

Package ‘parameters’

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Type Package

Title Processing of Model Parameters

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Description Utilities for processing the parameters of various statistical models. Beyond computing p values, CIs, and other indices for a wide variety of models (see list of supported models using the function ‘insight::supported_models()’), this package implements features like bootstrapping or simulating of parameters and models, feature reduction (feature extraction and variable selection) as well as functions to describe data and variable characteristics (e.g. skewness, kurtosis, smoothness or distribution).

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URL <https://easystats.github.io/parameters/>

BugReports <https://github.com/easystats/parameters/issues>

Depends R (>= 3.4)

Imports bayestestR (>= 0.11.5), datawizard (>= 0.4.1), insight (>= 0.17.1), graphics, methods, stats, utils

Suggests AER, afex, aod, BayesFactor, BayesFM, bbmle, betareg, biglm, blme, boot, brglm2, brms, broom, cAIC4, car, cgam, ClassDiscovery, clubSandwich, cluster, cplm, dbscan, drc, DRR, effectsize (>= 0.6.0), EGAnet (>= 0.7), emmeans (>= 1.7.0), factoextra, FactoMineR, fastICA, fixest, fpc, gam, gamlss, gee, geopack, ggplot2, GLMMadaptive, glmmTMB, GPArotation, gt, httr, ivprobit, ivreg, knitr, lavaan, lavaSearch2, lfe, lm.beta, lme4, lmerTest, lmtest, logspline, lqmm, M3C, magrittr, margineffects, MASS, Matrix, mclust, MCMCglmm, mediation, merDeriv, metaBMA, metafor, mfx, mgcv, mice, multcomp, MuMIn, NbClust, nFactors, nlme, nnet, openxlsx, ordinal, panelr, pbkrtest, PCDimension, performance (>= 0.8.0), plm, PMCMRplus, poorman, posterior, PROreg, pscl, psych, pvclust, quantreg, randomForest, rmarkdown, rms, rstanarm, sandwich, see (>=

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bootstrap_model	<i>Model bootstrapping</i>
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Description

Bootstrap a statistical model n times to return a data frame of estimates.

Usage

```
bootstrap_model(model, iterations = 1000, ...)
```

```
## Default S3 method:
bootstrap_model(
  model,
  iterations = 1000,
  type = "ordinary",
  parallel = c("no", "multicore", "snow"),
  n_cpus = 1,
  verbose = FALSE,
  ...
)
```

```
## S3 method for class 'merMod'
bootstrap_model(
  model,
  iterations = 1000,
  type = "parametric",
  parallel = c("no", "multicore", "snow"),
  n_cpus = 1,
  verbose = FALSE,
  ...
)
```

Arguments

model	Statistical model.
iterations	The number of draws to simulate/bootstrap.
...	Arguments passed to or from other methods.
type	Character string specifying the type of bootstrap. For mixed models of class merMod or glmmTMB, may be "parametric" (default) or "semiparametric" (see ?lme4::bootMer for details). For all other models, see argument sim in ?boot::boot (defaults to "ordinary").
parallel	The type of parallel operation to be used (if any).
n_cpus	Number of processes to be used in parallel operation.
verbose	Toggle warnings and messages.

Details

By default, `boot::boot()` is used to generate bootstraps from the model data, which are then used to update() the model, i.e. refit the model with the bootstrapped samples. For merMod objects (**lme4**) or models from **glmmTMB**, the `lme4::bootMer()` function is used to obtain bootstrapped samples. `bootstrap_parameters()` summarizes the bootstrapped model estimates.

Value

A data frame of bootstrapped estimates.

Using with emmeans

The output can be passed directly to the various functions from the **emmeans** package, to obtain bootstrapped estimates, contrasts, simple slopes, etc. and their confidence intervals. These can then be passed to `model_parameter()` to obtain standard errors, p-values, etc. (see example).

Note that that p-values returned here are estimated under the assumption of *translation equivariance*: that shape of the sampling distribution is unaffected by the null being true or not. If this assumption does not hold, p-values can be biased, and it is suggested to use proper permutation tests to obtain non-parametric p-values.

See Also

[bootstrap_parameters\(\)](#), [simulate_model\(\)](#), [simulate_parameters\(\)](#)

Examples

```
## Not run:
if (require("boot", quietly = TRUE)) {
  model <- lm(mpg ~ wt + factor(cyl), data = mtcars)
  b <- bootstrap_model(model)
  print(head(b))

  if (require("emmeans", quietly = TRUE)) {
    est <- emmeans(b, consec ~ cyl)
  }
}
```

```

    print(model_parameters(est))
  }
}

## End(Not run)

```

bootstrap_parameters *Parameters bootstrapping*

Description

Compute bootstrapped parameters and their related indices such as Confidence Intervals (CI) and p-values.

Usage

```

bootstrap_parameters(
  model,
  iterations = 1000,
  centrality = "median",
  ci = 0.95,
  ci_method = "quantile",
  test = "p-value",
  ...
)

```

Arguments

model	Statistical model.
iterations	The number of draws to simulate/bootstrap.
centrality	The point-estimates (centrality indices) to compute. Character (vector) or list with one or more of these options: "median", "mean", "MAP" or "all".
ci	Value or vector of probability of the CI (between 0 and 1) to be estimated. Default to .95 (95%).
ci_method	The type of index used for Credible Interval. Can be "ETI" (default, see eti()), "HDI" (see hdi()), "BCI" (see bci()), "SPI" (see spi()), or "SI" (see si()).
test	The indices to compute. Character (vector) with one or more of these options: "p-value" (or "p"), "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. bayestestR::rope() or bayestestR::p_direction()) and its results included in the summary output.
...	Arguments passed to or from other methods.

Details

This function first calls `bootstrap_model()` to generate bootstrapped coefficients. The resulting replicated for each coefficient are treated as "distribution", and is passed to `bayestestR::describe_posterior()` to calculate the related indices defined in the "test" argument.

Note that that p-values returned here are estimated under the assumption of *translation equivariance*: that shape of the sampling distribution is unaffected by the null being true or not. If this assumption does not hold, p-values can be biased, and it is suggested to use proper permutation tests to obtain non-parametric p-values.

Value

A data frame summarizing the bootstrapped parameters.

Using with emmeans

The output can be passed directly to the various functions from the **emmeans** package, to obtain bootstrapped estimates, contrasts, simple slopes, etc. and their confidence intervals. These can then be passed to `model_parameter()` to obtain standard errors, p-values, etc. (see example).

Note that that p-values returned here are estimated under the assumption of *translation equivariance*: that shape of the sampling distribution is unaffected by the null being true or not. If this assumption does not hold, p-values can be biased, and it is suggested to use proper permutation tests to obtain non-parametric p-values.

References

Davison, A. C., & Hinkley, D. V. (1997). Bootstrap methods and their application (Vol. 1). Cambridge university press.

See Also

`bootstrap_model()`, `simulate_parameters()`, `simulate_model()`

Examples

```
## Not run:
if (require("boot", quietly = TRUE)) {
  set.seed(2)
  model <- lm(Sepal.Length ~ Species * Petal.Width, data = iris)
  b <- bootstrap_parameters(model)
  print(b)

  if (require("emmeans")) {
    est <- emmeans(b, trt.vs.ctrl ~ Species)
    print(model_parameters(est))
  }
}

## End(Not run)
```

`check_clusterstructure`*Check suitability of data for clustering*

Description

This checks whether the data is appropriate for clustering using the Hopkins' H statistic of given data. If the value of Hopkins statistic is close to 0 (below 0.5), then we can reject the null hypothesis and conclude that the dataset is significantly clusterable. A value for H lower than 0.25 indicates a clustering tendency at the 90% confidence level. The visual assessment of cluster tendency (VAT) approach (Bezdek and Hathaway, 2002) consists in investigating the heatmap of the ordered dissimilarity matrix. Following this, one can potentially detect the clustering tendency by counting the number of square shaped blocks along the diagonal.

Usage

```
check_clusterstructure(x, standardize = TRUE, distance = "euclidean", ...)
```

Arguments

<code>x</code>	A data frame.
<code>standardize</code>	Standardize the dataframe before clustering (default).
<code>distance</code>	Distance method used. Other methods than "euclidean" (default) are exploratory in the context of clustering tendency. See <code>stats::dist()</code> for list of available methods.
<code>...</code>	Arguments passed to or from other methods.

Value

The H statistic (numeric)

References

- Lawson, R. G., & Jurs, P. C. (1990). New index for clustering tendency and its application to chemical problems. *Journal of chemical information and computer sciences*, 30(1), 36-41.
- Bezdek, J. C., & Hathaway, R. J. (2002, May). VAT: A tool for visual assessment of (cluster) tendency. In *Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN02* (3), 2225-2230. IEEE.

See Also

[check_kmo\(\)](#), [check_sphericity_bartlett\(\)](#) and [check_factorstructure\(\)](#).

Examples

```
library(parameters)
check_clusterstructure(iris[, 1:4])
plot(check_clusterstructure(iris[, 1:4]))
```

check_factorstructure *Check suitability of data for Factor Analysis (FA)*

Description

This checks whether the data is appropriate for Factor Analysis (FA) by running the [Bartlett's Test of Sphericity](#) and the [Kaiser, Meyer, Olkin \(KMO\) Measure of Sampling Adequacy \(MSA\)](#).

Usage

```
check_factorstructure(x, ...)
```

Arguments

x	A dataframe.
...	Arguments passed to or from other methods.

Value

A list of lists of indices related to sphericity and KMO.

See Also

[check_kmo\(\)](#), [check_sphericity_bartlett\(\)](#) and [check_clusterstructure\(\)](#).

Examples

```
library(parameters)
check_factorstructure(mtcars)
```

check_heterogeneity *Check model predictor for heterogeneity bias*

Description

check_heterogeneity() checks if model predictors or variables may cause a heterogeneity bias, i.e. if variables have a within- and/or between-effect.

Usage

```
check_heterogeneity(x, select = NULL, group = NULL)
```

Arguments

x	A data frame or a mixed model object.
select	Character vector (or formula) with names of variables to select that should be checked. If x is a mixed model object, this argument will be ignored.
group	Character vector (or formula) with the name of the variable that indicates the group- or cluster-ID. If x is a model object, this argument will be ignored.

Note

This function will be removed in a future update. Please use `performance::check_heterogeneity_bias()`.

See Also

For further details, see documentation for `?datawizard::demean`.

check_kmo *Kaiser, Meyer, Olkin (KMO) Measure of Sampling Adequacy (MSA) for Factor Analysis*

Description

Kaiser (1970) introduced a Measure of Sampling Adequacy (MSA), later modified by Kaiser and Rice (1974). The Kaiser-Meyer-Olkin (KMO) statistic, which can vary from 0 to 1, indicates the degree to which each variable in a set is predicted without error by the other variables.

Usage

```
check_kmo(x, ...)
```

Arguments

x	A dataframe.
...	Arguments passed to or from other methods.

Details

A value of 0 indicates that the sum of partial correlations is large relative to the sum correlations, indicating factor analysis is likely to be inappropriate. A KMO value close to 1 indicates that the sum of partial correlations is not large relative to the sum of correlations and so factor analysis should yield distinct and reliable factors.

Kaiser (1974) suggested that $KMO > .9$ were marvelous, in the .80s, meritorious, in the .70s, middling, in the .60s, mediocre, in the .50s, miserable, and less than .5, unacceptable. Hair et al. (2006) suggest accepting a value > 0.5 . Values between 0.5 and 0.7 are mediocre, and values between 0.7 and 0.8 are good.

This function is strongly inspired by the KMO function in the psych package (Revelle, 2016). All credit goes to its author.

Value

A list of indices related to KMO.

References

- Revelle, W. (2016). How To: Use the psych package for Factor Analysis and data reduction.
- Kaiser, H. F. (1970). A second generation little jiffy. *Psychometrika*, 35(4), 401-415.
- Kaiser, H. F., & Rice, J. (1974). Little jiffy, mark IV. *Educational and psychological measurement*, 34(1), 111-117.
- Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31-36.

Examples

```
library(parameters)
check_kmo(mtcars)
```

check_sphericity_bartlett

Bartlett's Test of Sphericity

Description

Bartlett's (1951) test of sphericity tests whether a matrix (of correlations) is significantly different from an identity matrix. The test provides probability that the correlation matrix has significant correlations among at least some of the variables in a dataset, a prerequisite for factor analysis to work. In other words, before starting with factor analysis, one needs to check whether Bartlett's test of sphericity is significant.

Usage

```
check_sphericity_bartlett(x, ...)
```

Arguments

x A dataframe.
 ... Arguments passed to or from other methods.

Details

This function is strongly inspired by the `cortest.bartlett()` function in the **psych** package (Revelle, 2016). All credit goes to its author.

Value

A list of indices related to sphericity.

References

- Revelle, W. (2016). How To: Use the psych package for Factor Analysis and data reduction.
- Bartlett, M. S. (1951). The effect of standardization on a Chi-square approximation in factor analysis. *Biometrika*, 38(3/4), 337-344.

Examples

```
library(parameters)
check_sphericity_bartlett(mtcars)
```

ci.default

Confidence Intervals (CI)

Description

Compute confidence intervals (CI) for frequentist models.

Usage

```
## Default S3 method:
ci(x, ci = 0.95, dof = NULL, method = NULL, ...)

## S3 method for class 'glimmTMB'
ci(
  x,
  ci = 0.95,
  dof = NULL,
  method = "wald",
  component = "all",
  verbose = TRUE,
  ...
)

## S3 method for class 'merMod'
ci(x, ci = 0.95, dof = NULL, method = "wald", iterations = 500, ...)
```

Arguments

x	A statistical model.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
dof	Number of degrees of freedom to be used when calculating confidence intervals. If NULL (default), the degrees of freedom are retrieved by calling degrees_of_freedom() with approximation method defined in method. If not NULL, use this argument to override the default degrees of freedom used to compute confidence intervals.
method	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): "residual", "normal", "likelihood", "satterthwaite", "kenward", "wald", "profile", "boot", "uniroot", "ml1", "betwithin", "hdi", "quantile", "ci", "eti", "si", "bci", or "bcai". See section <i>Confidence intervals and approximation of degrees of freedom</i> in model_parameters() for further details.
...	Additional arguments
component	Model component for which parameters should be shown. See the documentation for your object's class in model_parameters() or p_value() for further details.
verbose	Toggle warnings and messages.
iterations	The number of bootstrap replicates. Only applies to models of class merMod when method=boot.

Value

A data frame containing the CI bounds.

Confidence intervals and approximation of degrees of freedom

There are different ways of approximating the degrees of freedom depending on different assumptions about the nature of the model and its sampling distribution. The `ci_method` argument modulates the method for computing degrees of freedom (df) that are used to calculate confidence intervals (CI) and the related p-values. Following options are allowed, depending on the model class:

Classical methods:

Classical inference is generally based on the **Wald method**. The Wald approach to inference computes a test statistic by dividing the parameter estimate by its standard error (Coefficient / SE), then comparing this statistic against a t- or normal distribution. This approach can be used to compute CIs and p-values.

"wald":

- Applies to *non-Bayesian models*. For *linear models*, CIs computed using the Wald method (SE and a *t-distribution with residual df*); p-values computed using the Wald method with a *t-distribution with residual df*. For other models, CIs computed using the Wald method (SE and a *normal distribution*); p-values computed using the Wald method with a *normal distribution*.

"normal"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a normal distribution.

"residual"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a *t-distribution with residual df* when possible. If the residual df for a model cannot be determined, a normal distribution is used instead.

Methods for mixed models:

Compared to fixed effects (or single-level) models, determining appropriate df for Wald-based inference in mixed models is more difficult. See [the R GLMM FAQ](#) for a discussion.

Several approximate methods for computing df are available, but you should also consider instead using profile likelihood ("profile") or bootstrap ("boot") CIs and p-values instead.

"satterthwaite"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with Satterthwaite df*); p-values computed using the Wald method with a *t-distribution with Satterthwaite df*.

"kenward"

- Applies to *linear mixed models*. CIs computed using the Wald method (*Kenward-Roger SE* and a *t-distribution with Kenward-Roger df*); p-values computed using the Wald method with *Kenward-Roger SE* and *t-distribution with Kenward-Roger df*.

"m11"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with m-l-1 approximated df*); p-values computed using the Wald method with a *t-distribution with m-l-1 approximated df*. See [ci_m11\(\)](#).

"betwithin"

- Applies to *linear mixed models* and *generalized linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with between-within df*); p-values computed using the Wald method with a *t-distribution with between-within df*. See [ci_betwithin\(\)](#).

Likelihood-based methods:

Likelihood-based inference is based on comparing the likelihood for the maximum-likelihood estimate to the the likelihood for models with one or more parameter values changed (e.g., set to zero or a range of alternative values). Likelihood ratios for the maximum-likelihood and alternative models are compared to a χ -squared distribution to compute CIs and p-values.

"profile"

- Applies to *non-Bayesian models* of class `glm`, `polr` or `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using linear interpolation to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

"uniroot"

- Applies to *non-Bayesian models* of class `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using root finding to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

Methods for bootstrapped or Bayesian models:

Bootstrap-based inference is based on **resampling** and refitting the model to the resampled datasets. The distribution of parameter estimates across resampled datasets is used to approximate the parameter's sampling distribution. Depending on the type of model, several different methods for bootstrapping and constructing CIs and p-values from the bootstrap distribution are available.

For Bayesian models, inference is based on drawing samples from the model posterior distribution.

"quantile" (or "eti")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *equal tailed intervals* using the quantiles of the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::eti()`.

"hdi"

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *highest density intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::hdi()`.

"bci" (or "bcai")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *bias corrected and accelerated intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::bci()`.

"si"

- Applies to *Bayesian models* with proper priors. CIs computed as *support intervals* comparing the posterior samples against the prior samples; p-values are based on the *probability of direction*. See `bayestestR::si()`.

"boot"

- Applies to *non-Bayesian models* of class `merMod`. CIs computed using *parametric bootstrapping* (simulating data from the fitted model); p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!).

For all iteration-based methods other than "boot" ("hdi", "quantile", "ci", "eti", "si", "bci", "bcai"), p-values are based on the probability of direction (`bayestestR::p_direction()`), which is converted into a p-value using `bayestestR::pd_to_p()`.

Examples

```
library(parameters)
if (require("glmmTMB")) {
  model <- glmmTMB(
    count ~ spp + mined + (1 | site),
    ziformula = ~mined,
    family = poisson(),
    data = Salamanders
  )

  ci(model)
  ci(model, component = "zi")
}
```

 ci_betwithin

Between-within approximation for SEs, CIs and p-values

Description

Approximation of degrees of freedom based on a "between-within" heuristic.

Usage

```
ci_betwithin(model, ci = 0.95, ...)
```

```
dof_betwithin(model)
```

```
p_value_betwithin(model, dof = NULL, ...)
```

Arguments

model	A mixed model.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
...	Additional arguments
dof	Degrees of Freedom.

Details

Small Sample Cluster corrected Degrees of Freedom: Inferential statistics (like p-values, confidence intervals and standard errors) may be biased in mixed models when the number of clusters is small (even if the sample size of level-1 units is high). In such cases it is recommended to approximate a more accurate number of degrees of freedom for such inferential statistics (see *Li and Redden 2015*). The *Between-within* denominator degrees of freedom approximation is recommended in particular for (generalized) linear mixed models with repeated measurements (longitudinal design). `dof_betwithin()` implements a heuristic based on the between-within

approach. **Note** that this implementation does not return exactly the same results as shown in *Li and Redden 2015*, but similar.

Degrees of Freedom for Longitudinal Designs (Repeated Measures): In particular for repeated measure designs (longitudinal data analysis), the *between-within* heuristic is likely to be more accurate than simply using the residual or infinite degrees of freedom, because `dof_betwithin()` returns different degrees of freedom for within-cluster and between-cluster effects.

Value

A data frame.

References

- Elff, M.; Heisig, J.P.; Schaeffer, M.; Shikano, S. (2019). Multilevel Analysis with Few Clusters: Improving Likelihood-based Methods to Provide Unbiased Estimates and Accurate Inference, *British Journal of Political Science*.
- Li, P., Redden, D. T. (2015). Comparing denominator degrees of freedom approximations for the generalized linear mixed model in analyzing binary outcome in small sample cluster-randomized trials. *BMC Medical Research Methodology*, 15(1), 38. doi:10.1186/s12874015-0026x

See Also

`dof_betwithin()` is a small helper-function to calculate approximated degrees of freedom of model parameters, based on the "between-within" heuristic.

Examples

```
if (require("lme4")) {  
  data(sleepstudy)  
  model <- lmer(Reaction ~ Days + (1 + Days | Subject), data = sleepstudy)  
  dof_betwithin(model)  
  p_value_betwithin(model)  
}
```

ci_kenward

Kenward-Roger approximation for SEs, CIs and p-values

Description

An approximate F-test based on the Kenward-Roger (1997) approach.

Usage

```
ci_kenward(model, ci = 0.95)

dof_kenward(model)

p_value_kenward(model, dof = NULL)

se_kenward(model)
```

Arguments

model	A statistical model.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
dof	Degrees of Freedom.

Details

Inferential statistics (like p-values, confidence intervals and standard errors) may be biased in mixed models when the number of clusters is small (even if the sample size of level-1 units is high). In such cases it is recommended to approximate a more accurate number of degrees of freedom for such inferential statistics. Unlike simpler approximation heuristics like the "m-1-1" rule (`dof_m11`), the Kenward-Roger approximation is also applicable in more complex multilevel designs, e.g. with cross-classified clusters. However, the "m-1-1" heuristic also applies to generalized mixed models, while approaches like Kenward-Roger or Satterthwaite are limited to linear mixed models only.

Value

A data frame.

References

Kenward, M. G., & Roger, J. H. (1997). Small sample inference for fixed effects from restricted maximum likelihood. *Biometrics*, 983-997.

See Also

`dof_kenward()` and `se_kenward()` are small helper-functions to calculate approximated degrees of freedom and standard errors for model parameters, based on the Kenward-Roger (1997) approach.

[dof_satterthwaite\(\)](#) and [dof_m11\(\)](#) approximate degrees of freedom based on Satterthwaite's method or the "m-1-1" rule.

Examples

```
if (require("lme4", quietly = TRUE)) {
  model <- lmer(Petal.Length ~ Sepal.Length + (1 | Species), data = iris)
  p_value_kenward(model)
}
```

ci_ml1	<i>"m-l-1" approximation for SEs, CIs and p-values</i>
--------	--

Description

Approximation of degrees of freedom based on a "m-l-1" heuristic as suggested by Elff et al. (2019).

Usage

```
ci_ml1(model, ci = 0.95, ...)
dof_ml1(model)
p_value_ml1(model, dof = NULL, ...)
```

Arguments

model	A mixed model.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
...	Additional arguments
dof	Degrees of Freedom.

Details

Small Sample Cluster corrected Degrees of Freedom: Inferential statistics (like p-values, confidence intervals and standard errors) may be biased in mixed models when the number of clusters is small (even if the sample size of level-1 units is high). In such cases it is recommended to approximate a more accurate number of degrees of freedom for such inferential statistics (see *Li and Redden 2015*). The *m-l-1* heuristic is such an approach that uses a t-distribution with fewer degrees of freedom (`dof_ml1()`) to calculate p-values (`p_value_ml1()`) and confidence intervals (`ci(method = "ml1")`).

Degrees of Freedom for Longitudinal Designs (Repeated Measures): In particular for repeated measure designs (longitudinal data analysis), the *m-l-1* heuristic is likely to be more accurate than simply using the residual or infinite degrees of freedom, because `dof_ml1()` returns different degrees of freedom for within-cluster and between-cluster effects.

Limitations of the "m-l-1" Heuristic: Note that the "m-l-1" heuristic is not applicable (or at least less accurate) for complex multilevel designs, e.g. with cross-classified clusters. In such cases, more accurate approaches like the Kenward-Roger approximation (`dof_kenward()`) is recommended. However, the "m-l-1" heuristic also applies to generalized mixed models, while approaches like Kenward-Roger or Satterthwaite are limited to linear mixed models only.

Value

A data frame.

References

- Elff, M.; Heisig, J.P.; Schaeffer, M.; Shikano, S. (2019). Multilevel Analysis with Few Clusters: Improving Likelihood-based Methods to Provide Unbiased Estimates and Accurate Inference, *British Journal of Political Science*.
- Li, P., Redden, D. T. (2015). Comparing denominator degrees of freedom approximations for the generalized linear mixed model in analyzing binary outcome in small sample cluster-randomized trials. *BMC Medical Research Methodology*, 15(1), 38. doi:10.1186/s12874015-0026x

See Also

dof_ml1() is a small helper-function to calculate approximated degrees of freedom of model parameters, based on the "m-l-1" heuristic.

Examples

```
if (require("lme4")) {  
  model <- lmer(Petal.Length ~ Sepal.Length + (1 | Species), data = iris)  
  p_value_ml1(model)  
}
```

ci_satterthwaite *Satterthwaite approximation for SEs, CIs and p-values*

Description

An approximate F-test based on the Satterthwaite (1946) approach.

Usage

```
ci_satterthwaite(model, ci = 0.95, ...)  
  
dof_satterthwaite(model)  
  
p_value_satterthwaite(model, dof = NULL, ...)  
  
se_satterthwaite(model)
```

Arguments

model	A statistical model.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
...	Additional arguments
dof	Degrees of Freedom.

Details

Inferential statistics (like p-values, confidence intervals and standard errors) may be biased in mixed models when the number of clusters is small (even if the sample size of level-1 units is high). In such cases it is recommended to approximate a more accurate number of degrees of freedom for such inferential statistics. Unlike simpler approximation heuristics like the "m-l-1" rule (`dof_ml1`), the Satterthwaite approximation is also applicable in more complex multilevel designs. However, the "m-l-1" heuristic also applies to generalized mixed models, while approaches like Kenward-Roger or Satterthwaite are limited to linear mixed models only.

Value

A data frame.

References

Satterthwaite FE (1946) An approximate distribution of estimates of variance components. *Biometrics Bulletin* 2 (6):110–4.

See Also

`dof_satterthwaite()` and `se_satterthwaite()` are small helper-functions to calculate approximated degrees of freedom and standard errors for model parameters, based on the Satterthwaite (1946) approach.

`dof_kenward()` and `dof_ml1()` approximate degrees of freedom based on Kenward-Roger's method or the "m-l-1" rule.

Examples

```
if (require("lme4", quietly = TRUE)) {  
  model <- lmer(Petal.Length ~ Sepal.Length + (1 | Species), data = iris)  
  p_value_satterthwaite(model)  
}
```

Description

Compute hierarchical or kmeans cluster analysis and return the group assignment for each observation as vector.

Usage

```
cluster_analysis(
  x,
  n = NULL,
  method = "kmeans",
  include_factors = FALSE,
  standardize = TRUE,
  verbose = TRUE,
  distance_method = "euclidean",
  hclust_method = "complete",
  kmeans_method = "Hartigan-Wong",
  dbscan_eps = 15,
  iterations = 100,
  ...
)
```

Arguments

x	A data frame.
n	Number of clusters used for supervised cluster methods. If NULL, the number of clusters to extract is determined by calling <code>n_clusters()</code> . Note that this argument does not apply for unsupervised clustering methods like <code>dbscan</code> , <code>hdbscan</code> , <code>mixture</code> , <code>pvclust</code> , or <code>pamk</code> .
method	Method for computing the cluster analysis. Can be "kmeans" (default; k-means using <code>kmeans()</code>), "hkmeans" (hierarchical k-means using <code>factoextra::hkmeans()</code>), <code>pam</code> (K-Medoids using <code>cluster::pam()</code>), <code>pamk</code> (K-Medoids that finds out the number of clusters), "hclust" (hierarchical clustering using <code>hclust()</code> or <code>pvclust::pvclust()</code>), <code>dbscan</code> (DBSCAN using <code>dbscan::dbscan()</code>), <code>hdbscan</code> (Hierarchical DBSCAN using <code>dbscan::hdbscan()</code>), or <code>mixture</code> (Mixture modelling using <code>mclust::Mclust()</code> , which requires the user to run <code>library(mclust)</code> before).
include_factors	Logical, if TRUE, factors are converted to numerical values in order to be included in the data for determining the number of clusters. By default, factors are removed, because most methods that determine the number of clusters need numeric input only.
standardize	Standardize the dataframe before clustering (default).
verbose	Toggle warnings and messages.
distance_method	Distance measure to be used for methods based on distances (e.g., when <code>method = "hclust"</code> for hierarchical clustering. For other methods, such as "kmeans", this argument will be ignored). Must be one of "euclidean", "maximum", "manhattan", "canberra", "binary" or "minkowski". See <code>dist()</code> and <code>pvclust::pvclust()</code> for more information.
hclust_method	Agglomeration method to be used when <code>method = "hclust"</code> or <code>method = "hkmeans"</code> (for hierarchical clustering). This should be one of "ward", "ward.D2", "single", "complete", "average", "mcquitty", "median" or "centroid". Default is "complete" (see <code>hclust()</code>).

kmeans_method	Algorithm used for calculating kmeans cluster. Only applies, if method = "kmeans". May be one of "Hartigan-Wong" (default), "Lloyd" (used by SPSS), or "MacQueen". See <code>kmeans()</code> for details on this argument.
dbscan_eps	The 'eps' argument for DBSCAN method. See <code>n_clusters_dbscan()</code> .
iterations	The number of replications.
...	Arguments passed to or from other methods.

