, \texttt{BF} = 1, \ldots)

## S3 method for class 'BFBayesFactor'
\texttt{ci}(x, \texttt{ci} = 0.89, \texttt{method} = "ETI", \texttt{verbose} = \texttt{TRUE}, \texttt{BF} = 1, \ldots)
## S3 method for class 'MCMCglmm'

`ci(x, ci = 0.89, method = "ETI", verbose = TRUE, ...)`

### Arguments

- **x**: A `stanreg` or `brmsfit` model, or a vector representing a posterior distribution.
- **...**: Currently not used.
- **ci**: Value or vector of probability of the CI (between 0 and 1) to be estimated. Default to .89 (89%) for Bayesian models and .95 (95%) for frequentist models.
- **method**: Can be 'ETI' (default), 'HDI' or 'SI'.
- **verbose**: Toggle off warnings.
- **BF**: The amount of support required to be included in the support interval.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use `parameters` to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

### Details

- **Bayesian models**
- **Frequentist models**

### Value

A data frame with following columns:

- **Parameter**: The model parameter(s), if `x` is a model-object. If `x` is a vector, this column is missing.
- **CI**: The probability of the credible interval.
- **CI_low, CI_high**: The lower and upper credible interval limits for the parameters.

### Note

When it comes to interpretation, we recommend thinking of the CI in terms of an "uncertainty" or "compatibility" interval, the latter being defined as “Given any value in the interval and the background assumptions, the data should not seem very surprising” (Gelman & Greenland 2019).

### References

Gelman A, Greenland S. Are confidence intervals better termed "uncertainty intervals"? BMJ 2019;353:l5381. doi: 10.1136/bmj.l5381
Examples

```r
library(bayestestR)

posterior <- rnorm(1000)
ci(posterior, method = "ETI")
ci(posterior, method = "HDI")

df <- data.frame(replicate(4, rnorm(100)))
ci(df, method = "ETI", ci = c(.80, .89, .95))
ci(df, method = "HDI", ci = c(.80, .89, .95))

## Not run:
if (require("rstanarm")) {
  model <- stan_glm(mpg ~ wt, data = mtcars, chains = 2, iter = 200, refresh = 0)
ci(model, method = "ETI", ci = c(.80, .89))
ci(model, method = "HDI", ci = c(.80, .89))
ci(model, method = "SI")
}

if (require("brms")) {
  model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
ci(model, method = "ETI")
ci(model, method = "HDI")
ci(model, method = "SI")
}

if (require("BayesFactor")) {
  bf <- ttestBF(x = rnorm(100, 1, 1))
ci(bf, method = "ETI")
ci(bf, method = "HDI")
}

if (require("emmeans")) {
  model <- emtrends(model, ~1, "wt")
ci(model, method = "ETI")
ci(model, method = "HDI")
ci(model, method = "SI")
}

## End(Not run)
```

---

### contr.bayes

**Orthonormal Contrast Matrices for Bayesian Estimation**

### Description

Returns a design or model matrix of orthonormal contrasts such that the marginal prior on all effects is identical. Implementation from Singmann & Gronau’s `bfrms`, following the description in Rouder, Morey, Speckman, & Province (2012, p. 363).
contr.bayes

Usage

contr.bayes(n, contrasts = TRUE)

Arguments

n
a vector of levels for a factor, or the number of levels.

contrasts
logical indicating whether contrasts should be computed.

Details

Though using this factor coding scheme might obscure the interpretation of parameters, it is essential for correct estimation of Bayes factors for contrasts and multi-level order restrictions. See info on specifying correct priors for factors with more than 2 levels in the Bayes factors vignette.

Value

A matrix with n rows and k columns, with k=n-1 if contrasts is TRUE and k=n if contrasts is FALSE.

References


Examples

```r
## Not run:
contr.bayes(2) # Q_2 in Rouder et al. (2012, p. 363)
# [,1]
# [1,] -0.7071068
# [2,]  0.7071068

contr.bayes(5) # equivalent to Q_5 in Rouder et al. (2012, p. 363)
# [1,] 0.0000000 0.8944272 0.0000000 0.0000000
# [2,] 0.0000000 -0.2236068 -0.5000000 0.7071068
# [3,] 0.7071068 -0.2236068 -0.1666667 -0.4714045
# [4,] -0.7071068 -0.2236068 -0.1666667 -0.4714045
# [5,] 0.0000000 -0.2236068 0.8333333 0.2357023

## check decomposition
Q3 <- contr.bayes(3)
Q3 %*% t(Q3)
# [,1] [,2] [,3]
# [1,] 0.6666667 -0.3333333 -0.3333333
# [2,] -0.3333333 0.6666667 -0.3333333
# [3,] -0.3333333 -0.3333333 0.6666667
## 2/3 on diagonal and -1/3 on off-diagonal elements

## End(Not run)
```
convert_bayesian_as_frequentist

Convert (refit) a Bayesian model to frequentist

Description
Refit Bayesian model as frequentist. Can be useful for comparisons.

Usage
convert_bayesian_as_frequentist(model, data = NULL)
bayesian_as_frequentist(model, data = NULL)

Arguments
model A Bayesian model.
data Data used by the model. If NULL, will try to extract it from the model.

Examples

# Rstanarm ----------------------
if (require("rstanarm")) {
  # Simple regressions
  model <- stan_glm(Sepal.Length ~ Petal.Length * Species,
                   data = iris, chains = 2, refresh = 0)
  bayesian_as_frequentist(model)

  model <- stan_glm(vs ~ mpg,
                   family = "binomial",
                   data = mtcars, chains = 2, refresh = 0)
  bayesian_as_frequentist(model)

  # Mixed models
  model <- stan_glmer(Sepal.Length ~ Petal.Length + (1 | Species),
                      data = iris, chains = 2, refresh = 0)
  bayesian_as_frequentist(model)

  model <- stan_glmer(vs ~ mpg + (1 | cyl),
                      family = "binomial",
                      data = mtcars, chains = 2, refresh = 0)
  bayesian_as_frequentist(model)
}
density_at  

Density Probability at a Given Value

Description

Compute the density value at a given point of a distribution (i.e., the value of the y axis of a value x of a distribution).

Usage

density_at(posterior, x, precision = 2^10, method = "kernel", ...)

Arguments

- **posterior**: Vector representing a posterior distribution.
- **x**: The value of which to get the approximate probability.
- **precision**: Number of points of density data. See the n parameter in density.
- **method**: Density estimation method. Can be "kernel" (default), "logspline" or "KernSmooth".
- **...**: Currently not used.

Examples

```r
library(bayestestR)
posterior <- distribution_normal(n = 10)
density_at(posterior, 0)
density_at(posterior, c(0, 1))
```

describe_posterior  

Describe Posterior Distributions

Description

Compute indices relevant to describe and characterise the posterior distributions.

Usage

describe_posterior(
  posteriors,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.89,
  ci_method = "hdi",
  test = c("p_direction", "rope"),
  rope_range = "default",
  rope_ci = 0.89,
)
## S3 method for class 'numeric'
describe_posterior(
  posteriors,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.89,
  ci_method = "hdi",
  test = c("p_direction", "rope"),
  rope_range = "default",
  rope_ci = 0.89,
  bf_prior = NULL,
  BF = 1,
  ...
)

## S3 method for class 'stanreg'
describe_posterior(
  posteriors,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.89,
  ci_method = "hdi",
  test = c("p_direction", "rope"),
  rope_range = "default",
  rope_ci = 0.89,
  bf_prior = NULL,
  BF = 1,
  Diagnostic = c("ESS", "Rhat"),
  priors = FALSE,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  BF = 1,
  ...
)

## S3 method for class 'stanmvreg'
describe_posterior(
  posteriors,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.89,
  ci_method = "hdi",
  test = "p_direction",
  rope_range = "default",
  rope_ci = 0.89,
  bf_prior = NULL,
describe_posterior

diagnostic = c("ESS", "Rhat"),
priors = FALSE,
effects = c("fixed", "random", "all"),
parameters = NULL,
...
)

## S3 method for class 'MCMCglmm'
describe_posterior(
  posteriors,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.89,
  ci_method = "hdi",
  test = c("p_direction", "rope"),
  rope_range = "default",
  rope_ci = 0.89,
  diagnostic = "ESS",
  parameters = NULL,
  ...
)

## S3 method for class 'brmsfit'
describe_posterior(
  posteriors,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.89,
  ci_method = "hdi",
  test = c("p_direction", "rope"),
  rope_range = "default",
  rope_ci = 0.89,
  bf_prior = NULL,
  diagnostic = c("ESS", "Rhat"),
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  BF = 1,
  ...
)

## S3 method for class 'BFBayesFactor'
describe_posterior(
  posteriors,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.89,
  ci_method = "hdi",
describe_posterior

```r
test = c("p_direction", "rope", "bf"),
rope_range = "default",
rope_ci = 0.89,
priors = TRUE,
...)
```

### Arguments

- **postiors**: A vector, dataframe or model of posterior draws.
- **centrality**: The point-estimates (centrality indices) to compute. Character (vector) or list with one or more of these options: "median", "mean", "MAP" or "all".
- **dispersion**: Logical, if TRUE, computes indices of dispersion related to the estimate(s) (SD and MAD for mean and median, respectively).
- **ci**: Value or vector of probability of the CI (between 0 and 1) to be estimated. Default to .89 (89%) for Bayesian models and .95 (95%) for frequentist models.
- **ci_method**: The type of index used for Credible Interval. Can be "HDI" (default, see hdi), "ETI" (see eti) or "SI" (see si).
- **test**: The indices of effect existence to compute. Character (vector) or list with one or more of these options: "p_direction" (or "pd"), "rope", "p_map", "equivalence_test" (or "equitest"), "bayesfactor" (or "bf") or "all" to compute all tests. For each "test", the corresponding bayestestR function is called (e.g. rope or p_direction) and its results included in the summary output.
- **rope_range**: ROPE’s lower and higher bounds. Should be a list of two values (e.g., c(-0.1, 0.1)) or "default". If "default", the bounds are set to x +- 0.1*SD(response).
- **rope_ci**: The Credible Interval (CI) probability, corresponding to the proportion of HDI, to use for the percentage in ROPE.
- **bf_prior**: Distribution representing a prior for the computation of Bayes factors / SI. Used if the input is a posterior, otherwise (in the case of models) ignored.
- **BF**: The amount of support required to be included in the support interval.
- **diagnostic**: Diagnostic metrics to compute. Character (vector) or list with one or more of these options: "ESS", "Rhat", "MCSE" or "all".
- **priors**: Add the prior used for each parameter.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior_) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.
describe_posterior

Details

One or more components of point estimates (like posterior mean or median), intervals and tests can be omitted from the summary output by setting the related argument to NULL. For example, test = NULL and centrality = NULL would only return the HDI (or CI).

