

Package ‘MAIHDA’

July 9, 2026

Type Package

Title Multilevel Analysis of Individual Heterogeneity and
Discriminatory Accuracy

Version 0.2.1

Description Tools for Multilevel Analysis of Individual Heterogeneity and
Discriminatory Accuracy (MAIHDA) for intersectional inequality research.
Methods are described in Merlo (2018) <[doi:10.1016/j.socscimed.2017.12.026](https://doi.org/10.1016/j.socscimed.2017.12.026)>
and Evans et al. (2018) <[doi:10.1016/j.socscimed.2017.11.011](https://doi.org/10.1016/j.socscimed.2017.11.011)>. The package
creates intersectional strata, fits multilevel MAIHDA models, estimates
variance partition coefficients, proportional change in variance, stratum
effects, and discriminatory-accuracy summaries, and provides diagnostic and
presentation plots.

License MIT + file LICENSE

Encoding UTF-8

LazyData true

Depends R (>= 4.1.0)

Imports lme4 (>= 1.1-27), reformulas, cli, ggplot2 (>= 3.4.0), dplyr
(>= 1.0.0), tidyr (>= 1.1.0), generics, stats, rlang (>=
0.4.0), patchwork, ggrepel, tidyselect, tibble

Suggests shiny, bslib (>= 0.7.0), DT, future, promises, plotly, haven,
shinyjs, shinycssloaders, brms (>= 2.15.0), WeMix (>= 4.0.0),
ordinal, testthat (>= 3.0.0), knitr, MASS, rmarkdown

VignetteBuilder knitr

URL <https://github.com/hdbt/MAIHDA>, <https://hdbt.github.io/MAIHDA/>

BugReports <https://github.com/hdbt/MAIHDA/issues>

RoxygenNote 7.3.3

NeedsCompilation no

Author Hamid Bulut [aut, cre]

Maintainer Hamid Bulut <me@hamidbulut.com>

Repository CRAN

Date/Publication 2026-07-09 21:00:08 UTC

Contents

calculate_pcv	3
calculate_pvc	5
compare_maihda	6
compare_maihda_groups	7
fit_maihda	11
maihda	15
maihda_auc	21
maihda_country_data	22
maihda_cumulative	23
maihda_discriminatory_accuracy	24
maihda_glance	25
maihda_health_data	26
maihda_ic	27
maihda_interactions	29
maihda_long_data	31
maihda_mor	33
maihda_sim_data	34
maihda_sparse_data	34
maihda_table	36
maihda_tidiers	38
maihda_upset_size	39
maihda_vpc_response	40
make_strata	42
plot.maihda_analysis	43
plot.maihda_comparison	45
plot.maihda_group_comparison	46
plot.maihda_model	47
plot_prediction_deviation_panels	50
predict_maihda	51
print.maihda_analysis	53
print.maihda_group_comparison	53
print.maihda_ic	54
print.maihda_interactions	54
print.maihda_long_pcv	55
print.maihda_model	55
print.maihda_stepwise	56
print.maihda_strata	56
print.maihda_summary	57
print.maihda_table	57
print.pcv_result	58
run_maihda_app	58
stepwise_pcv	59
summary.maihda_analysis	61
summary.maihda_model	61
theme_maihda	64

calculate_pcv	<i>Calculate Proportional Change in Between-Stratum Variance (PCV)</i>
---------------	--

Description

Calculates the proportional change in between-stratum variance (PCV) between two MAIHDA models. The PCV measures how much the between-stratum variance changes when moving from one model to another, and is calculated as: $PCV = (Var_model1 - Var_model2) / Var_model1$.

Usage

```
calculate_pcv(
  model1,
  model2,
  bootstrap = FALSE,
  n_boot = 1000,
  conf_level = 0.95
)
```

Arguments

model1	A maihda_model object from fit_maihda(). This is the reference model (typically a simpler or baseline model).
model2	A maihda_model object from fit_maihda(). This is the comparison model (typically a more complex model with additional predictors).
bootstrap	Logical indicating whether to compute bootstrap confidence intervals for the PCV. Default is FALSE. lme4 engine only: the parametric bootstrap relies on lme4's simulate()/refit(), so for the brms, wemix, and ordinal engines the PCV is reported as a point estimate and bootstrap = TRUE is an error (see Details).
n_boot	Number of bootstrap samples if bootstrap = TRUE. Default is 1000.
conf_level	Confidence level for bootstrap intervals. Default is 0.95.

Details

The PCV is the proportional change in between-stratum variance when moving from model1 to model2: a positive value means model2 has lower between-stratum variance, a negative value means higher. It is the share of model1's between-stratum variance *explained* by model2 only in the canonical nested case, where model2 adds fixed-effect predictors to model1 on the same outcome, analytic sample and strata. The function does not require nesting, so for non-nested models the PCV is simply a model-dependent difference in variance, not an explained proportion.

REML vs ML. lmer fits Gaussian models by REML, whose between-stratum variance estimate is *not* comparable across models with different fixed effects – exactly the canonical null-vs-adjusted PCV, where the adjusted model adds the dimensions' main effects. calculate_pcv() therefore refits any REML lmer model with maximum likelihood (refitML) before reading the variances (and before the parametric bootstrap, so the interval matches), matching maihda_ic and anova()

on lme4 models. Using REML estimates here biases the PCV (it overstates the residual between-stratum variance of the adjusted model). GLMM fits (glmer) and the brms/wemix/ordinal engines are already on the maximum-likelihood scale and are unaffected; single-model VPC/ICC summaries keep their REML fit, since that comparison-free quantity is not subject to the pitfall.

Latent-scale families and rescaling. For families whose level-1 variance is a fixed latent-scale constant – binomial/Bernoulli ($\pi^2/3$ logit, 1 probit) and the cumulative (ordinal) model – the linear predictor is identified only up to scale. Adding predictors that explain *within-stratum* (individual-level) variation cannot shrink that fixed level-1 variance; the latent scale stretches instead, inflating the coefficients and the between-stratum variance alike (Bauer 2009; Mood 2010). Part of a null-vs-adjusted change in the between-stratum variance is then rescaling rather than genuinely explained variance, so latent-scale PCVs tend to be understated and can turn negative on this account alone. The canonical MAIHDA adjusted model – which adds the stratum dimensions’ main effects, constant *within* each stratum – is largely unaffected, but the caveat is first-order whenever an added predictor varies within strata (an individual-level covariate, as in the [stepwise_pcv](#) steps that add one). The count families’ level-1 variance is not a fixed constant, but as with any non-identity link the same non-collapsibility logic applies in attenuated form. Gaussian identity-link PCVs are not subject to this.

When `bootstrap = TRUE`, the function uses a parametric bootstrap: it simulates new responses from model2 and refits both models with `lme4::refit()` for each simulated response to obtain confidence intervals for the PCV estimate. For negative-binomial models (`glmer.nb`) `refit()` holds the dispersion parameter `theta` fixed at its original estimate, so the interval is conditional on the estimated `theta`.

The bootstrap is available for the lme4 engine only. For the other engines the PCV is a *point estimate*: a brms fit’s posterior credible interval (reported by [summary.maihda_model](#)) covers a single fit’s VPC/ICC, not the PCV, which compares two separately fitted models – no posterior interval for the PCV itself is computed – and a design-based (wemix) interval would require replicate weights.