Details

The `print()` and `plot()` methods show the (standardized) mean value for each variable within each cluster. Thus, a higher absolute value indicates that a certain variable characteristic is more pronounced within that specific cluster (as compared to other cluster groups with lower absolute mean values).

Value

The group classification for each observation as vector. The returned vector includes missing values, so it has the same length as `nrow(x)`.

Note

There is also a `plot()-method` implemented in the [see-package](#).

References

- Maechler M, Rousseeuw P, Struyf A, Hubert M, Hornik K (2014) cluster: Cluster Analysis Basics and Extensions. R package.

See Also

- `n_clusters()` to determine the number of clusters to extract, `cluster_discrimination()` to determine the accuracy of cluster group classification via linear discriminant analysis (LDA) and `check_clusterstructure()` to check suitability of data for clustering.
- <https://www.datanovia.com/en/lessons/>

Examples

```
set.seed(33)
# K-Means =====
rez <- cluster_analysis(iris[1:4], n = 3, method = "kmeans")
rez # Show results
predict(rez) # Get clusters
summary(rez) # Extract the centers values (can use 'plot()' on that)
if (requireNamespace("MASS", quietly = TRUE)) {
  cluster_discrimination(rez) # Perform LDA
}

# Hierarchical k-means (more robust k-means)
if (require("factoextra", quietly = TRUE)) {
  rez <- cluster_analysis(iris[1:4], n = 3, method = "hkmeans")
}
```

```

    rez # Show results
    predict(rez) # Get clusters
  }

# Hierarchical Clustering (hclust) =====
rez <- cluster_analysis(iris[1:4], n = 3, method = "hclust")
rez # Show results
predict(rez) # Get clusters

# K-Medoids (pam) =====
if (require("cluster", quietly = TRUE)) {
  rez <- cluster_analysis(iris[1:4], n = 3, method = "pam")
  rez # Show results
  predict(rez) # Get clusters
}

# PAM with automated number of clusters
if (require("fpc", quietly = TRUE)) {
  rez <- cluster_analysis(iris[1:4], method = "pamk")
  rez # Show results
  predict(rez) # Get clusters
}

# DBSCAN =====
if (require("dbscan", quietly = TRUE)) {
  # Note that you can assimilate more outliers (cluster 0) to neighbouring
  # clusters by setting borderPoints = TRUE.
  rez <- cluster_analysis(iris[1:4], method = "dbscan", dbscan_eps = 1.45)
  rez # Show results
  predict(rez) # Get clusters
}

# Mixture =====
if (require("mclust", quietly = TRUE)) {
  library(mclust) # Needs the package to be loaded
  rez <- cluster_analysis(iris[1:4], method = "mixture")
  rez # Show results
  predict(rez) # Get clusters
}

```

cluster_centers

Find the cluster centers in your data

Description

For each cluster, computes the mean (or other indices) of the variables. Can be used to retrieve the centers of clusters. Also returns the within Sum of Squares.

Usage

```
cluster_centers(data, clusters, fun = mean, ...)
```


Arguments

data	A data.frame.
clusters	A vector with clusters assignments (must be same length as rows in data).
fun	What function to use, mean by default.
...	Other arguments to be passed to or from other functions.

Value

A dataframe containing the cluster centers. Attributes include performance statistics and distance between each observation and its respective cluster centre.

Examples

```
k <- kmeans(iris[1:4], 3)
cluster_centers(iris[1:4], clusters = k$cluster)
cluster_centers(iris[1:4], clusters = k$cluster, fun = median)
```

cluster_discrimination

Compute a linear discriminant analysis on classified cluster groups

Description

Computes linear discriminant analysis (LDA) on classified cluster groups, and determines the goodness of classification for each cluster group. See `MASS::lda()` for details.

Usage

```
cluster_discrimination(x, cluster_groups = NULL, ...)
```

Arguments

x	A data frame
cluster_groups	Group classification of the cluster analysis, which can be retrieved from the cluster_analysis() function.
...	Other arguments to be passed to or from.

See Also

[n_clusters\(\)](#) to determine the number of clusters to extract, [cluster_analysis\(\)](#) to compute a cluster analysis and [check_clusterstructure\(\)](#) to check suitability of data for clustering.

Examples

```

if (requireNamespace("MASS", quietly = TRUE)) {
  # Retrieve group classification from hierarchical cluster analysis
  clustering <- cluster_analysis(iris[, 1:4], n = 3)

  # Goodness of group classification
  cluster_discrimination(clustering)
}

```

cluster_meta

Metaclustering

Description

One of the core "issue" of statistical clustering is that, in many cases, different methods will give different results. The **metaclustering** approach proposed by *easystats* (that finds echoes in *consensus clustering*; see Monti et al., 2003) consists of treating the unique clustering solutions as an ensemble, from which we can derive a probability matrix. This matrix contains, for each pair of observations, the probability of being in the same cluster. For instance, if the 6th and the 9th row of a dataframe has been assigned to a similar cluster by 5 out of 10 clustering methods, then its probability of being grouped together is 0.5.

Metaclustering is based on the hypothesis that, as each clustering algorithm embodies a different prism by which it sees the data, running an infinite amount of algorithms would result in the emergence of the "true" clusters. As the number of algorithms and parameters is finite, the probabilistic perspective is a useful proxy. This method is interesting where there is no obvious reasons to prefer one over another clustering method, as well as to investigate how robust some clusters are under different algorithms.

This metaclustering probability matrix can be transformed into a dissimilarity matrix (such as the one produced by `dist()`) and submitted for instance to hierarchical clustering (`hclust()`). See the example below.

Usage

```
cluster_meta(list_of_clusters, rownames = NULL, ...)
```

Arguments

<code>list_of_clusters</code>	A list of vectors with the clustering assignments from various methods.
<code>rownames</code>	An optional vector of row.names for the matrix.
<code>...</code>	Currently not used.

Value

A matrix containing all the pairwise (between each observation) probabilities of being clustered together by the methods.

Examples

```
## Not run:
data <- iris[1:4]

rez1 <- cluster_analysis(data, n = 2, method = "kmeans")
rez2 <- cluster_analysis(data, n = 3, method = "kmeans")
rez3 <- cluster_analysis(data, n = 6, method = "kmeans")

list_of_clusters <- list(rez1, rez2, rez3)

m <- cluster_meta(list_of_clusters)

# Visualize matrix without reordering
heatmap(m, Rowv = NA, Colv = NA, scale = "none") # Without reordering
# Reordered heatmap
heatmap(m, scale = "none")

# Convert to dissimilarity
d <- as.dist(abs(m - 1))
model <- hclust(d)
plot(model, hang = -1)

## End(Not run)
```

cluster_performance *Performance of clustering models*

Description

Compute performance indices for clustering solutions.

Usage

```
cluster_performance(model, ...)
```

S3 method for class 'kmeans'

```
cluster_performance(model, ...)
```

S3 method for class 'hclust'

```
cluster_performance(model, data, clusters, ...)
```

S3 method for class 'dbscan'

```
cluster_performance(model, data, ...)
```

S3 method for class 'parameters_clusters'

```
cluster_performance(model, ...)
```

Arguments

model	Cluster model.
...	Arguments passed to or from other methods.
data	A data.frame.
clusters	A vector with clusters assignments (must be same length as rows in data).

Examples

```
# kmeans
model <- kmeans(iris[1:4], 3)
cluster_performance(model)
# hclust
data <- iris[1:4]
model <- hclust(dist(data))
clusters <- cutree(model, 3)

rez <- cluster_performance(model, data, clusters)
rez
# DBSCAN
if (require("dbscan", quietly = TRUE)) {
  model <- dbscan::dbscan(iris[1:4], eps = 1.45, minPts = 10)

  rez <- cluster_performance(model, iris[1:4])
  rez
}
# Retrieve performance from parameters
params <- model_parameters(kmeans(iris[1:4], 3))
cluster_performance(params)
```

compare_parameters *Compare model parameters of multiple models*

Description

Compute and extract model parameters of multiple regression models. See [model_parameters\(\)](#) for further details.

Usage

```
compare_parameters(
  ...,
  ci = 0.95,
  effects = "fixed",
  component = "conditional",
  standardize = NULL,
  exponentiate = FALSE,
  ci_method = "wald",
```

```

    p_adjust = NULL,
    style = NULL,
    column_names = NULL,
    keep = NULL,
    drop = NULL,
    parameters = keep,
    verbose = TRUE,
    df_method = ci_method
)

compare_models(
  ...,
  ci = 0.95,
  effects = "fixed",
  component = "conditional",
  standardize = NULL,
  exponentiate = FALSE,
  ci_method = "wald",
  p_adjust = NULL,
  style = NULL,
  column_names = NULL,
  keep = NULL,
  drop = NULL,
  parameters = keep,
  verbose = TRUE,
  df_method = ci_method
)

```

Arguments

...	One or more regression model objects, or objects returned by <code>model_parameters()</code> . Regression models may be of different model types. Model objects may be passed comma separated, or as a list. If model objects are passed with names or the list has named elements, these names will be used as column names.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
effects	Should parameters for fixed effects ("fixed"), random effects ("random"), or both ("all") be returned? Only applies to mixed models. May be abbreviated. If the calculation of random effects parameters takes too long, you may use <code>effects = "fixed"</code> .
component	Model component for which parameters should be shown. See documentation for related model class in <code>model_parameters()</code> .
standardize	The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in <code>standardize_parameters()</code> .

Important:

- The "refit" method does *not* standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages

(such as **lm.beta**) or other software packages (like SPSS). to mimic such behaviours, either use `standardize="basic"` or standardize the data with `datawizard::standardize(force=TRUE)` before fitting the model.

- For mixed models, when using methods other than "refit", only the fixed effects will be returned.
- Robust estimation (i.e., `vcov` set to a value other than `NULL`) of standardized parameters only works when `standardize="refit"`.

exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
ci_method	Method for computing degrees of freedom for p-values and confidence intervals (CI). See documentation for related model class in <code>model_parameters()</code> .
p_adjust	Character vector, if not <code>NULL</code> , indicates the method to adjust p-values. See <code>stats::p.adjust()</code> for details. Further possible adjustment methods are "tukey", "scheffe", "sidak" and "none" to explicitly disable adjustment for <code>emmGrid</code> objects (from emmeans).
style	String, indicating which style of output is requested. Following templates are possible: <ul style="list-style-type: none"> • "ci": Estimate and confidence intervals, no asterisks for p-values. • "se": Estimate and standard errors, no asterisks for p-values. • "ci_p": Estimate, confidence intervals and asterisks for p-values. • "se_p": Estimate, standard errors and asterisks for p-values. • "ci_p2": Estimate, confidence intervals and numeric p-values, in two columns. • "se_p2": Estimate, standard errors and numeric p-values, in two columns.
column_names	Character vector with strings that should be used as column headers. Must be of same length as number of models in . . .
keep	Character containing a regular expression pattern that describes the parameters that should be included (for keep) or excluded (for drop) in the returned data frame. <code>keep</code> may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If <code>keep</code> is a character vector, every parameter name in the "Parameter" column that matches the regular expression in <code>keep</code> will be selected from the returned data frame (and vice versa, all parameter names matching <code>drop</code> will be excluded). Furthermore, if <code>keep</code> has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If <code>keep</code> is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where <code>model_parameters()</code> returns multiple columns with parameter

components, like in `model_parameters.lavaan()`. Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the `$Parameter` column of the parameters table to get the exact parameter names.

<code>drop</code>	See <code>keep</code> .
<code>parameters</code>	Deprecated, alias for <code>keep</code> .
<code>verbose</code>	Toggle warnings and messages.
<code>df_method</code>	Deprecated. Please use <code>ci_method</code> .

Details

This function is in an early stage and does not yet cope with more complex models, and probably does not yet properly render all model components. It should also be noted that when including models with interaction terms, not only do the values of the parameters change, but so does their meaning (from main effects, to simple slopes), thereby making such comparisons hard. Therefore, you should not use this function to compare models with interaction terms with models without interaction terms.

Value

A data frame of indices related to the model's parameters.

Examples

```
data(iris)
lm1 <- lm(Sepal.Length ~ Species, data = iris)
lm2 <- lm(Sepal.Length ~ Species + Petal.Length, data = iris)
compare_parameters(lm1, lm2)

data(mtcars)
m1 <- lm(mpg ~ wt, data = mtcars)
m2 <- glm(vs ~ wt + cyl, data = mtcars, family = "binomial")
compare_parameters(m1, m2)
## Not run:
# exponentiate coefficients, but not for lm
compare_parameters(m1, m2, exponentiate = "nongaussian")

# change column names
compare_parameters("linear model" = m1, "logistic reg." = m2)
compare_parameters(m1, m2, column_names = c("linear model", "logistic reg.))

# or as list
compare_parameters(list(m1, m2))
compare_parameters(list("linear model" = m1, "logistic reg." = m2))

## End(Not run)
```

convert_efa_to_cfa *Conversion between EFA results and CFA structure*

Description

Enables a conversion between Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) lavaan-ready structure.

Usage

```
convert_efa_to_cfa(model, ...)

## S3 method for class 'fa'
convert_efa_to_cfa(model, threshold = "max", names = NULL, ...)

efa_to_cfa(model, ...)
```

Arguments

model	An EFA model (e.g., a psych::fa object).
...	Arguments passed to or from other methods.
threshold	A value between 0 and 1 indicates which (absolute) values from the loadings should be removed. An integer higher than 1 indicates the n strongest loadings to retain. Can also be "max", in which case it will only display the maximum loading per variable (the most simple structure).
names	Vector containing dimension names.

Value

Converted index.

Examples

```
library(parameters)
if (require("psych") && require("lavaan")) {
  efa <- psych::fa(attitude, nfactors = 3)

  model1 <- efa_to_cfa(efa)
  model2 <- efa_to_cfa(efa, threshold = 0.3)

  anova(
    lavaan::cfa(model1, data = attitude),
    lavaan::cfa(model2, data = attitude)
  )
}
```

degrees_of_freedom *Degrees of Freedom (DoF)*

Description

Estimate or extract degrees of freedom of models parameters.

Usage

```
degrees_of_freedom(model, ...)

## Default S3 method:
degrees_of_freedom(model, method = "analytical", ...)

dof(model, ...)
```

Arguments

model	A statistical model.
...	Currently not used.
method	Can be "analytical" (default, DoFs are estimated based on the model type), "residual" in which case they are directly taken from the model if available (for Bayesian models, the goal (looking for help to make it happen) would be to refit the model as a frequentist one before extracting the DoFs), "ml1" (see dof_ml1()), "betwithin" (see dof_betwithin()), "satterthwaite" (see dof_satterthwaite()), "kenward" (see dof_kenward()) or "any", which tries to extract DoF by any of those methods, whichever succeeds. See 'Details'.

Details

Methods for calculating degrees of freedom:

- "analytical" for models of class `lmerMod`, Kenward-Roger approximated degrees of freedoms are calculated, for other models, $n-k$ (number of observations minus number of parameters).
- "residual" tries to extract residual degrees of freedom, and returns `Inf` if residual degrees of freedom could not be extracted.
- "any" first tries to extract residual degrees of freedom, and if these are not available, extracts analytical degrees of freedom.
- "nokr" same as "analytical", but does not Kenward-Roger approximation for models of class `lmerMod`. Instead, always uses $n-k$ to calculate `df` for any model.
- "normal" returns `Inf`.
- "wald" returns residual `df` for models with t-statistic, and `Inf` for all other models.
- "kenward" calls [dof_kenward\(\)](#).
- "satterthwaite" calls [dof_satterthwaite\(\)](#).

- "ml1" calls `dof_ml1()`.
- "betwithin" calls `dof_betwithin()`.

For models with z-statistic, the returned degrees of freedom for model parameters is Inf (unless `method = "ml1"` or `method = "betwithin"`), because there is only one distribution for the related test statistic.

Note

In many cases, `degrees_of_freedom()` returns the same as `df.residuals()`, or $n-k$ (number of observations minus number of parameters). However, `degrees_of_freedom()` refers to the model's *parameters* degrees of freedom of the distribution for the related test statistic. Thus, for models with z-statistic, results from `degrees_of_freedom()` and `df.residuals()` differ. Furthermore, for other approximation methods like "kenward" or "satterthwaite", each model parameter can have a different degree of freedom.

Examples

```
model <- lm(Sepal.Length ~ Petal.Length * Species, data = iris)
dof(model)

model <- glm(vs ~ mpg * cyl, data = mtcars, family = "binomial")
dof(model)
## Not run:
if (require("lme4", quietly = TRUE)) {
  model <- lmer(Sepal.Length ~ Petal.Length + (1 | Species), data = iris)
  dof(model)
}

if (require("rstanarm", quietly = TRUE)) {
  model <- stan_glm(
    Sepal.Length ~ Petal.Length * Species,
    data = iris,
    chains = 2,
    refresh = 0
  )
  dof(model)
}

## End(Not run)
```

display.parameters_model

Print tables in different output formats

Description

Prints tables (i.e. data frame) in different output formats. `print_md()` is a alias for `display(format = "markdown")`.

Usage

```
## S3 method for class 'parameters_model'
display(
  object,
  format = "markdown",
  pretty_names = TRUE,
  split_components = TRUE,
  select = NULL,
  caption = NULL,
  subtitle = NULL,
  footer = NULL,
  align = NULL,
  digits = 2,
  ci_digits = 2,
  p_digits = 3,
  footer_digits = 3,
  ci_brackets = c("(", ")"),
  show_sigma = FALSE,
  show_formula = FALSE,
  zap_small = FALSE,
  verbose = TRUE,
  ...
)

## S3 method for class 'parameters_sem'
display(
  object,
  format = "markdown",
  digits = 2,
  ci_digits = 2,
  p_digits = 3,
  ci_brackets = c("(", ")"),
  ...
)

## S3 method for class 'parameters_efa_summary'
display(object, format = "markdown", digits = 3, ...)

## S3 method for class 'parameters_efa'
display(
  object,
  format = "markdown",
  digits = 2,
  sort = FALSE,
  threshold = NULL,
  labels = NULL,
  ...
)
```

```
## S3 method for class 'equivalence_test_lm'  
display(object, format = "markdown", digits = 2, ...)
```

```
## S3 method for class 'parameters_model'  
format(  
  x,  
  pretty_names = TRUE,  
  split_components = TRUE,  
  select = NULL,  
  digits = 2,  
  ci_digits = 2,  
  p_digits = 3,  
  ci_width = NULL,  
  ci_brackets = NULL,  
  zap_small = FALSE,  
  format = NULL,  
  groups = NULL,  
  ...  
)
```

```
## S3 method for class 'parameters_model'  
print_html(  
  x,  
  pretty_names = TRUE,  
  split_components = TRUE,  
  select = NULL,  
  caption = NULL,  
  subtitle = NULL,  
  footer = NULL,  
  align = NULL,  
  digits = 2,  
  ci_digits = 2,  
  p_digits = 3,  
  footer_digits = 3,  
  ci_brackets = c("(", ")"),  
  show_sigma = FALSE,  
  show_formula = FALSE,  
  zap_small = FALSE,  
  groups = NULL,  
  verbose = TRUE,  
  ...  
)
```

```
## S3 method for class 'parameters_model'  
print_md(  
  x,  
  pretty_names = TRUE,
```

```

split_components = TRUE,
select = NULL,
caption = NULL,
subtitle = NULL,
footer = NULL,
align = NULL,
digits = 2,
ci_digits = 2,
p_digits = 3,
footer_digits = 3,
ci_brackets = c("(", ")"),
show_sigma = FALSE,
show_formula = FALSE,
zap_small = FALSE,
groups = NULL,
verbose = TRUE,
...
)

```

Arguments

object	An object returned by <code>model_parameters()</code> , <code>simulate_parameters()</code> , <code>equivalence_test()</code> or <code>principal_components()</code> .
format	String, indicating the output format. Can be "markdown" or "html".
pretty_names	Return "pretty" (i.e. more human readable) parameter names.
split_components	Logical, if TRUE (default), For models with multiple components (zero-inflation, smooth terms, ...), each component is printed in a separate table. If FALSE, model parameters are printed in a single table and a Component column is added to the output.
select	Character vector (or numeric index) of column names that should be printed. If NULL (default), all columns are printed. The shortcut <code>select = "minimal"</code> prints coefficient, confidence intervals and p-values, while <code>select = "short"</code> prints coefficient, standard errors and p-values.
caption	Table caption as string. If NULL, no table caption is printed.
subtitle	Table title (same as caption) and subtitle, as strings. If NULL, no title or subtitle is printed, unless it is stored as attributes (<code>table_title</code> , or its alias <code>table_caption</code> , and <code>table_subtitle</code>). If <code>x</code> is a list of data frames, caption may be a list of table captions, one for each table.
footer	Table footer, as string. For markdown-formatted tables, table footers, due to the limitation in markdown rendering, are actually just a new text line under the table. If <code>x</code> is a list of data frames, footer may be a list of table captions, one for each table.
align	Only applies to HTML tables. May be one of "left", "right" or "center".
digits, ci_digits, p_digits	Number of digits for rounding or significant figures. May also be "signif" to return significant figures or "scientific" to return scientific notation. Control

	the number of digits by adding the value as suffix, e.g. <code>digits = "scientific4"</code> to have scientific notation with 4 decimal places, or <code>digits = "signif5"</code> for 5 significant figures (see also <code>signif()</code>).
<code>footer_digits</code>	Number of decimal places for values in the footer summary.
<code>ci_brackets</code>	Logical, if TRUE (default), CI-values are encompassed in square brackets (else in parentheses).
<code>show_sigma</code>	Logical, if TRUE, adds information about the residual standard deviation.
<code>show_formula</code>	Logical, if TRUE, adds the model formula to the output.
<code>zap_small</code>	Logical, if TRUE, small values are rounded after <code>digits</code> decimal places. If FALSE, values with more decimal places than <code>digits</code> are printed in scientific notation.
<code>verbose</code>	Toggle messages and warnings.
<code>...</code>	Arguments passed to or from other methods.
<code>sort</code>	Sort the loadings.
<code>threshold</code>	A value between 0 and 1 indicates which (absolute) values from the loadings should be removed. An integer higher than 1 indicates the <code>n</code> strongest loadings to retain. Can also be "max", in which case it will only display the maximum loading per variable (the most simple structure).
<code>labels</code>	A character vector containing labels to be added to the loadings data. Usually, the question related to the item.
<code>x</code>	An object returned by <code>model_parameters()</code> .
<code>ci_width</code>	Minimum width of the returned string for confidence intervals. If not NULL and width is larger than the string's length, leading whitespaces are added to the string. If <code>width="auto"</code> , width will be set to the length of the longest string.
<code>groups</code>	Named list, can be used to group parameters in the printed output. List elements may either be character vectors that match the name of those parameters that belong to one group, or list elements can be row numbers of those parameter rows that should belong to one group. The names of the list elements will be used as group names, which will be inserted as "header row". A possible use case might be to emphasize focal predictors and control variables, see 'Examples'. Parameters will be re-ordered according to the order used in groups, while all non-matching parameters will be added to the end.

Details

`display()` is useful when the table-output from functions, which is usually printed as formatted text-table to console, should be formatted for pretty table-rendering in markdown documents, or if knitted from rmarkdown to PDF or Word files. See [vignette](#) for examples.

Value

If `format = "markdown"`, the return value will be a character vector in markdown-table format. If `format = "html"`, an object of class `gt_tbl`.

Examples

```
model <- lm(mpg ~ wt + cyl, data = mtcars)
mp <- model_parameters(model)
display(mp)
```

equivalence_test.lm *Equivalence test*

Description

Compute the (conditional) equivalence test for frequentist models.

Usage

```
## S3 method for class 'lm'
equivalence_test(
  x,
  range = "default",
  ci = 0.95,
  rule = "classic",
  verbose = TRUE,
  ...
)

## S3 method for class 'merMod'
equivalence_test(
  x,
  range = "default",
  ci = 0.95,
  rule = "classic",
  effects = c("fixed", "random"),
  verbose = TRUE,
  ...
)
```

Arguments

x	A statistical model.
range	The range of practical equivalence of an effect. May be "default", to automatically define this range based on properties of the model's data.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
rule	Character, indicating the rules when testing for practical equivalence. Can be "bayes", "classic" or "cet". See 'Details'.
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods.

effects Should parameters for fixed effects ("fixed"), random effects ("random"), or both ("all") be returned? Only applies to mixed models. May be abbreviated. If the calculation of random effects parameters takes too long, you may use effects = "fixed".

Details

In classical null hypothesis significance testing (NHST) within a frequentist framework, it is not possible to accept the null hypothesis, H_0 - unlike in Bayesian statistics, where such probability statements are possible. "... one can only reject the null hypothesis if the test statistics falls into the critical region(s), or fail to reject this hypothesis. In the latter case, all we can say is that no significant effect was observed, but one cannot conclude that the null hypothesis is true." (Pernet 2017). One way to address this issues without Bayesian methods is *Equivalence Testing*, as implemented in `equivalence_test()`. While you either can reject the null hypothesis or claim an inconclusive result in NHST, the equivalence test adds a third category, "accept". Roughly speaking, the idea behind equivalence testing in a frequentist framework is to check whether an estimate and its uncertainty (i.e. confidence interval) falls within a region of "practical equivalence". Depending on the rule for this test (see below), statistical significance does not necessarily indicate whether the null hypothesis can be rejected or not, i.e. the classical interpretation of the p-value may differ from the results returned from the equivalence test.

Calculation of equivalence testing:

"bayes" - Bayesian rule (Kruschke 2018) This rule follows the "HDI+ROPE decision rule" (Kruschke, 2014, 2018) used for the `Bayesian counterpart()`. This means, if the confidence intervals are completely outside the ROPE, the "null hypothesis" for this parameter is "rejected". If the ROPE completely covers the CI, the null hypothesis is accepted. Else, it's undecided whether to accept or reject the null hypothesis. Desirable results are low proportions inside the ROPE (the closer to zero the better).

"classic" - The TOST rule (Lakens 2017) This rule follows the "TOST rule", i.e. a two one-sided test procedure (Lakens 2017). Following this rule, practical equivalence of an effect (i.e. H_0) is *rejected*, when the coefficient is statistically significant *and* the narrow confidence intervals (i.e. $1-2*\alpha$) *include* or *exceed* the ROPE boundaries. Practical equivalence is assumed (i.e. H_0 accepted) when the narrow confidence intervals are completely inside the ROPE, no matter if the effect is statistically significant or not. Else, the decision whether to accept or reject H_0 is undecided.

"cet" - Conditional Equivalence Testing (Campbell/Gustafson 2018) The Conditional Equivalence Testing as described by *Campbell and Gustafson 2018*. According to this rule, practical equivalence is rejected when the coefficient is statistically significant. When the effect is *not* significant and the narrow confidence intervals are completely inside the ROPE, we accept H_0 , else it is undecided.

Levels of Confidence Intervals used for Equivalence Testing: For rule = "classic", "narrow" confidence intervals are used for equivalence testing. "Narrow" means, the the intervals is not $1 - \alpha$, but $1 - 2 * \alpha$. Thus, if $ci = .95$, α is assumed to be 0.05 and internally a ci-level of 0.90 is used. rule = "cet" uses both regular and narrow confidence intervals, while rule = "bayes" only uses the regular intervals.

p-Values: The equivalence p-value is the area of the (cumulative) confidence distribution that is outside of the region of equivalence. It can be interpreted as p-value for *rejecting* the alternative hypothesis and *accepting* the null hypothesis.