References

- Comparison of Point-Estimates
- Region of Practical Equivalence (ROPE)
- Bayes factors

Examples

library(bayestestR)

x <- rnorm(1000)
describe_posterior(x)
describe_posterior(x, centrality = "all", dispersion = TRUE, test = "all")
describe_posterior(x, ci = c(0.80, 0.90))

df <- data.frame(replicate(4, rnorm(100)))
describe_posterior(df)
describe_posterior(df, centrality = "all", dispersion = TRUE, test = "all")
describe_posterior(df, ci = c(0.80, 0.90))

## Not run:
# rstanarm models
# -----------------------------------------------
if (require("rstanarm") && require("emmeans")) {
  model <- stan_glm(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
describe_posterior(model)
describe_posterior(model, centrality = "all", dispersion = TRUE, test = "all")
describe_posterior(model, ci = c(0.80, 0.90))
}

# emmeans estimates
# -----------------------------------------------
describe_posterior(emtrends(model, ~1, "wt"))
}

# brms models
# -----------------------------------------------
if (require("brms")) {
  model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
describe_posterior(model)
describe_posterior(model, centrality = "all", dispersion = TRUE, test = "all")
describe_posterior(model, ci = c(0.80, 0.90))
}

# BayesFactor objects
# -----------------------------------------------
if (require("BayesFactor")) {
  bf <- ttestBF(x = rnorm(100, 1, 1))
describe_posterior(bf)
describe_posterior(bf, centrality = "all", dispersion = TRUE, test = "all")
describe_posterior(bf, ci = c(0.80, 0.90))
}

## End(Not run)

describe_prior Describe Priors

Description
Returns a summary of the priors used in the model.

Usage
describe_prior(model, ...)

Arguments
model A Bayesian model.
...
Currently not used.

Examples
## Not run:
library(bayestestR)

# rstanarm models
# -----------------------------------------------
if (require("rstanarm")) {
  model <- rstanarm::stan_glm(mpg ~ wt + cyl, data = mtcars)
describe_prior(model)
}

# brms models
# -----------------------------------------------
if (require("brms")) {
  model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
describe_prior(model)
}

# BayesFactor objects
# -----------------------------------------------
if (require("BayesFactor")) {
  bf <- ttestBF(x = rnorm(100, 1, 1))
describe_prior(bf)
}

## End(Not run)
**diagnostic_posterior**  
*Posterior Sampling Diagnostic*

**Description**

Extract diagnostic metrics (Effective Sample Size (ESS), Rhat and Monte Carlo Standard Error (MCSE)).

**Usage**

```r
diagnostic_posterior(posteriors, diagnostic = c("ESS", "Rhat"), ...)  
```

```r
## S3 method for class 'stanreg'
diagnostic_posterior(
  posteriors,
  diagnostic = "all",
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...
)
```

```r
## S3 method for class 'brmsfit'
diagnostic_posterior(
  posteriors,
  diagnostic = "all",
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  ...
)
```

**Arguments**

- `posteriors`  
  A stanreg or brms model.

- `diagnostic`  
  Diagnostic metrics to compute. Character (vector) or list with one or more of these options: "ESS", "Rhat", "MCSE" or "all".

- `effects`  
  Should parameters for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.

- `parameters`  
  Regular expression pattern that describes the parameters that should be returned.

- `component`  
  Should all parameters, parameters for the conditional model, the zero-inflated part of the model, the dispersion term or the instrumental variables be returned? Applies to models with zero-inflated and/or dispersion formula, or to models with instrumental variable (so called fixed-effects regressions). May be abbreviated. Note that the conditional component is also called count or mean component, depending on the model.
Details

**Effective Sample (ESS)** should be as large as possible, although for most applications, an effective sample size greater than 1000 is sufficient for stable estimates (Bürkner, 2017). The ESS corresponds to the number of independent samples with the same estimation power as the N autocorrelated samples. It is a measure of “how much independent information there is in autocorrelated chains” (Kruschke 2015, p182-3).

**Rhat** should be the closest to 1. It should not be larger than 1.1 (Gelman and Rubin, 1992) or 1.01 (Vehtari et al., 2019). The split R-hat statistic quantifies the consistency of an ensemble of Markov chains.

**Monte Carlo Standard Error (MCSE)** is another measure of accuracy of the chains. It is defined as standard deviation of the chains divided by their effective sample size (the formula for `mcse()` is from Kruschke 2015, p. 187). The MCSE “provides a quantitative suggestion of how big the estimation noise is”.

References


Examples

```r
## Not run:
# rstanarm models
# -----------------------------------------------
library(rstanarm)
model <- stan_glm(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
diagnostic_posterior(model)
# brms models
# -----------------------------------------------
library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
diagnostic_posterior(model)
## End(Not run)
```
distribution  

Empirical Distributions

Description
Generate a sequence of n-quantiles, i.e., a sample of size n with a near-perfect distribution.

Usage

distribution(type = "normal", ...)
distribution_normal(n, mean = 0, sd = 1, random = FALSE, ...)
distribution_binomial(n, size = 1, prob = 0.5, random = FALSE, ...)
distribution_cauchy(n, location = 0, scale = 1, random = FALSE, ...)
distribution_poisson(n, lambda = 1, random = FALSE, ...)
distribution_student(n, df, ncp, random = FALSE, ...)
distribution_chisquared(n, df, ncp = 0, random = FALSE, ...)
distribution_uniform(n, min = 0, max = 1, random = FALSE, ...)
distribution_betad(n, shape1, shape2, ncp = 0, random = FALSE, ...)
distribution_tweedie(n, xi = NULL, mu, phi, power = NULL, random = FALSE, ...)
distribution_reparam(n, shape, scale = 1, random = FALSE, ...)
distribution_custom(n, type = "norm", ..., random = FALSE)
distribution_mixture_normal(n, mean = c(-3, 3), sd = 1, random = FALSE, ...)
rnorm_perfect(n, mean = 0, sd = 1)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>type</td>
<td>Can be any of the names from base R’s Distributions, like “cauchy”, “pois” or “beta”.</td>
</tr>
<tr>
<td>...</td>
<td>Arguments passed to or from other methods.</td>
</tr>
<tr>
<td>n</td>
<td>number of observations. If length(n) &gt; 1, the length is taken to be the number required.</td>
</tr>
<tr>
<td>mean</td>
<td>vector of means.</td>
</tr>
<tr>
<td>sd</td>
<td>vector of standard deviations.</td>
</tr>
</tbody>
</table>
random: Generate near-perfect or random (simple wrappers for the base R r* functions) distributions.

size: number of trials (zero or more).

prob: probability of success on each trial.

location: location and scale parameters.

scale: location and scale parameters.

lambda: vector of (non-negative) means.

df: degrees of freedom (> 0, maybe non-integer). df = Inf is allowed.

ncp: non-centrality parameter δ; currently except for rt(), only for abs(ncp) <= 37.62. If omitted, use the central t distribution.

min: lower and upper limits of the distribution. Must be finite.

max: lower and upper limits of the distribution. Must be finite.

shape1: non-negative parameters of the Beta distribution.

shape2: non-negative parameters of the Beta distribution.

xi: the value of ξ such that the variance is var[Y] = φμξ

mu: the mean

phi: the dispersion

power: a synonym for ξ

shape: shape and scale parameters. Must be positive, scale strictly.

Examples

```r
library(bayestestR)
x <- distribution(n = 10)
plot(density(x))

x <- distribution(type = "gamma", n = 100, shape = 2)
plot(density(x))
```

effective_sample: Effective Sample Size (ESS)

Description

This function returns the effective sample size (ESS).
effective_sample

Usage

effective_sample(model, ...)

## S3 method for class 'brmsfit'
effective_sample(
  model,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  ...
)

## S3 method for class 'stanreg'
effective_sample(
  model,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...
)

## S3 method for class 'MCMCglmm'
effective_sample(
  model,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...
)

Arguments

model          A stanreg, stanfit, or brmsfit object.
...            Currently not used.
effects        Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
component      Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.
parameters     Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior__) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.

Details

Effective Sample (ESS) should be as large as possible, although for most applications, an effective sample size greater than 1,000 is sufficient for stable estimates (Bürkner, 2017). The ESS corresponds to the number of independent samples with the same estimation power as the N autocorre-
It is a measure of “how much independent information there is in autocorrelated chains” (Kruschke 2015, p182-3).

Value

A data frame with two columns: Parameter name and effective sample size (ESS).

References


Examples

```r
## Not run:
library(rstanarm)
model <- stan_glm(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
effective_sample(model)
## End(Not run)
```

equivalence_test

Test for Practical Equivalence

Description

Perform a **Test for Practical Equivalence** for Bayesian and frequentist models.