Value

A list containing:

<code>pcv</code>	The estimated proportional change in variance
<code>pvc</code>	Deprecated duplicate of <code>pcv</code> , kept so code written against the historical <code>calculate_pvc()</code> spelling keeps working; it will be removed in a future release
<code>var_model1</code>	Between-stratum variance from model1
<code>var_model2</code>	Between-stratum variance from model2
<code>ci_lower</code>	Lower bound of confidence interval (if <code>bootstrap = TRUE</code>)
<code>ci_upper</code>	Upper bound of confidence interval (if <code>bootstrap = TRUE</code>)
<code>bootstrap</code>	Logical indicating if bootstrap was used

References

- Bauer, D. J. (2009). A note on comparing the estimates of models for cluster-correlated or longitudinal data with binary or ordinal outcomes. *Psychometrika*, 74(1), 97-105.
- Mood, C. (2010). Logistic regression: why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, 26(1), 67-82.

See Also

[stepwise_pcv](#) for the sequential (one-variable-at-a-time) PCV, and [maihda](#) which computes the canonical null-vs-adjusted PCV automatically.

Examples

```
# Create strata and fit two models
strata_result <- make_strata(maihda_sim_data, c("gender", "race"))
model1 <- fit_maihda(health_outcome ~ age + (1 | stratum), data = strata_result$data)
model2 <- fit_maihda(health_outcome ~ age + gender + (1 | stratum), data = strata_result$data)

# Calculate PCV without bootstrap
pcv_result <- calculate_pcv(model1, model2)
print(pcv_result$pcv)

# Calculate PCV with bootstrap CI
# pcv_boot <- calculate_pcv(model1, model2, bootstrap = TRUE, n_boot = 500)
# print(pcv_boot)
```

calculate_pvc	<i>Deprecated: use calculate_pcv()</i>
---------------	--

Description

`calculate_pvc()` is the former name of [calculate_pcv](#): the statistic is the PCV (proportional change in variance), but the historical function name transposed the acronym. `calculate_pvc()` now forwards to `calculate_pcv()` with a deprecation warning and will be removed in a future release.

Usage

```
calculate_pvc(
  model1,
  model2,
  bootstrap = FALSE,
  n_boot = 1000,
  conf_level = 0.95
)
```

Arguments

<code>model1</code>	A <code>maihda_model</code> object from <code>fit_maihda()</code> . This is the reference model (typically a simpler or baseline model).
<code>model2</code>	A <code>maihda_model</code> object from <code>fit_maihda()</code> . This is the comparison model (typically a more complex model with additional predictors).

bootstrap	Logical indicating whether to compute bootstrap confidence intervals for the PCV. Default is FALSE. lme4 engine only: the parametric bootstrap relies on lme4's <code>simulate()/refit()</code> , so for the brms , wemix , and ordinal engines the PCV is reported as a point estimate and <code>bootstrap = TRUE</code> is an error (see Details).
n_boot	Number of bootstrap samples if <code>bootstrap = TRUE</code> . Default is 1000.
conf_level	Confidence level for bootstrap intervals. Default is 0.95.

Value

See [calculate_pcv](#).

compare_maihda	<i>Compare MAIHDA Models</i>
----------------	------------------------------

Description

Compares variance partition coefficients (VPC/ICC) across multiple MAIHDA models, with optional bootstrap confidence intervals.

Usage

```
compare_maihda(
  ...,
  model_names = NULL,
  bootstrap = FALSE,
  n_boot = 1000,
  conf_level = 0.95,
  ic = TRUE
)
```

Arguments

...	Multiple <code>maihda_model</code> objects to compare.
model_names	Optional character vector of names for the models.
bootstrap	Logical; for lme4 models, compute parametric-bootstrap VPC confidence intervals. Default FALSE. It does not apply to brms models, which always return a posterior credible interval (so passing <code>bootstrap = TRUE</code> with brms models errors) – their interval is included regardless.
n_boot	Number of bootstrap samples if <code>bootstrap = TRUE</code> . Default is 1000.
conf_level	Confidence level for the VPC interval (lme4 bootstrap CI or brms credible interval). Default is 0.95.
ic	Logical; append relative-fit information criteria to the table for comparing model structures: AIC/BIC for the likelihood engines (lme4 , ordinal) and WAIC/LOOIC for brms (see maihda_ic). Default TRUE. REML lmer fits are refitted with ML so AIC/BIC are comparable across different fixed effects. Set FALSE for the lean VPC-only table.

Details

VPCs are only directly comparable when the models share an outcome, family/link, analytic sample, and strata – the canonical use is nested models (e.g. null vs covariate-adjusted) on the *same* data and strata, to show how the VPC attenuates. If the supplied models differ in any of these, `compare_maihda()` still returns the table but issues a single warning, because the VPCs are then not directly comparable. The same comparability caveat applies to the appended information criteria (see [maihda_ic](#)). In addition, when the appended criteria mix scales – likelihood AIC/BIC (lme4/ordinal) shown alongside Bayesian WAIC/LOOIC (brms), which can happen for a same-family lme4-vs-brms comparison that the family/link check does not flag – `compare_maihda()` warns, because those criteria are on different scales and are not comparable to each other.

Value

A `maihda_comparison` data frame of VPC/ICC by model. Interval columns (`ci_lower/ci_upper`) are included when any model supplies an interval – an lme4 bootstrap CI or a brms posterior credible interval. When `ic = TRUE`, information-criteria columns (AIC/BIC or WAIC/LOOIC, whichever apply) are appended.

Examples

```
# Canonical use: nested models on the SAME data and strata (null vs adjusted)
strata <- make_strata(maihda_sim_data, vars = c("gender", "race"))

null_model <- fit_maihda(health_outcome ~ 1 + (1 | stratum), data = strata$data)
adj_model  <- fit_maihda(health_outcome ~ age + (1 | stratum), data = strata$data)

# Compare without bootstrap
comparison <- compare_maihda(null_model, adj_model,
                             model_names = c("Null", "Adjusted"))

# Compare with bootstrap CI
comparison_boot <- compare_maihda(null_model, adj_model,
                                  model_names = c("Null", "Adjusted"),
                                  bootstrap = TRUE, n_boot = 500)
```

`compare_maihda_groups` *Compare MAIHDA Metrics Across Levels of a Grouping Variable*

Description

Fits a separate random-intercept MAIHDA model (intercept-only *random* effects; any fixed-effect covariates in formula are still used) within each level of a higher-level grouping variable (for example country, region, or survey wave) and reports how the variance partition coefficient (VPC/ICC) and the between-/within-stratum variance components differ across those groups. When the strata are defined by at least two dimensions it also fits the adjusted model (the dimensions' additive main effects) within each group and reports the per-group `pcv` – the proportional change in between-stratum variance, i.e. the additive share of that group's intersectional inequality.