Second Generation p-Value (SGPV): Second generation p-values (SGPV) were proposed as a statistic that represents “the proportion of data-supported hypotheses that are also null hypotheses” (Blume *et al.* 2018). This statistic is actually computed in the same way as the percentage inside the ROPE as returned by `equivalence_test()` (see Lakens and Delacre 2020 for details on computation of the SGPV). Thus, the “inside ROPE” column reflects the SGPV.

ROPE range: Some attention is required for finding suitable values for the ROPE limits (argument `range`). See ‘Details’ in `bayestestR::rope_range()` for further information.

Value

A data frame.

Note

There is also a `plot()`-method implemented in the [see-package](#).

References

- Blume, J. D., D’Agostino McGowan, L., Dupont, W. D., & Greevy, R. A. (2018). Second-generation p-values: Improved rigor, reproducibility, & transparency in statistical analyses. *PLOS ONE*, 13(3), e0188299. <https://doi.org/10.1371/journal.pone.0188299>
- Campbell, H., & Gustafson, P. (2018). Conditional equivalence testing: An alternative remedy for publication bias. *PLOS ONE*, 13(4), e0195145. doi: 10.1371/journal.pone.0195145
- Kruschke, J. K. (2014). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*. Academic Press
- Kruschke, J. K. (2018). Rejecting or accepting parameter values in Bayesian estimation. *Advances in Methods and Practices in Psychological Science*, 1(2), 270-280. doi: 10.1177/2515245918771304
- Lakens, D. (2017). Equivalence Tests: A Practical Primer for t Tests, Correlations, and Meta-Analyses. *Social Psychological and Personality Science*, 8(4), 355–362. doi: 10.1177/1948550617697177
- Lakens, D., & Delacre, M. (2020). Equivalence Testing and the Second Generation P-Value. *Meta-Psychology*, 4. <https://doi.org/10.15626/MP.2018.933>
- Pernet, C. (2017). Null hypothesis significance testing: A guide to commonly misunderstood concepts and recommendations for good practice. *F1000Research*, 4, 621. doi: 10.12688/f1000research.6963.5

See Also

For more details, see `bayestestR::equivalence_test()`. Further readings can be found in the references.

Examples

```
data(qol_cancer)
model <- lm(QoL ~ time + age + education, data = qol_cancer)

# default rule
equivalence_test(model)
```

```
# conditional equivalence test
equivalence_test(model, rule = "cet")

# plot method
if (require("see", quietly = TRUE)) {
  result <- equivalence_test(model)
  plot(result)
}
```

factor_analysis *Principal Component Analysis (PCA) and Factor Analysis (FA)*

Description

The functions `principal_components()` and `factor_analysis()` can be used to perform a principal component analysis (PCA) or a factor analysis (FA). They return the loadings as a data frame, and various methods and functions are available to access / display other information (see the Details section).

Usage

```
factor_analysis(
  x,
  n = "auto",
  rotation = "none",
  sort = FALSE,
  threshold = NULL,
  standardize = TRUE,
  cor = NULL,
  ...
)

principal_components(
  x,
  n = "auto",
  rotation = "none",
  sort = FALSE,
  threshold = NULL,
  standardize = TRUE,
  ...
)

rotated_data(pca_results)

## S3 method for class 'parameters_efa'
predict(object, newdata = NULL, names = NULL, keep_na = TRUE, ...)

## S3 method for class 'parameters_efa'
```

```
print(x, digits = 2, sort = FALSE, threshold = NULL, labels = NULL, ...)

## S3 method for class 'parameters_efa'
sort(x, ...)

closest_component(pca_results)
```

Arguments

x	A data frame or a statistical model.
n	Number of components to extract. If n="all", then n is set as the number of variables minus 1 (ncol(x)-1). If n="auto" (default) or n=NULL, the number of components is selected through n_factors() resp. n_components() . In reduce_parameters() , can also be "max", in which case it will select all the components that are maximally pseudo-loaded (i.e., correlated) by at least one variable.
rotation	If not "none", the PCA / FA will be computed using the psych package. Possible options include "varimax", "quartimax", "promax", "oblimin", "simplimax", or "cluster" (and more). See psych::fa() for details.
sort	Sort the loadings.
threshold	A value between 0 and 1 indicates which (absolute) values from the loadings should be removed. An integer higher than 1 indicates the n strongest loadings to retain. Can also be "max", in which case it will only display the maximum loading per variable (the most simple structure).
standardize	A logical value indicating whether the variables should be standardized (centered and scaled) to have unit variance before the analysis (in general, such scaling is advisable).
cor	An optional correlation matrix that can be used (note that the data must still be passed as the first argument). If NULL, will compute it by running <code>cor()</code> on the passed data.
...	Arguments passed to or from other methods.
pca_results	The output of the <code>principal_components()</code> function.
object	An object of class <code>parameters_pca</code> or <code>parameters_efa</code>
newdata	An optional data frame in which to look for variables with which to predict. If omitted, the fitted values are used.
names	Optional character vector to name columns of the returned data frame.
keep_na	Logical, if TRUE, predictions also return observations with missing values from the original data, hence the number of rows of predicted data and original data is equal.
digits, labels	Arguments for <code>print()</code> .

Details

Methods and Utilities:

- `n_components()` and `n_factors()` automatically estimates the optimal number of dimensions to retain.
- `check_factorstructure()` checks the suitability of the data for factor analysis using the `sphericity()` and the `sphericity()` KMO measure.
- `performance::check_itemscale()` computes various measures of internal consistencies applied to the (sub)scales (i.e., components) extracted from the PCA.
- Running `summary` returns information related to each component/factor, such as the explained variance and the Eivenvalues.
- Running `get_scores()` computes scores for each subscale.
- Running `closest_component()` will return a numeric vector with the assigned component index for each column from the original data frame.
- Running `rotated_data()` will return the rotated data, including missing values, so it matches the original data frame.
- Running `plot()` visually displays the loadings (that requires the [see-package](#) to work).

Complexity: Complexity represents the number of latent components needed to account for the observed variables. Whereas a perfect simple structure solution has a complexity of 1 in that each item would only load on one factor, a solution with evenly distributed items has a complexity greater than 1 (*Hofman, 1978; Pettersson and Turkheimer, 2010*).

Uniqueness: Uniqueness represents the variance that is 'unique' to the variable and not shared with other variables. It is equal to $1 - \text{communality}$ (variance that is shared with other variables). A uniqueness of 0.20 suggests that 20% of that variable's variance is not shared with other variables in the overall factor model. The greater 'uniqueness' the lower the relevance of the variable in the factor model.

MSA: MSA represents the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (*Kaiser and Rice, 1974*) for each item. It indicates whether there is enough data for each factor give reliable results for the PCA. The value should be > 0.6 , and desirable values are > 0.8 (*Tabachnick and Fidell, 2013*).

PCA or FA?: There is a simplified rule of thumb that may help do decide whether to run a factor analysis or a principal component analysis:

- Run *factor analysis* if you assume or wish to test a theoretical model of *latent factors* causing observed variables.
- Run *principal component analysis* If you want to simply *reduce* your correlated observed variables to a smaller set of important independent composite variables.

(Source: [CrossValidated](#))

Computing Item Scores: Use `get_scores()` to compute scores for the "subscales" represented by the extracted principal components. `get_scores()` takes the results from `principal_components()` and extracts the variables for each component found by the PCA. Then, for each of these "subscales", raw means are calculated (which equals adding up the single items and dividing by the number of items). This results in a sum score for each component from the PCA, which is on the same scale as the original, single items that were used to compute the PCA. One can also use `predict()` to back-predict scores for each component, to which one can provide `newdata` or a vector of names for the components.

Explained Variance and Eigenvalues: Use `summary()` to get the Eigenvalues and the explained variance for each extracted component. The eigenvectors and eigenvalues represent the "core" of a PCA: The eigenvectors (the principal components) determine the directions of the new feature space, and the eigenvalues determine their magnitude. In other words, the eigenvalues explain the variance of the data along the new feature axes.

Value

A data frame of loadings.

References

- Kaiser, H.F. and Rice. J. (1974). Little jiffy, mark iv. *Educational and Psychological Measurement*, 34(1):111–117
- Hofmann, R. (1978). Complexity and simplicity as objective indices descriptive of factor solutions. *Multivariate Behavioral Research*, 13:2, 247-250, doi:[10.1207/s15327906mbr1302_9](https://doi.org/10.1207/s15327906mbr1302_9)
- Pettersson, E., & Turkheimer, E. (2010). Item selection, evaluation, and simple structure in personality data. *Journal of research in personality*, 44(4), 407-420, doi:[10.1016/j.jrp.2010.03.002](https://doi.org/10.1016/j.jrp.2010.03.002)
- Tabachnick, B. G., and Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Boston: Pearson Education.

Examples

```
library(parameters)

# Principal Component Analysis (PCA) -----
if (require("psych")) {
  principal_components(mtcars[, 1:7], n = "all", threshold = 0.2)
  principal_components(mtcars[, 1:7],
    n = 2, rotation = "oblimin",
    threshold = "max", sort = TRUE
  )
  principal_components(mtcars[, 1:7], n = 2, threshold = 2, sort = TRUE)

  pca <- principal_components(mtcars[, 1:5], n = 2, rotation = "varimax")
  pca # Print loadings
  summary(pca) # Print information about the factors
  predict(pca, names = c("Component1", "Component2")) # Back-predict scores

  # which variables from the original data belong to which extracted component?
  closest_component(pca)
  # rotated_data(pca) # TODO: doesn't work

  # Automated number of components
  principal_components(mtcars[, 1:4], n = "auto")
}
```

```

# Factor Analysis (FA) -----
if (require("psych")) {
  factor_analysis(mtcars[, 1:7], n = "all", threshold = 0.2)
  factor_analysis(mtcars[, 1:7], n = 2, rotation = "oblimin", threshold = "max", sort = TRUE)
  factor_analysis(mtcars[, 1:7], n = 2, threshold = 2, sort = TRUE)

  efa <- factor_analysis(mtcars[, 1:5], n = 2)
  summary(efa)
  predict(efa)

  # Automated number of components
  factor_analysis(mtcars[, 1:4], n = "auto")
}

```

fish	<i>Sample data set</i>
------	------------------------

Description

A sample data set, used in tests and some examples.

format_df_adjust	<i>Format the name of the degrees-of-freedom adjustment methods</i>
------------------	---

Description

Format the name of the degrees-of-freedom adjustment methods.

Usage

```

format_df_adjust(
  method,
  approx_string = "-approximated",
  dof_string = " degrees of freedom"
)

```

Arguments

method	Name of the method.
approx_string, dof_string	Suffix added to the name of the method in the returned string.

Value

A formatted string.

Examples

```
library(parameters)

format_df_adjust("kenward")
format_df_adjust("kenward", approx_string = "", dof_string = " DoF")
```

format_order	<i>Order (first, second, ...) formatting</i>
--------------	--

Description

Format order.

Usage

```
format_order(order, textual = TRUE, ...)
```

Arguments

order	value or vector of orders.
textual	Return number as words. If FALSE, will run <code>insight::format_value()</code> .
...	Arguments to be passed to <code>insight::format_value()</code> if textual is FALSE.

Value

A formatted string.

Examples

```
format_order(2)
format_order(8)
format_order(25, textual = FALSE)
```

format_parameters	<i>Parameter names formatting</i>
-------------------	-----------------------------------

Description

This functions formats the names of model parameters (coefficients) to make them more human-readable.

Usage

```
format_parameters(model, ...)

## Default S3 method:
format_parameters(model, brackets = c("[", "]"), ...)
```

Arguments

model	A statistical model.
...	Currently not used.
brackets	A character vector of length two, indicating the opening and closing brackets.

Value

A (names) character vector with formatted parameter names. The value names refer to the original names of the coefficients.

Interpretation of Interaction Terms

Note that the *interpretation* of interaction terms depends on many characteristics of the model. The number of parameters, and overall performance of the model, can differ *or not* between $a * b$, $a : b$, and a / b , suggesting that sometimes interaction terms give different parameterizations of the same model, but other times it gives completely different models (depending on a or b being factors of covariates, included as main effects or not, etc.). Their interpretation depends of the full context of the model, which should not be inferred from the parameters table alone - rather, we recommend to use packages that calculate estimated marginal means or marginal effects, such as **modelbased**, **emmeans** or **ggeffects**. To raise awareness for this issue, you may use `print(..., show_formula=TRUE)` to add the model-specification to the output of the `print()` method for `model_parameters()`.

Examples

```
model <- lm(Sepal.Length ~ Species * Sepal.Width, data = iris)
format_parameters(model)

model <- lm(Sepal.Length ~ Petal.Length + (Species / Sepal.Width), data = iris)
format_parameters(model)

model <- lm(Sepal.Length ~ Species + poly(Sepal.Width, 2), data = iris)
format_parameters(model)

model <- lm(Sepal.Length ~ Species + poly(Sepal.Width, 2, raw = TRUE), data = iris)
format_parameters(model)
```

format_p_adjust

Format the name of the p-value adjustment methods

Description

Format the name of the p-value adjustment methods.

Usage

```
format_p_adjust(method)
```


Arguments

method Name of the method.

Value

A string with the full surname(s) of the author(s), including year of publication, for the adjustment-method.

Examples

```
library(parameters)

format_p_adjust("holm")
format_p_adjust("bonferroni")
```

get_scores *Get Scores from Principal Component Analysis (PCA)*

Description

get_scores() takes n_items amount of items that load the most (either by loading cutoff or number) on a component, and then computes their average.

Usage

```
get_scores(x, n_items = NULL)
```

Arguments

x An object returned by [principal_components\(\)](#).

n_items Number of required (i.e. non-missing) items to build the sum score. If NULL, the value is chosen to match half of the number of columns in a data frame.

Details

get_scores() takes the results from [principal_components\(\)](#) and extracts the variables for each component found by the PCA. Then, for each of these "subscales", row means are calculated (which equals adding up the single items and dividing by the number of items). This results in a sum score for each component from the PCA, which is on the same scale as the original, single items that were used to compute the PCA.

Value

A data frame with subscales, which are average sum scores for all items from each component.

Examples

```

if (require("psych")) {
  pca <- principal_components(mtcars[, 1:7], n = 2, rotation = "varimax")

  # PCA extracted two components
  pca

  # assignment of items to each component
  closest_component(pca)

  # now we want to have sum scores for each component
  get_scores(pca)

  # compare to manually computed sum score for 2nd component, which
  # consists of items "hp" and "qsec"
  (mtcars$hp + mtcars$qsec) / 2
}

```

model_parameters

Model Parameters

Description

Compute and extract model parameters. See the documentation for your object's class:

- [Correlations, t-tests, ...](#) (`htest`, `pairwise.htest`)
- [ANOVAs](#) (`aov`, `anova`, `afex`, ...)
- [Regression models](#) (`lm`, `glm`, `survey`, ...)
- [Mixed models](#) (`lme4`, `nlme`, `glmmTMB`, `afex`, ...)
- [Additive models](#) (`gam`, `gamm`, ...)
- [Zero-inflated models](#) (`hurdle`, `zeroinfl`, `zerocount`)
- [Multinomial, ordinal and cumulative link models](#) (`brac1`, `multinom`, `mlm`, **ordinal**, ...)
- [Other special models](#) (`model.avg`, `betareg`, `glmx`, ...)
- [Bayesian tests](#) (**BayesFactor**)
- [Bayesian models](#) (`rstanarm`, `brms`, `MCMCglmm`, `blavaan`, ...)
- [PCA and FA](#) (`psych`)
- [CFA and SEM](#) (`lavaan`)
- [Cluster models](#) (`k-means`, ...)
- [Meta-Analysis via linear \(mixed\) models](#) (`rma`, `metaplas`, **metaBMA**, ...)
- [Hypothesis testing](#) (`glht`, **PMCMRplus**)
- [Robust statistical tests](#) (**WRS2**)
- [Multiply imputed repeated analyses](#) (`mira`)

Usage

```
model_parameters(model, ...)
```

```
parameters(model, ...)
```

Arguments

model	Statistical Model.
...	Arguments passed to or from other methods. Non-documented arguments are <code>digits</code> , <code>p_digits</code> , <code>ci_digits</code> and <code>footer_digits</code> to set the number of digits for the output. <code>group</code> can also be passed to the <code>print()</code> method. See details in <code>print.parameters_model()</code> and 'Examples' in <code>model_parameters.default()</code> .

Value

A data frame of indices related to the model's parameters.

Standardization of model coefficients

Standardization is based on `standardize_parameters()`. In case of `standardize = "refit"`, the data used to fit the model will be standardized and the model is completely refitted. In such cases, standard errors and confidence intervals refer to the standardized coefficient. The default, `standardize = "refit"`, never standardizes categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages or other software packages (like SPSS). To mimic behaviour of SPSS or packages such as **lm.beta**, use `standardize = "basic"`.

Standardization Methods

- **refit**: This method is based on a complete model re-fit with a standardized version of the data. Hence, this method is equal to standardizing the variables before fitting the model. It is the "purest" and the most accurate (Neter et al., 1989), but it is also the most computationally costly and long (especially for heavy models such as Bayesian models). This method is particularly recommended for complex models that include interactions or transformations (e.g., polynomial or spline terms). The robust (default to FALSE) argument enables a robust standardization of data, i.e., based on the median and MAD instead of the mean and SD. **See `standardize()` for more details.** **Note** that `standardize_parameters(method = "refit")` may not return the same results as fitting a model on data that has been standardized with `standardize()`; `standardize_parameters()` used the data used by the model fitting function, which might not be same data if there are missing values. see the `remove_na` argument in `standardize()`.
- **posthoc**: Post-hoc standardization of the parameters, aiming at emulating the results obtained by "refit" without refitting the model. The coefficients are divided by the standard deviation (or MAD if robust) of the outcome (which becomes their expression 'unit'). Then, the coefficients related to numeric variables are additionally multiplied by the standard deviation (or MAD if robust) of the related terms, so that they correspond to changes of 1 SD of the predictor (e.g., "A change in 1 SD of x is related to a change of 0.24 of the SD of y). This does not apply to binary variables or factors, so the coefficients are still related to changes in levels. This method is not accurate and tend to give aberrant results when interactions are specified.

- **basic**: This method is similar to `method = "posthoc"`, but treats all variables as continuous: it also scales the coefficient by the standard deviation of model's matrix' parameter of factors levels (transformed to integers) or binary predictors. Although being inappropriate for these cases, this method is the one implemented by default in other software packages, such as `lm.beta::lm.beta()`.
- **smart** (Standardization of Model's parameters with Adjustment, Reconnaissance and Transformation - *experimental*): Similar to `method = "posthoc"` in that it does not involve model refitting. The difference is that the SD (or MAD if robust) of the response is computed on the relevant section of the data. For instance, if a factor with 3 levels A (the intercept), B and C is entered as a predictor, the effect corresponding to B vs. A will be scaled by the variance of the response at the intercept only. As a results, the coefficients for effects of factors are similar to a Glass' delta.
- **pseudo** (*for 2-level (G)LMMs only*): In this (post-hoc) method, the response and the predictor are standardized based on the level of prediction (levels are detected with `performance::check_heterogeneity_bias`). Predictors are standardized based on their SD at level of prediction (see also `datawizard::demean()`); The outcome (in linear LMMs) is standardized based on a fitted random-intercept-model, where `sqrt(random-intercept-variance)` is used for level 2 predictors, and `sqrt(residual-variance)` is used for level 1 predictors (Hoffman 2015, page 342). A warning is given when a within-group variable is found to have access between-group variance.

Labeling the Degrees of Freedom

Throughout the **parameters** package, we decided to label the residual degrees of freedom `df_error`. The reason for this is that these degrees of freedom not always refer to the residuals. For certain models, they refer to the estimate error - in a linear model these are the same, but in - for instance - any mixed effects model, this isn't strictly true. Hence, we think that `df_error` is the most generic label for these degrees of freedom.

Confidence intervals and approximation of degrees of freedom

There are different ways of approximating the degrees of freedom depending on different assumptions about the nature of the model and its sampling distribution. The `ci_method` argument modulates the method for computing degrees of freedom (df) that are used to calculate confidence intervals (CI) and the related p-values. Following options are allowed, depending on the model class:

Classical methods:

Classical inference is generally based on the **Wald method**. The Wald approach to inference computes a test statistic by dividing the parameter estimate by its standard error (Coefficient / SE), then comparing this statistic against a t- or normal distribution. This approach can be used to compute CIs and p-values.

"wald":

- Applies to *non-Bayesian models*. For *linear models*, CIs computed using the Wald method (SE and a *t-distribution with residual df*); p-values computed using the Wald method with a *t-distribution with residual df*. For other models, CIs computed using the Wald method (SE and a *normal distribution*); p-values computed using the Wald method with a *normal distribution*.

"normal"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a normal distribution.

"residual"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a *t-distribution with residual df* when possible. If the residual df for a model cannot be determined, a normal distribution is used instead.

Methods for mixed models:

Compared to fixed effects (or single-level) models, determining appropriate df for Wald-based inference in mixed models is more difficult. See [the R GLMM FAQ](#) for a discussion.

Several approximate methods for computing df are available, but you should also consider instead using profile likelihood ("profile") or bootstrap ("boot") CIs and p-values instead.

"satterthwaite"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with Satterthwaite df*); p-values computed using the Wald method with a *t-distribution with Satterthwaite df*.

"kenward"

- Applies to *linear mixed models*. CIs computed using the Wald method (*Kenward-Roger SE* and a *t-distribution with Kenward-Roger df*); p-values computed using the Wald method with *Kenward-Roger SE and t-distribution with Kenward-Roger df*.

"m11"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with m-1-1 approximated df*); p-values computed using the Wald method with a *t-distribution with m-1-1 approximated df*. See [ci_m11\(\)](#).

"betwithin"

- Applies to *linear mixed models* and *generalized linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with between-within df*); p-values computed using the Wald method with a *t-distribution with between-within df*. See [ci_betwithin\(\)](#).

Likelihood-based methods:

Likelihood-based inference is based on comparing the likelihood for the maximum-likelihood estimate to the the likelihood for models with one or more parameter values changed (e.g., set to zero or a range of alternative values). Likelihood ratios for the maximum-likelihood and alternative models are compared to a χ -squared distribution to compute CIs and p-values.

"profile"

- Applies to *non-Bayesian models* of class `glm`, `polr` or `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using linear interpolation to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

"uniroot"

- Applies to *non-Bayesian models* of class `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using root finding to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

Methods for bootstrapped or Bayesian models:

Bootstrap-based inference is based on **resampling** and refitting the model to the resampled datasets. The distribution of parameter estimates across resampled datasets is used to approximate the parameter's sampling distribution. Depending on the type of model, several different methods for bootstrapping and constructing CIs and p-values from the bootstrap distribution are available.

For Bayesian models, inference is based on drawing samples from the model posterior distribution.

"quantile" (or "eti")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *equal tailed intervals* using the quantiles of the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::eti()`.

"hdi"

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *highest density intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::hdi()`.

"bci" (or "bcai")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *bias corrected and accelerated intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::bci()`.

"si"

- Applies to *Bayesian models* with proper priors. CIs computed as *support intervals* comparing the posterior samples against the prior samples; p-values are based on the *probability of direction*. See `bayestestR::si()`.

"boot"

- Applies to *non-Bayesian models* of class `merMod`. CIs computed using *parametric bootstrapping* (simulating data from the fitted model); p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!).

For all iteration-based methods other than "boot" ("hdi", "quantile", "ci", "eti", "si", "bci", "bcai"), p-values are based on the probability of direction (`bayestestR::p_direction()`), which is converted into a p-value using `bayestestR::pd_to_p()`.

Interpretation of Interaction Terms

Note that the *interpretation* of interaction terms depends on many characteristics of the model. The number of parameters, and overall performance of the model, can differ *or not* between $a * b$, $a : b$, and a / b , suggesting that sometimes interaction terms give different parameterizations of the same model, but other times it gives completely different models (depending on a or b being factors of covariates, included as main effects or not, etc.). Their interpretation depends of the full context of the model, which should not be inferred from the parameters table alone - rather, we recommend to use packages that calculate estimated marginal means or marginal effects, such as **modelbased**, **emmeans** or **ggeffects**. To raise awareness for this issue, you may use `print(..., show_formula=TRUE)` to add the model-specification to the output of the `print()` method for `model_parameters()`.

Note

The `print()` method has several arguments to tweak the output. There is also a `plot()-method` implemented in the **see-package**, and a dedicated method for use inside rmarkdown files, `print_md()`.

For developers, if speed performance is an issue, you can use the (undocumented) `pretty_names` argument, e.g. `model_parameters(..., pretty_names = FALSE)`. This will skip the formatting of the coefficient names and make `model_parameters()` faster.

References

- Hoffman, L. (2015). Longitudinal analysis: Modeling within-person fluctuation and change. Routledge.
- Neter, J., Wasserman, W., & Kutner, M. H. (1989). Applied linear regression models.

See Also

`insight::standardize_names()` to rename columns into a consistent, standardized naming scheme.

model_parameters.aov *Parameters from ANOVAs*

Description

Parameters from ANOVAs

Usage

```
## S3 method for class 'aov'
model_parameters(
  model,
  omega_squared = NULL,
  eta_squared = NULL,
  epsilon_squared = NULL,
  df_error = NULL,
```

```

type = NULL,
ci = NULL,
alternative = NULL,
test = NULL,
power = FALSE,
keep = NULL,
drop = NULL,
parameters = keep,
table_wide = FALSE,
verbose = TRUE,
...
)

```

Arguments

model	Object of class <code>aov()</code> , <code>anova()</code> , <code>aovlist</code> , <code>Gam</code> , <code>manova()</code> , <code>Anova.mlm</code> , <code>afex_aov</code> or <code>maov</code> .
omega_squared	Compute omega squared as index of effect size. Can be "partial" (the default, adjusted for effect size) or "raw".
eta_squared	Compute eta squared as index of effect size. Can be "partial" (the default, adjusted for effect size), "raw" or "adjusted" (the latter option only for ANOVA-tables from mixed models).
epsilon_squared	Compute epsilon squared as index of effect size. Can be "partial" (the default, adjusted for effect size) or "raw".
df_error	Denominator degrees of freedom (or degrees of freedom of the error estimate, i.e., the residuals). This is used to compute effect sizes for ANOVA-tables from mixed models. See 'Examples'. Ignored for <code>afex_aov</code> .
type	Numeric, type of sums of squares. May be 1, 2 or 3. If 2 or 3, ANOVA-tables using <code>car::Anova()</code> will be returned. Ignored for <code>afex_aov</code> .
ci	Confidence Interval (CI) level for effect sizes <code>omega_squared</code> , <code>eta_squared</code> etc. The default, <code>NULL</code> , will compute no confidence intervals. <code>ci</code> should be a scalar between 0 and 1.
alternative	A character string specifying the alternative hypothesis; Controls the type of CI returned: "two.sided" (default, two-sided CI), "greater" or "less" (one-sided CI). Partial matching is allowed (e.g., "g", "1", "two"...). See section <i>One-Sided CIs</i> in the effectsize_CIs vignette .
test	String, indicating the type of test for <code>Anova.mlm</code> to be returned. If "multivariate" (or <code>NULL</code>), returns the summary of the multivariate test (that is also given by the <code>print</code> -method). If <code>test = "univariate"</code> , returns the summary of the univariate test.
power	Logical, if <code>TRUE</code> , adds a column with power for each parameter.
keep	Character containing a regular expression pattern that describes the parameters that should be included (for <code>keep</code>) or excluded (for <code>drop</code>) in the returned data frame. <code>keep</code> may also be a named list of regular expressions. All non-matching

parameters will be removed from the output. If `keep` is a character vector, every parameter name in the *"Parameter"* column that matches the regular expression in `keep` will be selected from the returned data frame (and vice versa, all parameter names matching `drop` will be excluded). Furthermore, if `keep` has more than one element, these will be merged with an OR operator into a regular expression pattern like this: *"(one|two|three)"*. If `keep` is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where `model_parameters()` returns multiple columns with parameter components, like in `model_parameters.lavaan()`. Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the *\$Parameter* column of the parameters table to get the exact parameter names.