Usage

```r
equivalence_test(x, ...)
```

## Default S3 method:
```r
equivalence_test(x, ...)
```

## S3 method for class 'numeric'
```r
equivalence_test(x, range = "default", ci = 0.89, verbose = TRUE, ...)
```

## S3 method for class 'data.frame'
```r
equivalence_test(x, range = "default", ci = 0.89, verbose = TRUE, ...)
```

## S3 method for class 'emmGrid'
```r
equivalence_test(x, range = "default", ci = 0.89, verbose = TRUE, ...)
```

## S3 method for class 'BFBayesFactor'
```r
equivalence_test(x, range = "default", ci = 0.89, verbose = TRUE, ...)
```
## S3 method for class 'stanreg'
equivalence_test(
  x,
  range = "default",
  ci = 0.89,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'brmsfit'
equivalence_test(
  x,
  range = "default",
  ci = 0.89,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)

### Arguments

- **x**: Vector representing a posterior distribution. Can also be a `stanreg` or `brmsfit` model.
- **...**: Currently not used.
- **range**: ROPE's lower and higher bounds. Should be a vector of length two (e.g., `c(-0.1,0.1)`) or "default". If "default", the range is set to `c(-0.1,0.1)` if input is a vector, and based on `rope_range()` if a Bayesian model is provided.
- **ci**: The Credible Interval (CI) probability, corresponding to the proportion of HDI, to use for the percentage in ROPE.
- **verbose**: Toggle off warnings.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use parameters to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

### Details

Documentation is accessible for:
For Bayesian models, the Test for Practical Equivalence is based on the "HDI+ROPE decision rule" (Kruschke, 2014, 2018) to check whether parameter values should be accepted or rejected against an explicitly formulated "null hypothesis" (i.e., a ROPE). In other words, it checks the percentage of the 89% HDI that is the null region (the ROPE). If this percentage is sufficiently low, the null hypothesis is rejected. If this percentage is sufficiently high, the null hypothesis is accepted.

Using the ROPE and the HDI, Kruschke (2018) suggests using the percentage of the 95% (or 89%, considered more stable) HDI that falls within the ROPE as a decision rule. If the HDI is completely outside the ROPE, the "null hypothesis" for this parameter is "rejected". If the ROPE completely covers the HDI, i.e., all most credible values of a parameter are inside the region of practical equivalence, the null hypothesis is accepted. Else, it’s undecided whether to accept or reject the null hypothesis. If the full ROPE is used (i.e., 100% of the HDI), then the null hypothesis is rejected or accepted if the percentage of the posterior within the ROPE is smaller than to 2.5% or greater than 97.5%. Desirable results are low proportions inside the ROPE (the closer to zero the better).

Some attention is required for finding suitable values for the ROPE limits (argument range). See 'Details' in rope_range() for further information.

**Multicollinearity: Non-independent covariates**

When parameters show strong correlations, i.e. when covariates are not independent, the joint parameter distributions may shift towards or away from the ROPE. In such cases, the test for practical equivalence may have inappropriate results. Collinearity invalidates ROPE and hypothesis testing based on univariate marginals, as the probabilities are conditional on independence. Most problematic are the results of the "undecided" parameters, which may either move further towards "rejection" or away from it (Kruschke 2014, 340f).

equivalence_test() performs a simple check for pairwise correlations between parameters, but as there can be collinearity between more than two variables, a first step to check the assumptions of this hypothesis testing is to look at different pair plots. An even more sophisticated check is the projection predictive variable selection (Piironen and Vehtari 2017).

**Value**

A data frame with following columns:

- **Parameter** The model parameter(s), if x is a model-object. If x is a vector, this column is missing.
- **CI** The probability of the HDI.
- **ROPE_low, ROPE_high** The limits of the ROPE. These values are identical for all parameters.
- **ROPE_Percentage** The proportion of the HDI that lies inside the ROPE.
- **ROPE_Equivalence** The "test result", as character. Either "rejected", "accepted" or "undecided".
- **HDI_low, HDI_high** The lower and upper HDI limits for the parameters.
**Note**

There is a `print()`-method with a `digits`-argument to control the amount of digits in the output, and there is a `plot()`-method to visualize the results from the equivalence-test (for models only).

**References**


**Examples**

```r
library(bayestestR)

equivalence_test(x = rnorm(1000, 0, 0.01), range = c(-0.1, 0.1))
equivalence_test(x = rnorm(1000, 0, 1), range = c(-0.1, 0.1))
equivalence_test(x = rnorm(1000, 1, 0.01), range = c(-0.1, 0.1))
equivalence_test(x = rnorm(1000, 1, 1), ci = c(.50, .99))

# print more digits
test <- equivalence_test(x = rnorm(1000, 1, 1), ci = c(.50, .99))
print(test, digits = 4)
## Not run:
library(rstanarm)
model <- rstanarm::stan_glm(mpg ~ wt + cyl, data = mtcars)
equivalence_test(model)
equivalence_test(model, ci = c(.50, 1))

# plot result
test <- equivalence_test(model)
plot(test)

library(emmeans)
equivalence_test(emtrends(model, ~1, "wt"))

library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
equivalence_test(model)
equivalence_test(model, ci = c(.50, .99))

library(BayesFactor)
bf <- ttestBF(x = rnorm(100, 1, 1))
equivalence_test(bf)
equivalence_test(bf, ci = c(.50, .99))
## End(Not run)
```
**estimate_density**  

**Density Estimation**

**Description**

This function is a wrapper over different methods of density estimation. By default, it uses the base R `density` with by default uses a different smoothing bandwidth ("SJ") from the legacy default implemented the base R `density` function ("nrd0"). However, Deng & Wickham suggest that method = "KernSmooth" is the fastest and the most accurate.

**Usage**

```r
estimate_density(
  x,
  method = "kernel",
  precision = 2^10,
  extend = FALSE,
  extend_scale = 0.1,
  bw = "SJ",
  ...
)
```

**Arguments**

- `x` Vector representing a posterior distribution. Can also be a `stanreg`, `brmsfit` or a `BayesFactor` model.
- `method` Density estimation method. Can be "kernel" (default), "logspline" or "KernSmooth".
- `precision` Number of points of density data. See the n parameter in `density`.
- `extend` Extend the range of the x axis by a factor of `extend_scale`.
- `extend_scale` Ratio of range by which to extend the x axis. A value of 0.1 means that the x axis will be extended by 1/10 of the range of the data.
- `bw` the smoothing bandwidth to be used. The kernels are scaled such that this is the standard deviation of the smoothing kernel. (Note this differs from the reference books cited below, and from S-PLUS.)
- `bw` can also be a character string giving a rule to choose the bandwidth. See `bw.nrd`.
  - The default, "nrd0", has remained the default for historical and compatibility reasons, rather than as a general recommendation, where e.g., "SJ" would rather fit, see also Venables and Ripley (2002).
  - The specified (or computed) value of `bw` is multiplied by `adj`.
- `...` Currently not used.

**References**

etis

Examples

library(bayestestR)
set.seed(1)
x <- rnorm(250, 1)

# Methods
density_kernel <- estimate_density(x, method = "kernel")
density_logspline <- estimate_density(x, method = "logspline")
density_KernSmooth <- estimate_density(x, method = "KernSmooth")
density_mixture <- estimate_density(x, method = "mixture")

hist(x, prob = TRUE)
lines(density_kernel$x, density_kernel$y, col = "black", lwd = 2)
lines(density_logspline$x, density_logspline$y, col = "red", lwd = 2)
lines(density_KernSmooth$x, density_KernSmooth$y, col = "blue", lwd = 2)
lines(density_mixture$x, density_mixture$y, col = "green", lwd = 2)

# Extension
density_extented <- estimate_density(x, extend = TRUE)
density_default <- estimate_density(x, extend = FALSE)

hist(x, prob = TRUE)
lines(density_extented$x, density_extented$y, col = "red", lwd = 3)
lines(density_default$x, density_default$y, col = "black", lwd = 3)

df <- data.frame(replicate(4, rnorm(100)))
head(estimate_density(df))
## Not run:
# rstanarm models
# -----------------------------------------------
library(rstanarm)
model <- stan_glm(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
head(estimate_density(model))

library(emmeans)
head(estimate_density(emtrends(model, ~1, "wt")))

# brms models
# -----------------------------------------------
library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
estimate_density(model)

## End(Not run)

eti

Equal-Tailed Interval (ETI)
Description

Compute the Equal-Tailed Interval (ETI) of posterior distributions using the quantiles method. The probability of being below this interval is equal to the probability of being above it. The ETI can be used in the context of uncertainty characterisation of posterior distributions as Credible Interval (CI).

Usage

eti(x, ...)

## S3 method for class 'numeric'
eti(x, ci = 0.89, verbose = TRUE, ...)

## S3 method for class 'data.frame'
eti(x, ci = 0.89, verbose = TRUE, ...)

## S3 method for class 'MCMCglmm'
eti(x, ci = 0.89, verbose = TRUE, ...)

## S3 method for class 'sim.merMod'
eti(
  x,
  ci = 0.89,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'sim'
eti(x, ci = 0.89, parameters = NULL, verbose = TRUE, ...)

## S3 method for class 'emmGrid'
eti(x, ci = 0.89, verbose = TRUE, ...)

## S3 method for class 'stanreg'
eti(
  x,
  ci = 0.89,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'brmsfit'
eti(
  x,
ci = 0.89,
effects = c("fixed", "random", "all"),
component = c("conditional", "zi", "zero_inflated", "all"),
parameters = NULL,
verbose = TRUE,
...
)

## S3 method for class 'BFBayesFactor'
eti(x, ci = 0.89, verbose = TRUE, ...)

### Arguments

- **x**: Vector representing a posterior distribution. Can also be a `stanreg`, `brmsfit` or a `BayesFactor` model.
- **ci**: Value or vector of probability of the (credible) interval - CI (between 0 and 1) to be estimated. Default to 0.89 (89%).
- **verbose**: Toggle off warnings.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use parameters to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

### Details

Unlike equal-tailed intervals (see `eti()`) that typically exclude 2.5% from each tail of the distribution and always include the median, the HDI is not equal-tailed and therefore always includes the mode(s) of posterior distributions.