Usage

```
compare_maihda_groups(
  formula,
  data,
  group,
  engine = "lme4",
  family = "gaussian",
  shared_strata = TRUE,
  min_group_n = 30,
  bootstrap = FALSE,
  n_boot = 1000,
  conf_level = 0.95,
  autobin = TRUE,
  decomposition = c("two-model", "crossed-dimensions"),
  context = NULL,
  sampling_weights = NULL,
  warn_linear = TRUE,
  ...
)
```

Arguments

formula	A model formula. Either the shorthand intersectional form <code>outcome ~ covars + (1 var1:var2)</code> (strata are built automatically) or <code>outcome ~ covars + (1 stratum)</code> when data already contains a <code>stratum</code> column from make_strata .
data	A data frame containing the variables in formula and the grouping variable.
group	Character string naming the grouping variable in data (e.g. "country"). A separate model is fitted for each non-missing level.
engine	Modeling engine, "lme4" (default), "brms", "wemix" (the design-weighted fit; requires <code>sampling_weights</code> and is selected automatically when they are supplied with the default engine), or "ordinal" (cumulative link mixed model via <code>ordinal::clmm()</code> ; selected automatically for an ordinal family or an ordered-factor outcome).
family	Model family. Default "gaussian". As in fit_maihda , a binary outcome is auto-detected once on the full data and switched to "binomial" (with a warning) so every group uses the same family.
shared_strata	Logical. When TRUE (default) intersectional strata are defined once on the full data so that a stratum denotes the same combination in every group; this makes the stratum <i>definitions</i> comparable across groups. Note that a group may still not contain every stratum, so two groups' VPCs can be estimated over different sets of populated strata – they are then not strictly directly comparable, and the function warns when this happens. When FALSE, strata are rebuilt independently within each group (stratum identities are then not comparable across groups at all).
min_group_n	Minimum size of the <i>analytic</i> sample a group must have – the rows that survive the model frame (covariate transformations applied, rows with a missing

	outcome/covariate dropped) – to be modelled. Groups with a smaller usable sample are skipped with a warning, even if they have more raw rows. Default 30.
bootstrap	Logical; compute per-group parametric-bootstrap VPC confidence intervals. lme4 engine only. Default FALSE.
n_boot	Number of bootstrap samples when bootstrap = TRUE. Default 1000.
conf_level	Confidence level for bootstrap intervals. Default 0.95.
autobin	Logical passed to make_strata controlling tertile binning of numeric grouping variables. Default TRUE.
decomposition	Per-group additive-vs-interaction decomposition: the two-model null -> adjusted PCV ("two-model", default) or the single crossed-dimensions model ("crossed-dimensions"; "cross-classified" is a deprecated alias that warns). The crossed-dimensions form requires shared_strata = TRUE and at least two stratum dimensions, and adds the var_additive, var_interaction, additive_share and interaction_share columns (in place of pcv / var_between_adjusted); var_between is then the total between-strata variance (additive + interaction). See maihda for the underlying model and its caveats.
context	Optional character vector naming higher-level <i>context</i> column(s) in data (e.g. "school", "region"). Each per-group fit then becomes a contextual cross-classified model – outcome ~ covars + (1 stratum) + (1 context) – so within every group the stratum random intercept is crossed with the context random intercept(s). vpc/var_between are then the between-stratum quantities <i>net of</i> the context, and two columns report the per-group context partition: var_context (the between-context variance, summed over contexts) and vpc_context (the contexts' share of the group's unexplained variance). The per-context split is kept on the "context_per" attribute. A per-group subset shrinks each context's level count, so groups with too few context levels (< 10) to identify the context variance are named in a single warning. Forwarded to fit_maihda ; not available for the wemix/ordinal engines (they fit no crossed random effect), and the context may not name the group variable itself.
sampling_weights	Optional name of a sampling-weight column in data for design-weighted per-group fits; see fit_maihda . The column is sliced with each group's rows, so every group is fitted with its own members' weights. Not compatible with engine = "lme4", bootstrap = TRUE, or (under the wemix engine) decomposition = "crossed-dimensions".
warn_linear	Logical; when TRUE (default) a one-time warning is emitted if a numeric stratum-defining dimension enters the per-group <i>adjusted</i> models as a raw linear slope rather than as categorical main effects, which silently changes the PCV/decomposition interpretation (see maihda_adjusted_terms). Set to FALSE internally when maihda delegates here, because it has already warned on the same data.
...	Additional arguments passed to fit_maihda (and on to lmer/glmer).

Details

It estimates one VPC per group as a stratified analysis: each group is modelled independently. It is *not* a cross-classified model and does not adjust the strata for the grouping variable.

The VPC is the *share* of the unexplained variance that lies between strata, not the absolute magnitude of intersectional inequality. Because it is a ratio, a group's VPC can differ from another's because the between-stratum variance differs, because the within-stratum (residual) variance differs, or both – two groups with the same between-stratum variance can have very different VPCs. To compare the absolute amount of between-stratum (intersectional) variation across groups, read the returned `var_between` column alongside the VPC rather than treating a higher VPC as "more inequality".

It is **descriptive**: it reports each group's VPC (with an interval when available – an lme4 bootstrap CI or a brms credible interval) for side-by-side comparison, but does not test whether the VPCs differ between groups. The per-group intervals describe each group's own uncertainty; whether two intervals overlap is *not* a valid test of the difference between their VPCs, which would require modelling that difference directly.

Robustness: a group whose *analytic* sample (rows surviving the model frame) has fewer than `min_group_n` observations is always skipped with a warning. A group with fewer than two populated strata is also skipped (VPC is undefined with a single stratum) when the stratum membership is known before fitting – that is, when `shared_strata = TRUE` or data already carries a stratum column. Under `shared_strata = FALSE` strata are rebuilt inside each group, so a degenerate single-stratum group is instead reported with a "fit failed" status rather than a pre-fit skip. A singular fit yields a VPC of 0 rather than an error (unlike `calculate_pcv`). A hard fit failure in one group records NA and a status note without aborting the whole comparison.

Fit-quality diagnostics: for the lme4 engine, groups whose model is singular or fails to converge keep a status of "ok" (the fit did complete) but are named in a single aggregated warning, because their VPC/ICC may be unreliable – a singular fit usually pins the between-stratum variance at the boundary, giving a VPC of 0.

Value

A data.frame of class `maihda_group_comparison` with one row per group and columns `group`, `n`, `n_strata`, `vpc`, `var_between`, `var_other`, `var_residual`, `status` (and `ci_lower/ci_upper` when `bootstrap = TRUE`). When the strata are defined by at least two dimensions, two further columns report the per-group null $\rightarrow$ adjusted decomposition: `pcv` (proportional change in between-stratum variance when the dimensions' additive main effects are added; computed on the maximum-likelihood scale – see `calculate_pcv` – because REML variances are not comparable across the null vs. adjusted fixed effects), `var_between_adjusted` (a *derived* coherence quantity, reported as `var_between * (1 - pcv)` so it shares the scale of the REML `var_between/vpc` and the table satisfies `pcv = (var_between - var_between_adjusted) / var_between` exactly – it is **not** the adjusted fit's own variance), and `var_between_adjusted_ml` (the adjusted model's *actual* between-stratum variance, read straight off the adjusted fit on the same maximum-likelihood scale as the PCV; it differs from `var_between_adjusted` only by the small REML-vs-ML gap in the null variance). All three are NA for a group whose adjusted fit failed, and the columns are omitted entirely when the strata have a single dimension. When context is supplied, two further columns report each group's contextual partition: `var_context` (the between-context variance, summed over contexts) and `vpc_context` (the contexts' share of the group's unexplained variance); the per-context split is on the "context_per" attribute and the context name(s) on "context_var". These are dropped when no context is supplied. `n` is the analytic sample size used by the model (after dropping rows with a missing outcome/covariate) for both fitted and skipped groups, falling back to the raw row count only when the model frame cannot be built. `var_other` is the variance of any additional random effects and is 0 for the canonical single-stratum model. Groups that were skipped or

failed have NA metrics and an explanatory status.