<code>drop</code>	See <code>keep</code> .
<code>parameters</code>	Deprecated, alias for <code>keep</code> .
<code>table_wide</code>	Logical that decides whether the ANOVA table should be in wide format, i.e. should the numerator and denominator degrees of freedom be in the same row. Default: FALSE.
<code>verbose</code>	Toggle warnings and messages.
<code>...</code>	Arguments passed to or from other methods.

Value

A data frame of indices related to the model's parameters.

Note

For ANOVA-tables from mixed models (i.e. `anova(lmer())`), only partial or adjusted effect sizes can be computed. Note that type 3 ANOVAs with interactions involved only give sensible and informative results when covariates are mean-centred and factors are coded with orthogonal contrasts (such as those produced by `contr.sum`, `contr.poly`, or `contr.helmert`, but *not* by the default `contr.treatment`).

Examples

```
if (requireNamespace("effectsize", quietly = TRUE)) {
  df <- iris
  df$Sepal.Big <- ifelse(df$Sepal.Width >= 3, "Yes", "No")

  model <- aov(Sepal.Length ~ Sepal.Big, data = df)
  model_parameters(
    model,
    omega_squared = "partial",
    eta_squared = "partial",
    epsilon_squared = "partial"
  )

  model_parameters(
    model,
```

```

    omega_squared = "partial",
    eta_squared = "partial",
    ci = .9
  )

model <- anova(lm(Sepal.Length ~ Sepal.Big, data = df))
model_parameters(model)
model_parameters(
  model,
  omega_squared = "partial",
  eta_squared = "partial",
  epsilon_squared = "partial"
)

model <- aov(Sepal.Length ~ Sepal.Big + Error(Species), data = df)
model_parameters(model)

## Not run:
if (require("lme4")) {
  mm <- lmer(Sepal.Length ~ Sepal.Big + Petal.Width + (1 | Species),
    data = df
  )
  model <- anova(mm)

  # simple parameters table
  model_parameters(model)

  # parameters table including effect sizes
  model_parameters(
    model,
    eta_squared = "partial",
    ci = .9,
    df_error = dof_satterthwaite(mm)[2:3]
  )
}

## End(Not run)
}

```

model_parameters.averaging

Parameters from special models

Description

Parameters from special regression models not listed under one of the previous categories yet.

Usage

```
## S3 method for class 'averaging'
```

```

model_parameters(
  model,
  ci = 0.95,
  component = c("conditional", "full"),
  exponentiate = FALSE,
  p_adjust = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'betareg'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  component = c("conditional", "precision", "all"),
  standardize = NULL,
  exponentiate = FALSE,
  p_adjust = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'glmx'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  component = c("all", "conditional", "extra"),
  standardize = NULL,
  exponentiate = FALSE,
  p_adjust = NULL,
  verbose = TRUE,
  ...
)

```

Arguments

model	Model object.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
component	Model component for which parameters should be shown. May be one of "conditional", "precision" (betareg), "scale" (ordinal), "extra" (glmx), "marginal" (mf), "conditional" or "full" (for <code>MuMIn::model.avg()</code>) or "all".
exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more gener-

ally speaking, for models with log or logit links. **Note:** Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For `compare_parameters()`, `exponentiate = "nongaussian"` will only exponentiate coefficients from non-Gaussian families.

<code>p_adjust</code>	Character vector, if not NULL, indicates the method to adjust p-values. See <code>stats::p.adjust()</code> for details. Further possible adjustment methods are "tukey", "scheffe", "sidak" and "none" to explicitly disable adjustment for <code>emmGrid</code> objects (from <code>emmeans</code>).
<code>verbose</code>	Toggle warnings and messages.
<code>...</code>	Arguments passed to or from other methods. For instance, when <code>bootstrap = TRUE</code> , arguments like <code>type</code> or <code>parallel</code> are passed down to <code>bootstrap_model()</code> , and arguments like <code>ci_method</code> are passed down to <code>bayestestR::describe_posterior()</code> .
<code>bootstrap</code>	Should estimates be based on bootstrapped model? If TRUE, then arguments of Bayesian regressions apply (see also <code>bootstrap_parameters()</code>).
<code>iterations</code>	The number of bootstrap replicates. This only apply in the case of bootstrapped frequentist models.
<code>standardize</code>	The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in <code>standardize_parameters()</code> . Important: <ul style="list-style-type: none"> • The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as <code>lm.beta</code>) or other software packages (like SPSS). to mimic such behaviours, either use <code>standardize="basic"</code> or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. • For mixed models, when using methods other than "refit", only the fixed effects will be returned. • Robust estimation (i.e., <code>vcov</code> set to a value other than NULL) of standardized parameters only works when <code>standardize="refit"</code>.

Value

A data frame of indices related to the model's parameters.

See Also

`insight::standardize_names()` to rename columns into a consistent, standardized naming scheme.

Examples

```
library(parameters)
if (require("brglm2", quietly = TRUE)) {
  data("stemcell")
  model <- brglm2(
```

```

    research ~ as.numeric(religion) + gender,
    weights = frequency,
    data = stemcell,
    type = "ML"
  )
  model_parameters(model)
}

```

model_parameters.befa *Parameters from Bayesian Exploratory Factor Analysis*

Description

Format Bayesian Exploratory Factor Analysis objects from the BayesFM package.

Usage

```

## S3 method for class 'befa'
model_parameters(
  model,
  sort = FALSE,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.95,
  ci_method = "eti",
  test = NULL,
  verbose = TRUE,
  ...
)

```

Arguments

model	Bayesian EFA created by the BayesFM: :befa.
sort	Sort the loadings.
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 .95 (95%).
ci_method	The type of index used for Credible Interval. Can be "ETI" (default, see eti()), "HDI" (see hdi()), "BCI" (see bci()), "SPI" (see spi()), 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.

verbose Toggle warnings and messages.
 ... Arguments passed to or from other methods.

Value

A data frame of loadings.

Examples

```
library(parameters)

if (require("BayesFM")) {
  efa <- BayesFM::befa(mtcars, iter = 1000)
  results <- model_parameters(efa, sort = TRUE)
  results
  efa_to_cfa(results)
}
```

model_parameters.BFBayesFactor

Parameters from BayesFactor objects

Description

Parameters from BFBayesFactor objects from {BayesFactor} package.

Usage

```
## S3 method for class 'BFBayesFactor'
model_parameters(
  model,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.95,
  ci_method = "eti",
  test = c("pd", "rope"),
  rope_range = "default",
  rope_ci = 0.95,
  priors = TRUE,
  cohens_d = NULL,
  crammers_v = NULL,
  include_proportions = FALSE,
  verbose = TRUE,
  ...
)
```

Arguments

model	Object of class BFBayesFactor.
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 .95 (95%).
ci_method	The type of index used for Credible Interval. Can be "ETI" (default, see <code>eti()</code>), "HDI" (see <code>hdi()</code>), "BCI" (see <code>bci()</code>), "SPI" (see <code>spi()</code>), or "SI" (see <code>si()</code>).
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. <code>rope()</code> or <code>p_direction()</code>) 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., <code>c(-0.1, 0.1)</code>) or "default". If "default", the bounds are set to $x \pm 0.1 * SD(\text{response})$.
rope_ci	The Credible Interval (CI) probability, corresponding to the proportion of HDI, to use for the percentage in ROPE.
priors	Add the prior used for each parameter.
cohens_d	If TRUE, compute Cohens' <i>d</i> as index of effect size. Only applies to objects from <code>ttestBF()</code> . See <code>effectsize::cohens_d()</code> for details.
cramers_v	Compute Cramer's V or phi as index of effect size. Can be "raw" or "adjusted" (effect size will be bias-corrected). Only applies to objects from <code>chisq.test()</code> .
include_proportions	Logical that decides whether to include posterior cell proportions/counts for Bayesian contingency table analysis (from <code>BayesFactor::contingencyTableBF()</code>). Defaults to FALSE, as this information is often redundant.
verbose	Toggle warnings and messages.
...	Additional arguments to be passed to or from methods.

Details

The meaning of the extracted parameters:

- For `BayesFactor::ttestBF()`: Difference is the raw difference between the means.
- For `BayesFactor::correlationBF()`: rho is the linear correlation estimate (equivalent to Pearson's *r*).
- For `BayesFactor::lmBF()` / `BayesFactor::generalTestBF()` / `BayesFactor::regressionBF()` / `BayesFactor::anovaBF()`: in addition to parameters of the fixed and random effects, there are: mu is the (mean-centered) intercept; sig2 is the model's sigma; *g* / *g_** are the *g* parameters; See the *Bayes Factors for ANOVAs* paper ([doi:10.1016/j.jmp.2012.08.001](https://doi.org/10.1016/j.jmp.2012.08.001)).

Value

A data frame of indices related to the model's parameters.

Examples

```
if (require("BayesFactor")) {  
  # Bayesian t-test  
  model <- ttestBF(x = rnorm(100, 1, 1))  
  model_parameters(model)  
  model_parameters(model, cohens_d = TRUE, ci = .9)  
  
  # Bayesian contingency table analysis  
  data(raceDolls)  
  bf <- contingencyTableBF(raceDolls, sampleType = "indepMulti", fixedMargin = "cols")  
  model_parameters(bf,  
    centrality = "mean",  
    dispersion = TRUE,  
    verbose = FALSE,  
    cramers_v = TRUE  
  )  
}
```

model_parameters.cgam *Parameters from Generalized Additive (Mixed) Models*

Description

Extract and compute indices and measures to describe parameters of generalized additive models (GAM(M)s).

Usage

```
## S3 method for class 'cgam'  
model_parameters(  
  model,  
  ci = 0.95,  
  ci_method = "residual",  
  bootstrap = FALSE,  
  iterations = 1000,  
  standardize = NULL,  
  exponentiate = FALSE,  
  p_adjust = NULL,  
  keep = NULL,  
  drop = NULL,  
  parameters = keep,  
  verbose = TRUE,
```



```

    ...
  )

  ## S3 method for class 'gam'
  model_parameters(
    model,
    ci = 0.95,
    ci_method = "residual",
    bootstrap = FALSE,
    iterations = 1000,
    standardize = NULL,
    exponentiate = FALSE,
    p_adjust = NULL,
    keep = NULL,
    drop = NULL,
    parameters = keep,
    verbose = TRUE,
    ...
  )

  ## S3 method for class 'rqss'
  model_parameters(
    model,
    ci = 0.95,
    ci_method = "residual",
    bootstrap = FALSE,
    iterations = 1000,
    standardize = NULL,
    exponentiate = FALSE,
    p_adjust = NULL,
    keep = NULL,
    drop = NULL,
    parameters = keep,
    verbose = TRUE,
    ...
  )

```

Arguments

model	A gam/gamm model.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
ci_method	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): "residual", "normal", "likelihood", "satterthwaite", "kenward", "wald", "profile", "boot", "uniroot", "ml1", "betwithin", "hdi", "quantile", "ci", "eti", "si", "bci", or "bcai". See section <i>Confidence intervals and approximation of degrees of freedom</i> in <code>model_parameters()</code> for further details. When ci_method=NULL, in most cases "wald" is used then.

bootstrap	Should estimates be based on bootstrapped model? If TRUE, then arguments of Bayesian regressions apply (see also bootstrap_parameters()).
iterations	The number of bootstrap replicates. This only apply in the case of bootstrapped frequentist models.
standardize	The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in standardize_parameters() . Important: <ul style="list-style-type: none"> • The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as lm.beta) or other software packages (like SPSS). to mimic such behaviours, either use <code>standardize="basic"</code> or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. • For mixed models, when using methods other than "refit", only the fixed effects will be returned. • Robust estimation (i.e., <code>vcov</code> set to a value other than NULL) of standardized parameters only works when <code>standardize="refit"</code>.
exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
p_adjust	Character vector, if not NULL, indicates the method to adjust p-values. See stats::p.adjust() for details. Further possible adjustment methods are "tukey", "scheffe", "sidak" and "none" to explicitly disable adjustment for <code>emmGrid</code> objects (from emmeans).
keep	Character containing a regular expression pattern that describes the parameters that should be included (for keep) or excluded (for drop) in the returned data frame. <code>keep</code> may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If <code>keep</code> is a character vector, every parameter name in the "Parameter" column that matches the regular expression in <code>keep</code> will be selected from the returned data frame (and vice versa, all parameter names matching <code>drop</code> will be excluded). Furthermore, if <code>keep</code> has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If <code>keep</code> is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where <code>model_parameters()</code> returns multiple columns with parameter components, like in model_parameters.lavaan() . Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the <code>\$Parameter</code> column of the parameters table to get the exact parameter names.

drop	See keep.
parameters	Deprecated, alias for keep.
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods. For instance, when <code>bootstrap = TRUE</code> , arguments like <code>type</code> or <code>parallel</code> are passed down to <code>bootstrap_model()</code> , and arguments like <code>ci_method</code> are passed down to <code>bayestestR::describe_posterior()</code> .

Details

The reporting of degrees of freedom *for the spline terms* slightly differs from the output of `summary(model)`, for example in the case of `mgcv::gam()`. The *estimated degrees of freedom*, column `edf` in the summary-output, is named `df` in the returned data frame, while the column `df_error` in the returned data frame refers to the residual degrees of freedom that are returned by `df.residual()`. Hence, the values in the the column `df_error` differ from the column `Ref.df` from the summary, which is intentional, as these reference degrees of freedom “is not very interpretable” ([web](#)).

Value

A data frame of indices related to the model’s parameters.

See Also

[insight::standardize_names\(\)](#) to rename columns into a consistent, standardized naming scheme.

Examples

```
library(parameters)
if (require("mgcv")) {
  dat <- gamSim(1, n = 400, dist = "normal", scale = 2)
  model <- gam(y ~ s(x0) + s(x1) + s(x2) + s(x3), data = dat)
  model_parameters(model)
}
```

model_parameters.cpglmm

Parameters from Mixed Models

Description

Parameters from (linear) mixed models.

Usage

```
## S3 method for class 'cpglmm'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  standardize = NULL,
  effects = "all",
  group_level = FALSE,
  exponentiate = FALSE,
  ci_method = NULL,
  p_adjust = NULL,
  verbose = TRUE,
  df_method = ci_method,
  include_sigma = FALSE,
  ...
)

## S3 method for class 'glmmTMB'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  effects = "all",
  component = "all",
  group_level = FALSE,
  standardize = NULL,
  exponentiate = FALSE,
  ci_method = "wald",
  p_adjust = NULL,
  wb_component = TRUE,
  summary = getOption("parameters_mixed_summary", FALSE),
  keep = NULL,
  drop = NULL,
  parameters = keep,
  verbose = TRUE,
  df_method = ci_method,
  include_sigma = FALSE,
  ...
)

## S3 method for class 'merMod'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
```

```
    ci_method = NULL,  
    iterations = 1000,  
    standardize = NULL,  
    effects = "all",  
    group_level = FALSE,  
    exponentiate = FALSE,  
    p_adjust = NULL,  
    wb_component = TRUE,  
    summary = getOption("parameters_mixed_summary", FALSE),  
    keep = NULL,  
    drop = NULL,  
    parameters = keep,  
    verbose = TRUE,  
    df_method = ci_method,  
    include_sigma = FALSE,  
    vcov = NULL,  
    vcov_args = NULL,  
    ...  
  )  
  
## S3 method for class 'mixor'  
model_parameters(  
  model,  
  ci = 0.95,  
  effects = "all",  
  bootstrap = FALSE,  
  iterations = 1000,  
  standardize = NULL,  
  exponentiate = FALSE,  
  verbose = TRUE,  
  include_sigma = FALSE,  
  ...  
)  
  
## S3 method for class 'clmm'  
model_parameters(  
  model,  
  ci = 0.95,  
  bootstrap = FALSE,  
  iterations = 1000,  
  standardize = NULL,  
  effects = "all",  
  group_level = FALSE,  
  exponentiate = FALSE,  
  ci_method = NULL,  
  p_adjust = NULL,  
  verbose = TRUE,  
  df_method = ci_method,
```

```

include_sigma = FALSE,
...
)

```

Arguments

model	A mixed model.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
bootstrap	Should estimates be based on bootstrapped model? If TRUE, then arguments of Bayesian regressions apply (see also bootstrap_parameters()).
iterations	The number of draws to simulate/bootstrap.
standardize	The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in standardize_parameters() . Important: <ul style="list-style-type: none"> • The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as lm.beta) or other software packages (like SPSS). to mimic such behaviours, either use standardize="basic" or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. • For mixed models, when using methods other than "refit", only the fixed effects will be returned. • Robust estimation (i.e., vcov set to a value other than NULL) of standardized parameters only works when standardize="refit".
effects	Should parameters for fixed effects ("fixed"), random effects ("random"), or both ("all") be returned? Only applies to mixed models. May be abbreviated. If the calculation of random effects parameters takes too long, you may use <code>effects = "fixed"</code> .
group_level	Logical, for multilevel models (i.e. models with random effects) and when <code>effects = "all"</code> or <code>effects = "random"</code> , include the parameters for each group level from random effects. If <code>group_level = FALSE</code> (the default), only information on SD and COR are shown.
exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
ci_method	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): "residual", "normal", "likelihood", "satterthwaite", "kenward", "wald", "profile", "boot", "uniroot", "ml1", "betwithin",

	"hdi", "quantile", "ci", "eti", "si", "bci", or "bcai". See section <i>Confidence intervals and approximation of degrees of freedom</i> in <code>model_parameters()</code> for further details. When <code>ci_method=NULL</code> , in most cases "wald" is used then.
<code>p_adjust</code>	Character vector, if not <code>NULL</code> , indicates the method to adjust p-values. See <code>stats::p.adjust()</code> for details. Further possible adjustment methods are "tukey", "scheffe", "sidak" and "none" to explicitly disable adjustment for <code>emmGrid</code> objects (from <code>emmeans</code>).
<code>verbose</code>	Toggle warnings and messages.
<code>df_method</code>	Deprecated. Please use <code>ci_method</code> .
<code>include_sigma</code>	Logical, if <code>TRUE</code> , includes the residual standard deviation. For mixed models, this is defined as the sum of the distribution-specific variance and the variance for the additive overdispersion term (see <code>insight::get_variance()</code> for details). Defaults to <code>FALSE</code> for mixed models due to the longer computation time.
<code>...</code>	Arguments passed to or from other methods.
<code>component</code>	Should all parameters, parameters for the conditional model, for the zero-inflated part of the model, or the dispersion model be returned? Applies to models with zero-inflated and/or dispersion component. <code>component</code> may be one of "conditional", "zi", "zero-inflated", "dispersion" or "all" (default). May be abbreviated.
<code>wb_component</code>	Logical, if <code>TRUE</code> and models contains within- and between-effects (see <code>datawizard::demean()</code>), the <code>Component</code> column will indicate which variables belong to the within-effects, between-effects, and cross-level interactions. By default, the <code>Component</code> column indicates, which parameters belong to the conditional or zero-inflated component of the model.
<code>summary</code>	Logical, if <code>TRUE</code> , prints summary information about the model (model formula, number of observations, residual standard deviation and more).
<code>keep</code>	Character containing a regular expression pattern that describes the parameters that should be included (for <code>keep</code>) or excluded (for <code>drop</code>) in the returned data frame. <code>keep</code> may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If <code>keep</code> is a character vector, every parameter name in the " <i>Parameter</i> " column that matches the regular expression in <code>keep</code> will be selected from the returned data frame (and vice versa, all parameter names matching <code>drop</code> will be excluded). Furthermore, if <code>keep</code> has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If <code>keep</code> is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where <code>model_parameters()</code> returns multiple columns with parameter components, like in <code>model_parameters.lavaan()</code> . Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the <code>\$Parameter</code> column of the parameters table to get the exact parameter names.
<code>drop</code>	See <code>keep</code> .
<code>parameters</code>	Deprecated, alias for <code>keep</code> .

vcov	<p>Variance-covariance matrix used to compute uncertainty estimates (e.g., for robust standard errors). This argument accepts a covariance matrix, a function which returns a covariance matrix, or a string which identifies the function to be used to compute the covariance matrix.</p> <ul style="list-style-type: none"> • A covariance matrix • A function which returns a covariance matrix (e.g., <code>stats::vcov()</code>) • A string which indicates the kind of uncertainty estimates to return. <ul style="list-style-type: none"> – Heteroskedasticity-consistent: "vcovHC", "HC", "HC0", "HC1", "HC2", "HC3", "HC4", "HC4m", "HC5". See <code>?sandwich::vcovHC</code>. – Cluster-robust: "vcovCR", "CR0", "CR1", "CR1p", "CR1S", "CR2", "CR3". See <code>?clubSandwich::vcovCR</code>. – Bootstrap: "vcovBS", "xy", "residual", "wild", "mammen", "webb". See <code>?sandwich::vcovBS</code>. – Other sandwich package functions: "vcovHAC", "vcovPC", "vcovCL", "vcovPL".
vcov_args	<p>List of arguments to be passed to the function identified by the <code>vcov</code> argument. This function is typically supplied by the sandwich or clubSandwich packages. Please refer to their documentation (e.g., <code>?sandwich::vcovHAC</code>) to see the list of available arguments.</p>

Value

A data frame of indices related to the model's parameters.

Confidence intervals for random effect variances

For models of class `merMod` and `glmmTMB`, confidence intervals for random effect variances can be calculated.

- For models of from package **lme4**, when `ci_method` is either "profile" or "boot", and `effects` is either "random" or "all", profiled resp. bootstrapped confidence intervals are computed for the random effects.
- For all other options of `ci_method`, and only when the **merDeriv** package is installed, confidence intervals for random effects are based on normal-distribution approximation, using the delta-method to transform standard errors for constructing the intervals around the log-transformed SD parameters. These are then back-transformed, so that random effect variances, standard errors and confidence intervals are shown on the original scale. Due to the transformation, the intervals are asymmetrical, however, they are within the correct bounds (i.e. no negative interval for the SD, and the interval for the correlations is within the range from -1 to +1).
- For models of class `glmmTMB`, confidence intervals for random effect variances always use a Wald t-distribution approximation.

Dispersion parameters in `glmmTMB`

For some models from package **glmmTMB**, both the dispersion parameter and the residual variance from the random effects parameters are shown. Usually, these are the same but presented on different scales, e.g.


```

model <- glmmTMB(Sepal.Width ~ Petal.Length + (1|Species), data = iris)
exp(fixef(model)$disp) # 0.09902987
sigma(model)^2        # 0.09902987

```

For models where the dispersion parameter and the residual variance are the same, only the residual variance is shown in the output.

Confidence intervals and approximation of degrees of freedom

There are different ways of approximating the degrees of freedom depending on different assumptions about the nature of the model and its sampling distribution. The `ci_method` argument modulates the method for computing degrees of freedom (df) that are used to calculate confidence intervals (CI) and the related p-values. Following options are allowed, depending on the model class:

Classical methods:

Classical inference is generally based on the **Wald method**. The Wald approach to inference computes a test statistic by dividing the parameter estimate by its standard error (Coefficient / SE), then comparing this statistic against a t- or normal distribution. This approach can be used to compute CIs and p-values.

"wald":

- Applies to *non-Bayesian models*. For *linear models*, CIs computed using the Wald method (SE and a *t-distribution with residual df*); p-values computed using the Wald method with a *t-distribution with residual df*. For other models, CIs computed using the Wald method (SE and a *normal distribution*); p-values computed using the Wald method with a *normal distribution*.

"normal"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a normal distribution.

"residual"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a *t-distribution with residual df* when possible. If the residual df for a model cannot be determined, a normal distribution is used instead.

Methods for mixed models:

Compared to fixed effects (or single-level) models, determining appropriate df for Wald-based inference in mixed models is more difficult. See [the R GLMM FAQ](#) for a discussion.

Several approximate methods for computing df are available, but you should also consider instead using profile likelihood ("profile") or bootstrap ("boot") CIs and p-values instead.

"satterthwaite"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with Satterthwaite df*); p-values computed using the Wald method with a *t-distribution with Satterthwaite df*.

"kenward"

- Applies to *linear mixed models*. CIs computed using the Wald method (*Kenward-Roger SE* and a *t-distribution with Kenward-Roger df*); p-values computed using the Wald method with *Kenward-Roger SE and t-distribution with Kenward-Roger df*.

"m11"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with m-l-1 approximated df*); p-values computed using the Wald method with a *t-distribution with m-l-1 approximated df*. See [ci_m11\(\)](#).

"betwithin"

- Applies to *linear mixed models* and *generalized linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with between-within df*); p-values computed using the Wald method with a *t-distribution with between-within df*. See [ci_betwithin\(\)](#).

Likelihood-based methods:

Likelihood-based inference is based on comparing the likelihood for the maximum-likelihood estimate to the the likelihood for models with one or more parameter values changed (e.g., set to zero or a range of alternative values). Likelihood ratios for the maximum-likelihood and alternative models are compared to a χ -squared distribution to compute CIs and p-values.

"profile"

- Applies to *non-Bayesian models* of class `glm`, `polr` or `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using linear interpolation to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

"uniroot"

- Applies to *non-Bayesian models* of class `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using root finding to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

Methods for bootstrapped or Bayesian models:

Bootstrap-based inference is based on **resampling** and refitting the model to the resampled datasets. The distribution of parameter estimates across resampled datasets is used to approximate the parameter's sampling distribution. Depending on the type of model, several different methods for bootstrapping and constructing CIs and p-values from the bootstrap distribution are available.

For Bayesian models, inference is based on drawing samples from the model posterior distribution.

"quantile" (or "eti")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *equal tailed intervals* using the quantiles of the bootstrap or posterior samples; p-values are based on the *probability of direction*. See [bayestestR::eti\(\)](#).

"hdi"

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *highest density intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::hdi()`.

"bci" (or "bcai")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *bias corrected and accelerated intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::bci()`.

"si"

- Applies to *Bayesian models* with proper priors. CIs computed as *support intervals* comparing the posterior samples against the prior samples; p-values are based on the *probability of direction*. See `bayestestR::si()`.

"boot"

- Applies to *non-Bayesian models* of class `merMod`. CIs computed using *parametric bootstrapping* (simulating data from the fitted model); p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!).

For all iteration-based methods other than "boot" ("hdi", "quantile", "ci", "eti", "si", "bci", "bcai"), p-values are based on the probability of direction (`bayestestR::p_direction()`), which is converted into a p-value using `bayestestR::pd_to_p()`.

Note

If the calculation of random effects parameters takes too long, you may use `effects = "fixed"`. There is also a `plot()-method` implemented in the [see-package](#).

See Also

`insight::standardize_names()` to rename columns into a consistent, standardized naming scheme.

Examples

```
library(parameters)
if (require("lme4")) {
  data(mtcars)
  model <- lmer(mpg ~ wt + (1 | gear), data = mtcars)
  model_parameters(model)
}
```

```
if (require("glmmTMB")) {
  data(Salamanders)
  model <- glmmTMB(
    count ~ spp + mined + (1 | site),
    ziformula = ~mined,
    family = poisson(),
    data = Salamanders
  )
}
```

```

model_parameters(model, effects = "all")
}

if (require("lme4")) {
  model <- lmer(mpg ~ wt + (1 | gear), data = mtcars)
  model_parameters(model, bootstrap = TRUE, iterations = 50)
}

```

```
model_parameters.data.frame
```

Parameters from Bayesian Models

Description

Parameters from Bayesian models.