By default, `hdi()` and `eti()` return the 89% intervals (ci = 0.89), deemed to be more stable than, for instance, 95% intervals (Kruschke, 2014). An effective sample size of at least 10,000 is recommended if 95% intervals should be computed (Kruschke, 2014, p. 183ff). Moreover, 89 indicates the arbitrariness of interval limits - its only remarkable property is being the highest prime number that does not exceed the already unstable 95% threshold (McElreath, 2015).

A 90% equal-tailed interval (ETI) has 5% of the distribution on either side of its limits. It indicates the 5th percentile and the 95th percentile. In symmetric distributions, the two methods of computing credible intervals, the ETI and the HDI, return similar results.

This is not the case for skewed distributions. Indeed, it is possible that parameter values in the ETI have lower credibility (are less probable) than parameter values outside the ETI. This property
seems undesirable as a summary of the credible values in a distribution.

On the other hand, the ETI range does change when transformations are applied to the distribution (for instance, for a log odds scale to probabilities): the lower and higher bounds of the transformed distribution will correspond to the transformed lower and higher bounds of the original distribution. On the contrary, applying transformations to the distribution will change the resulting HDI.

**Value**

A data frame with following columns:

- **Parameter** The model parameter(s), if x is a model-object. If x is a vector, this column is missing.
- **CI** The probability of the credible interval.
- **CI_low, CI_high** The lower and upper credible interval limits for the parameters.

**Examples**

```r
library(bayestestR)

posterior <- rnorm(1000)
eti(posterior)
eti(posterior, ci = c(.80, .89, .95))

df <- data.frame(replicate(4, rnorm(100)))
eti(df)
eti(df, ci = c(.80, .89, .95))
## Not run:
library(rstanarm)
model <- stan_glmer(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
eti(model)
eti(model, ci = c(.80, .89, .95))

library(emmeans)
eti(emtrends(model, ~1, "wt"))

library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
eti(model)
eti(model, ci = c(.80, .89, .95))

library(BayesFactor)
bf <- ttestBF(x = rnorm(100, 1, 1))
eti(bf)
eti(bf, ci = c(.80, .89, .95))
## End(Not run)
```
**hdi**

*Highest Density Interval (HDI)*

**Description**

Compute the Highest Density Interval (HDI) of posterior distributions. All points within this interval have a higher probability density than points outside the interval. The HDI can be used in the context of uncertainty characterisation of posterior distributions as Credible Interval (CI).

**Usage**

```r
hdi(x, ...) # S3 method for class 'numeric'
hdi(x, ci = 0.89, verbose = TRUE, ...)

# S3 method for class 'data.frame'
hdi(x, ci = 0.89, verbose = TRUE, ...)

# S3 method for class 'MCMCglmm'
hdi(x, ci = 0.89, verbose = TRUE, ...)

# S3 method for class 'sim.merMod'
hdi(
  x,
  ci = 0.89,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...)

# S3 method for class 'sim'

hdi(x, ci = 0.89, parameters = NULL, verbose = TRUE, ...)

# S3 method for class 'emmGrid'

hdi(x, ci = 0.89, verbose = TRUE, ...)

# S3 method for class 'stanreg'

hdi(
  x,
  ci = 0.89,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)
```
## S3 method for class 'brmsfit'

```r
hdi(
  x,
  ci = 0.89,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)
```  

## S3 method for class 'BFBayesFactor'

```r
hdi(x, ci = 0.89, verbose = TRUE, ...)
```  

### Arguments

- **x** Vector representing a posterior distribution. Can also be a `stanreg`, `brmsfit` or a `BayesFactor` model.
- **...** Currently not used.
- **ci** Value or vector of probability of the (credible) interval - CI (between 0 and 1) to be estimated. Default to 0.89 (89%).
- **verbose** Toggle off warnings.
- **effects** Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters** Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use `parameters` to select specific parameters for the output.
- **component** Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

### Details

Unlike equal-tailed intervals (see `eti()`) that typically exclude 2.5% from each tail of the distribution and always include the median, the HDI is not equal-tailed and therefore always includes the mode(s) of posterior distributions.

By default, `hdi()` and `eti()` return the 89% intervals (ci = 0.89), deemed to be more stable than, for instance, 95% intervals (Kruschke, 2014). An effective sample size of at least 10,000 is recommended if 95% intervals should be computed (Kruschke, 2014, p. 183ff). Moreover, 89 indicates the arbitrariness of interval limits - its only remarkable property is being the highest prime number that does not exceed the already unstable 95% threshold (McElreath, 2015).

A 90% equal-tailed interval (ETI) has 5% of the distribution on either side of its limits. It indicates the 5th percentile and the 95th percentile. In symmetric distributions, the two methods of
computing credible intervals, the ETI and the HDI, return similar results.

This is not the case for skewed distributions. Indeed, it is possible that parameter values in the ETI have lower credibility (are less probable) than parameter values outside the ETI. This property seems undesirable as a summary of the credible values in a distribution.

On the other hand, the ETI range does change when transformations are applied to the distribution (for instance, for a log odds scale to probabilities): the lower and higher bounds of the transformed distribution will correspond to the transformed lower and higher bounds of the original distribution. On the contrary, applying transformations to the distribution will change the resulting HDI.

**Value**

A data frame with following columns:

- **Parameter** The model parameter(s), if x is a model-object. If x is a vector, this column is missing.
- **CI** The probability of the credible interval.
- **CI_low, CI_high** The lower and upper credible interval limits for the parameters.

**Author(s)**

Credits go to ggdistribute and HDInterval.

**References**


**Examples**

```r
library(bayestestR)
posterior <- rnorm(1000)
hdi(posterior, ci = .89)
hdi(posterior, ci = c(.80, .90, .95))

df <- data.frame(replicate(4, rnorm(100)))
hdi(df)
hdi(df, ci = c(.80, .90, .95))

## Not run:
library(rstanarm)
model <- stan_glm(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
hdi(model)
hdi(model, ci = c(.80, .90, .95))

library(emmeans)
```
```r
library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
hdi(model)
hdi(model, ci = c(.80, .90, .95))

library(BayesFactor)
bf <- ttestBF(x = rnorm(100, 1, 1))
hdi(bf)
hdi(bf, ci = c(.80, .90, .95))
```

---

### map_estimate

**Maximum A Posteriori probability estimate (MAP)**

#### Description

Find the **Highest Maximum A Posteriori probability estimate (MAP)** of a posterior, i.e., the value associated with the highest probability density (the "peak" of the posterior distribution). In other words, it is an estimation of the mode for continuous parameters. Note that this function relies on `estimate_density`, which by default uses a different smoothing bandwidth ("SJ") compared to the legacy default implemented the base R `density` function ("nrd0").

#### Usage

```r
map_estimate(x, precision = 2^10, method = "kernel", ...)
```

**S3 method for class 'numeric'**

```r
map_estimate(x, precision = 2^10, method = "kernel", ...)
```

**S3 method for class 'stanreg'**

```r
map_estimate(
  x,
  precision = 2^10,
  method = "kernel",
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...
)
```

**S3 method for class 'brmsfit'**

```r
map_estimate(
  x,
  precision = 2^10,
  method = "kernel",
)```
map_estimate

effects = c("fixed", "random", "all"),
component = c("conditional", "zi", "zero_inflated", "all"),
parameters = NULL,
...
)

Arguments

x Vector representing a posterior distribution. Can also be a stanreg, brmsfit or a BayesFactor model.
precision Number of points of density data. See the n parameter in density.
method Density estimation method. Can be "kernel" (default), "logspline" or "KernSmooth".
... Currently not used.
effects Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
parameters Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior__) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.
component Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.

Value

A numeric value if posterior is a vector. If posterior is a model-object, returns a data frame with following columns:

- Parameter The model parameter(s), if x is a model-object. If x is a vector, this column is missing.
- MAP_Estimate The MAP estimate for the posterior or each model parameter.

Examples

## Not run:
library(bayestestR)

posterior <- rnorm(10000)
map_estimate(posterior)

plot(density(posterior))
abline(v = map_estimate(posterior), col = "red")

library(rstanarm)
model <- rstanarm::stan_glm(mpg ~ wt + cyl, data = mtcars)
map_estimate(model)

library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
map_estimate(model)

## End(Not run)

---

**mcse**

*Monte-Carlo Standard Error (MCSE)*

**Description**

This function returns the Monte Carlo Standard Error (MCSE).

**Usage**

```r
mcse(model, ...)
```

```r
## S3 method for class 'stanreg'
mcse(model, effects = c("fixed", "random", "all"), parameters = NULL, ...)
```

**Arguments**

- `model`: A `stanreg`, `stanfit`, or `brmsfit` object.
- `...`: Currently not used.
- `effects`: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- `parameters`: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior_) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use `parameters` to select specific parameters for the output.

**Details**

**Monte Carlo Standard Error (MCSE)** is another measure of accuracy of the chains. It is defined as standard deviation of the chains divided by their effective sample size (the formula for `mcse()` is from Kruschke 2015, p. 187). The MCSE “provides a quantitative suggestion of how big the estimation noise is”.

**References**

Examples

```r
## Not run:
library(bayestestR)
library(rstanarm)

model <- stan_glm(mpg ~ wt + am, data = mtcars, chains = 1, refresh = 0)
mcse(model)

## End(Not run)
```

mhdior

**Maximum HDI level inside/outside ROPE (MHDIOR)**

Description

The MHDIOR (pronounced 'em-eich-dior') is an exploratory and non-validated index representing the maximum percentage of HDI that does not contain (or is entirely contained, in which case the value is prefixed with a negative sign), in the negligible values space defined by the ROPE. It differs from the ROPE percentage, *i.e.*, from the proportion of a given CI in the ROPE, as it represents the maximum CI values needed to reach a ROPE proportion of 0% or 100%. Whether the index reflects the ROPE reaching 0% or 100% is indicated through the sign: a negative sign is added to indicate that the probability corresponds to the probability of a not significant effect (a percentage in ROPE of 100%). For instance, a MHDIOR of 97% means that there is a probability of .97 that a parameter (described by its posterior distribution) is outside the ROPE. In other words, the 97% HDI is the maximum HDI level for which the percentage in ROPE is 0%. On the contrary, a ROPE-based p of -97% indicates that there is a probability of .97 that the parameter is inside the ROPE (percentage in ROPE of 100%). A value close to 0% would indicate that the mode of the distribution falls perfectly at the edge of the ROPE, in which case the percentage of HDI needed to be on either side of the ROPE becomes infinitely small. Negative values do not refer to negative values *per se*, simply indicating that the value corresponds to non-significance rather than significance.

Usage