See Also

[compare_maihda](#) for comparing different models on the same data; [plot.maihda_group_comparison](#) for visualising the result.

Examples

```
data(maihda_country_data)
# How does gender x SES inequality in PISA math scores differ across countries?
cmp <- compare_maihda_groups(
  math ~ 1 + (1 | gender:ses),
  data = maihda_country_data,
  group = "country"
)
print(cmp)
plot(cmp, type = "vpc")
```

fit_maihda

Fit MAIHDA Model

Description

Fits a multilevel model for MAIHDA (Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy) using lme4, brms, WeMix (for design-weighted (survey) data), or – for an ordered-factor outcome – a cumulative link mixed model via `ordinal::clmm()`.

Usage

```
fit_maihda(
  formula,
  data,
  engine = "lme4",
  family = "gaussian",
  autobin = TRUE,
  context = NULL,
  sampling_weights = NULL,
  id = NULL,
  time = NULL,
  time_degree = 1,
  interactions = FALSE,
  ...
)
```

Arguments

formula	A formula specifying the model. Can include a random effect for stratum (e.g., <code>outcome ~ fixed_vars + (1 stratum)</code>) or can directly specify the intersection variables to be used for forming strata (e.g., <code>outcome ~ fixed_vars + (1 var1:var2:var3)</code>). If variables other than "stratum" are provided in the random effect, <code>make_strata</code> will be called internally to compute the strata and the formula will be updated.
data	A data frame containing the variables in the formula.
engine	Character string specifying which engine to use: "lme4" (default), "brms", "wemix" (design-weighted pseudo-maximum-likelihood via <code>WeMix::mix()</code> ; requires <code>sampling_weights</code>), or "ordinal" (cumulative link mixed model via <code>ordinal::clmm()</code> ; requires an ordinal family). When <code>sampling_weights</code> is supplied and engine is left at its default, the engine switches to "wemix" automatically (with a message); likewise an ordinal family (or an auto-detected ordered-factor outcome) switches the default engine to "ordinal".
family	Character string, family object, or family function specifying the model family. Common options: "gaussian", "binomial", "poisson", "negbinomial". Default is "gaussian". <code>family = "negbinomial"</code> fits an overdispersed count model with the dispersion parameter θ <i>estimated</i> from the data: lme4 via <code>lme4::glmer.nb()</code> and brms via its shape parameter (log link only; not supported by the wemix engine). A fixed- θ MASS::negative.binomial(θ) family object is also accepted with engine = "lme4" and is fitted with <code>glmer()</code> , honouring the supplied θ . <code>family = "ordinal"</code> (alias "cumulative"; or <code>mai_hda_cumulative("probit")</code> / <code>brms::cumulative()</code> for a non-logit link) fits a cumulative (proportional-odds) model for an <i>ordered-factor</i> outcome: <code>ordinal::clmm()</code> under the automatic "ordinal" engine, <code>brms::cumulative()</code> under engine = "brms". The VPC/ICC lives on the latent scale (level-1 variance $\pi^2/3$ logit / 1 probit, as for binomial models) and response-scale predictions are <i>expected category scores</i> (categories scored 1..K in order). An ordered-factor outcome with 3+ levels under the default family selects this model automatically, with a warning. The logit and probit links are supported; <code>sampling_weights</code> , <code>context</code> , and lme4-style <code>weights/subset/offset</code> arguments are not available on the clmm path. If the outcome variable appears to be binary and the default family is used, the function will automatically switch to "binomial", recode two-level responses to 0/1 for <code>glmer()</code> , and issue a warning. When a two-level non-0/1 response is recoded (on either the auto-detected or an explicit <code>family = "binomial"</code> path), the mapping follows the usual convention – the first level becomes 0 (reference) and the second becomes 1 (the modeled event), where "first/second" means alphabetical order for a character outcome and the declared order for a factor. The chosen mapping is reported via a <code>message()</code> and stored on the result as <code>\$response_recoding</code> ; set the factor levels (or supply a 0/1 outcome) to control which level is the event. Although any valid family object is accepted for fitting, the MAIHDA variance summaries (<code>summary.maihda_model</code> , VPC/ICC, PCV) are only defined for <code>gaussian("identity")</code> , the binomial/Bernoulli families with a logit or probit link, <code>poisson("log")</code> , and the negative binomial with a log link (level-1 variance $\log(1 + 1/\lambda + 1/\theta)$) at the <i>marginal</i> expected count λ ; Nakagawa, Johnson & Schielzeth 2017 – see <code>summary.maihda_model</code>

for how `lambda` is computed). Other families (for example `Gamma(link = "log")`) will fit, but `summary()` and the VPC/PCV helpers will stop with an "not implemented" error because no level-1 variance is defined for them.

autobin	Logical indicating whether numeric variables used only for automatic strata creation should be binned by <code>make_strata</code> . Default is TRUE.
context	Optional character vector naming one or more higher-level <i>context</i> columns in data (e.g. "school", "hospital", "region"). Each enters the model as a crossed intercept-only random effect alongside the intersectional stratum effect – outcome ~ covars + (1 stratum) + (1 context) – giving the <i>contextual cross-classified MAIHDA</i> of the literature (individuals cross-classified by stratum and place/institution). <code>summary.maihda_model</code> then partitions the unexplained variance into between-stratum vs. between-context vs. residual, and the headline VPC/ICC remains the between-stratum share (now net of the context). A context variable may not be a stratum dimension or "stratum" itself, and may not already appear as a fixed-effect term (its variance would then be absorbed by the fixed part). A context with few levels (say < 10) weakly identifies its variance and often yields a singular lme4 fit; the brms engine handles this better. Writing the random effect directly in the formula (... + (1 school)) fits the same model but is summarised generically as "Other random effects"; only context = activates the labelled contextual partition. Not supported by the wemix engine.
sampling_weights	Optional single character string naming a numeric column of data holding individual <i>sampling</i> (survey/design) weights, for a design-weighted MAIHDA on complex-survey data (e.g. NHANES, PISA). Sampling weights are not the same thing as lme4's weights= (precision weights, which rescale the residual variance), so combining sampling_weights with engine = "lme4" is an error. Two engines support them: • engine = "wemix" (chosen automatically when engine is left at its default): weighted pseudo-maximum-likelihood via <code>WeMix::mix()</code> (Rabe-Hesketh & Skrondal 2006), the estimator used for NAEP/PISA analysis. The individual weights enter at level 1 unchanged and the level-2 (stratum) weights are 1, because intersectional strata are exhaustive population cells included with certainty. Supports <code>gaussian(identity)</code> and <code>binomial(logit)</code> models with the canonical single (1 stratum) random intercept. Fixed-effect standard errors are design-consistent (sandwich); the VPC/PCV are reported as point estimates (no bootstrap – see <code>summary.maihda_model</code>). • engine = "brms": the weights enter the model as likelihood weights (y weights(w)), normalized to mean 1, giving a <i>pseudo-posterior</i>: point estimates target the population-weighted estimand but credible intervals are not design-based – interpret them cautiously. Full design-based (replicate-weight / linearised) variances for the variance components are not computed. Rows with a missing or non-positive sampling weight are dropped with a warning. The column names <code>.maihda_sw</code> (brms likelihood weight) and <code>.maihda_l2wt</code> (WeMix level-2 weight) are reserved for the design-weighted engines: they are written into the analytic data internally, so a model that supplies sampling_weights