Usage

```

## S3 method for class 'data.frame'
model_parameters(model, as_draws = FALSE, verbose = TRUE, ...)

## S3 method for class 'brmsfit'
model_parameters(
  model,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.95,
  ci_method = "eti",
  test = c("pd", "rope"),
  rope_range = "default",
  rope_ci = 0.95,
  bf_prior = NULL,
  diagnostic = c("ESS", "Rhat"),
  priors = FALSE,
  effects = "fixed",
  component = "all",
  exponentiate = FALSE,
  standardize = NULL,
  group_level = FALSE,
  keep = NULL,
  drop = NULL,
  parameters = keep,
  verbose = TRUE,
  ...
)

```

```

## S3 method for class 'draws'
model_parameters(
  model,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.95,
  ci_method = "eti",
  test = c("pd", "rope"),
  rope_range = "default",
  rope_ci = 0.95,
  keep = NULL,
  drop = NULL,
  parameters = keep,
  verbose = TRUE,
  ...
)

## S3 method for class 'stanreg'
model_parameters(
  model,
  centrality = "median",
  dispersion = FALSE,
  ci = 0.95,
  ci_method = "eti",
  test = c("pd", "rope"),
  rope_range = "default",
  rope_ci = 0.95,
  bf_prior = NULL,
  diagnostic = c("ESS", "Rhat"),
  priors = TRUE,
  effects = "fixed",
  exponentiate = FALSE,
  standardize = NULL,
  group_level = FALSE,
  keep = NULL,
  drop = NULL,
  parameters = keep,
  verbose = TRUE,
  ...
)

```

Arguments

model	Bayesian model (including SEM from blavaan . May also be a data frame with posterior samples, however, <code>as_draws</code> must be set to TRUE (else, for data frames NULL is returned).
as_draws	Logical, if TRUE and <code>model</code> is of class <code>data.frame</code> , the data frame is treated as posterior samples and handled similar to Bayesian models. All arguments in

	... are passed to <code>model_parameters.draws()</code> .
<code>verbose</code>	Toggle messages and warnings.
<code>...</code>	Currently not used.
<code>centrality</code>	The point-estimates (centrality indices) to compute. Character (vector) or list with one or more of these options: "median", "mean", "MAP" or "all".
<code>dispersion</code>	Logical, if TRUE, computes indices of dispersion related to the estimate(s) (SD and MAD for mean and median, respectively).
<code>ci</code>	Credible Interval (CI) level. Default to 0.95 (95%). See <code>bayestestR::ci()</code> for further details.
<code>ci_method</code>	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): "residual", "normal", "likelihood", "satterthwaite", "kenward", "wald", "profile", "boot", "uniroot", "ml1", "betwithin", "hdi", "quantile", "ci", "eti", "si", "bci", or "bcai". See section <i>Confidence intervals and approximation of degrees of freedom</i> in <code>model_parameters()</code> for further details. When <code>ci_method=NULL</code> , in most cases "wald" is used then.
<code>test</code>	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 <code>bayestestR</code> function is called (e.g. <code>rope()</code> or <code>p_direction()</code>) and its results included in the summary output.
<code>rope_range</code>	ROPE's lower and higher bounds. Should be a list of two values (e.g., <code>c(-0.1, 0.1)</code>) or "default". If "default", the bounds are set to $x \pm 0.1 \times \text{SD}(\text{response})$.
<code>rope_ci</code>	The Credible Interval (CI) probability, corresponding to the proportion of HDI, to use for the percentage in ROPE.
<code>bf_prior</code>	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.
<code>diagnostic</code>	Diagnostic metrics to compute. Character (vector) or list with one or more of these options: "ESS", "Rhat", "MCSE" or "all".
<code>priors</code>	Add the prior used for each parameter.
<code>effects</code>	Should results for fixed effects, random effects or both be returned? Only applies to mixed models. May be abbreviated.
<code>component</code>	Which type of parameters to return, such as parameters for the conditional model, the zero-inflated part of the model, the dispersion term, or other auxiliary parameters be returned? Applies to models with zero-inflated and/or dispersion formula, or if parameters such as <code>sigma</code> should be included. May be abbreviated. Note that the <i>conditional</i> component is also called <i>count</i> or <i>mean</i> component, depending on the model. There are three convenient shortcuts: <code>component = "all"</code> returns all possible parameters. If <code>component = "location"</code> , location parameters such as <code>conditional</code> , <code>zero_inflated</code> , or <code>smooth_terms</code> , are returned (everything that are fixed or random effects - depending on the <code>effects</code> argument - but no auxiliary parameters). For <code>component = "distributional"</code> (or "auxiliary"), components like <code>sigma</code> , <code>dispersion</code> , or <code>beta</code> (and other auxiliary parameters) are returned.

exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
standardize	<p>The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in standardize_parameters().</p> <p>Important:</p> <ul style="list-style-type: none"> • The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as lm.beta) or other software packages (like SPSS). to mimic such behaviours, either use <code>standardize="basic"</code> or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. • For mixed models, when using methods other than "refit", only the fixed effects will be returned. • Robust estimation (i.e., <code>vcov</code> set to a value other than NULL) of standardized parameters only works when <code>standardize="refit"</code>.
group_level	Logical, for multilevel models (i.e. models with random effects) and when <code>effects = "all"</code> or <code>effects = "random"</code> , include the parameters for each group level from random effects. If <code>group_level = FALSE</code> (the default), only information on SD and COR are shown.
keep	Character containing a regular expression pattern that describes the parameters that should be included (for keep) or excluded (for drop) in the returned data frame. <code>keep</code> may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If <code>keep</code> is a character vector, every parameter name in the "Parameter" column that matches the regular expression in <code>keep</code> will be selected from the returned data frame (and vice versa, all parameter names matching <code>drop</code> will be excluded). Furthermore, if <code>keep</code> has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If <code>keep</code> is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where <code>model_parameters()</code> returns multiple columns with parameter components, like in model_parameters.lavaan() . Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the <code>\$Parameter</code> column of the parameters table to get the exact parameter names.
drop	See <code>keep</code> .
parameters	Deprecated, alias for <code>keep</code> .

Value

A data frame of indices related to the model's parameters.

Confidence intervals and approximation of degrees of freedom

There are different ways of approximating the degrees of freedom depending on different assumptions about the nature of the model and its sampling distribution. The `ci_method` argument modulates the method for computing degrees of freedom (df) that are used to calculate confidence intervals (CI) and the related p-values. Following options are allowed, depending on the model class:

Classical methods:

Classical inference is generally based on the **Wald method**. The Wald approach to inference computes a test statistic by dividing the parameter estimate by its standard error (Coefficient / SE), then comparing this statistic against a t- or normal distribution. This approach can be used to compute CIs and p-values.

"wald":

- Applies to *non-Bayesian models*. For *linear models*, CIs computed using the Wald method (SE and a *t-distribution with residual df*); p-values computed using the Wald method with a *t-distribution with residual df*. For other models, CIs computed using the Wald method (SE and a *normal distribution*); p-values computed using the Wald method with a *normal distribution*.

"normal"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a normal distribution.

"residual"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a *t-distribution with residual df* when possible. If the residual df for a model cannot be determined, a normal distribution is used instead.

Methods for mixed models:

Compared to fixed effects (or single-level) models, determining appropriate df for Wald-based inference in mixed models is more difficult. See [the R GLMM FAQ](#) for a discussion.

Several approximate methods for computing df are available, but you should also consider instead using profile likelihood ("profile") or bootstrap ("boot") CIs and p-values instead.

"satterthwaite"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with Satterthwaite df*); p-values computed using the Wald method with a *t-distribution with Satterthwaite df*.

"kenward"

- Applies to *linear mixed models*. CIs computed using the Wald method (*Kenward-Roger SE* and a *t-distribution with Kenward-Roger df*); p-values computed using the Wald method with *Kenward-Roger SE* and *t-distribution with Kenward-Roger df*.

"ml1"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with m-1-1 approximated df*); p-values computed using the Wald method with a *t-distribution with m-1-1 approximated df*. See `ci_ml1()`.

"betwithin"

- Applies to *linear mixed models* and *generalized linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with between-within df*); p-values computed using the Wald method with a *t-distribution with between-within df*. See `ci_betwithin()`.

Likelihood-based methods:

Likelihood-based inference is based on comparing the likelihood for the maximum-likelihood estimate to the the likelihood for models with one or more parameter values changed (e.g., set to zero or a range of alternative values). Likelihood ratios for the maximum-likelihood and alternative models are compared to a χ -squared distribution to compute CIs and p-values.

"profile"

- Applies to *non-Bayesian models* of class `glm`, `polr` or `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using linear interpolation to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

"uniroot"

- Applies to *non-Bayesian models* of class `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using root finding to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

Methods for bootstrapped or Bayesian models:

Bootstrap-based inference is based on **resampling** and refitting the model to the resampled datasets. The distribution of parameter estimates across resampled datasets is used to approximate the parameter's sampling distribution. Depending on the type of model, several different methods for bootstrapping and constructing CIs and p-values from the bootstrap distribution are available.

For Bayesian models, inference is based on drawing samples from the model posterior distribution.

"quantile" (or "eti")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *equal tailed intervals* using the quantiles of the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::eti()`.

"hdi"

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *highest density intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::hdi()`.

"bci" (or "bcai")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *bias corrected and accelerated intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::bci()`.

"si"

- Applies to *Bayesian models* with proper priors. CIs computed as *support intervals* comparing the posterior samples against the prior samples; p-values are based on the *probability of direction*. See `bayestestR::si()`.

"boot"

- Applies to *non-Bayesian models* of class `merMod`. CIs computed using *parametric bootstrapping* (simulating data from the fitted model); p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!).

For all iteration-based methods other than "boot" ("hdi", "quantile", "ci", "eti", "si", "bci", "bcai"), p-values are based on the probability of direction (`bayestestR::p_direction()`), which is converted into a p-value using `bayestestR::pd_to_p()`.

Note

When `standardize = "refit"`, columns `diagnostic`, `bf_prior` and `priors` refer to the *original* model. If `model` is a data frame, arguments `diagnostic`, `bf_prior` and `priors` are ignored.

There is also a `plot()`-method implemented in the [see-package](#).

See Also

`insight::standardize_names()` to rename columns into a consistent, standardized naming scheme.

Examples

```
## Not run:
library(parameters)
if (require("rstanarm")) {
  model <- stan_glm(
    Sepal.Length ~ Petal.Length * Species,
    data = iris, iter = 500, refresh = 0
  )
  model_parameters(model)
}

## End(Not run)
```

 model_parameters.dbscan

Parameters from Cluster Models (k-means, ...)

Description

Format cluster models obtained for example by `kmeans()`.

Usage

```
## S3 method for class 'dbscan'
model_parameters(model, data = NULL, clusters = NULL, ...)

## S3 method for class 'hclust'
model_parameters(model, data = NULL, clusters = NULL, ...)

## S3 method for class 'pvclust'
model_parameters(model, data = NULL, clusters = NULL, ci = 0.95, ...)

## S3 method for class 'kmeans'
model_parameters(model, ...)

## S3 method for class 'hkmeans'
model_parameters(model, ...)

## S3 method for class 'Mclust'
model_parameters(model, data = NULL, clusters = NULL, ...)

## S3 method for class 'pam'
model_parameters(model, data = NULL, clusters = NULL, ...)
```

Arguments

<code>model</code>	Cluster model.
<code>data</code>	A data.frame.
<code>clusters</code>	A vector with clusters assignments (must be same length as rows in data).
<code>...</code>	Arguments passed to or from other methods.
<code>ci</code>	Confidence Interval (CI) level. Default to 0.95 (95%).

Examples

```
# DBSCAN -----
if (require("dbscan", quietly = TRUE)) {
  model <- dbscan::dbscan(iris[1:4], eps = 1.45, minPts = 10)
```

```

rez <- model_parameters(model, iris[1:4])
rez

# Get clusters
predict(rez)

# Clusters centers in long form
attributes(rez)$means

# Between and Total Sum of Squares
attributes(rez)$Sum_Squares_Total
attributes(rez)$Sum_Squares_Between

# HDBSCAN
model <- dbscan::hdbscan(iris[1:4], minPts = 10)
model_parameters(model, iris[1:4])
}

#
# Hierarchical clustering (hclust) -----
data <- iris[1:4]
model <- hclust(dist(data))
clusters <- cutree(model, 3)

rez <- model_parameters(model, data, clusters)
rez

# Get clusters
predict(rez)

# Clusters centers in long form
attributes(rez)$means

# Between and Total Sum of Squares
attributes(rez)$Total_Sum_Squares
attributes(rez)$Between_Sum_Squares

#
# pvclust (finds "significant" clusters) -----
if (require("pvclust", quietly = TRUE)) {
  data <- iris[1:4]
  # NOTE: pvclust works on transposed data
  model <- pvclust::pvclust(datawizard::data_transpose(data),
    method.dist = "euclidean",
    nboot = 50,
    quiet = TRUE
  )

  rez <- model_parameters(model, data, ci = 0.90)
  rez

# Get clusters
predict(rez)

```

```

# Clusters centers in long form
attributes(rez)$means

# Between and Total Sum of Squares
attributes(rez)$Sum_Squares_Total
attributes(rez)$Sum_Squares_Between
}

## Not run:
#
# K-means -----
model <- kmeans(iris[1:4], centers = 3)
rez <- model_parameters(model)
rez

# Get clusters
predict(rez)

# Clusters centers in long form
attributes(rez)$means

# Between and Total Sum of Squares
attributes(rez)$Sum_Squares_Total
attributes(rez)$Sum_Squares_Between

## End(Not run)
## Not run:
#
# Hierarchical K-means (factoextra::hkclust) -----
if (require("factoextra", quietly = TRUE)) {
  data <- iris[1:4]
  model <- factoextra::hkmeans(data, k = 3)

  rez <- model_parameters(model)
  rez

# Get clusters
predict(rez)

# Clusters centers in long form
attributes(rez)$means

# Between and Total Sum of Squares
attributes(rez)$Sum_Squares_Total
attributes(rez)$Sum_Squares_Between
}

## End(Not run)
if (require("mclust", quietly = TRUE)) {
  model <- mclust::Mclust(iris[1:4], verbose = FALSE)
  model_parameters(model)
}

```

```

## Not run:
#
# K-Medoids (PAM and HPAM) =====
if (require("cluster", quietly = TRUE)) {
  model <- cluster::pam(iris[1:4], k = 3)
  model_parameters(model)
}
if (require("fpc", quietly = TRUE)) {
  model <- fpc::pamk(iris[1:4], criterion = "ch")
  model_parameters(model)
}

## End(Not run)

```

```
model_parameters.default
```

Parameters from (General) Linear Models

Description

Extract and compute indices and measures to describe parameters of (general) linear models (GLMs).

Usage

```

## Default S3 method:
model_parameters(
  model,
  ci = 0.95,
  ci_method = NULL,
  bootstrap = FALSE,
  iterations = 1000,
  standardize = NULL,
  exponentiate = FALSE,
  p_adjust = NULL,
  summary = getOption("parameters_summary", FALSE),
  keep = NULL,
  drop = NULL,
  parameters = keep,
  verbose = TRUE,
  vcov = NULL,
  vcov_args = NULL,
  ...
)

## S3 method for class 'glm'
model_parameters(
  model,
  ci = 0.95,

```

```
    ci_method = NULL,  
    bootstrap = FALSE,  
    iterations = 1000,  
    standardize = NULL,  
    exponentiate = FALSE,  
    p_adjust = NULL,  
    summary = getOption("parameters_summary", FALSE),  
    df_method = ci_method,  
    vcov = NULL,  
    vcov_args = NULL,  
    verbose = TRUE,  
    ...  
  )  
  
## S3 method for class 'logitor'  
model_parameters(  
  model,  
  ci = 0.95,  
  bootstrap = FALSE,  
  iterations = 1000,  
  standardize = NULL,  
  exponentiate = TRUE,  
  p_adjust = NULL,  
  verbose = TRUE,  
  ...  
)  
  
## S3 method for class 'poissonmfx'  
model_parameters(  
  model,  
  ci = 0.95,  
  bootstrap = FALSE,  
  iterations = 1000,  
  component = c("all", "conditional", "marginal"),  
  standardize = NULL,  
  exponentiate = FALSE,  
  p_adjust = NULL,  
  verbose = TRUE,  
  ...  
)  
  
## S3 method for class 'betamfx'  
model_parameters(  
  model,  
  ci = 0.95,  
  bootstrap = FALSE,  
  iterations = 1000,  
  component = c("all", "conditional", "precision", "marginal"),
```

```

standardize = NULL,
exponentiate = FALSE,
p_adjust = NULL,
verbose = TRUE,
...
)

```

Arguments

model	Model object.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
ci_method	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): "residual", "normal", "likelihood", "satterthwaite", "kenward", "wald", "profile", "boot", "uniroot", "ml1", "betwithin", "hdi", "quantile", "ci", "eti", "si", "bci", or "bcai". See section <i>Confidence intervals and approximation of degrees of freedom</i> in <code>model_parameters()</code> for further details. When <code>ci_method=NULL</code> , in most cases "wald" is used then.
bootstrap	Should estimates be based on bootstrapped model? If TRUE, then arguments of Bayesian regressions apply (see also <code>bootstrap_parameters()</code>).
iterations	The number of bootstrap replicates. This only apply in the case of bootstrapped frequentist models.
standardize	The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in <code>standardize_parameters()</code> . Important: <ul style="list-style-type: none"> • The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as lm.beta) or other software packages (like SPSS). to mimic such behaviours, either use <code>standardize="basic"</code> or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. • For mixed models, when using methods other than "refit", only the fixed effects will be returned. • Robust estimation (i.e., <code>vcov</code> set to a value other than NULL) of standardized parameters only works when <code>standardize="refit"</code>.
exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
p_adjust	Character vector, if not NULL, indicates the method to adjust p-values. See <code>stats::p.adjust()</code> for details. Further possible adjustment methods are "tukey",

	"scheffe", "sidak" and "none" to explicitly disable adjustment for emmGrid objects (from emmeans).
summary	Logical, if TRUE, prints summary information about the model (model formula, number of observations, residual standard deviation and more).
keep	Character containing a regular expression pattern that describes the parameters that should be included (for keep) or excluded (for drop) in the returned data frame. keep may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If keep is a character vector, every parameter name in the "Parameter" column that matches the regular expression in keep will be selected from the returned data frame (and vice versa, all parameter names matching drop will be excluded). Furthermore, if keep has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If keep is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where model_parameters() returns multiple columns with parameter components, like in <code>model_parameters.lavaan()</code> . Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the \$Parameter column of the parameters table to get the exact parameter names.
drop	See keep.
parameters	Deprecated, alias for keep.
verbose	Toggle warnings and messages.
vcov	Variance-covariance matrix used to compute uncertainty estimates (e.g., for robust standard errors). This argument accepts a covariance matrix, a function which returns a covariance matrix, or a string which identifies the function to be used to compute the covariance matrix. <ul style="list-style-type: none"> • A covariance matrix • A function which returns a covariance matrix (e.g., <code>stats::vcov()</code>) • A string which indicates the kind of uncertainty estimates to return. <ul style="list-style-type: none"> – Heteroskedasticity-consistent: "vcovHC", "HC", "HC0", "HC1", "HC2", "HC3", "HC4", "HC4m", "HC5". See <code>?sandwich::vcovHC</code>. – Cluster-robust: "vcovCR", "CR0", "CR1", "CR1p", "CR1S", "CR2", "CR3". See <code>?clubSandwich::vcovCR</code>. – Bootstrap: "vcovBS", "xy", "residual", "wild", "mammen", "webb". See <code>?sandwich::vcovBS</code>. – Other sandwich package functions: "vcovHAC", "vcovPC", "vcovCL", "vcovPL".
vcov_args	List of arguments to be passed to the function identified by the vcov argument. This function is typically supplied by the sandwich or clubSandwich packages. Please refer to their documentation (e.g., <code>?sandwich::vcovHAC</code>) to see the list of available arguments.
...	Arguments passed to or from other methods. For instance, when <code>bootstrap = TRUE</code> , arguments like <code>type</code> or <code>parallel</code> are passed down to <code>bootstrap_model()</code> , and arguments like <code>ci_method</code> are passed down to <code>bayestestR::describe_posterior()</code> .

df_method	Deprecated. Please use ci_method.
component	Model component for which parameters should be shown. May be one of "conditional", "precision" (betareg), "scale" (ordinal), "extra" (glmx), "marginal" (mf), "conditional" or "full" (for MuMIn::model.avg()) or "all".

Value

A data frame of indices related to the model's parameters.

Confidence intervals and approximation of degrees of freedom

There are different ways of approximating the degrees of freedom depending on different assumptions about the nature of the model and its sampling distribution. The `ci_method` argument modulates the method for computing degrees of freedom (df) that are used to calculate confidence intervals (CI) and the related p-values. Following options are allowed, depending on the model class:

Classical methods:

Classical inference is generally based on the **Wald method**. The Wald approach to inference computes a test statistic by dividing the parameter estimate by its standard error (Coefficient / SE), then comparing this statistic against a t- or normal distribution. This approach can be used to compute CIs and p-values.

"wald":

- Applies to *non-Bayesian models*. For *linear models*, CIs computed using the Wald method (SE and a *t-distribution with residual df*); p-values computed using the Wald method with a *t-distribution with residual df*. For other models, CIs computed using the Wald method (SE and a *normal distribution*); p-values computed using the Wald method with a *normal distribution*.

"normal"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a normal distribution.

"residual"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a *t-distribution with residual df* when possible. If the residual df for a model cannot be determined, a normal distribution is used instead.

Methods for mixed models:

Compared to fixed effects (or single-level) models, determining appropriate df for Wald-based inference in mixed models is more difficult. See [the R GLMM FAQ](#) for a discussion.

Several approximate methods for computing df are available, but you should also consider instead using profile likelihood ("profile") or bootstrap ("boot") CIs and p-values instead.

"satterthwaite"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with Satterthwaite df*); p-values computed using the Wald method with a *t-distribution with Satterthwaite df*.

"kenward"

- Applies to *linear mixed models*. CIs computed using the Wald method (*Kenward-Roger SE* and a *t-distribution with Kenward-Roger df*); p-values computed using the Wald method with *Kenward-Roger SE* and *t-distribution with Kenward-Roger df*.

"ml1"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with m-l-1 approximated df*); p-values computed using the Wald method with a *t-distribution with m-l-1 approximated df*. See `ci_ml1()`.

"betwithin"

- Applies to *linear mixed models* and *generalized linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with between-within df*); p-values computed using the Wald method with a *t-distribution with between-within df*. See `ci_betwithin()`.

Likelihood-based methods:

Likelihood-based inference is based on comparing the likelihood for the maximum-likelihood estimate to the the likelihood for models with one or more parameter values changed (e.g., set to zero or a range of alternative values). Likelihood ratios for the maximum-likelihood and alternative models are compared to a χ -squared distribution to compute CIs and p-values.

"profile"

- Applies to *non-Bayesian models* of class `glm`, `polr` or `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using linear interpolation to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

"uniroot"

- Applies to *non-Bayesian models* of class `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using root finding to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

Methods for bootstrapped or Bayesian models:

Bootstrap-based inference is based on **resampling** and refitting the model to the resampled datasets. The distribution of parameter estimates across resampled datasets is used to approximate the parameter's sampling distribution. Depending on the type of model, several different methods for bootstrapping and constructing CIs and p-values from the bootstrap distribution are available.

For Bayesian models, inference is based on drawing samples from the model posterior distribution.

"quantile" (or "eti")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *equal tailed intervals* using the quantiles of the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::eti()`.

"hdi"

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *highest density intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::hdi()`.

"bci" (or "bcai")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *bias corrected and accelerated intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::bci()`.

"si"

- Applies to *Bayesian models* with proper priors. CIs computed as *support intervals* comparing the posterior samples against the prior samples; p-values are based on the *probability of direction*. See `bayestestR::si()`.

"boot"

- Applies to *non-Bayesian models* of class `merMod`. CIs computed using *parametric bootstrapping* (simulating data from the fitted model); p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!).

For all iteration-based methods other than "boot" ("hdi", "quantile", "ci", "eti", "si", "bci", "bcai"), p-values are based on the probability of direction (`bayestestR::p_direction()`), which is converted into a p-value using `bayestestR::pd_to_p()`.

See Also

`insight::standardize_names()` to rename columns into a consistent, standardized naming scheme.

Examples

```
library(parameters)
model <- lm(mpg ~ wt + cyl, data = mtcars)

model_parameters(model)

# bootstrapped parameters
if (require("boot", quietly = TRUE)) {
  model_parameters(model, bootstrap = TRUE)
}

# standardized parameters
model_parameters(model, standardize = "refit")

# robust, heteroskedasticity-consistent standard errors
if (require("sandwich") && require("clubSandwich")) {
  model_parameters(model, vcov = "HC3")

  model_parameters(model,
    vcov = "vcovCL",
    vcov_args = list(cluster = mtcars$cyl)
```

```

    )
  }

  # different p-value style in output
  model_parameters(model, p_digits = 5)
  model_parameters(model, digits = 3, ci_digits = 4, p_digits = "scientific")

  # logistic regression model
  model <- glm(vs ~ wt + cyl, data = mtcars, family = "binomial")
  model_parameters(model)

  # show odds ratio / exponentiated coefficients
  model_parameters(model, exponentiate = TRUE)

```

```
model_parameters.DirichletRegModel
```

Parameters from multinomial or cumulative link models

Description

Parameters from multinomial or cumulative link models

Usage

```

## S3 method for class 'DirichletRegModel'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  component = c("all", "conditional", "precision"),
  standardize = NULL,
  exponentiate = FALSE,
  verbose = TRUE,
  ...
)

## S3 method for class 'bifeAPes'
model_parameters(model, ...)

## S3 method for class 'bracl'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  standardize = NULL,

```

```

    exponentiate = FALSE,
    p_adjust = NULL,
    verbose = TRUE,
    ...
)

## S3 method for class 'm1m'
model_parameters(
  model,
  ci = 0.95,
  vcov = NULL,
  vcov_args = NULL,
  bootstrap = FALSE,
  iterations = 1000,
  standardize = NULL,
  exponentiate = FALSE,
  p_adjust = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'clm2'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  component = c("all", "conditional", "scale"),
  standardize = NULL,
  exponentiate = FALSE,
  p_adjust = NULL,
  verbose = TRUE,
  ...
)

```

Arguments

model	A model with multinomial or categorical response value.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
bootstrap	Should estimates be based on bootstrapped model? If TRUE, then arguments of Bayesian regressions apply (see also bootstrap_parameters()).
iterations	The number of bootstrap replicates. This only apply in the case of bootstrapped frequentist models.
component	Model component for which parameters should be shown. May be one of "conditional", "precision" (betareg), "scale" (ordinal), "extra" (glmx), "marginal" (mfx), "conditional" or "full" (for <code>MuMIn::model.avg()</code>) or "all".

standardize	<p>The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in standardize_parameters().</p> <p>Important:</p> <ul style="list-style-type: none"> • The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as lm.beta) or other software packages (like SPSS). to mimic such behaviours, either use <code>standardize="basic"</code> or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. • For mixed models, when using methods other than "refit", only the fixed effects will be returned. • Robust estimation (i.e., <code>vcov</code> set to a value other than NULL) of standardized parameters only works when <code>standardize="refit"</code>.
exponentiate	<p>Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code>, <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.</p>
verbose	Toggle warnings and messages.
...	<p>Arguments passed to or from other methods. For instance, when <code>bootstrap = TRUE</code>, arguments like <code>type</code> or <code>parallel</code> are passed down to <code>bootstrap_model()</code>, and arguments like <code>ci_method</code> are passed down to <code>bayestestR::describe_posterior()</code>.</p>
p_adjust	<p>Character vector, if not NULL, indicates the method to adjust p-values. See stats::p.adjust() for details. Further possible adjustment methods are "tukey", "scheffe", "sidak" and "none" to explicitly disable adjustment for <code>emmGrid</code> objects (from emmeans).</p>
vcov	<p>Variance-covariance matrix used to compute uncertainty estimates (e.g., for robust standard errors). This argument accepts a covariance matrix, a function which returns a covariance matrix, or a string which identifies the function to be used to compute the covariance matrix.</p> <ul style="list-style-type: none"> • A covariance matrix • A function which returns a covariance matrix (e.g., <code>stats::vcov()</code>) • A string which indicates the kind of uncertainty estimates to return. <ul style="list-style-type: none"> – Heteroskedasticity-consistent: "vcovHC", "HC", "HC0", "HC1", "HC2", "HC3", "HC4", "HC4m", "HC5". See <code>?sandwich::vcovHC</code>. – Cluster-robust: "vcovCR", "CR0", "CR1", "CR1p", "CR1S", "CR2", "CR3". See <code>?clubSandwich::vcovCR</code>. – Bootstrap: "vcovBS", "xy", "residual", "wild", "mammen", "webb". See <code>?sandwich::vcovBS</code>. – Other sandwich package functions: "vcovHAC", "vcovPC", "vcovCL", "vcovPL".

`vcov_args` List of arguments to be passed to the function identified by the `vcov` argument. This function is typically supplied by the **sandwich** or **clubSandwich** packages. Please refer to their documentation (e.g., `?sandwich::vcovHAC`) to see the list of available arguments.