```r
mhdior(x, ...)
```

```
## S3 method for class 'numeric'
mhdior(x, range = "default", precision = 0.1, ...)
```

```
## S3 method for class 'data.frame'
mhdior(x, range = "default", precision = 0.1, ...)
```

```
## S3 method for class 'emmGrid'
mhdior(x, range = "default", precision = 0.1, ...)
```

```
## S3 method for class 'BFBayesFactor'
mhdior(x, range = "default", precision = 0.1, ...)
```
## S3 method for class 'stanreg'
mhdior(
  x,
  range = "default",
  precision = 0.1,
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...
)

## S3 method for class 'brmsfit'
mhdior(
  x,
  range = "default",
  precision = 0.1,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  ...
)

### Arguments

- **x**: Vector representing a posterior distribution. Can also be a stanreg or brmsfit model.
- **range**: ROPE's lower and higher bounds. Should be a vector of length two (e.g., c(-0.1,0.1)) or "default". If "default", the range is set to c(-0.1,0.1) if input is a vector, and based on rope_range() if a Bayesian model is provided.
- **precision**: The precision by which to explore the ROPE space (in percentage). Lower values increase the precision of the returned p value but can be quite computationally costly.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior_) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.

### Examples

## Not run:
library(bayestestR)
# precision = 1 is used to speed up examples...

mhdior(
  x = rnorm(1000, mean = 1, sd = 1),
  range = c(-0.1, 0.1),
  precision = 1
)

df <- data.frame(replicate(4, rnorm(100)))
mhdior(df, precision = 1)

if (require("rstanarm")) {
  model <- stan_glmer(
    mpg ~ wt + gear, data = mtcars,
    chains = 2,
    iter = 200,
    refresh = 0
  )
  mhdior(model, precision = 1)
}

if (require("emmeans")) {
  mhdior(emtrends(model, ~1, "wt"))
}

if (require("brms")) {
  model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
  mhdior(model)
}

if (require("BayesFactor")) {
  bf <- ttestBF(x = rnorm(100, 1, 1))
  mhdior(bf)
}

## End(Not run)

### overlap

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A method to calculate the overlap coefficient between two empirical distributions (that can be used as a measure of similarity between two samples).</td>
</tr>
</tbody>
</table>

### Usage

```r
doi(x, y, precision)
```
method_density = "kernel",
method_auc = "trapezoid",
precision = 2^10,
extend = TRUE,
extend_scale = 0.1,
...
)

Arguments

x Vector of x values.
y Vector of x values.
method_density Density estimation method. See estimate_density.
method_auc Area Under the Curve (AUC) estimation method. See area_under_curve.
precision Number of points of density data. See the n parameter in density.
extend Extend the range of the x axis by a factor of extend_scale.
extend_scale Ratio of range by which to extend the x axis. A value of 0.1 means that the x axis will be extended by 1/10 of the range of the data.
...
Currently not used.

Examples

library(bayestestR)

x <- distribution_normal(1000, 2, 0.5)
y <- distribution_normal(1000, 0, 1)

overlap(x, y)
plot(overlap(x, y))

daisy

pd_to_p

 Convert between Probability of Direction (pd) and p-value.

Description

Enables a conversion between Probability of Direction (pd) and p-value.

Usage

pd_to_p(pd, direction = "two-sided", ...)
p_to_pd(p, direction = "two-sided", ...)
convert_p_to_pd(p, direction = "two-sided", ...)
convert_pd_to_p(pd, direction = "two-sided", ...)
point_estimate

Arguments

- **pd**: A Probability of Direction (pd) value (between 0 and 1).
- **direction**: What type of p-value is requested or provided. Can be "two-sided" (default, two tailed) or "one-sided" (one tailed).
- **...**: Arguments passed to or from other methods.
- **p**: A p-value.

Examples

```r
pd_to_p(pd = 0.95)
pd_to_p(pd = 0.95, direction = "one-sided")
```

---

point_estimate  
Point-estimates of posterior distributions

Description

Compute various point-estimates, such as the mean, the median or the MAP, to describe posterior distributions.

Usage

```r
point_estimate(x, centrality = "all", dispersion = FALSE, ...)
```

## S3 method for class 'stanreg'
```r
point_estimate(  
  x,  
  centrality = "all",  
  dispersion = FALSE,  
  effects = c("fixed", "random", "all"),  
  parameters = NULL,  
  ...)
```

## S3 method for class 'brmsfit'
```r
point_estimate(  
  x,  
  centrality = "all",  
  dispersion = FALSE,  
  effects = c("fixed", "random", "all"),  
  component = c("conditional", "zi", "zero_inflated", "all"),  
  parameters = NULL,  
  ...
)
```

## S3 method for class 'BFBayesFactor'
```r
point_estimate(x, centrality = "all", dispersion = FALSE, ...)
```
Arguments

- **x**: Vector representing a posterior distribution. Can also be a `stanreg`, `brmsfit` or a `BayesFactor` model.
- **centrality**: The point-estimates (centrality indices) to compute. Character (vector) or list with one or more of these options: "median", "mean", "MAP" or "all".
- **dispersion**: Logical, if `TRUE`, computes indices of dispersion related to the estimate(s) (SD and MAD for mean and median, respectively).
- **...**: Additional arguments to be passed to or from methods.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use parameters to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

References

Vignette In-Depth 1: Comparison of Point-Estimates

Examples

```r
library(bayestestR)

point_estimate(rnorm(1000))
point_estimate(rnorm(1000), centrality = "all", dispersion = TRUE)
point_estimate(rnorm(1000), centrality = c("median", "MAP"))

df <- data.frame(replicate(4, rnorm(100)))
point_estimate(df, centrality = "all", dispersion = TRUE)
point_estimate(df, centrality = c("median", "MAP"))
## Not run:
# rstanarm models
# -----------------------------------------------
library(rstanarm)
model <- rstanarm::stan_glm(mpg ~ wt + cyl, data = mtcars)
point_estimate(model, centrality = "all", dispersion = TRUE)
point_estimate(model, centrality = c("median", "MAP"))

# emmeans estimates
# -----------------------------------------------
library(emmeans)
point_estimate(emtrends(model, ~1, "wt"), centrality = c("median", "MAP"))

# brms models
# -----------------------------------------------
```
library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
point_estimate(model, centrality = "all", dispersion = TRUE)
point_estimate(model, centrality = c("median", "MAP"))

# BayesFactor objects
# -----------------------------------------------
library(BayesFactor)
bf <- ttestBF(x = rnorm(100, 1, 1))
point_estimate(bf, centrality = "all", dispersion = TRUE)
point_estimate(bf, centrality = c("median", "MAP"))

## End(Not run)

---

**p_direction**

**Probability of Direction (pd)**

### Description

Compute the **Probability of Direction (pd)**, also known as the Maximum Probability of Effect - MPE. It varies between 50% and 100% (i.e., 0.5 and 1) and can be interpreted as the probability (expressed in percentage) that a parameter (described by its posterior distribution) is strictly positive or negative (whichever is the most probable). It is mathematically defined as the proportion of the posterior distribution that is of the median’s sign. Although differently expressed, this index is fairly similar (i.e., is strongly correlated) to the frequentist p-value.

### Usage

`p_direction(x, ...)

pd(x, ...)`

```r
## S3 method for class 'numeric'
p_direction(x, method = "direct", ...)

## S3 method for class 'data.frame'
p_direction(x, method = "direct", ...)

## S3 method for class 'MCMCglmm'
p_direction(x, method = "direct", ...)

## S3 method for class 'emmGrid'
p_direction(x, method = "direct", ...)

## S3 method for class 'stanreg'
p_direction(x,)
```

## Examples

```r
# Example usage
x <- rnorm(100)
p_direction(x)
```
effect = c("fixed", "random", "all"),
parameters = NULL,
method = "direct",
...)

## S3 method for class 'brmsfit'
p_direction(
x,
effects = c("fixed", "random", "all"),
component = c("conditional", "zi", "zero_inflated", "all"),
parameters = NULL,
method = "direct",
...)

## S3 method for class 'BFBayesFactor'
p_direction(x, method = "direct", ...)

Arguments

x Vector representing a posterior distribution. Can also be a Bayesian model (stanreg, brmsfit or BayesFactor).

... Currently not used.

method Can be "direct" or one of methods of density estimation, such as "kernel", "logspline" or "KernSmooth". If "direct" (default), the computation is based on the raw ratio of samples superior and inferior to 0. Else, the result is based on the Area under the Curve (AUC) of the estimated density function.

effects Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.

parameters Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior__) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.

component Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.

Details

What is the pd?: The Probability of Direction (pd) is an index of effect existence, ranging from 50% to 100%, representing the certainty with which an effect goes in a particular direction (i.e., is positive or negative). Beyond its simplicity of interpretation, understanding and computation, this index also presents other interesting properties:

- It is independent from the model: It is solely based on the posterior distributions and does not require any additional information from the data or the model.
- It is robust to the scale of both the response variable and the predictors.
• It is strongly correlated with the frequentist p-value, and can thus be used to draw parallels and give some reference to readers non-familiar with Bayesian statistics.

**Relationship with the p-value:** In most cases, it seems that the \( p_d \) has a direct correspondence with the frequentist one-sided \( p \)-value through the formula \( p_{onesided} = 1 - \frac{p_d}{100} \) and to the two-sided \( p \)-value (the most commonly reported one) through the formula \( p_{twosided} = 2 \times (1 - \frac{p_d}{100}) \). Thus, a two-sided \( p \)-value of respectively .1, .05, .01 and .001 would correspond approximately to a \( p_d \) of 95%, 97.5%, 99.5% and 99.95%.

**Methods of computation:** The most simple and direct way to compute the \( p_d \) is to 1) look at the median’s sign, 2) select the portion of the posterior of the same sign and 3) compute the percentage that this portion represents. This “simple” method is the most straightforward, but its precision is directly tied to the number of posterior draws. The second approach relies on density estimation. It starts by estimating the density function (for which many methods are available), and then computing the area under the curve (AUC) of the density curve on the other side of 0.

**Strengths and Limitations:**

**Strengths:** Straightforward computation and interpretation. Objective property of the posterior distribution. 1:1 correspondence with the frequentist p-value.

**Limitations:** Limited information favoring the null hypothesis.

**Value**

Values between 0.5 and 1 corresponding to the probability of direction (pd).

**References**


**Examples**