	may not also reference a variable of either name in its formula (fitting would error). Default NULL (unweighted).
id	Optional single character string naming a person/unit identifier column for a longitudinal (growth-curve) MAIHDA on long-format data (one row per measurement occasion). Supplied together with time, it makes the model a 3-level growth curve – occasions within individuals (id) within intersectional strata – with a random intercept and slope on time at <i>both</i> the individual and stratum levels. The growth random effects are added automatically: write the strata shorthand (1 var1:var2) (or (1 stratum)) only, not the slopes. The between-stratum variance (and hence the VPC) then becomes a function of time; summary.maihda_model reports the time-varying VPC. Longitudinal fits are supported by engine = "lme4"/"brms" only (not wemix/ordinal), and are incompatible with context and sampling_weights. Default NULL (cross-sectional). See Bell, Evans, Holman & Leckie (2024).
time	Optional single character string naming a numeric measurement-time column (e.g. wave 0, 1, 2, ... or age), required for a longitudinal MAIHDA; see id. When the time axis does not start at 0 (age, calendar year, waves coded 10, 11, ...), the growth terms are fit on internally <i>centered</i> time (time - min(time), with a message): the raw polynomial basis over an offset range is ill-conditioned and can silently converge to a wrong solution. All results (the time-varying VPC, the PCV, plots, predictions) are reported on the original time scale; the column name .maihda_ctime is reserved for the internal centered variable. Default NULL.
time_degree	Polynomial degree of the growth curve when time is supplied: 1 (default) linear, 2 quadratic, etc. The brms engine supports degree 1 only.
interactions	Opt-in per-stratum interaction diagnostic (maihda_interactions), attached as the interactions slot and shown by print(). FALSE (default) skips it; TRUE computes it with the diagnostic's default correction (adjust = "BH"); or pass a p.adjust method name, including "none" for the uncorrected view. It is meaningful only on an <i>adjusted</i> model (the dimensions' main effects in the fixed part); on a null model maihda_interactions warns. This is the single-fit parallel to the default-on interactions of maihda .
...	Additional arguments passed to lmer/glmer (lme4), brm (brms), or WeMix::mix() (wemix; e.g. nQuad, fast). The lme4-style weights/subset/offset arguments are not supported by the wemix engine.

Value

A maihda_model object containing:

model	The fitted model object (lme4, brms, WeMix, or ordinal::clmm)
engine	The engine used ("lme4", "brms", "wemix", or "ordinal")
sampling_weights	The sampling-weight column name when supplied, NULL otherwise
formula	The model formula
data	The data used for fitting

family	The family used
strata_info	The strata information from make_strata() if available, NULL otherwise
context_vars	The context variable name(s) when context was supplied, NULL otherwise
interactions	The maihda_interactions diagnostic when interactions is not FALSE, NULL otherwise
response_recoding	For a recoded two-level outcome, a data frame mapping each original level to its 0/1 value and role (reference/event); NULL when no recoding occurred
diagnostics	Fit-quality diagnostics (singular fit / convergence) for lme4 models, surfaced by the print and summary methods

Examples

```
# Standard approach: manually create strata first
strata_result <- make_strata(maihda_sim_data, vars = c("gender", "race", "education"))
model <- fit_maihda(health_outcome ~ age + (1 | stratum),
  data = strata_result$data,
  engine = "lme4")

# Simplified approach: specify stratifying variables directly in the grouping structure
# The function internally calls make_strata() to create intersectionals
model2 <- fit_maihda(health_outcome ~ age + (1 | gender:race:education),
  data = maihda_sim_data,
  engine = "lme4")

# Contextual cross-classified MAIHDA: strata crossed with a higher-level
# context (here country) -- the literature's cross-classified MAIHDA.
data(maihda_country_data)
model3 <- fit_maihda(math ~ 1 + (1 | gender:ses),
  data = maihda_country_data,
  context = "country")
summary(model3) # between-stratum vs. between-country vs. residual
```

maihda

Run a Complete MAIHDA Analysis

Description

A single high-level entry point that runs the standard two-model MAIHDA workflow and returns one bundled object. It fits the **null** model (covariates plus the intersectional random intercept, *excluding* the stratum dimensions' main effects) and the **adjusted** model (the null plus the additive main effects of the stratum-defining dimensions), summarises the variance partition (VPC/ICC) of the null model, and reports the **PCV** – the proportional change in between-stratum variance from the null to the adjusted model, i.e. the additive share of the intersectional inequality. When a higher-level grouping variable is supplied it also compares this decomposition across that variable's levels.

Usage

```
maihda(
  formula,
  data,
  group = NULL,
  context = NULL,
  engine = "lme4",
  family = "gaussian",
  decomposition = c("two-model", "crossed-dimensions", "longitudinal"),
  autobin = TRUE,
  shared_strata = TRUE,
  min_group_n = 30,
  bootstrap = FALSE,
  n_boot = 1000,
  conf_level = 0.95,
  response_vpc = FALSE,
  seed = NULL,
  sampling_weights = NULL,
  id = NULL,
  time = NULL,
  time_degree = 1,
  interactions = TRUE,
  ...
)
```

Arguments

formula	A model formula, using either the intersectional shorthand <code>outcome ~ covars + (1 var1:var2)</code> or <code>... + (1 stratum)</code> when data already has a stratum column from make_strata . The dimensions' additive main effects may be listed (the fully-specified adjusted model) or omitted (added automatically, with a message); see Details.
data	A data frame with the model variables (and the group variable, if used).
group	Optional character string naming a higher-level grouping variable (e.g. "country"). When supplied, compare_maihda_groups is run and attached to the result. <code>group</code> runs a <i>stratified</i> analysis (one independent model per level); to instead model a higher level <i>jointly</i> , crossed with the strata, use <code>context</code> . The two are different designs but they <i>compose</i> : supplying both runs the stratified comparison where each per-group fit is itself a contextual cross-classified model (see <code>context</code>).
context	Optional character vector naming higher-level <i>context</i> column(s) in data (e.g. "school", "hospital", "region"), forwarded to fit_maihda . Each context enters every fitted model as a crossed random intercept – <code>outcome ~ covars + (1 stratum) + (1 context)</code> – the <i>contextual cross-classified MAIHDA</i> of the literature. The summaries then partition the unexplained variance into between-stratum vs. between-context vs. residual, the headline VPC/ICC becomes the between-stratum share <i>net of</i> the context, and the PCV decomposition is computed with the context partialled out (the context random intercept is carried