Details

Multinomial or cumulative link models, i.e. models where the response value (dependent variable) is categorical and has more than two levels, usually return coefficients for each response level. Hence, the output from `model_parameters()` will split the coefficient tables by the different levels of the model's response.

Value

A data frame of indices related to the model's parameters.

See Also

[insight::standardize_names\(\)](#) to rename columns into a consistent, standardized naming scheme.

Examples

```
library(parameters)
if (require("brglm2", quietly = TRUE)) {
  data("stemcell")
  model <- bracl(
    research ~ as.numeric(religion) + gender,
    weights = frequency,
    data = stemcell,
    type = "ML"
  )
  model_parameters(model)
}
```

model_parameters.htest

Parameters from hypothesis tests

Description

Parameters of h-tests (correlations, t-tests, chi-squared, ...).

Usage

```
## S3 method for class 'htest'
model_parameters(
  model,
  crammers_v = NULL,
  phi = NULL,
```



```

    standardized_d = NULL,
    hedges_g = NULL,
    omega_squared = NULL,
    eta_squared = NULL,
    epsilon_squared = NULL,
    cohens_g = NULL,
    rank_biserial = NULL,
    rank_epsilon_squared = NULL,
    kendalls_w = NULL,
    ci = 0.95,
    alternative = NULL,
    bootstrap = FALSE,
    verbose = TRUE,
    ...
)

## S3 method for class 'pairwise.htest'
model_parameters(model, verbose = TRUE, ...)

```

Arguments

model	Object of class <code>htest</code> or <code>pairwise.htest</code> .
cramers_v, phi	Compute Cramer's V or phi as index of effect size. Can be "raw" or "adjusted" (effect size will be bias-corrected). Only applies to objects from <code>chisq.test()</code> .
standardized_d	If TRUE, compute standardized d as index of effect size. Only applies to objects from <code>t.test()</code> . Calculation of d is based on the t-value (see <code>effectsize::t_to_d()</code>) for details.
hedges_g	If TRUE, compute Hedge's g as index of effect size. Only applies to objects from <code>t.test()</code> .
omega_squared, eta_squared, epsilon_squared	Logical, if TRUE, returns the non-partial effect size Omega, Eta or Epsilon squared. Only applies to objects from <code>oneway.test()</code> .
cohens_g	If TRUE, compute Cohen's g as index of effect size. Only applies to objects from <code>mcnemar.test()</code> .
rank_biserial	If TRUE, compute the rank-biserial correlation as effect size measure. Only applies to objects from <code>wilcox.test()</code> .
rank_epsilon_squared	If TRUE, compute the rank epsilon squared as effect size measure. Only applies to objects from <code>kruskal.test()</code> .
kendalls_w	If TRUE, compute the Kendall's coefficient of concordance as effect size measure. Only applies to objects from <code>friedman.test()</code> .
ci	Level of confidence intervals for effect size statistic. Currently only applies to objects from <code>chisq.test()</code> or <code>oneway.test()</code> .
alternative	A character string specifying the alternative hypothesis; Controls the type of CI returned: "two.sided" (default, two-sided CI), "greater" or "less" (one-sided CI). Partial matching is allowed (e.g., "g", "1", "two" ...). See section <i>One-Sided CIs</i> in the effectsize_CIs vignette .

bootstrap	Should estimates be bootstrapped?
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods.

Value

A data frame of indices related to the model's parameters.

Examples

```

model <- cor.test(mtcars$mpg, mtcars$cyl, method = "pearson")
model_parameters(model)

model <- t.test(iris$Sepal.Width, iris$Sepal.Length)
model_parameters(model, hedges_g = TRUE)

model <- t.test(mtcars$mpg ~ mtcars$vs)
model_parameters(model, hedges_g = TRUE)

model <- t.test(iris$Sepal.Width, mu = 1)
model_parameters(model, standardized_d = TRUE)

data(airquality)
airquality$Month <- factor(airquality$Month, labels = month.abb[5:9])
model <- pairwise.t.test(airquality$Ozone, airquality$Month)
model_parameters(model)

smokers <- c(83, 90, 129, 70)
patients <- c(86, 93, 136, 82)
model <- pairwise.prop.test(smokers, patients)
model_parameters(model)

model <- stats::chisq.test(table(mtcars$am, mtcars$cyl))
model_parameters(model, cramers_v = "adjusted")

```

model_parameters.lavaan

Parameters from CFA/SEM models

Description

Format CFA/SEM objects from the lavaan package (Rosseel, 2012; Merkle and Rosseel 2018).

Usage

```
## S3 method for class 'lavaan'
model_parameters(
  model,
  ci = 0.95,
  standardize = FALSE,
  component = c("regression", "correlation", "loading", "defined"),
  keep = NULL,
  drop = NULL,
  parameters = keep,
  verbose = TRUE,
  ...
)
```

Arguments

model	CFA or SEM created by the <code>lavaan::cfa</code> or <code>lavaan::sem</code> functions.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
standardize	Return standardized parameters (standardized coefficients). Can be TRUE (or "all" or "std.all") for standardized estimates based on both the variances of observed and latent variables; "latent" (or "std.lv") for standardized estimates based on the variances of the latent variables only; or "no_exogenous" (or "std.noX") for standardized estimates based on both the variances of observed and latent variables, but not the variances of exogenous covariates. See <code>lavaan::standardizedsolution</code> for details.
component	What type of links to return. Can be "all" or some of <code>c("regression", "correlation", "loading", "variance", "mean")</code> .
keep	Character containing a regular expression pattern that describes the parameters that should be included (for keep) or excluded (for drop) in the returned data frame. keep may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If keep is a character vector, every parameter name in the "Parameter" column that matches the regular expression in keep will be selected from the returned data frame (and vice versa, all parameter names matching drop will be excluded). Furthermore, if keep has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If keep is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where <code>model_parameters()</code> returns multiple columns with parameter components, like in <code>model_parameters.lavaan()</code> . Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the \$Parameter column of the parameters table to get the exact parameter names.
drop	See keep.
parameters	Deprecated, alias for keep.
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods.

Value

A data frame of indices related to the model's parameters.

Note

There is also a `plot()`-method implemented in the [see-package](#).

References

- Rosseel Y (2012). lavaan: An R Package for Structural Equation Modeling. Journal of Statistical Software, 48(2), 1-36.
- Merkle EC , Rosseel Y (2018). blavaan: Bayesian Structural Equation Models via Parameter Expansion. Journal of Statistical Software, 85(4), 1-30. <http://www.jstatsoft.org/v85/i04/>

Examples

```
library(parameters)

# lavaan -----
if (require("lavaan", quietly = TRUE)) {

  # Confirmatory Factor Analysis (CFA) -----

  structure <- " visual =~ x1 + x2 + x3
               textual =~ x4 + x5 + x6
               speed  =~ x7 + x8 + x9 "
  model <- lavaan::cfa(structure, data = HolzingerSwineford1939)
  model_parameters(model)
  model_parameters(model, standardize = TRUE)

  # filter parameters
  model_parameters(
    model,
    parameters = list(
      To = "^(?!visual)",
      From = "^(?!(x7|x8))"
    )
  )

  # Structural Equation Model (SEM) -----

  structure <- "
  # latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + a*y2 + b*y3 + c*y4
  dem65 =~ y5 + a*y6 + b*y7 + c*y8
  # regressions
  dem60 ~ ind60
  dem65 ~ ind60 + dem60
  # residual correlations
  y1 ~~ y5
```

```

      y2 ~~ y4 + y6
      y3 ~~ y7
      y4 ~~ y8
      y6 ~~ y8
    "
    model <- lavaan::sem(structure, data = PoliticalDemocracy)
    model_parameters(model)
    model_parameters(model, standardize = TRUE)
  }

```

model_parameters.mira *Parameters from multiply imputed repeated analyses*

Description

Format models of class `mira`, obtained from `mice::width.mids()`.

Usage

```

## S3 method for class 'mira'
model_parameters(
  model,
  ci = 0.95,
  exponentiate = FALSE,
  p_adjust = NULL,
  verbose = TRUE,
  ...
)

```

Arguments

<code>model</code>	An object of class <code>mira</code> .
<code>ci</code>	Confidence Interval (CI) level. Default to 0.95 (95%).
<code>exponentiate</code>	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
<code>p_adjust</code>	Character vector, if not <code>NULL</code> , indicates the method to adjust p-values. See stats::p.adjust() for details. Further possible adjustment methods are "tukey", "scheffe", "sidak" and "none" to explicitly disable adjustment for <code>emmGrid</code> objects (from emmeans).
<code>verbose</code>	Toggle warnings and messages.
<code>...</code>	Arguments passed to or from other methods.

Details

model_parameters() for objects of class mira works similar to summary(mice::pool()), i.e. it generates the pooled summary of multiple imputed repeated regression analyses.

Examples

```
library(parameters)
if (require("mice", quietly = TRUE)) {
  data(nhanes2)
  imp <- mice(nhanes2)
  fit <- with(data = imp, exp = lm(bmi ~ age + hyp + chl))
  model_parameters(fit)
}
## Not run:
# model_parameters() also works for models that have no "tidy"-method in mice
if (require("mice", quietly = TRUE) && require("gee", quietly = TRUE)) {
  data(warpbreaks)
  set.seed(1234)
  warpbreaks$tension[sample(1:nrow(warpbreaks), size = 10)] <- NA
  imp <- mice(warpbreaks)
  fit <- with(data = imp, expr = gee(breaks ~ tension, id = wool))

  # does not work:
  # summary(pool(fit))

  model_parameters(fit)
}
## End(Not run)

# and it works with pooled results
if (require("mice")) {
  data("nhanes2")
  imp <- mice(nhanes2)
  fit <- with(data = imp, exp = lm(bmi ~ age + hyp + chl))
  pooled <- pool(fit)

  model_parameters(pooled)
}
```

model_parameters.PCA *Parameters from Structural Models (PCA, EFA, ...)*

Description

Format structural models from the **psych** or **FactoMineR** packages.

Usage

```
## S3 method for class 'PCA'
model_parameters(
  model,
  sort = FALSE,
  threshold = NULL,
  labels = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'principal'
model_parameters(
  model,
  sort = FALSE,
  threshold = NULL,
  labels = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'omega'
model_parameters(model, verbose = TRUE, ...)
```

Arguments

model	PCA or FA created by the psych or FactoMineR packages (e.g. through <code>psych::principal</code> , <code>psych::fa</code> or <code>psych::omega</code>).
sort	Sort the loadings.
threshold	A value between 0 and 1 indicates which (absolute) values from the loadings should be removed. An integer higher than 1 indicates the n strongest loadings to retain. Can also be "max", in which case it will only display the maximum loading per variable (the most simple structure).
labels	A character vector containing labels to be added to the loadings data. Usually, the question related to the item.
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods.

Details

For the structural models obtained with **psych**, the following indices are present:

- **Complexity** (*Hoffman's, 1978; Pettersson and Turkheimer, 2010*) represents the number of latent components needed to account for the observed variables. Whereas a perfect simple structure solution has a complexity of 1 in that each item would only load on one factor, a solution with evenly distributed items has a complexity greater than 1.

- **Uniqueness** represents the variance that is 'unique' to the variable and not shared with other variables. It is equal to $1 - \text{communality}$ (variance that is shared with other variables). A uniqueness of 0.20 suggests that 20% of that variable's variance is not shared with other variables in the overall factor model. The greater 'uniqueness' the lower the relevance of the variable in the factor model.
- **MSA** represents the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (*Kaiser and Rice, 1974*) for each item. It indicates whether there is enough data for each factor give reliable results for the PCA. The value should be > 0.6 , and desirable values are > 0.8 (*Tabachnick and Fidell, 2013*).

Value

A data frame of loadings.

References

- Kaiser, H.F. and Rice. J. (1974). Little jiffy, mark iv. Educational and Psychological Measurement, 34(1):111–117
- Pettersson, E., & Turkheimer, E. (2010). Item selection, evaluation, and simple structure in personality data. Journal of research in personality, 44(4), 407-420.
- Revelle, W. (2016). How To: Use the psych package for Factor Analysis and data reduction.
- Tabachnick, B. G., and Fidell, L. S. (2013). Using multivariate statistics (6th ed.). Boston: Pearson Education.

Examples

```
library(parameters)
if (require("psych", quietly = TRUE)) {
  # Principal Component Analysis (PCA) -----
  pca <- psych::principal(attitude)
  model_parameters(pca)

  pca <- psych::principal(attitude, nfactors = 3, rotate = "none")
  model_parameters(pca, sort = TRUE, threshold = 0.2)

  principal_components(attitude, n = 3, sort = TRUE, threshold = 0.2)

  # Exploratory Factor Analysis (EFA) -----
  efa <- psych::fa(attitude, nfactors = 3)
  model_parameters(efa, threshold = "max", sort = TRUE, labels = as.character(1:ncol(attitude)))

  # Omega -----
  omega <- psych::omega(mtcars, nfactors = 3)
  params <- model_parameters(omega)
  params
  summary(params)
}
```



```

# FactoMineR -----
if (require("FactoMineR", quietly = TRUE)) {
  model <- FactoMineR::PCA(iris[, 1:4], ncp = 2)
  model_parameters(model)
  attributes(model_parameters(model))$scores

  model <- FactoMineR::FAMD(iris, ncp = 2)
  model_parameters(model)
}

```

model_parameters.PMCMR

Parameters from Hypothesis Testing

Description

Parameters from Hypothesis Testing.

Usage

```

## S3 method for class 'PMCMR'
model_parameters(model, ...)

## S3 method for class 'glht'
model_parameters(model, ci = 0.95, exponentiate = FALSE, verbose = TRUE, ...)

```

Arguments

model	Object of class <code>multcomp::glht()</code> (multcomp) or of class <code>PMCMR</code> , <code>trendPMCMR</code> or <code>osrt</code> (PMCMRplus).
...	Arguments passed to or from other methods. For instance, when <code>bootstrap = TRUE</code> , arguments like <code>type</code> or <code>parallel</code> are passed down to <code>bootstrap_model()</code> , and arguments like <code>ci_method</code> are passed down to <code>bayestestR::describe_posterior()</code> .
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
verbose	Toggle warnings and messages.

Value

A data frame of indices related to the model's parameters.

Examples

```
if (require("multcomp", quietly = TRUE)) {
  # multiple linear model, swiss data
  lmod <- lm(Fertility ~ ., data = swiss)
  mod <- glht(
    model = lmod,
    linfct = c(
      "Agriculture = 0",
      "Examination = 0",
      "Education = 0",
      "Catholic = 0",
      "Infant.Mortality = 0"
    )
  )
  model_parameters(mod)
}
if (require("PMCMRplus", quietly = TRUE)) {
  model <- kwAllPairsConoverTest(count ~ spray, data = InsectSprays)
  model_parameters(model)
}
```

model_parameters.rma *Parameters from Meta-Analysis*

Description

Extract and compute indices and measures to describe parameters of meta-analysis models.

Usage

```
## S3 method for class 'rma'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  standardize = NULL,
  exponentiate = FALSE,
  include_studies = TRUE,
  verbose = TRUE,
  ...
)
```

Arguments

model	Model object.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
bootstrap	Should estimates be based on bootstrapped model? If TRUE, then arguments of Bayesian regressions apply (see also bootstrap_parameters()).
iterations	The number of bootstrap replicates. This only apply in the case of bootstrapped frequentist models.
standardize	The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in standardize_parameters() . Important: <ul style="list-style-type: none"> • The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as lm.beta) or other software packages (like SPSS). to mimic such behaviours, either use standardize="basic" or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. • For mixed models, when using methods other than "refit", only the fixed effects will be returned. • Robust estimation (i.e., vcov set to a value other than NULL) of standardized parameters only works when standardize="refit".
exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
include_studies	Logical, if TRUE (default), includes parameters for all studies. Else, only parameters for overall-effects are shown.
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods. For instance, when <code>bootstrap = TRUE</code> , arguments like <code>type</code> or <code>parallel</code> are passed down to <code>bootstrap_model()</code> , and arguments like <code>ci_method</code> are passed down to <code>bayestestR::describe_posterior()</code> .

Value

A data frame of indices related to the model's parameters.

Examples

```
library(parameters)
mydat <- data.frame(
  effectsize = c(-0.393, 0.675, 0.282, -1.398),
```

```

  stderr = c(0.317, 0.317, 0.13, 0.36)
)
if (require("metafor", quietly = TRUE)) {
  model <- rma(yi = effectsize, sei = stderr, method = "REML", data = mydat)
  model_parameters(model)
}
## Not run:
# with subgroups
if (require("metafor", quietly = TRUE)) {
  data(dat.bcg)
  dat <- escalc(
    measure = "RR",
    ai = tpos,
    bi = tneg,
    ci = cpos,
    di = cneg,
    data = dat.bcg
  )
  dat$alloc <- ifelse(dat$alloc == "random", "random", "other")
  model <- rma(yi, vi, mods = ~alloc, data = dat, digits = 3, slab = author)
  model_parameters(model)
}

if (require("metaBMA", quietly = TRUE)) {
  data(towels)
  m <- meta_random(logOR, SE, study, data = towels)
  model_parameters(m)
}

## End(Not run)

```

model_parameters.t1way

Parameters from robust statistical objects in WRS2

Description

Parameters from robust statistical objects in WRS2

Usage

```
## S3 method for class 't1way'
model_parameters(model, keep = NULL, verbose = TRUE, ...)
```

Arguments

model Object from WRS2 package.

keep	Character containing a regular expression pattern that describes the parameters that should be included (for keep) or excluded (for drop) in the returned data frame. keep may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If keep is a character vector, every parameter name in the "Parameter" column that matches the regular expression in keep will be selected from the returned data frame (and vice versa, all parameter names matching drop will be excluded). Furthermore, if keep has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If keep is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where model_parameters() returns multiple columns with parameter components, like in <code>model_parameters.lavaan()</code> . Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the \$Parameter column of the parameters table to get the exact parameter names.
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods.

Value

A data frame of indices related to the model's parameters.

Examples

```
if (require("WRS2") && packageVersion("WRS2") >= "1.1.3") {
  model <- tlway(libido ~ dose, data = viagra)
  model_parameters(model)
}
```

model_parameters.zcpglm

Parameters from Zero-Inflated Models

Description

Parameters from zero-inflated models (from packages like **pscl**, **cplm** or **countreg**).

Usage

```
## S3 method for class 'zcpglm'
model_parameters(
  model,
  ci = 0.95,
  bootstrap = FALSE,
  iterations = 1000,
  component = c("all", "conditional", "zi", "zero_inflated"),
```

```

standardize = NULL,
exponentiate = FALSE,
p_adjust = NULL,
keep = NULL,
drop = NULL,
parameters = keep,
summary = getOption("parameters_summary", FALSE),
verbose = TRUE,
...
)

```

Arguments

model	A model with zero-inflation component.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
bootstrap	Should estimates be based on bootstrapped model? If TRUE, then arguments of Bayesian regressions apply (see also bootstrap_parameters()).
iterations	The number of bootstrap replicates. This only apply in the case of bootstrapped frequentist models.
component	Model component for which parameters should be shown. May be one of "conditional", "precision" (betareg), "scale" (ordinal), "extra" (glmx), "marginal" (mf), "conditional" or "full" (for <code>MuMIn::model.avg()</code>) or "all".
standardize	The method used for standardizing the parameters. Can be NULL (default; no standardization), "refit" (for re-fitting the model on standardized data) or one of "basic", "posthoc", "smart", "pseudo". See 'Details' in standardize_parameters() . Important: <ul style="list-style-type: none"> The "refit" method does <i>not</i> standardized categorical predictors (i.e. factors), which may be a different behaviour compared to other R packages (such as lm.beta) or other software packages (like SPSS). to mimic such behaviours, either use <code>standardize="basic"</code> or standardize the data with <code>datawizard::standardize(force=TRUE)</code> <i>before</i> fitting the model. For mixed models, when using methods other than "refit", only the fixed effects will be returned. Robust estimation (i.e., <code>vcov</code> set to a value other than NULL) of standardized parameters only works when <code>standardize="refit"</code>.
exponentiate	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.

p_adjust	Character vector, if not NULL, indicates the method to adjust p-values. See stats::p.adjust() for details. Further possible adjustment methods are "tukey", "scheffe", "sidak" and "none" to explicitly disable adjustment for emmGrid objects (from emmeans).
keep	Character containing a regular expression pattern that describes the parameters that should be included (for keep) or excluded (for drop) in the returned data frame. keep may also be a named list of regular expressions. All non-matching parameters will be removed from the output. If keep is a character vector, every parameter name in the "Parameter" column that matches the regular expression in keep will be selected from the returned data frame (and vice versa, all parameter names matching drop will be excluded). Furthermore, if keep has more than one element, these will be merged with an OR operator into a regular expression pattern like this: "(one two three)". If keep is a named list of regular expression patterns, the names of the list-element should equal the column name where selection should be applied. This is useful for model objects where model_parameters() returns multiple columns with parameter components, like in model_parameters.lavaan() . Note that the regular expression pattern should match the parameter names as they are stored in the returned data frame, which can be different from how they are printed. Inspect the \$Parameter column of the parameters table to get the exact parameter names.
drop	See keep.
parameters	Deprecated, alias for keep.
summary	Logical, if TRUE, prints summary information about the model (model formula, number of observations, residual standard deviation and more).
verbose	Toggle warnings and messages.
...	Arguments passed to or from other methods. For instance, when bootstrap = TRUE, arguments like type or parallel are passed down to bootstrap_model(), and arguments like ci_method are passed down to bayestestR::describe_posterior() .

Value

A data frame of indices related to the model's parameters.

See Also

[insight::standardize_names\(\)](#) to rename columns into a consistent, standardized naming scheme.

Examples

```
library(parameters)
if (require("pscl")) {
  data("bioChemists")
  model <- zeroinfl(art ~ fem + mar + kid5 + ment | kid5 + phd, data = bioChemists)
  model_parameters(model)
}
```

`n_clusters`*Find number of clusters in your data*

Description

Similarly to `n_factors()` for factor / principal component analysis, `n_clusters` is the main function to find out the optimal numbers of clusters present in the data based on the maximum consensus of a large number of methods.

Essentially, there exist many methods to determine the optimal number of clusters, each with pros and cons, benefits and limitations. The main `n_clusters` function proposes to run all of them, and find out the number of clusters that is suggested by the majority of methods (in case of ties, it will select the most parsimonious solution with fewer clusters).

Note that we also implement some specific, commonly used methods, like the Elbow or the Gap method, with their own visualization functionalities. See the examples below for more details.

Usage

```
n_clusters(  
  x,  
  standardize = TRUE,  
  include_factors = FALSE,  
  package = c("easystats", "NbClust", "mclust"),  
  fast = TRUE,  
  nbclust_method = "kmeans",  
  n_max = 10,  
  ...  
)
```

```
n_clusters_elbow(  
  x,  
  standardize = TRUE,  
  include_factors = FALSE,  
  clustering_function = stats::kmeans,  
  n_max = 10,  
  ...  
)
```

```
n_clusters_gap(  
  x,  
  standardize = TRUE,  
  include_factors = FALSE,  
  clustering_function = stats::kmeans,  
  n_max = 10,  
  gap_method = "firstSEmax",  
  ...  
)
```



```

n_clusters_silhouette(
  x,
  standardize = TRUE,
  include_factors = FALSE,
  clustering_function = stats::kmeans,
  n_max = 10,
  ...
)

n_clusters_dbSCAN(
  x,
  standardize = TRUE,
  include_factors = FALSE,
  method = c("kNN", "SS"),
  min_size = 0.1,
  eps_n = 50,
  eps_range = c(0.1, 3),
  ...
)

n_clusters_hclust(
  x,
  standardize = TRUE,
  include_factors = FALSE,
  distance_method = "correlation",
  hclust_method = "average",
  ci = 0.95,
  iterations = 100,
  ...
)

```

Arguments

x	A data frame.
standardize	Standardize the dataframe before clustering (default).
include_factors	Logical, if TRUE, factors are converted to numerical values in order to be included in the data for determining the number of clusters. By default, factors are removed, because most methods that determine the number of clusters need numeric input only.
package	Package from which methods are to be called to determine the number of clusters. Can be "all" or a vector containing "easystats", "NbClust", "mclust", and "M3C".
fast	If FALSE, will compute 4 more indices (sets index = "allong" in NbClust). This has been deactivated by default as it is computationally heavy.
nbclust_method	The clustering method (passed to NbClust::NbClust() as method).
n_max	Maximal number of clusters to test.

```

...           Arguments passed to or from other methods.
clustering_function, gap_method
              Other arguments passed to other functions. clustering_function is used by
              fviz_nbclust and can be kmeans, codecluster::pam, codecluster::clara, codeclus-
              ter::fanny, and more. gap_method is used by cluster::maxSE to extract the
              optimal numbers of clusters (see its method argument).
method, min_size, eps_n, eps_range
              Arguments for DBSCAN algorithm.
distance_method
              The distance method (passed to dist()). Used by algorithms relying on the
              distance matrix, such as hclust or dbscan.
hclust_method  The hierarchical clustering method (passed to hclust()).
ci             Confidence Interval (CI) level. Default to 0.95 (95%).
iterations    The number of bootstrap replicates. This only apply in the case of bootstrapped
              frequentist models.

```

Note

There is also a `plot()`-method implemented in the [see-package](#).

Examples

```

## Not run:
library(parameters)

# The main 'n_clusters' function =====
if (require("mclust", quietly = TRUE) && require("NbClust", quietly = TRUE) &&
    require("cluster", quietly = TRUE) && require("see", quietly = TRUE)) {
  n <- n_clusters(iris[, 1:4], package = c("NbClust", "mclust")) # package can be "all"
  n
  summary(n)
  as.data.frame(n) # Duration is the time elapsed for each method in seconds
  plot(n)

  # The following runs all the method but it significantly slower
  # n_clusters(iris[1:4], standardize = FALSE, package = "all", fast = FALSE)
}

## End(Not run)

#
# Specific Methods =====
# Elbow method -----
if (require("openxlsx", quietly = TRUE) &&
    require("see", quietly = TRUE) &&
    require("factoextra", quietly = TRUE)) {
  x <- n_clusters_elbow(iris[1:4])
  x
  as.data.frame(x)
  plot(x)
}

```

```

}

#
# Gap method -----
if (require("see", quietly = TRUE) &&
    require("cluster", quietly = TRUE) &&
    require("factoextra", quietly = TRUE)) {
  x <- n_clusters_gap(iris[1:4])
  x
  as.data.frame(x)
  plot(x)
}

#
# Silhouette method -----
if (require("factoextra", quietly = TRUE)) {
  x <- n_clusters_silhouette(iris[1:4])
  x
  as.data.frame(x)
  plot(x)
}

#
if (require("dbscan", quietly = TRUE)) {
  # DBSCAN method -----
  # NOTE: This actually primarily estimates the 'eps' parameter, the number of
  # clusters is a side effect (it's the number of clusters corresponding to
  # this 'optimal' EPS parameter).
  x <- n_clusters_dbscan(iris[1:4], method = "kNN", min_size = 0.05) # 5 percent
  x
  head(as.data.frame(x))
  plot(x)

  x <- n_clusters_dbscan(iris[1:4], method = "SS", eps_n = 100, eps_range = c(0.1, 2))
  x
  head(as.data.frame(x))
  plot(x)
}

#
# hclust method -----
if (require("pvclust", quietly = TRUE) &&
    getRversion() >= "3.6.0") {
  # iterations should be higher for real analyses
  x <- n_clusters_hclust(iris[1:4], iterations = 50, ci = 0.90)
  x
  head(as.data.frame(x), n = 10) # Print 10 first rows
  plot(x)
}

```

n_factors

Number of components/factors to retain in PCA/FA

Description

This function runs many existing procedures for determining how many factors to retain/extract from factor analysis (FA) or dimension reduction (PCA). It returns the number of factors based on the maximum consensus between methods. In case of ties, it will keep the simplest model and select the solution with the fewer factors.