```r
library(bayestestR)

# Simulate a posterior distribution of mean 1 and SD 1
# ----------------------------------------------------
posterior <- rnorm(1000, mean = 1, sd = 1)
p_direction(posterior)
p_direction(posterior, method = "kernel")

# Simulate a dataframe of posterior distributions
# -----------------------------------------------
df <- data.frame(replicate(4, rnorm(100)))
p_direction(df)
p_direction(df, method = "kernel")

## Not run:
# rstanarm models
# -----------------------------------------------
if (require("rstanarm")) {
```
model <- rstanarm::stan_glm(mpg ~ wt + cyl, data = mtcars, chains = 2, refresh = 0)
p_direction(model)
p_direction(model, method = "kernel")

# emmeans
# -----------------------------------------------
if (require("emmeans")) {
p_direction(emtrends(model, ~1, "wt"))
}

# brms models
# -----------------------------------------------
if (require("brms")) {
  model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
p_direction(model)
p_direction(model, method = "kernel")
}

# BayesFactor objects
# -----------------------------------------------
if (require("BayesFactor")) {
  bf <- ttestBF(x = rnorm(100, 1, 1))
p_direction(bf)
p_direction(bf, method = "kernel")
}

## End(Not run)

---

**p_map**

Bayesian p-value based on the density at the Maximum A Posteriori (MAP)

---

**Description**

Compute a Bayesian equivalent of the \(p\)-value, related to the odds that a parameter (described by its posterior distribution) has against the null hypothesis \(h0\) using Mills' (2014, 2017) *Objective Bayesian Hypothesis Testing* framework. It corresponds to the density value at 0 divided by the density at the Maximum A Posteriori (MAP).

**Usage**

\[
p_{\text{map}}(x, \text{precision} = 2^{10}, \text{method} = "kernel", \ldots)
\]

\[
p_{\text{pointnull}}(x, \text{precision} = 2^{10}, \text{method} = "kernel", \ldots)
\]
### S3 method for class 'stanreg'

```r
p_map(  
  x,  
  precision = 2^10,  
  method = "kernel",  
  effects = c("fixed", "random", "all"),  
  parameters = NULL,  
  ...  
)
```

### S3 method for class 'brmsfit'

```r
p_map(  
  x,  
  precision = 2^10,  
  method = "kernel",  
  effects = c("fixed", "random", "all"),  
  component = c("conditional", "zi", "zero_inflated", "all"),  
  parameters = NULL,  
  ...  
)
```

#### Arguments

- **x**: Vector representing a posterior distribution. Can also be a `stanreg`, `brmsfit` or a `BayesFactor` model.
- **precision**: Number of points of density data. See the `n` parameter in `density`.
- **method**: Density estimation method. Can be "kernel" (default), "logspline" or "KernSmooth".
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use `parameters` to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

#### Details

Note that this method is sensitive to the density estimation method (see the section in the examples below).

**Strengths and Limitations:**

- **Strengths**: Straightforward computation. Objective property of the posterior distribution.
**Limitations:** Limited information favoring the null hypothesis. Relates on density approximation. Indirect relationship between mathematical definition and interpretation. Only suitable for weak / very diffused priors.

**References**


**See Also**

Jeff Mill’s talk

**Examples**

```r
library(bayestestR)

p_map(rnorm(1000, 0, 1))
p_map(rnorm(1000, 10, 1))

## Not run:
library(rstanarm)
model <- stan_glm(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
p_map(model)

library(emmeans)
p_map(emtrends(model, ~1, "wt"))

library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
p_map(model)

library(BayesFactor)
bf <- ttestBF(x = rnorm(100, 1, 1))
p_map(bf)

## End(Not run)
```

# -----------------------------
# Robustness to density estimation method
set.seed(333)
data <- data.frame()
for (iteration in 1:250) {
  x <- rnorm(1000, 1, 1)
  result <- data.frame(
    "Kernel" = p_map(x, method = "kernel"),
    "KernSmooth" = p_map(x, method = "KernSmooth"),
    "logspline" = p_map(x, method = "logspline")
  )
}
```
p_rope <- function(x, ..., range = "default", effects = c("fixed", "random", "all"), parameters = NULL)
{
  if (class(x) == "data.frame")
    x <- as(x, "numeric")

  if (is.null(parameters) || parameters == NULL)
    parameters <- names(x)

  for (param in parameters)
    if (class(param) == "character")
      parameters <- param

  if (is.null(effects) || effects == "all")
    effects <- c("fixed", "random")

  if (is.null(range))
    range <- "default"

  if (range == "default")
    range <- range(x)

  # Compute the proportion of the posterior distribution that doesn't lie within a region of practical equivalence (ROPE).
  # It is equivalent to running rope(..., ci = 1).

  # Compute the probability of not being in ROPE
  p <- mean(x < range[1] | x > range[2])

  return(p)
}

# Default S3 method
p_rope(x, ...)

# S3 method for class 'numeric'
p_rope(x, range = "default", ...)

# S3 method for class 'data.frame'
p_rope(x, range = "default", ...)

# S3 method for class 'emmGrid'
p_rope(x, range = "default", ...)

# S3 method for class 'BFBayesFactor'
p_rope(x, range = "default", ...)

# S3 method for class 'MCMCglmm'
p_rope(x, range = "default", ...)

# S3 method for class 'stanreg'
p_rope(
  x,
  range = "default",
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...)

# Compute the proportion of the posterior distribution that doesn't lie within a region of practical equivalence (ROPE).
# It is equivalent to running rope(..., ci = 1).

# Probability of not being in ROPE

# Description

# Compute the proportion of the posterior distribution that doesn’t lie within a region of practical equivalence (ROPE). It is equivalent to running rope(..., ci = 1).

# Usage

# p_rope(x, ...)

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

# ## S3 method for class 'numeric'
p_rope(x, range = "default", ...)

# ## S3 method for class 'data.frame'
p_rope(x, range = "default", ...)

# ## S3 method for class 'emmGrid'
p_rope(x, range = "default", ...)

# ## S3 method for class 'BFBayesFactor'
p_rope(x, range = "default", ...)

# ## S3 method for class 'MCMCglmm'
p_rope(x, range = "default", ...)

# ## S3 method for class 'stanreg'
p_rope(
  x,
  range = "default",
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...)

# Summary:

# p_rope <- function(x, ...)

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

# ## S3 method for class 'numeric'
p_rope(x, range = "default", ...)

# ## S3 method for class 'data.frame'
p_rope(x, range = "default", ...)

# ## S3 method for class 'emmGrid'
p_rope(x, range = "default", ...)

# ## S3 method for class 'BFBayesFactor'
p_rope(x, range = "default", ...)

# ## S3 method for class 'MCMCglmm'
p_rope(x, range = "default", ...)

# ## S3 method for class 'stanreg'
p_rope(
  x,
  range = "default",
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  ...)

# boxplot(data[c("KernSmooth", "logspline")])

# summary(data$KernSmooth)
# summary(data$logspline)

# data <- rbind(data, result)
}
data$KernSmooth <- data$Kernel - data$KernSmooth
data$logspline <- data$Kernel - data$logspline

summary(data$KernSmooth)
summary(data$logspline)
boxplot(data[,c("KernSmooth", "logspline")])
## S3 method for class 'brmsfit'
p_rope(
  x,
  range = "default",
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  ...
)

### Arguments

- **x**: Vector representing a posterior distribution. Can also be a stanreg or brmsfit model.
- **range**: ROPE's lower and higher bounds. Should be a vector of length two (e.g., `c(-0.1, 0.1)` or "default". If "default", the range is set to `c(-0.1, 0.1)` if input is a vector, and based on `rope_range()` if a Bayesian model is provided.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use parameters to select specific parameters for the output.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.

### Examples

```r
library(bayestestR)
p_rope(x = rnorm(1000, 0, 0.01), range = c(-0.1, 0.1))
p_rope(x = mtcars, range = c(-0.1, 0.1))
```

---

### Description

Compute the probability of **Practical Significance (ps)**, which can be conceptualized as a unidirectional equivalence test. It returns the probability that effect is above a given threshold corresponding to a negligible effect in the median's direction. Mathematically, it is defined as the proportion of the posterior distribution of the median sign above the threshold.
p_significance

Usage

p_significance(x, ...)

## S3 method for class 'numeric'
p_significance(x, threshold = "default", ...)

## S3 method for class 'emmGrid'
p_significance(x, threshold = "default", ...)

## S3 method for class 'stanreg'
p_significance(
  x,
  threshold = "default",
  effects = c("fixed", "random", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'brmsfit'
p_significance(
  x,
  threshold = "default",
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL,
  verbose = TRUE,
  ...
)

Arguments

x Vector representing a posterior distribution. Can also be a stanreg or brmsfit model.