	by both the null and the adjusted model). May be combined with group: the stratified comparison then fits a contextual cross-classified model within each group and reports each group's stratum-vs-context partition (a per-group subset shrinks the context level count, so weak identification is warned about per group). Not available for the wemix/ordinal engines (they fit no crossed random effect); a context with few levels weakly identifies its variance (consider engine = "brms").
engine	Modeling engine, "lme4" (default), "brms", "wemix" (the design-weighted pseudo-maximum-likelihood fit; requires <code>sampling_weights</code> and is selected automatically when they are supplied with the default engine), or "ordinal" (cumulative link mixed model via <code>ordinal::clmm()</code> ; selected automatically for an ordinal family or an ordered-factor outcome).
family	Model family. Default "gaussian". As in <code>fit_maihda</code> , a binary outcome is auto-detected when family is left at the default, and the same resolved family is then used for the group comparison so all models agree.
decomposition	How to decompose the intersectional inequality into additive and interaction parts. "two-model" (default) is the classic MAIHDA approach: a null model and an adjusted model (the dimensions' additive main effects as <i>fixed</i> effects), with the additive share read from the PCV (proportional change in between-stratum variance). "crossed-dimensions" fits a single model that enters each dimension's additive main effect as a <i>random</i> intercept – outcome ~ covars + (1 dim1) + ... + (1 stratum) – so each dimension's RE variance is its additive contribution and the intersection (stratum) RE variance is the interaction beyond additive; the additive and interaction <i>shares</i> of the total between-strata variance are read directly from that one fit. The two modes target the same scientific question with different estimators, so their additive shares are conceptually parallel but not numerically identical. The crossed-dimensions additive share is a partial-pooling estimate: dimensions with few levels (e.g. a binary sex variable, whose variance is estimated from two groups) are poorly identified and often give a singular lme4 fit – the brms engine handles this better. See Details. ("cross-classified" is accepted as a deprecated alias for "crossed-dimensions", with a warning: in the MAIHDA literature "cross-classified" refers to the contextual stratum-by-place model, which this package fits via context.) "longitudinal" fits a 3-level growth-curve MAIHDA (requires id and time; selected automatically when they are supplied): a null and an adjusted growth model, where the adjusted model adds the dimensions' main effects <i>and their interactions with time</i> (dim:time). The between-stratum variance is then time-varying and the PCV is reported separately for the baseline (intercept) and the slope variance – the additive-vs-multiplicative split of the intersectional trajectory inequality (Bell, Evans, Holman & Leckie 2024). As with the two-model PCV, REML lmer growth fits are refitted with maximum likelihood before the null-vs-adjusted variance comparison (REML variances are not comparable across different fixed effects; see <code>calculate_pcv</code>), while the reported time-varying VPC keeps each fit's own (REML) estimate. See <code>fit_maihda</code> .
autobin	Logical passed to <code>make_strata</code> ; tertile-bins numeric grouping variables. Default TRUE.

shared_strata	Logical, forwarded to compare_maihda_groups when group is supplied: build strata once on the full data so VPCs are comparable across groups (TRUE, default) or rebuild them within each group.
min_group_n	Minimum group size for the per-group comparison, forwarded to compare_maihda_groups . Default 30.
bootstrap	Logical; compute parametric-bootstrap VPC confidence intervals (lme4 only) for both the overall summary and the per-group comparison. Default FALSE.
n_boot	Number of bootstrap samples when bootstrap = TRUE.
conf_level	Confidence level for bootstrap intervals. Default 0.95.
response_vpc	Logical; for a binomial (lme4) outcome, also attach the response-scale VPC (maihda_vpc_response) to the model summaries. It is estimated by simulation, so it is opt-in (default FALSE) and uses seed. The discriminatory accuracy (AUC + MOR) is attached automatically for a binomial/Bernoulli outcome regardless of this flag (see Details).
seed	Optional integer seed for the response-scale VPC simulation.
sampling_weights	Optional name of a sampling-weight column for a design-weighted MAIHDA on complex-survey data; see fit_maihda for the full semantics (engine selection, the pseudo-likelihood weighting, and what is/is not design-based). Both the null and the adjusted model (and any per-group fits) use the same weights, so the PCV is a design-weighted decomposition. Not compatible with engine = "lme4", decomposition = "crossed-dimensions" under the wemix engine, or bootstrap = TRUE.
id, time, time_degree	For a longitudinal MAIHDA: the person/unit identifier column, the numeric measurement-time column, and the growth-curve polynomial degree (1 = linear). Supplying id/time selects decomposition = "longitudinal". See fit_maihda for the model structure; group, context, and sampling_weights are not supported alongside them. Default NULL (cross-sectional).
interactions	Whether to compute the per-stratum interaction diagnostic (maihda_interactions) on the adjusted / crossed-dimensions model and attach it as the interactions slot, surfaced in <code>print()</code> . TRUE (default) uses the diagnostic's own default correction (<code>adjust = "BH"</code> , FDR – since scanning all strata is a screening question); FALSE skips it; or pass a p.adjust method name – including "none" for the uncorrected, per-stratum individual-testing view. Uses <code>conf_level</code> . Not computed for a longitudinal decomposition. The computation is cheap (it reads the stratum estimates the summary already holds; no refit).
...	Additional arguments passed to fit_maihda (and on to <code>lmer/glm</code>).

Details

Binomial companions. For a binary outcome the model summaries also carry the discriminatory accuracy (AUC / C-statistic and Median Odds Ratio) – the "DA" in MAIHDA – automatically, so the null model's strata-only AUC sits alongside its VPC; set `response_vpc = TRUE` to add the (simulation-based) response-scale VPC as well. These are read from `summary(x)` and the attached `summary_adjusted`, and the headline `print()` shows the null-model AUC.

This is a convenience wrapper around `fit_maihda`, `calculate_pcv`, `summary.maihda_model` and `compare_maihda_groups`. It is *intrinsically* a two-model decomposition and has no single-model mode – for a single fit (e.g. just the null-model VPC / discriminatory accuracy), call `fit_maihda` directly.

The dimensions' additive main effects. You may write them in the formula – the fully-specified, lme4-native adjusted model outcome $\sim \text{covars} + \text{var1} + \text{var2} + (1 \mid \text{var1}:\text{var2})$ – or omit them. Either way the null *excludes* the dimension main effects and the adjusted *includes* them: when the formula already lists them it is taken as the adjusted model and the null is derived by dropping them; when they are missing `maihda()` adds them to the adjusted model and emits a message() so the decomposition stays explicit. Only the *additive* main effects belong here: a fixed interaction among the stratum dimensions – $\text{var1} * \text{var2}$, which R expands to $\text{var1} + \text{var2} + \text{var1}:\text{var2}$ – duplicates the intersectional stratum random intercept (it absorbs the between-stratum variance into fixed cell means, which makes the PCV invalid), so it is **rejected with an error**. Write $\text{var1} + \text{var2}$; the intersection is estimated by the stratum random effect (and quantified by `decomposition = "crossed-dimensions"` or `maihda_interactions`). The dimensions themselves are read from the random term: the shorthand $(1 \mid \text{var1}:\text{var2})$ and `make_strata` both record them, and a numeric dimension that `make_strata()` auto-binned enters the adjusted model as its reconstructed tertile factor (matching the strata), not as a linear term. Because `maihda()` is intrinsically a decomposition, it **errors** (rather than returning a null-only result) when it cannot build the adjusted model – when the dimensions cannot be recovered (a hand-built stratum column records none) or there is only one dimension (no intersection to decompose). Use `fit_maihda` for those single-model fits.