Usage

```
n_factors(
  x,
  type = "FA",
  rotation = "varimax",
  algorithm = "default",
  package = c("nFactors", "psych"),
  cor = NULL,
  safe = TRUE,
  n_max = NULL,
  ...
)
```

```
n_components(
  x,
  type = "PCA",
  rotation = "varimax",
  algorithm = "default",
  package = c("nFactors", "psych"),
  cor = NULL,
  safe = TRUE,
  ...
)
```

Arguments

x	A data frame.
type	Can be "FA" or "PCA", depending on what you want to do.
rotation	Only used for VSS (Very Simple Structure criterion, see psych::VSS()). The rotation to apply. Can be "none", "varimax", "quartimax", "bentlerT", "equamax", "varimin", "geominT" and "bifactor" for orthogonal rotations, and "promax", "oblimin", "simplimax", "bentlerQ", "geominQ", "biquartimin" and "cluster" for oblique transformations.

algorithm	Factoring method used by VSS. Can be "pa" for Principal Axis Factor Analysis, "minres" for minimum residual (OLS) factoring, "mle" for Maximum Likelihood FA and "pc" for Principal Components. "default" will select "minres" if type = "FA" and "pc" if type = "PCA".
package	Package from which respective methods are used. Can be "all" or a vector containing "nFactors", "psych", "PCDimension", "fit" or "EGAnet". Note that "fit" (which actually also relies on the psych package) and "EGAnet" can be very slow for bigger datasets. Thus, the default is c("nFactors", "psych"). You must have the respective packages installed for the methods to be used.
cor	An optional correlation matrix that can be used (note that the data must still be passed as the first argument). If NULL, will compute it by running cor() on the passed data.
safe	If TRUE, the function will run all the procedures in try blocks, and will only return those that work and silently skip the ones that may fail.
n_max	If set to a value (e.g., 10), will drop from the results all methods that suggest a higher number of components. The interpretation becomes 'from all the methods that suggested a number lower than n_max, the results are ...'.
...	Arguments passed to or from other methods.

Details

n_components is actually an alias for n_factors, with different defaults for the function arguments.

Value

A data frame.

Note

There is also a `plot()`-method implemented in the [see-package](#). `n_components()` is a convenient short for `n_factors(type = "PCA")`.

References

- Bartlett, M. S. (1950). Tests of significance in factor analysis. *British Journal of statistical psychology*, 3(2), 77-85.
- Bentler, P. M., & Yuan, K. H. (1996). Test of linear trend in eigenvalues of a covariance matrix with application to data analysis. *British Journal of Mathematical and Statistical Psychology*, 49(2), 299-312.
- Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate behavioral research*, 1(2), 245-276.
- Finch, W. H. (2019). Using Fit Statistic Differences to Determine the Optimal Number of Factors to Retain in an Exploratory Factor Analysis. *Educational and Psychological Measurement*.
- Zoski, K. W., & Jurs, S. (1996). An objective counterpart to the visual scree test for factor analysis: The standard error scree. *Educational and Psychological Measurement*, 56(3), 443-451.

- Zoski, K., & Jurs, S. (1993). Using multiple regression to determine the number of factors to retain in factor analysis. *Multiple Linear Regression Viewpoints*, 20(1), 5-9.
- Nasser, F., Benson, J., & Wisenbaker, J. (2002). The performance of regression-based variations of the visual scree for determining the number of common factors. *Educational and psychological measurement*, 62(3), 397-419.
- Golino, H., Shi, D., Garrido, L. E., Christensen, A. P., Nieto, M. D., Sadana, R., & Thiyagarajan, J. A. (2018). Investigating the performance of Exploratory Graph Analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial.
- Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PloS one*, 12(6), e0174035.
- Revelle, W., & Rocklin, T. (1979). Very simple structure: An alternative procedure for estimating the optimal number of interpretable factors. *Multivariate Behavioral Research*, 14(4), 403-414.
- Velicer, W. F. (1976). Determining the number of components from the matrix of partial correlations. *Psychometrika*, 41(3), 321-327.

Examples

```
library(parameters)
if (require("nFactors", quietly = TRUE) && require("EGAnet", quietly = TRUE)) {
  n_factors(mtcars, type = "PCA")

  result <- n_factors(mtcars[1:5], type = "FA")
  as.data.frame(result)
  summary(result)
  ## Not run:
  if (require("PCDimension", quietly = TRUE)) {
    # Setting package = 'all' will increase the number of methods (but is slow)
    n_factors(mtcars, type = "PCA", package = "all")
    n_factors(mtcars, type = "FA", algorithm = "mle", package = "all")
  }

  ## End(Not run)
}
```

parameters_type

Type of model parameters

Description

In a regression model, the parameters do not all have the meaning. For instance, the intercept has to be interpreted as theoretical outcome value under some conditions (when predictors are set to 0), whereas other coefficients are to be interpreted as amounts of change. Others, such as interactions, represent changes in another of the parameter. The `parameters_type` function attempts to retrieve information and meaning of parameters. It outputs a dataframe of information for each parameters, such as the Type (whether the parameter corresponds to a factor or a numeric predictor, or whether it is a (regular) interaction or a nested one), the Link (whether the parameter can be interpreted as a mean value, the slope of an association or a difference between two levels) and, in the case of interactions, which other parameters is impacted by which parameter.

Usage

```
parameters_type(model, ...)
```

Arguments

```
model      A statistical model.  
...        Arguments passed to or from other methods.
```

Value

A data frame.

Examples

```
library(parameters)  
  
model <- lm(Sepal.Length ~ Petal.Length + Species, data = iris)  
parameters_type(model)  
  
model <- lm(Sepal.Length ~ Species + poly(Sepal.Width, 2), data = iris)  
parameters_type(model)  
  
model <- lm(Sepal.Length ~ Species + poly(Sepal.Width, 2, raw = TRUE), data = iris)  
parameters_type(model)  
  
# Interactions  
model <- lm(Sepal.Length ~ Sepal.Width * Species, data = iris)  
parameters_type(model)  
  
model <- lm(Sepal.Length ~ Sepal.Width * Species * Petal.Length, data = iris)  
parameters_type(model)  
  
model <- lm(Sepal.Length ~ Species * Sepal.Width, data = iris)  
parameters_type(model)  
  
model <- lm(Sepal.Length ~ Species / Sepal.Width, data = iris)  
parameters_type(model)  
  
# Complex interactions  
data <- iris  
data$fac2 <- ifelse(data$Sepal.Width > mean(data$Sepal.Width), "A", "B")  
model <- lm(Sepal.Length ~ Species / fac2 / Petal.Length, data = data)  
parameters_type(model)  
  
model <- lm(Sepal.Length ~ Species / fac2 * Petal.Length, data = data)  
parameters_type(model)
```

pool_parameters *Pool Model Parameters*

Description

This function "pools" (i.e. combines) model parameters in a similar fashion as `mice::pool()`. However, this function pools parameters from `parameters_model` objects, as returned by `model_parameters()`.

Usage

```
pool_parameters(
  x,
  exponentiate = FALSE,
  effects = "fixed",
  component = "conditional",
  verbose = TRUE,
  ...
)
```

Arguments

<code>x</code>	A list of <code>parameters_model</code> objects, as returned by <code>model_parameters()</code> , or a list of model-objects that is supported by <code>model_parameters()</code> .
<code>exponentiate</code>	Logical, indicating whether or not to exponentiate the the coefficients (and related confidence intervals). This is typical for logistic regression, or more generally speaking, for models with log or logit links. Note: Delta-method standard errors are also computed (by multiplying the standard errors by the transformed coefficients). This is to mimic behaviour of other software packages, such as Stata, but these standard errors poorly estimate uncertainty for the transformed coefficient. The transformed confidence interval more clearly captures this uncertainty. For <code>compare_parameters()</code> , <code>exponentiate = "nongaussian"</code> will only exponentiate coefficients from non-Gaussian families.
<code>effects</code>	Should parameters for fixed effects ("fixed"), random effects ("random"), or both ("all") be returned? Only applies to mixed models. May be abbreviated. If the calculation of random effects parameters takes too long, you may use <code>effects = "fixed"</code> .
<code>component</code>	Model component for which parameters should be shown. May be one of "conditional", "precision" (betareg), "scale" (ordinal), "extra" (glmx), "marginal" (mfx), "conditional" or "full" (for <code>MuMIn::model.avg()</code>) or "all".
<code>verbose</code>	Toggle warnings and messages.
<code>...</code>	Currently not used.

Details

Averaging of parameters follows Rubin's rules (*Rubin, 1987, p. 76*). The pooled degrees of freedom is based on the Barnard-Rubin adjustment for small samples (*Barnard and Rubin, 1999*).

Value

A data frame of indices related to the model's parameters.

Note

Models with multiple components, (for instance, models with zero-inflation, where predictors appear in the count and zero-inflated part) may fail in case of identical names for coefficients in the different model components, since the coefficient table is grouped by coefficient names for pooling. In such cases, coefficients of count and zero-inflated model parts would be combined. Therefore, the component argument defaults to "conditional" to avoid this.

References

Barnard, J. and Rubin, D.B. (1999). Small sample degrees of freedom with multiple imputation. *Biometrika*, 86, 948-955. Rubin, D.B. (1987). *Multiple Imputation for Nonresponse in Surveys*. New York: John Wiley and Sons.

Examples

```
# example for multiple imputed datasets
if (require("mice")) {
  data("nhanes2")
  imp <- mice(nhanes2, printFlag = FALSE)
  models <- lapply(1:5, function(i) {
    lm(bmi ~ age + hyp + chl, data = complete(imp, action = i))
  })
  pool_parameters(models)

  # should be identical to:
  m <- with(data = imp, exp = lm(bmi ~ age + hyp + chl))
  summary(pool(m))
}
```

predict.parameters_clusters

Predict method for parameters_clusters objects

Description

Predict method for parameters_clusters objects

Usage

```
## S3 method for class 'parameters_clusters'
predict(object, newdata = NULL, names = NULL, ...)
```

Arguments

object	a model object for which prediction is desired.
newdata	data.frame
names	character vector or list
...	additional arguments affecting the predictions produced.

```
print.parameters_model
```

Print model parameters

Description

A print()-method for objects from [model_parameters\(\)](#).

Usage

```
## S3 method for class 'parameters_model'
print(
  x,
  pretty_names = TRUE,
  split_components = TRUE,
  select = NULL,
  caption = NULL,
  digits = 2,
  ci_digits = 2,
  p_digits = 3,
  footer_digits = 3,
  show_sigma = FALSE,
  show_formula = FALSE,
  zap_small = FALSE,
  groups = NULL,
  column_width = NULL,
  ci_brackets = c("[", "]"),
  ...
)

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

Arguments

x, object	An object returned by model_parameters() .
pretty_names	Return "pretty" (i.e. more human readable) parameter names.

split_components	Logical, if TRUE (default), For models with multiple components (zero-inflation, smooth terms, ...), each component is printed in a separate table. If FALSE, model parameters are printed in a single table and a Component column is added to the output.
select	Character vector (or numeric index) of column names that should be printed. If NULL (default), all columns are printed. The shortcut select = "minimal" prints coefficient, confidence intervals and p-values, while select = "short" prints coefficient, standard errors and p-values.
caption	Table caption as string. If NULL, no table caption is printed.
digits, ci_digits, p_digits	Number of digits for rounding or significant figures. May also be "signif" to return significant figures or "scientific" to return scientific notation. Control the number of digits by adding the value as suffix, e.g. digits = "scientific4" to have scientific notation with 4 decimal places, or digits = "signif5" for 5 significant figures (see also signif()).
footer_digits	Number of decimal places for values in the footer summary.
show_sigma	Logical, if TRUE, adds information about the residual standard deviation.
show_formula	Logical, if TRUE, adds the model formula to the output.
zap_small	Logical, if TRUE, small values are rounded after digits decimal places. If FALSE, values with more decimal places than digits are printed in scientific notation.
groups	Named list, can be used to group parameters in the printed output. List elements may either be character vectors that match the name of those parameters that belong to one group, or list elements can be row numbers of those parameter rows that should belong to one group. The names of the list elements will be used as group names, which will be inserted as "header row". A possible use case might be to emphasize focal predictors and control variables, see 'Examples'. Parameters will be re-ordered according to the order used in groups, while all non-matching parameters will be added to the end.
column_width	Width of table columns. Can be either NULL, a named numeric vector, or "fixed". If NULL, the width for each table column is adjusted to the minimum required width. If a named numeric vector, value names are matched against column names, and for each match, the specified width is used. If "fixed", and table is split into multiple components, columns across all table components are adjusted to have the same width.
ci_brackets	Logical, if TRUE (default), CI-values are encompassed in square brackets (else in parentheses).
...	Arguments passed to or from other methods.

Details

summary() is a convenient shortcut for print(object, select = "minimal", show_sigma = TRUE, show_formula = TRUE).

Value

Invisibly returns the original input object.

Interpretation of Interaction Terms

Note that the *interpretation* of interaction terms depends on many characteristics of the model. The number of parameters, and overall performance of the model, can differ *or not* between $a * b$, $a : b$, and a / b , suggesting that sometimes interaction terms give different parameterizations of the same model, but other times it gives completely different models (depending on a or b being factors of covariates, included as main effects or not, etc.). Their interpretation depends of the full context of the model, which should not be inferred from the parameters table alone - rather, we recommend to use packages that calculate estimated marginal means or marginal effects, such as **modelbased**, **emmeans** or **ggeffects**. To raise awareness for this issue, you may use `print(..., show_formula=TRUE)` to add the model-specification to the output of the `print()` method for `model_parameters()`.

Labeling the Degrees of Freedom

Throughout the **parameters** package, we decided to label the residual degrees of freedom `df_error`. The reason for this is that these degrees of freedom not always refer to the residuals. For certain models, they refer to the estimate error - in a linear model these are the same, but in - for instance - any mixed effects model, this isn't strictly true. Hence, we think that `df_error` is the most generic label for these degrees of freedom.

See Also

There is a dedicated method to use inside rmarkdown files, `print_md()`.

Examples

```
library(parameters)
if (require("glmmTMB", quietly = TRUE)) {
  model <- glmmTMB(
    count ~ spp + mined + (1 | site),
    ziformula = ~mined,
    family = poisson(),
    data = Salamanders
  )
  mp <- model_parameters(model)

  print(mp, pretty_names = FALSE)

  print(mp, split_components = FALSE)

  print(mp, select = c("Parameter", "Coefficient", "SE"))

  print(mp, select = "minimal")
}
```

```

# group parameters -----

data(iris)
model <- lm(
  Sepal.Width ~ Sepal.Length + Species + Petal.Length,
  data = iris
)
# don't select "Intercept" parameter
mp <- model_parameters(model, parameters = "^(?!\\(Intercept)")
groups <- list(
  "Focal Predictors" = c("Speciesversicolor", "Speciesvirginica"),
  "Controls" = c("Sepal.Length", "Petal.Length")
)
print(mp, groups = groups)

# or use row indices
print(mp, groups = list(
  "Focal Predictors" = c(1, 4),
  "Controls" = c(2, 3)
))

# only show coefficients, CI and p,
# put non-matched parameters to the end

data(mtcars)
mtcars$cyl <- as.factor(mtcars$cyl)
mtcars$gear <- as.factor(mtcars$gear)
model <- lm(mpg ~ hp + gear * vs + cyl + drat, data = mtcars)

# don't select "Intercept" parameter
mp <- model_parameters(model, parameters = "^(?!\\(Intercept)")
print(mp, groups = list(
  "Engine" = c("cyl6", "cyl8", "vs", "hp"),
  "Interactions" = c("gear4:vs", "gear5:vs")
))

```

p_value

p-values

Description

This function attempts to return, or compute, p-values of a model's parameters. See the documentation for your object's class:

- [Bayesian models](#) (`rstanarm`, `brms`, `MCMCglmm`, ...)
- [Zero-inflated models](#) (`hurdle`, `zeroinfl`, `zerocount`, ...)
- [Marginal effects models](#) (`mf`)
- [Models with special components](#) (`DirichletRegModel`, `clm2`, `cgam`, ...)

Usage

```
p_value(model, ...)

## Default S3 method:
p_value(
  model,
  dof = NULL,
  method = NULL,
  component = "all",
  vcov = NULL,
  vcov_args = NULL,
  verbose = TRUE,
  ...
)

## S3 method for class 'emmGrid'
p_value(model, ci = 0.95, adjust = "none", ...)
```

Arguments

model	A statistical model.
...	Additional arguments
dof	Number of degrees of freedom to be used when calculating confidence intervals. If NULL (default), the degrees of freedom are retrieved by calling degrees_of_freedom() with approximation method defined in method. If not NULL, use this argument to override the default degrees of freedom used to compute confidence intervals.
method	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): "residual", "normal", "likelihood", "satterthwaite", "kenward", "wald", "profile", "boot", "uniroot", "ml1", "betwithin", "hdi", "quantile", "ci", "eti", "si", "bci", or "bcai". See section <i>Confidence intervals and approximation of degrees of freedom</i> in model_parameters() for further details.
component	Model component for which parameters should be shown. See the documentation for your object's class in model_parameters() or p_value() for further details.
vcov	Variance-covariance matrix used to compute uncertainty estimates (e.g., for robust standard errors). This argument accepts a covariance matrix, a function which returns a covariance matrix, or a string which identifies the function to be used to compute the covariance matrix. <ul style="list-style-type: none"> • A covariance matrix • A function which returns a covariance matrix (e.g., <code>stats::vcov()</code>) • A string which indicates the kind of uncertainty estimates to return. <ul style="list-style-type: none"> – Heteroskedasticity-consistent: "vcovHC", "HC", "HC0", "HC1", "HC2", "HC3", "HC4", "HC4m", "HC5". See <code>?sandwich::vcovHC</code>.

	<ul style="list-style-type: none"> – Cluster-robust: "vcovCR", "CR0", "CR1", "CR1p", "CR1S", "CR2", "CR3". See ?clubSandwich::vcovCR. – Bootstrap: "vcovBS", "xy", "residual", "wild", "mammen", "webb". See ?sandwich::vcovBS. – Other sandwich package functions: "vcovHAC", "vcovPC", "vcovCL", "vcovPL".
vcov_args	List of arguments to be passed to the function identified by the vcov argument. This function is typically supplied by the sandwich or clubSandwich packages. Please refer to their documentation (e.g., ?sandwich::vcovHAC) to see the list of available arguments.
verbose	Toggle warnings and messages.
ci	Confidence Interval (CI) level. Default to 0.95 (95%).
adjust	Character value naming the method used to adjust p-values or confidence intervals. See ?emmeans::summary.emmGrid for details.

Value

A data frame with at least two columns: the parameter names and the p-values. Depending on the model, may also include columns for model components etc.

Confidence intervals and approximation of degrees of freedom

There are different ways of approximating the degrees of freedom depending on different assumptions about the nature of the model and its sampling distribution. The `ci_method` argument modulates the method for computing degrees of freedom (df) that are used to calculate confidence intervals (CI) and the related p-values. Following options are allowed, depending on the model class:

Classical methods:

Classical inference is generally based on the **Wald method**. The Wald approach to inference computes a test statistic by dividing the parameter estimate by its standard error (Coefficient / SE), then comparing this statistic against a t- or normal distribution. This approach can be used to compute CIs and p-values.

"wald":

- Applies to *non-Bayesian models*. For *linear models*, CIs computed using the Wald method (SE and a *t-distribution with residual df*); p-values computed using the Wald method with a *t-distribution with residual df*. For other models, CIs computed using the Wald method (SE and a *normal distribution*); p-values computed using the Wald method with a *normal distribution*.

"normal"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a normal distribution.

"residual"

- Applies to *non-Bayesian models*. Compute Wald CIs and p-values, but always use a *t-distribution with residual df* when possible. If the residual df for a model cannot be determined, a normal distribution is used instead.

Methods for mixed models:

Compared to fixed effects (or single-level) models, determining appropriate df for Wald-based inference in mixed models is more difficult. See [the R GLMM FAQ](#) for a discussion.

Several approximate methods for computing df are available, but you should also consider instead using profile likelihood ("profile") or bootstrap ("boot") CIs and p-values instead.

"satterthwaite"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with Satterthwaite df*); p-values computed using the Wald method with a *t-distribution with Satterthwaite df*.

"kenward"

- Applies to *linear mixed models*. CIs computed using the Wald method (*Kenward-Roger SE* and a *t-distribution with Kenward-Roger df*); p-values computed using the Wald method with *Kenward-Roger SE* and *t-distribution with Kenward-Roger df*.

"m11"

- Applies to *linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with m-l-1 approximated df*); p-values computed using the Wald method with a *t-distribution with m-l-1 approximated df*. See [ci_m11\(\)](#).

"betwithin"

- Applies to *linear mixed models* and *generalized linear mixed models*. CIs computed using the Wald method (SE and a *t-distribution with between-within df*); p-values computed using the Wald method with a *t-distribution with between-within df*. See [ci_betwithin\(\)](#).

Likelihood-based methods:

Likelihood-based inference is based on comparing the likelihood for the maximum-likelihood estimate to the the likelihood for models with one or more parameter values changed (e.g., set to zero or a range of alternative values). Likelihood ratios for the maximum-likelihood and alternative models are compared to a χ -squared distribution to compute CIs and p-values.

"profile"

- Applies to *non-Bayesian models* of class `glm`, `polr` or `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using linear interpolation to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

"uniroot"

- Applies to *non-Bayesian models* of class `glmmTMB`. CIs computed by *profiling the likelihood curve for a parameter*, using root finding to find where likelihood ratio equals a critical value; p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!)

Methods for bootstrapped or Bayesian models:

Bootstrap-based inference is based on **resampling** and refitting the model to the resampled datasets. The distribution of parameter estimates across resampled datasets is used to approximate the parameter's sampling distribution. Depending on the type of model, several different methods for bootstrapping and constructing CIs and p-values from the bootstrap distribution are available.

For Bayesian models, inference is based on drawing samples from the model posterior distribution.

"quantile" (or "eti")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *equal tailed intervals* using the quantiles of the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::eti()`.

"hdi"

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *highest density intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::hdi()`.

"bci" (or "bcai")

- Applies to *all models (including Bayesian models)*. For non-Bayesian models, only applies if `bootstrap = TRUE`. CIs computed as *bias corrected and accelerated intervals* for the bootstrap or posterior samples; p-values are based on the *probability of direction*. See `bayestestR::bci()`.

"si"

- Applies to *Bayesian models* with proper priors. CIs computed as *support intervals* comparing the posterior samples against the prior samples; p-values are based on the *probability of direction*. See `bayestestR::si()`.

"boot"

- Applies to *non-Bayesian models* of class `merMod`. CIs computed using *parametric bootstrapping* (simulating data from the fitted model); p-values computed using the Wald method with a *normal-distribution* (note: this might change in a future update!).

For all iteration-based methods other than "boot" ("hdi", "quantile", "ci", "eti", "si", "bci", "bcai"), p-values are based on the probability of direction (`bayestestR::p_direction()`), which is converted into a p-value using `bayestestR::pd_to_p()`.

Examples

```
data(iris)
model <- lm(Petal.Length ~ Sepal.Length + Species, data = iris)
p_value(model)
```

`p_value.BFBayesFactor` *p-values for Bayesian Models*

Description

This function attempts to return, or compute, p-values of Bayesian models.

Usage

```
## S3 method for class 'BFBayesFactor'
p_value(model, ...)
```

Arguments

<code>model</code>	A statistical model.
<code>...</code>	Additional arguments

Details

For Bayesian models, the p-values corresponds to the *probability of direction* (`bayestestR::p_direction()`), which is converted to a p-value using `bayestestR::convert_pd_to_p()`.

Value

The p-values.

Examples

```
data(iris)
model <- lm(Petal.Length ~ Sepal.Length + Species, data = iris)
p_value(model)
```

`p_value.DirichletRegModel`
p-values for Models with Special Components

Description

This function attempts to return, or compute, p-values of models with special model components.

Usage

```
## S3 method for class 'DirichletRegModel'
p_value(model, component = c("all", "conditional", "precision"), ...)

## S3 method for class 'averaging'
p_value(model, component = c("conditional", "full"), ...)

## S3 method for class 'betareg'
p_value(
  model,
  component = c("all", "conditional", "precision"),
  verbose = TRUE,
  ...
)

## S3 method for class 'cgam'
p_value(model, component = c("all", "conditional", "smooth_terms"), ...)

## S3 method for class 'clm2'
p_value(model, component = c("all", "conditional", "scale"), ...)
```

Arguments

model	A statistical model.
component	Should all parameters, parameters for the conditional model, precision- or scale-component or smooth_terms be returned? component may be one of "conditional", "precision", "scale", "smooth_terms", "full" or "all" (default).
...	Additional arguments
verbose	Toggle warnings and messages.

Value

The p-values.

p_value.poissonmfx *p-values for Marginal Effects Models*

Description

This function attempts to return, or compute, p-values of marginal effects models from package **mfx**.

Usage

```
## S3 method for class 'poissonmfx'
p_value(model, component = c("all", "conditional", "marginal"), ...)

## S3 method for class 'betaor'
p_value(model, component = c("all", "conditional", "precision"), ...)

## S3 method for class 'betamfx'
p_value(
  model,
  component = c("all", "conditional", "precision", "marginal"),
  ...
)
```

Arguments

model	A statistical model.
component	Should all parameters, parameters for the conditional model, precision-component or marginal effects be returned? component may be one of "conditional", "precision", "marginal" or "all" (default).
...	Currently not used.

Value

A data frame with at least two columns: the parameter names and the p-values. Depending on the model, may also include columns for model components etc.

Examples

```
if (require("mfx", quietly = TRUE)) {
  set.seed(12345)
  n <- 1000
  x <- rnorm(n)
  y <- rnegbin(n, mu = exp(1 + 0.5 * x), theta = 0.5)
  d <- data.frame(y, x)
  model <- poissonmfx(y ~ x, data = d)

  p_value(model)
  p_value(model, component = "marginal")
}
```

p_value.zcpglm

p-values for Models with Zero-Inflation

Description

This function attempts to return, or compute, p-values of hurdle and zero-inflated models.

Usage

```
## S3 method for class 'zcpglm'
p_value(model, component = c("all", "conditional", "zi", "zero_inflated"), ...)