... Currently not used.

threshold The threshold value that separates significant from negligible effect. If "default", the range is set to 0.1 if input is a vector, and based on rope_range() if a Bayesian model is provided.

effects Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.

parameters Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior_) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.

verbose Toggle off warnings.
component

Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to \texttt{brms}-models.

Details

\texttt{p_significance()} returns the proportion of a probability distribution (x) that is outside a certain range (the negligible effect, or ROPE, see argument \texttt{threshold}). If there are values of the distribution both below and above the ROPE, \texttt{p_significance()} returns the higher probability of a value being outside the ROPE. Typically, this value should be larger than 0.5 to indicate practical significance. However, if the range of the negligible effect is rather large compared to the range of the probability distribution x, \texttt{p_significance()} will be less than 0.5, which indicates no clear practical significance.

Value

Values between 0 and 1 corresponding to the probability of practical significance (ps).

Examples

library(bayestestR)

# Simulate a posterior distribution of mean 1 and SD 1
# ----------------------------------------------------
posterior <- rnorm(1000, mean = 1, sd = 1)
p_significance(posterior)

# Simulate a dataframe of posterior distributions
# -----------------------------------------------
df <- data.frame(replicate(4, rnorm(100)))
p_significance(df)

## Not run:
# rstanarm models
# -----------------------------------------------
if (require("rstanarm")) {
  model <- rstanarm::stan_glm(mpg ~ wt + cyl,
                               data = mtcars,
                               chains = 2, refresh = 0
  )
p_significance(model)
}

## End(Not run)
Described

Reshape CI between wide/long formats.

Usage

reshape_ci(x)

Arguments

x A data.frame containing CI_low and CI_high.

Examples

library(bayestestR)

x <- data.frame(replicate(4, rnorm(100)))
x <- ci(x, ci = c(0.68, 0.89, 0.95))
reshape_ci(x)
reshape_ci(reshape_ci(x))

x <- data.frame(replicate(4, rnorm(100)))
x <- describe_posterior(x, ci = c(0.68, 0.89, 0.95))
reshape_ci(x)
reshape_ci(reshape_ci(x))

-----------

rope Region of Practical Equivalence (ROPE)

Description

Compute the proportion of the HDI (default to the 89% HDI) of a posterior distribution that lies within a region of practical equivalence.

Usage

rope(x, ...)

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

## S3 method for class 'numeric'
rope(x, range = "default", ci = 0.89, ci_method = "HDI", verbose = TRUE, ...)

## S3 method for class 'data.frame'
rope(x, range = "default", ci = 0.89, ci_method = "HDI", verbose = TRUE, ...)

## S3 method for class 'emmGrid'
rope(x, range = "default", ci = 0.89, ci_method = "HDI", verbose = TRUE, ...)
Arguments

- **x**: Vector representing a posterior distribution. Can also be a `stanreg` or `brmsfit` model.
- **range**: ROPE’s lower and higher bounds. Should be a vector of length two (e.g., `c(-0.1, 0.1)`) or "default". If "default", the range is set to `c(-0.1, 0.1)` if input is a vector, and based on `rope_range()` if a Bayesian model is provided.
- **ci**: The Credible Interval (CI) probability, corresponding to the proportion of HDI, to use for the percentage in ROPE.
- **ci_method**: The type of interval to use to quantify the percentage in ROPE. Can be 'HDI' (default) or 'ETI'. See `ci`.
- **verbose**: Toggle off warnings.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
parameters Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior__) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.

cOMPONENT Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.

Details

ROPE: Statistically, the probability of a posterior distribution of being different from 0 does not make much sense (the probability of a single value null hypothesis in a continuous distribution is 0). Therefore, the idea underlining ROPE is to let the user define an area around the null value enclosing values that are equivalent to the null value for practical purposes (Kruschke 2010, 2011, 2014).

Kruschke (2018) suggests that such null value could be set, by default, to the -0.1 to 0.1 range of a standardized parameter (negligible effect size according to Cohen, 1988). This could be generalized: For instance, for linear models, the ROPE could be set as $\theta +/-.1 * sd(y)$. This ROPE range can be automatically computed for models using the rope_range function.

Kruschke (2010, 2011, 2014) suggests using the proportion of the 95% (or 89%, considered more stable) HDI that falls within the ROPE as an index for “null-hypothesis” testing (as understood under the Bayesian framework, see equivalence_test()).

Sensitivity to parameter’s scale: It is important to consider the unit (i.e., the scale) of the predictors when using an index based on the ROPE, as the correct interpretation of the ROPE as representing a region of practical equivalence to zero is dependent on the scale of the predictors. Indeed, the percentage in ROPE depend on the unit of its parameter. In other words, as the ROPE represents a fixed portion of the response’s scale, its proximity with a coefficient depends on the scale of the coefficient itself.

Multicollinearity: Non-independent covariates: When parameters show strong correlations, i.e. when covariates are not independent, the joint parameter distributions may shift towards or away from the ROPE. Collinearity invalidates ROPE and hypothesis testing based on univariate marginals, as the probabilities are conditional on independence. Most problematic are parameters that only have partial overlap with the ROPE region. In case of collinearity, the (joint) distributions of these parameters may either get an increased or decreased ROPE, which means that inferences based on rope() are inappropriate (Kruschke 2014, 340f).

rope() performs a simple check for pairwise correlations between parameters, but as there can be collinearity between more than two variables, a first step to check the assumptions of this hypothesis testing is to look at different pair plots. An even more sophisticated check is the projection predictive variable selection (Piironen and Vehtari 2017).

Strengths and Limitations: Strengths: Provides information related to the practical relevance of the effects.

Limitations: A ROPE range needs to be arbitrarily defined. Sensitive to the scale (the unit) of the predictors. Not sensitive to highly significant effects.
References


Examples

```r
library(bayestestR)
rope(x = rnorm(1000, 0, 0.01), range = c(-0.1, 0.1))
rope(x = rnorm(1000, 0, 1), range = c(-0.1, 0.1))
rope(x = rnorm(1000, 1, 0.01), range = c(-0.1, 0.1))
rope(x = rnorm(1000, 1, 1), ci = c(.90, .95))
```

```r
## Not run:
library(rstanarm)
model <- stan_glm(mpg ~ wt + gear, data = mtcars, chains = 2, iter = 200, refresh = 0)
rope(model)
rope(model, ci = c(.90, .95))
```

```r
library(emmeans)
rope(emtrends(model, ~1, "wt"), ci = c(.90, .95))
```

```r
library(brms)
model <- brms::brm(mpg ~ wt + cyl, data = mtcars)
rope(model)
rope(model, ci = c(.90, .95))
```

```r
library(BayesFactor)
bf <- ttestBF(x = rnorm(100, 1, 1))
rope(bf)
rope(bf, ci = c(.90, .95))
```

## End(Not run)
rope_range

Find Default Equivalence (ROPE) Region Bounds

Description

This function attempts at automatically finding suitable "default" values for the Region Of Practical Equivalence (ROPE).

Usage

rope_range(x, ...)

Arguments

x A stanreg, brmsfit or BFBayesFactor object.
... Currently not used.

Details

Kruschke (2018) suggests that the region of practical equivalence could be set, by default, to a range from $-0.1$ to $0.1$ of a standardized parameter (negligible effect size according to Cohen, 1988).

- For linear models (lm), this can be generalised to $[-0.1 \times SD_y, 0.1 \times SD_y]$.
- For logistic models, the parameters expressed in log odds ratio can be converted to standardized difference through the formula $\pi/\sqrt{3}$, resulting in a range of $-0.18$ to $0.18$.
- For other models with binary outcome, it is strongly recommended to manually specify the rope argument. Currently, the same default is applied that for logistic models.
- For t-tests, the standard deviation of the response is used, similarly to linear models (see above).
- For correlations, $-0.05, 0.05$ is used, i.e., half the value of a negligible correlation as suggested by Cohen’s (1988) rules of thumb.
- For all other models, $-0.1, 0.1$ is used to determine the ROPE limits, but it is strongly advised to specify it manually.

References


Examples

```r
## Not run:
if (require("rstanarm")) {
  model <- stan_glm(
    mpg ~ wt + gear,
    data = mtcars,
```
sensitivity_to_prior

Sensitivity to Prior

Description
Computes the sensitivity to priors specification. This represents the proportion of change in some indices when the model is fitted with an antagonistic prior (a prior of same shape located on the opposite of the effect).

Usage
sensitivity_to_prior(model, index = "Median", magnitude = 10, ...)

Arguments

- **model**: A Bayesian model (stanreg or brmsfit).
- **index**: The indices from which to compute the sensitivity. Can be one or multiple names of the columns returned by `describe_posterior`. The case is important here (e.g., write 'Median' instead of 'median').
- **magnitude**: This represents the magnitude by which to shift the antagonistic prior (to test the sensitivity). For instance, a magnitude of 10 (default) means that the mode will be updated with a prior located at 10 standard deviations from its original location.
- **...**: Arguments passed to or from other methods.
Compute Support Intervals

Description

A support interval contains only the values of the parameter that predict the observed data better than average, by some degree $k$; these are values of the parameter that are associated with an updating factor greater or equal than $k$. From the perspective of the Savage-Dickey Bayes factor, testing against a point null hypothesis for any value within the support interval will yield a Bayes factor smaller than $1/k$.

For more info, in particular on specifying correct priors for factors with more than 2 levels, see the Bayes factors vignette.