Value

An object of class `maihda_analysis`: a list with

<code>model</code>	the fitted <code>maihda_model</code> (see <code>fit_maihda</code>); the null model in "two-model" mode, or the single crossed-dimensions model in "crossed-dimensions" mode
<code>summary</code>	the model's <code>maihda_summary</code> (VPC/ICC, variance components, stratum estimates; plus the additive/interaction decomposition in crossed-dimensions mode, and the stratum-vs-context context partition when context is supplied)
<code>model_adjusted</code>	the fitted adjusted <code>maihda_model</code> ("two-model" and "longitudinal" modes; NULL otherwise)
<code>summary_adjusted</code>	the adjusted model's <code>maihda_summary</code> , or NULL
<code>pcv</code>	the proportional change in variance: the <code>pcv_result</code> from <code>calculate_pcv</code> in "two-model" mode, or a <code>maihda_long_pcv</code> (the intercept/slope and time-specific PCV) in "longitudinal" mode; NULL otherwise. Both are computed on the maximum-likelihood scale (REML lmer fits are ML-refitted for the comparison; see <code>calculate_pcv</code>)
<code>decomposition</code>	the additive/interaction partition (additive and interaction variances and shares, per-dimension variances; "crossed-dimensions" mode only, NULL otherwise)
<code>groups</code>	a <code>maihda_group_comparison</code> when group is supplied, otherwise NULL
<code>interactions</code>	the <code>maihda_interactions</code> diagnostic (per-stratum interaction BLUPs and flags) when interactions is not FALSE, otherwise NULL
<code>mode</code>	"two-model", "crossed-dimensions", or "longitudinal"

context_vars the context variable name(s) when context was supplied, otherwise NULL
 formula, adjusted_formula, group_var, call
 bookkeeping for printing

Numeric stratum dimensions

The stratum-defining dimensions are categorical. A factor or character dimension enters the adjusted model as a categorical main effect, and a numeric dimension with more than 10 unique values is tertile-binned when autobin = TRUE (see [make_strata](#)). A numeric dimension that is *not* auto-binned – a category code such as education = 1, 2, 3 (few unique values), or a many-valued numeric fitted with autobin = FALSE – enters the adjusted model as a single *linear* fixed effect rather than categorical main effects, which changes the PCV/decomposition interpretation. `maihda()` therefore **warns** in that case (for three or more distinct values – a binary numeric dimension is exempt, since with two levels a linear term and a factor are equivalent): wrap category codes in `factor()` before fitting, or, for a genuinely continuous variable, use it as a covariate rather than a stratum dimension.

See Also

[fit_maihda](#) for the single-model fitter, [compare_maihda_groups](#) for the group comparison, and [summary.maihda_model](#) for the variance summary.

Examples

```
data(maihda_health_data)

# One call: null + adjusted fit, VPC summary, and PCV decomposition. Writing the
# dimensions' additive main effects (Gender + Race) gives the fully-specified
# adjusted model; maihda() derives the null by dropping them.
a <- maihda(BMI ~ Age + Gender + Race + (1 | Gender:Race), data = maihda_health_data)
a                                     # VPC (null) and PCV (null -> adjusted)
a$pcv                                # proportional change in between-stratum variance
a$formula                            # null: BMI ~ Age + (1 | stratum)
a$adjusted_formula                    # adjusted: null + Gender + Race main effects

# Omitting them is equivalent -- maihda() adds them to the adjusted model and
# emits a message; the null and PCV are identical to the explicit form above.
a0 <- maihda(BMI ~ Age + (1 | Gender:Race), data = maihda_health_data)

plot(a, type = "vpc")                 # null model
plot(a, type = "effect_decomp")       # adjusted model (additive vs intersectional)

# Crossed-dimensions decomposition: one model, the dimensions' main effects entered
# as RANDOM intercepts. The additive and interaction shares of the between-strata
# variance are read directly from the single fit (no null/adjusted pair).
cc <- maihda(BMI ~ Age + (1 | Gender:Race), data = maihda_health_data,
             decomposition = "crossed-dimensions")
cc                                     # VPC and additive/interaction shares
cc$decomposition$additive_share        # crossed-dimensions analogue of the PCV
cc$formula                             # BMI ~ Age + (1|Gender) + (1|Race) + (1|stratum)
```

```
# Add a higher-level grouping variable to also compare across its levels.
# maihda_country_data has a real country grouping (PISA achievement data):
data(maihda_country_data)
a2 <- maihda(math ~ 1 + (1 | gender:ses), data = maihda_country_data,
             group = "country")
a2
plot(a2, type = "group_vpc")
plot(a2, type = "group_pcv")

# Contextual cross-classified MAIHDA: instead of one model per country (group=),
# model the strata CROSSED with country in a single fit. The summary partitions
# the unexplained variance into between-stratum vs. between-country vs. residual,
# and the PCV is computed with country partialled out.
a3 <- maihda(math ~ 1 + (1 | gender:ses), data = maihda_country_data,
             context = "country")
a3
a3$summary$context$vpv_context_total # the country (general contextual) share
plot(a3, type = "context_vpc")
```

maihda_auc

Area under the ROC curve (C-statistic), rank-based

Description

Computes the AUC / C-statistic as the Mann-Whitney U statistic: the probability that a randomly chosen case ($y == 1$) is assigned a higher predicted value than a randomly chosen non-case ($y == 0$), with ties counting as one half. This needs no external package. An AUC of 0.5 is chance; 1 is perfect separation.

Usage

```
maihda_auc(prob, y)
```

Arguments

prob	Numeric vector of predicted probabilities (or any score where larger means more case-like).
y	Observed binary outcome as 0/1 numeric or logical, the same length as prob.

Value

A single number in $[0, 1]$, or NA_real_ if either class is absent.

References

Merlo, J., Wagner, P., Ghith, N., & Leckie, G. (2016). An original stepwise multilevel logistic regression analysis of discriminatory accuracy: the case of neighbourhoods and health. *PLOS ONE*, 11(4), e0153778.

Examples

```
maihda_auc(c(0.1, 0.4, 0.35, 0.8), c(0, 0, 1, 1))
```

maihda_country_data	<i>Cross-National Educational Achievement Data for MAIHDA</i>
---------------------	---

Description

A cross-national dataset for demonstrating how Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) can be used to compare intersectional inequality *across* a higher-level grouping variable (here, country) with [compare_maihda_groups](#) and [maihda](#). Each row is a 15-year-old student; the intersectional strata are formed by gender and socioeconomic status (ses), and the outcome is the PISA mathematics score.

Usage

```
maihda_country_data
```

Format

A data frame with 3,600 rows (600 students in each of 6 countries) and 7 variables:

country Factor; one of Finland, Germany, United Kingdom, Italy, Japan, Mexico. The higher-level grouping variable.

gender Factor; student gender (female/male). A stratum dimension.

ses Factor; socioeconomic status as global tertiles (Low/Medium/High) of *escs*, computed on the pooled sample so a band means the same in every country. A stratum dimension.

escs Numeric; the PISA index of economic, social and cultural status (the continuous measure underlying *ses*).

math Numeric; PISA mathematics score (first plausible value). The primary outcome.

reading Numeric; PISA reading score (first plausible value).

low_math Factor; "Yes" if math is below 420 (PISA proficiency Level 2 baseline), else "No". A binary outcome for logistic examples.

Details

Intersectional inequality (the between-stratum share of variance, VPC/ICC) in mathematics achievement differs across the six countries, which is what makes the dataset a useful showcase for the group-comparison workflow.

The intersectional strata are `gender:ses` ($2 \times 3 = 6$ strata). A canonical MAIHDA "null" model is $\text{math} \sim 1 + (1 \mid \text{gender:ses})$; comparing its VPC across countries quantifies how much joint gender-by-class inequality in achievement varies between countries.

Note

This is a teaching/illustration dataset only. It uses a single PISA plausible value for each score and does **not** carry the PISA survey weights or complex sampling design, so results are **not** survey-representative and should not be used for substantive cross-national inference. (For your own survey data, the package supports design-weighted MAIHDA via the `sampling_weights` argument of `fit_maihda` / `maihda`.)