## S3 method for class 'zeroinfl'
p_value(
  model,
  component = c("all", "conditional", "zi", "zero_inflated"),
  method = NULL,
  verbose = TRUE,
  ...
)
```

Arguments

model	A statistical model.
component	Model component for which parameters should be shown. See the documentation for your object's class in model_parameters() or p_value() for further details.
...	Additional arguments
method	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): "residual", "normal", "likelihood", "satterthwaite", "kenward", "wald", "profile", "boot", "uniroot", "ml1", "betwithin", "hdi", "quantile", "ci", "eti", "si", "bci", or "bcai". See section <i>Confidence intervals and approximation of degrees of freedom</i> in model_parameters() for further details.
verbose	Toggle warnings and messages.

Value

A data frame with at least two columns: the parameter names and the p-values. Depending on the model, may also include columns for model components etc.

Examples

```
if (require("pscl", quietly = TRUE)) {
  data("bioChemists")
  model <- zeroinfl(art ~ fem + mar + kid5 | kid5 + phd, data = bioChemists)
  p_value(model)
  p_value(model, component = "zi")
}
```

 qol_cancer

Sample data set

Description

A sample data set with longitudinal data, used in the vignette describing the `datawizard::demean()` function. Health-related quality of life from cancer-patients was measured at three time points (pre-surgery, 6 and 12 months after surgery).

Format

A data frame with 564 rows and 7 variables:

ID Patient ID

QoL Quality of Life Score

time Timepoint of measurement

age Age in years

phq4 Patients' Health Questionnaire, 4-item version

hospital Hospital ID, where patient was treated

education Patients' educational level

 random_parameters

Summary information from random effects

Description

This function extracts the different variance components of a mixed model and returns the result as a data frame.

Usage

```
random_parameters(model, component = "conditional")
```

Arguments

model A mixed effects model (including stanreg models).

component Should all parameters, parameters for the conditional model, for the zero-inflated part of the model, or the dispersion model be returned? Applies to models with zero-inflated and/or dispersion component. `component` may be one of "conditional", "zi", "zero-inflated", "dispersion" or "all" (default). May be abbreviated.

Details

The variance components are obtained from `insight::get_variance()` and are denoted as following:

Within-group (or residual) variance: The residual variance, σ_ϵ^2 , is the sum of the distribution-specific variance and the variance due to additive dispersion. It indicates the *within-group variance*.

Between-group random intercept variance: The random intercept variance, or *between-group* variance for the intercept (τ_{00}), is obtained from `VarCorr()`. It indicates how much groups or subjects differ from each other.

Between-group random slope variance: The random slope variance, or *between-group* variance for the slopes (τ_{11}) is obtained from `VarCorr()`. This measure is only available for mixed models with random slopes. It indicates how much groups or subjects differ from each other according to their slopes.

Random slope-intercept correlation: The random slope-intercept correlation (ρ_{01}) is obtained from `VarCorr()`. This measure is only available for mixed models with random intercepts and slopes.

Note: For the within-group and between-group variance, variance and standard deviations (which are simply the square root of the variance) are shown.

Value

A data frame with random effects statistics for the variance components, including number of levels per random effect group, as well as complete observations in the model.

Examples

```
if (require("lme4")) {
  data(sleepstudy)
  model <- lmer(Reaction ~ Days + (1 + Days | Subject), data = sleepstudy)
  random_parameters(model)
}
```

reduce_parameters

Dimensionality reduction (DR) / Features Reduction

Description

This function performs a reduction in the parameter space (the number of variables). It starts by creating a new set of variables, based on the given method (the default method is "PCA", but other are available via the method argument, such as "cMDS", "DRR" or "ICA"). Then, it names this new dimensions using the original variables that correlates the most with it. For instance, a variable named 'V1_0.97/V4_-0.88' means that the V1 and the V4 variables correlate maximally (with respective coefficients of .97 and -.88) with this dimension. Although this function can be useful

in exploratory data analysis, it's best to perform the dimension reduction step in a separate and dedicated stage, as this is a very important process in the data analysis workflow. `reduce_data()` is an alias for `reduce_parameters.data.frame()`.

Usage

```
reduce_parameters(x, method = "PCA", n = "max", distance = "euclidean", ...)
```

```
reduce_data(x, method = "PCA", n = "max", distance = "euclidean", ...)
```

Arguments

<code>x</code>	A data frame or a statistical model.
<code>method</code>	The feature reduction method. Can be one of "PCA", "cMDS", "DRR", "ICA" (see the 'Details' section).
<code>n</code>	Number of components to extract. If <code>n="all"</code> , then <code>n</code> is set as the number of variables minus 1 (<code>ncol(x)-1</code>). If <code>n="auto"</code> (default) or <code>n=NULL</code> , the number of components is selected through <code>n_factors()</code> resp. <code>n_components()</code> . In <code>reduce_parameters()</code> , can also be "max", in which case it will select all the components that are maximally pseudo-loaded (i.e., correlated) by at least one variable.
<code>distance</code>	The distance measure to be used. Only applies when <code>method = "cMDS"</code> . This must be one of "euclidean", "maximum", "manhattan", "canberra", "binary" or "minkowski". Any unambiguous substring can be given.
<code>...</code>	Arguments passed to or from other methods.

Details

The different methods available are described below:

Supervised Methods:

- **PCA**: See `principal_components()`.
- **cMDS / PCoA**: Classical Multidimensional Scaling (cMDS) takes a set of dissimilarities (i.e., a distance matrix) and returns a set of points such that the distances between the points are approximately equal to the dissimilarities.
- **DRR**: Dimensionality Reduction via Regression (DRR) is a very recent technique extending PCA (*Laparra et al., 2015*). Starting from a rotated PCA, it predicts redundant information from the remaining components using non-linear regression. Some of the most notable advantages of performing DRR are avoidance of multicollinearity between predictors and overfitting mitigation. DRR tends to perform well when the first principal component is enough to explain most of the variation in the predictors. Requires the **DRR** package to be installed.
- **ICA**: Performs an Independent Component Analysis using the FastICA algorithm. Contrary to PCA, which attempts to find uncorrelated sources (through least squares minimization), ICA attempts to find independent sources, i.e., the source space that maximizes the "non-gaussianity" of all sources. Contrary to PCA, ICA does not rank each source, which makes it a poor tool for dimensionality reduction. Requires the **fastICA** package to be installed.

See also [package vignette](#).

References

- Nguyen, L. H., & Holmes, S. (2019). Ten quick tips for effective dimensionality reduction. *PLOS Computational Biology*, 15(6).
- Laparra, V., Malo, J., & Camps-Valls, G. (2015). Dimensionality reduction via regression in hyperspectral imagery. *IEEE Journal of Selected Topics in Signal Processing*, 9(6), 1026-1036.

Examples

```
data(iris)
model <- lm(Sepal.Width ~ Species * Sepal.Length + Petal.Width, data = iris)
model
reduce_parameters(model)

out <- reduce_data(iris, method = "PCA", n = "max")
head(out)
```

reshape_loadings *Reshape loadings between wide/long formats*

Description

Reshape loadings between wide/long formats.

Usage

```
reshape_loadings(x, ...)

## S3 method for class 'parameters_efa'
reshape_loadings(x, threshold = NULL, ...)

## S3 method for class 'data.frame'
reshape_loadings(x, threshold = NULL, loadings_columns = NULL, ...)
```

Arguments

x	A data frame or a statistical model.
...	Arguments passed to or from other methods.
threshold	A value between 0 and 1 indicates which (absolute) values from the loadings should be removed. An integer higher than 1 indicates the n strongest loadings to retain. Can also be "max", in which case it will only display the maximum loading per variable (the most simple structure).
loadings_columns	Vector indicating the columns corresponding to loadings.

Examples

```

if (require("psych")) {
  pca <- model_parameters(psych::fa(attitude, nfactors = 3))
  loadings <- reshape_loadings(pca)

  loadings
  reshape_loadings(loadings)
}

```

select_parameters	<i>Automated selection of model parameters</i>
-------------------	--

Description

This function performs an automated selection of the 'best' parameters, updating and returning the "best" model.

Usage

```

select_parameters(model, ...)

## S3 method for class 'lm'
select_parameters(model, direction = "both", steps = 1000, k = 2, ...)

## S3 method for class 'merMod'
select_parameters(model, direction = "backward", steps = 1000, ...)

```

Arguments

model	A statistical model (of class <code>lm</code> , <code>glm</code> , or <code>merMod</code>).
...	Arguments passed to or from other methods.
direction	the mode of stepwise search, can be one of "both", "backward", or "forward", with a default of "both". If the scope argument is missing the default for direction is "backward". Values can be abbreviated.
steps	the maximum number of steps to be considered. The default is 1000 (essentially as many as required). It is typically used to stop the process early.
k	the multiple of the number of degrees of freedom used for the penalty. Only $k = 2$ gives the genuine AIC: $k = \log(n)$ is sometimes referred to as BIC or SBC.

Details

Classical lm and glm: For frequentist GLMs, `select_parameters()` performs an AIC-based stepwise selection.

Mixed models: For mixed-effects models of class `merMod`, stepwise selection is based on `cAIC4::stepcAIC()`. This step function only searches the "best" model based on the random-effects structure, i.e. `select_parameters()` adds or excludes random-effects until the `cAIC` can't be improved further.

Value

The model refitted with optimal number of parameters.

Examples

```

model <- lm(mpg ~ ., data = mtcars)
select_parameters(model)

model <- lm(mpg ~ cyl * disp * hp * wt, data = mtcars)
select_parameters(model)

# lme4 -----
if (require("lme4")) {
  model <- lmer(
    Sepal.Width ~ Sepal.Length * Petal.Width * Petal.Length + (1 | Species),
    data = iris
  )
  select_parameters(model)
}

```

simulate_model

Simulated draws from model coefficients

Description

Simulate draws from a statistical model to return a data frame of estimates.

Usage

```

simulate_model(model, iterations = 1000, ...)

## S3 method for class 'glmmTMB'
simulate_model(
  model,
  iterations = 1000,
  component = c("all", "conditional", "zi", "zero_inflated", "dispersion"),
  verbose = FALSE,
  ...
)

```

Arguments

model	Statistical model (no Bayesian models).
iterations	The number of draws to simulate/bootstrap.
...	Arguments passed to or from other methods.

component	Should all parameters, parameters for the conditional model, for the zero-inflated part of the model, or the dispersion model be returned? Applies to models with zero-inflated and/or dispersion component. component may be one of "conditional", "zi", "zero-inflated", "dispersion" or "all" (default). May be abbreviated.
verbose	Toggle warnings and messages.

Details

Technical Details: `simulate_model()` is a computationally faster alternative to `bootstrap_model()`. Simulated draws for coefficients are based on a multivariate normal distribution (`MASS::mvrnorm()`) with mean $\mu = \text{coef}(\text{model})$ and variance $\Sigma = \text{vcov}(\text{model})$.

Models with Zero-Inflation Component: For models from packages **glmmTMB**, **pscl**, **GLM-Madadaptive** and **countreg**, the `component` argument can be used to specify which parameters should be simulated. For all other models, parameters from the conditional component (fixed effects) are simulated. This may include smooth terms, but not random effects.

Value

A data frame.

See Also

[simulate_parameters\(\)](#), [bootstrap_model\(\)](#), [bootstrap_parameters\(\)](#)

Examples

```
model <- lm(Sepal.Length ~ Species * Petal.Width + Petal.Length, data = iris)
head(simulate_model(model))
```

```
if (require("glmmTMB", quietly = TRUE)) {
  model <- glmmTMB(
    count ~ spp + mined + (1 | site),
    ziformula = ~mined,
    family = poisson(),
    data = Salamanders
  )
  head(simulate_model(model))
  head(simulate_model(model, component = "zero_inflated"))
}
```

```
simulate_parameters.glmmTMB
  Simulate Model Parameters
```

Description

Compute simulated draws of parameters and their related indices such as Confidence Intervals (CI) and p-values. Simulating parameter draws can be seen as a (computationally faster) alternative to bootstrapping.

Usage

```
## S3 method for class 'glmmTMB'
simulate_parameters(
  model,
  iterations = 1000,
  centrality = "median",
  ci = 0.95,
  ci_method = "quantile",
  test = "p-value",
  ...
)

simulate_parameters(model, ...)

## Default S3 method:
simulate_parameters(
  model,
  iterations = 1000,
  centrality = "median",
  ci = 0.95,
  ci_method = "quantile",
  test = "p-value",
  ...
)
```

Arguments

model	Statistical model (no Bayesian models).
iterations	The number of draws to simulate/bootstrap.
centrality	The point-estimates (centrality indices) to compute. Character (vector) or list with one or more of these options: "median", "mean", "MAP" or "all".
ci	Value or vector of probability of the CI (between 0 and 1) to be estimated. Default to .95 (95%).
ci_method	The type of index used for Credible Interval. Can be "ETI" (default, see eti()), "HDI" (see hdi()), "BCI" (see bci()), "SPI" (see spi()), 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. <code>rope()</code> or <code>p_direction()</code>) and its results included in the summary output.
...	Arguments passed to or from other methods.

Details

Technical Details: `simulate_parameters()` is a computationally faster alternative to `bootstrap_parameters()`. Simulated draws for coefficients are based on a multivariate normal distribution (`MASS::mvrnorm()`) with mean `mu = coef(model)` and variance `Sigma = vcov(model)`.

Models with Zero-Inflation Component: For models from packages **glmmTMB**, **pscl**, **GLM-Madaptive** and **countreg**, the `component` argument can be used to specify which parameters should be simulated. For all other models, parameters from the conditional component (fixed effects) are simulated. This may include smooth terms, but not random effects.

Value

A data frame with simulated parameters.

Note

There is also a `plot()-method` implemented in the [see-package](#).

References

Gelman A, Hill J. Data analysis using regression and multilevel/hierarchical models. Cambridge; New York: Cambridge University Press 2007: 140-143

See Also

[bootstrap_model\(\)](#), [bootstrap_parameters\(\)](#), [simulate_model\(\)](#)

Examples

```
model <- lm(Sepal.Length ~ Species * Petal.Width + Petal.Length, data = iris)
simulate_parameters(model)

## Not run:
if (require("glmmTMB", quietly = TRUE)) {
  model <- glmmTMB(
    count ~ spp + mined + (1 | site),
    ziformula = ~mined,
    family = poisson(),
    data = Salamanders
  )
  simulate_parameters(model, centrality = "mean")
  simulate_parameters(model, ci = c(.8, .95), component = "zero_inflated")
}
```

```
## End(Not run)
```

```
sort_parameters      Sort parameters by coefficient values
```

Description

Sort parameters by coefficient values

Usage

```
sort_parameters(x, ...)

## Default S3 method:
sort_parameters(x, sort = "none", column = "Coefficient", ...)
```

Arguments

x	A data frame or a parameters_model object.
...	Arguments passed to or from other methods.
sort	If "none" (default) do not sort, "ascending" sort by increasing coefficient value, or "descending" sort by decreasing coefficient value.
column	The column containing model parameter estimates. This will be "Coefficient" (default) in <i>easystats</i> packages, "estimate" in <i>broom</i> package, etc.

Value

A sorted data frame or original object.

Examples

```
# creating object to sort (can also be a regular data frame)
mod <- model_parameters(stats::lm(wt ~ am * cyl, data = mtcars))

# original output
mod

# sorted outputs
sort_parameters(mod, sort = "ascending")
sort_parameters(mod, sort = "descending")
```

standardize_info *Get Standardization Information*

Description

This function extracts information, such as the deviations (SD or MAD) from parent variables, that are necessary for post-hoc standardization of parameters. This function gives a window on how standardized are obtained, i.e., by what they are divided. The "basic" method of standardization uses.

Usage

```
standardize_info(
  model,
  robust = FALSE,
  two_sd = FALSE,
  include_pseudo = FALSE,
  ...
)
```

Arguments

model	A statistical model.
robust	Logical, if TRUE, centering is done by subtracting the median from the variables and dividing it by the median absolute deviation (MAD). If FALSE, variables are standardized by subtracting the mean and dividing it by the standard deviation (SD).
two_sd	If TRUE, the variables are scaled by two times the deviation (SD or MAD depending on robust). This method can be useful to obtain model coefficients of continuous parameters comparable to coefficients related to binary predictors, when applied to the predictors (not the outcome) (Gelman, 2008).
include_pseudo	(For (G)LMMs) Should Pseudo-standardized information be included?
...	Arguments passed to or from other methods.

Value

A data frame with information on each parameter (see [parameters_type\(\)](#)), and various standardization coefficients for the post-hoc methods (see [standardize_parameters\(\)](#)) for the predictor and the response.

See Also

Other standardize: [standardize_parameters\(\)](#)

Examples

```
model <- lm(mpg ~ ., data = mtcars)
standardize_info(model)
standardize_info(model, robust = TRUE)
standardize_info(model, two_sd = TRUE)
```

standardize_parameters

Parameters standardization

Description

Compute standardized model parameters (coefficients).

Usage

```
standardize_parameters(  
  model,  
  method = "refit",  
  ci = 0.95,  
  robust = FALSE,  
  two_sd = FALSE,  
  include_response = TRUE,  
  verbose = TRUE,  
  ...  
)  
  
standardize_posteriors(  
  model,  
  method = "refit",  
  robust = FALSE,  
  two_sd = FALSE,  
  include_response = TRUE,  
  verbose = TRUE,  
  ...  
)
```

Arguments

model	A statistical model.
method	The method used for standardizing the parameters. Can be "refit" (default), "posthoc", "smart", "basic" or "pseudo". See 'Details'.
ci	Confidence Interval (CI) level
robust	Logical, if TRUE, centering is done by subtracting the median from the variables and dividing it by the median absolute deviation (MAD). If FALSE, variables are standardized by subtracting the mean and dividing it by the standard deviation (SD).

two_sd	If TRUE, the variables are scaled by two times the deviation (SD or MAD depending on robust). This method can be useful to obtain model coefficients of continuous parameters comparable to coefficients related to binary predictors, when applied to the predictors (not the outcome) (Gelman, 2008).
include_response	If TRUE (default), the response value will also be standardized. If FALSE, only the predictors will be standardized. For GLMs the response value will never be standardized (see <i>Generalized Linear Models</i> section).
verbose	Toggle warnings and messages on or off.
...	For <code>standardize_parameters()</code> , arguments passed to <code>model_parameters()</code> , such as: <ul style="list-style-type: none"> • <code>ci_method</code>, centrality for Mixed models and Bayesian models... • <code>exponentiate</code>, ... • etc.

Value

A data frame with the standardized parameters (`Std_*`, depending on the model type) and their CIs (`CI_low` and `CI_high`). Where applicable, standard errors (SEs) are returned as an attribute (`attr(x, "standard_error")`).

Standardization Methods

- **refit**: This method is based on a complete model re-fit with a standardized version of the data. Hence, this method is equal to standardizing the variables before fitting the model. It is the "purest" and the most accurate (Neter et al., 1989), but it is also the most computationally costly and long (especially for heavy models such as Bayesian models). This method is particularly recommended for complex models that include interactions or transformations (e.g., polynomial or spline terms). The robust (default to FALSE) argument enables a robust standardization of data, i.e., based on the median and MAD instead of the mean and SD. **See `standardize()` for more details.**
 - **Note** that `standardize_parameters(method = "refit")` may not return the same results as fitting a model on data that has been standardized with `standardize()`; `standardize_parameters()` used the data used by the model fitting function, which might not be same data if there are missing values. see the `remove_na` argument in `standardize()`.
- **posthoc**: Post-hoc standardization of the parameters, aiming at emulating the results obtained by "refit" without refitting the model. The coefficients are divided by the standard deviation (or MAD if robust) of the outcome (which becomes their expression 'unit'). Then, the coefficients related to numeric variables are additionally multiplied by the standard deviation (or MAD if robust) of the related terms, so that they correspond to changes of 1 SD of the predictor (e.g., "A change in 1 SD of x is related to a change of 0.24 of the SD of y). This does not apply to binary variables or factors, so the coefficients are still related to changes in levels. This method is not accurate and tend to give aberrant results when interactions are specified.
- **basic**: This method is similar to `method = "posthoc"`, but treats all variables as continuous: it also scales the coefficient by the standard deviation of model's matrix' parameter of factors levels (transformed to integers) or binary predictors. Although being inappropriate for these

cases, this method is the one implemented by default in other software packages, such as `lm.beta::lm.beta()`.

- **smart** (Standardization of Model's parameters with Adjustment, Reconnaissance and Transformation - *experimental*): Similar to `method = "posthoc"` in that it does not involve model refitting. The difference is that the SD (or MAD if robust) of the response is computed on the relevant section of the data. For instance, if a factor with 3 levels A (the intercept), B and C is entered as a predictor, the effect corresponding to B vs. A will be scaled by the variance of the response at the intercept only. As a results, the coefficients for effects of factors are similar to a Glass' delta.
- **pseudo** (*for 2-level (G)LMMs only*): In this (post-hoc) method, the response and the predictor are standardized based on the level of prediction (levels are detected with `performance::check_heterogeneity_bias`). Predictors are standardized based on their SD at level of prediction (see also `datawizard::demean()`); The outcome (in linear LMMs) is standardized based on a fitted random-intercept-model, where `sqrt(random-intercept-variance)` is used for level 2 predictors, and `sqrt(residual-variance)` is used for level 1 predictors (Hoffman 2015, page 342). A warning is given when a within-group variable is found to have access between-group variance.

Transformed Variables

When the model's formula contains transformations (e.g. $y \sim \exp(X)$) `method = "refit"` will give different results compared to `method = "basic"` ("`posthoc`" and "`smart`" do not support such transformations): While "`refit`" standardizes the data *prior* to the transformation (e.g. equivalent to `exp(scale(X))`), the "`basic`" method standardizes the transformed data (e.g. equivalent to `scale(exp(X))`).

See the *Transformed Variables* section in `standardize.default()` for more details on how different transformations are dealt with when `method = "refit"`.

Confidence Intervals

The returned confidence intervals are re-scaled versions of the unstandardized confidence intervals, and not "true" confidence intervals of the standardized coefficients (cf. Jones & Waller, 2015).

Generalized Linear Models

Standardization for generalized linear models (GLM, GLMM, etc) is done only with respect to the predictors (while the outcome remains as-is, unstandardized) - maintaining the interpretability of the coefficients (e.g., in a binomial model: the exponent of the standardized parameter is the OR of a change of 1 SD in the predictor, etc.)

Dealing with Factors

`standardize(model)` or `standardize_parameters(model, method = "refit")` do *not* standardize categorical predictors (i.e. factors) / their dummy-variables, which may be a different behaviour compared to other R packages (such as **lm.beta**) or other software packages (like SPSS). To mimic such behaviours, either use `standardize_parameters(model, method = "basic")` to obtain post-hoc standardized parameters, or standardize the data with `datawizard::standardize(data, force = TRUE)` *before* fitting the model.

References

- Hoffman, L. (2015). Longitudinal analysis: Modeling within-person fluctuation and change. Routledge.
- Jones, J. A., & Waller, N. G. (2015). The normal-theory and asymptotic distribution-free (ADF) covariance matrix of standardized regression coefficients: theoretical extensions and finite sample behavior. *Psychometrika*, 80(2), 365-378.
- Neter, J., Wasserman, W., & Kutner, M. H. (1989). Applied linear regression models.
- Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in medicine*, 27(15), 2865-2873.

See Also

Other standardize: [standardize_info\(\)](#)

Examples

```

model <- lm(len ~ supp * dose, data = ToothGrowth)
standardize_parameters(model, method = "refit")

standardize_parameters(model, method = "posthoc")
standardize_parameters(model, method = "smart")
standardize_parameters(model, method = "basic")

# Robust and 2 SD
standardize_parameters(model, robust = TRUE)
standardize_parameters(model, two_sd = TRUE)

model <- glm(am ~ cyl * mpg, data = mtcars, family = "binomial")
standardize_parameters(model, method = "refit")
standardize_parameters(model, method = "posthoc")
standardize_parameters(model, method = "basic", exponentiate = TRUE)

if (require("lme4")) {
  m <- lme4::lmer(mpg ~ cyl + am + vs + (1 | cyl), mtcars)
  standardize_parameters(m, method = "pseudo", ci_method = "satterthwaite")
}

## Not run:
if (require("rstanarm")) {
  model <- rstanarm::stan_glm(rating ~ critical + privileges, data = attitude, refresh = 0)
  standardize_posteriors(model, method = "refit")
  standardize_posteriors(model, method = "posthoc")
  standardize_posteriors(model, method = "smart")
  head(standardize_posteriors(model, method = "basic"))
}

## End(Not run)

```

standard_error	<i>Standard Errors</i>
----------------	------------------------

Description

standard_error() attempts to return standard errors of model parameters

Usage

```
standard_error(model, ...)  
  
## Default S3 method:  
standard_error(  
  model,  
  component = "all",  
  vcov = NULL,  
  vcov_args = NULL,  
  verbose = TRUE,  
  ...  
)  
  
## S3 method for class 'factor'  
standard_error(model, force = FALSE, verbose = TRUE, ...)  
  
## S3 method for class 'glmmTMB'  
standard_error(  
  model,  
  effects = "fixed",  
  component = "all",  
  verbose = TRUE,  
  ...  
)  
  
## S3 method for class 'merMod'  
standard_error(  
  model,  
  effects = "fixed",  
  method = NULL,  
  vcov = NULL,  
  vcov_args = NULL,  
  ...  
)
```

Arguments

model	A model.
...	Arguments passed to or from other methods.

component	Model component for which standard errors should be shown. See the documentation for your object's class in <code>model_parameters()</code> or <code>p_value()</code> for further details.
vcov	Variance-covariance matrix used to compute uncertainty estimates (e.g., for robust standard errors). This argument accepts a covariance matrix, a function which returns a covariance matrix, or a string which identifies the function to be used to compute the covariance matrix. <ul style="list-style-type: none"> • A covariance matrix • A function which returns a covariance matrix (e.g., <code>stats::vcov()</code>) • A string which indicates the kind of uncertainty estimates to return. <ul style="list-style-type: none"> – Heteroskedasticity-consistent: <code>"vcovHC"</code>, <code>"HC"</code>, <code>"HC0"</code>, <code>"HC1"</code>, <code>"HC2"</code>, <code>"HC3"</code>, <code>"HC4"</code>, <code>"HC4m"</code>, <code>"HC5"</code>. See <code>?sandwich::vcovHC</code>. – Cluster-robust: <code>"vcovCR"</code>, <code>"CR0"</code>, <code>"CR1"</code>, <code>"CR1p"</code>, <code>"CR1S"</code>, <code>"CR2"</code>, <code>"CR3"</code>. See <code>?clubSandwich::vcovCR</code>. – Bootstrap: <code>"vcovBS"</code>, <code>"xy"</code>, <code>"residual"</code>, <code>"wild"</code>, <code>"mammen"</code>, <code>"webb"</code>. See <code>?sandwich::vcovBS</code>. – Other sandwich package functions: <code>"vcovHAC"</code>, <code>"vcovPC"</code>, <code>"vcovCL"</code>, <code>"vcovPL"</code>.
vcov_args	List of arguments to be passed to the function identified by the <code>vcov</code> argument. This function is typically supplied by the sandwich or clubSandwich packages. Please refer to their documentation (e.g., <code>?sandwich::vcovHAC</code>) to see the list of available arguments.
verbose	Toggle warnings and messages.
force	Logical, if TRUE, factors are converted to numerical values to calculate the standard error, with the lowest level being the value 1 (unless the factor has numeric levels, which are converted to the corresponding numeric value). By default, NA is returned for factors or character vectors.
effects	Should standard errors for fixed effects (<code>"fixed"</code>), random effects (<code>"random"</code>), or both (<code>"all"</code>) be returned? Only applies to mixed models. May be abbreviated. When standard errors for random effects are requested, for each grouping factor a list of standard errors (per group level) for random intercepts and slopes is returned.
method	Method for computing degrees of freedom for confidence intervals (CI) and the related p-values. Allowed are following options (which vary depending on the model class): <code>"residual"</code> , <code>"normal"</code> , <code>"likelihood"</code> , <code>"satterthwaite"</code> , <code>"kenward"</code> , <code>"wald"</code> , <code>"profile"</code> , <code>"boot"</code> , <code>"uniroot"</code> , <code>"ml1"</code> , <code>"betwithin"</code> , <code>"hdi"</code> , <code>"quantile"</code> , <code>"ci"</code> , <code>"eti"</code> , <code>"si"</code> , <code>"bci"</code> , or <code>"bcai"</code> . See section <i>Confidence intervals and approximation of degrees of freedom</i> in <code>model_parameters()</code> for further details.

Value

A data frame with at least two columns: the parameter names and the standard errors. Depending on the model, may also include columns for model components etc.

Note

For Bayesian models (from **rstanarm** or **brms**), the standard error is the SD of the posterior samples.

Examples

```
model <- lm(Petal.Length ~ Sepal.Length * Species, data = iris)
standard_error(model)

if (require("sandwich") && require("clubSandwich")) {
  standard_error(model, vcov = "HC3")

  standard_error(model,
    vcov = "vcovCL",
    vcov_args = list(cluster = iris$Species)
  )
}
```

`standard_error_robust` *Robust standard errors. Superseded by the `vcov*` arguments in `standard_error()`*

Description

Robust standard errors. Superseded by the `vcov*` arguments in `standard_error()`

Usage

```
standard_error_robust(
  model,
  vcov = "HC3",
  vcov_args = NULL,
  component = "conditional",
  ...
)
```

Arguments

<code>model</code>	A model.
<code>vcov</code>	Variance-covariance matrix used to compute uncertainty estimates (e.g., for robust standard errors). This argument accepts a covariance matrix, a function which returns a covariance matrix, or a string which identifies the function to be used to compute the covariance matrix.

- A covariance matrix
- A function which returns a covariance matrix (e.g., `stats::vcov()`)
- A string which indicates the kind of uncertainty estimates to return.

- Heteroskedasticity-consistent: "vcovHC", "HC", "HC0", "HC1", "HC2", "HC3", "HC4", "HC4m", "HC5". See ?sandwich::vcovHC.
 - Cluster-robust: "vcovCR", "CR0", "CR1", "CR1p", "CR1S", "CR2", "CR3". See ?clubSandwich::vcovCR.
 - Bootstrap: "vcovBS", "xy", "residual", "wild", "mammen", "webb". See ?sandwich::vcovBS.
 - Other sandwich package functions: "vcovHAC", "vcovPC", "vcovCL", "vcovPL".
- vcov_args List of arguments to be passed to the function identified by the vcov argument. This function is typically supplied by the **sandwich** or **clubSandwich** packages. Please refer to their documentation (e.g., ?sandwich::vcovHAC) to see the list of available arguments.
- component Model component for which standard errors should be shown. See the documentation for your object's class in [model_parameters\(\)](#) or [p_value\(\)](#) for further details.
- ... Arguments passed to or from other methods.

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