Usage

```
si(posterior, prior = NULL, BF = 1, verbose = TRUE, ...)
```

## S3 method for class 'numeric'
```
si(posterior, prior = NULL, BF = 1, verbose = TRUE, ...)
```
## S3 method for class 'stanreg'
si(
posterior,
prior = NULL,
BF = 1,
verbose = TRUE,
effects = c("fixed", "random", "all"),
component = c("conditional", "zi", "zero_inflated", "all"),
parameters = NULL,
...
)

## S3 method for class 'brmsfit'
si(
posterior,
prior = NULL,
BF = 1,
verbose = TRUE,
effects = c("fixed", "random", "all"),
component = c("conditional", "zi", "zero_inflated", "all"),
parameters = NULL,
...
)

## S3 method for class 'emmGrid'
si(posterior, prior = NULL, BF = 1, verbose = TRUE, ...)

## S3 method for class 'data.frame'
si(posterior, prior = NULL, BF = 1, verbose = TRUE, ...)

### Arguments

- **posterior**: A numerical vector, stanreg / brmsfit object, emmGrid or a data frame - representing a posterior distribution(s) from (see 'Details').
- **prior**: An object representing a prior distribution (see 'Details').
- **BF**: The amount of support required to be included in the support interval.
- **verbose**: Toggle off warnings.
- **...**: Arguments passed to and from other methods.
- **effects**: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- **component**: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to brms-models.
- **parameters**: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like lp__ or prior__) are filtered by default, so only parameters that typically appear in the summary() are returned. Use parameters to select specific parameters for the output.
Details

This method is used to compute support intervals based on prior and posterior distributions. For the computation of support intervals, the model priors must be proper priors (at the very least they should be not flat, and it is preferable that they be informative - note that by default, \texttt{brms::brm()} uses flat priors for fixed-effects; see example below).

**Setting the correct prior:** It is important to provide the correct prior for meaningful results.

- When posterior is a numerical vector, prior should also be a numerical vector.
- When posterior is a data.frame, prior should also be a data.frame, with matching column order.
- When posterior is a \texttt{stanreg} or \texttt{brmsfit} model:
  - prior can be set to NULL, in which case prior samples are drawn internally.
  - prior can also be a model equivalent to posterior but with samples from the priors only.
- When posterior is an \texttt{emmGrid} object:
  - prior should be the \texttt{stanreg} or \texttt{brmsfit} model used to create the \texttt{emmGrid} objects.
  - prior can also be an \texttt{emmGrid} object equivalent to posterior but created with a model of priors samples only.

**Choosing a value of BF:** The choice of BF (the level of support) depends on what we want our interval to represent:

- A BF = 1 contains values whose credibility is not decreased by observing the data.
- A BF > 1 contains values who received more impressive support from the data.
- A BF < 1 contains values whose credibility has not been impressively decreased by observing the data. Testing against values outside this interval will produce a Bayes factor larger than 1/BF in support of the alternative. E.g., if an SI (BF = 1/3) excludes 0, the Bayes factor against the point-null will be larger than 3.

Value

A data frame containing the lower and upper bounds of the SI.
Note that if the level of requested support is higher than observed in the data, the interval will be [NA, NA].

References


Examples

```r
library(bayestestR)

prior <- distribution_normal(1000, mean = 0, sd = 1)
posterior <- distribution_normal(1000, mean = .5, sd = .3)

si(posterior, prior)
# Not run:
# rstanarm models
```
simulate_correlation

Data Simulation

Description

Simulate data with specific characteristics.

Usage

simulate_correlation(n = 100, r = 0.5, mean = 0, sd = 1, names = NULL, ...)

simulate_ttest(n = 100, d = 0.5, names = NULL, ...)

Arguments

n The number of observations to be generated.

r A value or vector corresponding to the desired correlation coefficients.

mean A value or vector corresponding to the mean of the variables.

sd A value or vector corresponding to the SD of the variables.
names A character vector of desired variable names.
...
Arguments passed to or from other methods.
d A value or vector corresponding to the desired difference between the groups.

Examples

# Correlation --------------------------------
data <- simulate_correlation(r = 0.5)
plot(data$V1, data$V2)
cor.test(data$V1, data$V2)
summary(lm(V2 ~ V1, data = data))

# Specify mean and SD
data <- simulate_correlation(r = 0.5, n = 50, mean = c(0, 1), sd = c(0.7, 1.7))
cor.test(data$V1, data$V2)
round(c(mean(data$V1), sd(data$V1)), 1)
round(c(mean(data$V2), sd(data$V2)), 1)
summary(lm(V2 ~ V1, data = data))

# Generate multiple variables
cor_matrix <- matrix(c(1.0, 0.2, 0.4,
  0.2, 1.0, 0.3,
  0.4, 0.3, 1.0
),
  nrow = 3
)
data <- simulate_correlation(r = cor_matrix, names = c("y", "x1", "x2"))
cor(data)
summary(lm(y ~ x1, data = data))

# t-test --------------------------------
data <- simulate_ttest(n = 30, d = 0.3)
plot(data$V1, data$V0)
round(c(mean(data$V1), sd(data$V1)), 1)
diff(t.test(data$V1 ~ data$V0)$estimate)
summary(lm(V1 ~ V0, data = data))
summary(glm(V0 ~ V1, data = data, family = "binomial"))

simulate_prior

Returns Priors of a Model as Empirical Distributions

Description

Transforms priors information to actual distributions.
Usage

simulate_prior(model, n = 1000, ...)

Arguments

model A stanreg, stanfit, or brmsfit object.
n Size of the simulated prior distributions.
... Currently not used.

Examples

## Not run:
library(bayestestR)
if (require("rstanarm")) {
  model <- stan_glm(mpg ~ wt + am, data = mtcars, chains = 1, refresh = 0)
  simulate_prior(model)
}
## End(Not run)

update.bayesfactor_models

Update bayesfactor_models

Description

Update bayesfactor_models

Usage

## S3 method for class 'bayesfactor_models'
update(object, subset = NULL, reference = NULL, ...)

Arguments

object A bayesfactor_models object.
subset Vector of model indices to keep or remove.
reference Index of model to rereference to, or "top" to reference to the best model, or "bottom" to reference to the worst model.
... Currently not used.
#### Examples

```r
## Not run:
library(lme4)
lmer1 <- lmer(Sepal.Length ~ Petal.Length + (1 | Species), data = iris)
lmer2 <- lmer(Sepal.Length ~ Petal.Length + (Petal.Length | Species), data = iris)
lmer3 <- lmer(
  Sepal.Length ~ Petal.Length + (Petal.Length | Species) + (1 | Petal.Width),
  data = iris
)

m <- bayesfactor_models(lmer1, lmer2, lmer3, denominator = 1)
m
update(m, reference = "bottom")
## End(Not run)
```

---

**weighted_posteriors**  
*Generate posterior distributions weighted across models*

#### Description

Extract posterior samples of parameters, weighted across models. Weighting is done by comparing posterior model probabilities, via `bayesfactor_models`.

#### Usage

```r
weighted_posteriors(..., prior_odds = NULL, missing = 0, verbose = TRUE)
```

## S3 method for class 'stanreg'

```r
weighted_posteriors(
  ...,
  prior_odds = NULL,
  missing = 0,
  verbose = TRUE,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL
)
```

## S3 method for class 'brmsfit'

```r
weighted_posteriors(
  ...,
  prior_odds = NULL,
  missing = 0,
  verbose = TRUE,
  effects = c("fixed", "random", "all"),
  component = c("conditional", "zi", "zero_inflated", "all"),
  parameters = NULL
)
```
## weighted_posteriors

```
parameters = NULL
```

```
## S3 method for class 'BFBayesFactor'
weighted_posteriors(..., prior_odds = NULL, missing = 0, verbose = TRUE)
```

### Arguments

- `...`: Fitted models (see details), all fit on the same data, or a single `BFBayesFactor` object (see 'Details').
- `prior_odds`: Optional vector of prior odds for the models. See `BayesFactor::priorOdds<-`.
- `missing`: An optional numeric value to use if a model does not contain a parameter that appears in other models. Defaults to 0.
- `verbose`: Toggle off warnings.
- `effects`: Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
- `component`: Should results for all parameters, parameters for the conditional model or the zero-inflated part of the model be returned? May be abbreviated. Only applies to `brms`-models.
- `parameters`: Regular expression pattern that describes the parameters that should be returned. Meta-parameters (like `lp__` or `prior_`) are filtered by default, so only parameters that typically appear in the `summary()` are returned. Use `parameters` to select specific parameters for the output.

### Details

Note that across models some parameters might play different roles. For example, the parameter `A` plays a different role in the model `Y ~ A + B` (where it is a main effect) than it does in the model `Y ~ A + B + A:B` (where it is a simple effect). In many cases centering of predictors (mean subtracting for continuous variables, and effects coding via `contr.sum` or orthonormal coding via `contr.bayes` for factors) can reduce this issue. In any case you should be mindful of this issue.

See `bayesfactor_models` details for more info on passed models.

Note that for `BayesFactor` models, posterior samples cannot be generated from intercept only models.

This function is similar in function to `brms::posterior_average`.

### Value

A data frame with posterior distributions (weighted across models).

### References


See Also

bayesfactor_inclusion for Bayesian model averaging.

Examples

```r
library(rstanarm)
library(see)

stan_m0 <- stan_glm(extra ~ 1, data = sleep,
  family = gaussian(),
  refresh=0,
  diagnostic_file = file.path(tempdir(), "df0.csv"))

stan_m1 <- stan_glm(extra ~ group, data = sleep,
  family = gaussian(),
  refresh=0,
  diagnostic_file = file.path(tempdir(), "df1.csv"))

res <- weighted_posteriors(stan_m0, stan_m1)
plot(eti(res))

# With BayesFactor and brms
library(BayesFactor)
library(brms)

BFmods <- anovaBF(extra ~ group + ID, sleep, whichRandom = "ID")
res <- weighted_posteriors(BFmods)[1:3]
plot(eti(res))

# Compare to brms::posterior_average
fit1 <- brm(rating ~ treat + period + carry,
  data = inhaler,
  save_all_pars = TRUE)
fit2 <- brm(rating ~ period + carry,
  data = inhaler,
  save_all_pars = TRUE)

res_BT <- weighted_posteriors(fit1, fit2)
res_brms <- brms::posterior_average(fit1, fit2, weights = "marglik", missing = 0)[, 1:4]
```
plot(eti(res_BT))
plot(eti(res_brms))
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