Source

Derived from the OECD Programme for International Student Assessment (PISA) 2018 student questionnaire data (OECD (2019), *PISA 2018 Database*), accessed and cleaned via the **learning-tower** R package (MIT licensed), <https://CRAN.R-project.org/package=learningtower>. A balanced random subsample of 600 complete-case students per country was taken (seed 2026). The data preparation script is in `data-raw/maihda_country_data.R`.

Examples

```
data(maihda_country_data)

# Compare intersectional (gender x SES) inequality across countries
analysis <- maihda(
  math ~ 1 + (1 | gender:ses),
  data = maihda_country_data,
  group = "country"
)
analysis
plot(analysis, type = "group_vpc")
```

maihda_cumulative	<i>Cumulative (ordinal) family marker for MAIHDA models</i>
-------------------	---

Description

Specifies a cumulative (proportional-odds) model for an ordinal outcome in `fit_maihda` / `maihda`, with a choice of link: `maihda_cumulative("logit")` (the default, equivalent to `family = "ordinal"`) or `maihda_cumulative("probit")`. It plays the role a stats family object plays for the other families – there is no cumulative family constructor in stats, and using `brms::cumulative()` would require brms for a frequentist fit.

Usage

```
maihda_cumulative(link = c("logit", "probit"))
```

Arguments

link	The cumulative link: "logit" (default) or "probit". These are the links for which the latent-scale VPC is defined (level-1 variance $\pi^2/3$ and 1 respectively).
------	--

Value

A family marker list with elements family = "cumulative" and link.

See Also

[fit_maihda](#)

Examples

```
maihda_cumulative()
maihda_cumulative("probit")
```

```
maihda_discriminatory_accuracy
```

Discriminatory accuracy of a binary MAIHDA model

Description

Bundles the individual-level discriminatory-accuracy summaries for a binomial MAIHDA model: the AUC / C-statistic (how well the model's predicted probabilities separate cases from non-cases) and the Median Odds Ratio. Applied to a strata-only (null) model, the AUC is the discriminatory accuracy of the intersectional strata themselves – Merlo's central quantity; comparing it with an adjusted model shows whether individual covariates beyond stratum membership sharpen classification. The AUC is computed for any binomial link; the Median Odds Ratio is reported only for the logit link and is NA otherwise (e.g. for a probit fit), since the MOR is an odds-ratio-scale quantity.

Aggregated-binomial fits are supported on both engines that fit them – an lme4 cbind(success, failure) response and a brms y | trials(n) response: the AUC is the count-weighted C-statistic over the implied individual-level 0/1 data, and n_case / n_control are the total successes / failures.

Usage

```
maihda_discriminatory_accuracy(model)
```

Arguments

model	A maihda_model from fit_maihda fitted with a binomial family – including an aggregated response (an lme4 cbind(success, failure) or a brms y trials(n)) – or the bernoulli family a binary 0/1 outcome is fit with under engine = "brms".
-------	---

Value

An object of class maihda_da: a list with auc, mor, n_case, n_control, family, link and engine. mor is NA for a non-logit binomial link, where the AUC is still reported. For an aggregated-binomial fit n_case / n_control are the total successes / failures.

References

Merlo, J. (2018). Multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) within an intersectional framework. *Social Science & Medicine*, 203, 74-80.

See Also

[maihda_auc](#), [maihda_mor](#)

Examples

```
# Obese (Yes/No) by intersectional strata of Gender x Race
strata <- make_strata(maihda_health_data, vars = c("Gender", "Race"))
d <- maihda_health_data
d$stratum <- strata$data$stratum
m <- fit_maihda(Obese ~ (1 | stratum), data = d, family = "binomial")
maihda_discriminatory_accuracy(m)
```

maihda_glance

Glance at a MAIHDA model or analysis

Description

[glance](#) methods that return the MAIHDA headline as a one-row tibble: the variance partition coefficient (VPC/ICC), and – for a `maihda_analysis` – the proportional change in variance (PCV), plus the additive/interaction shares and the discriminatory accuracy (AUC, MOR) for a binomial outcome. The layout is uniform across the `lme4`, `brms`, `WeMix` and `ordinal` engines. No other package emits this row from the underlying fit, because PCV needs the null+adjusted pair that only a `maihda_analysis` holds.

Usage

```
## S3 method for class 'maihda_summary'
glance(x, ...)

## S3 method for class 'maihda_model'
glance(x, ...)

## S3 method for class 'maihda_analysis'
glance(x, ...)
```

Arguments

<code>x</code>	A <code>maihda_summary</code> , <code>maihda_model</code> , or <code>maihda_analysis</code> .
<code>...</code>	Unused, for S3 consistency.

Value

A one-row tibble. `glance.maihda_analysis` adds `pcv` (with `pcv.conf.low/pcv.conf.high` when bootstrapped or from a `brms` posterior), the adjusted-model `auc.adjusted`, `nobs`, `family` and `mode` to the columns produced for a single summary.

See Also

[maihda_tidiers](#) for the per-estimate `tidy()` methods.

Examples

```
data("maihda_health_data")
a <- maihda(BMI ~ Age + Gender + Race + Education + (1 | Gender:Race:Education),
            data = maihda_health_data)
glance(a)
```

maihda_health_data	<i>NHANES Health Data Subset for MAIHDA Use</i>
--------------------	---

Description

A pedagogical subset of the National Health and Nutrition Examination Survey (NHANES) dataset, serving as a real-world example for Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA). Contains selected records demonstrating intersectional demographic health inequalities.

Usage

```
maihda_health_data
```

Format

A data frame with 3,000 rows and 7 variables:

BMI Body Mass Index (kg/m^2), a continuous outcome variable.

Obese Factor indicating obesity status (No/Yes).

Age Age in years at screening, a continuous covariate.

Gender Gender of the participant (male/female).

Race Self-reported race/ethnicity.

Education Educational attainment level.

Poverty Poverty to income ratio, a continuous covariate. Some values may be missing.

Note

This is a teaching/illustration dataset only. It is a non-random subsample and does **not** carry the NHANES survey weights or complex sampling design, so results are **not** survey-representative and should not be used for substantive population inference. (For your own survey data, the package supports design-weighted MAIHDA via the `sampling_weights` argument of `fit_maihda / maihda`.)

Source

Derived from the NHANES R package. Original data collected by the Centers for Disease Control and Prevention (CDC).

Examples

```
data(maihda_health_data)

# Example usage:
# strata_result <- make_strata(maihda_health_data, vars = c("Gender", "Race", "Education"))
# model <- fit_maihda(BMI ~ Age + (1 | stratum), data = strata_result$data)
```

maihda_ic	<i>Information criteria for MAIHDA models</i>
-----------	---

Description

Reports the relative-fit information criteria for one or more MAIHDA models, to help choose between model *structures* (different covariate sets, strata definitions, or families) – a question the VPC/ICC and PCV do not address. The criteria reported depend on the engine: **AIC** and **BIC** for the likelihood engines (lme4, and ordinal::clmm), and the Bayesian **WAIC** and **LOOIC** (leave-one-out information criterion) for brms. Lower is better for all four.

Usage

```
maihda_ic(..., model_names = NULL)
```

Arguments

- ... One or more maihda_model objects (from `fit_maihda`) or maihda_analysis objects (from `maihda`). A maihda_analysis contributes its null model and, when present, its adjusted model as separate rows.
- model_names Optional character vector of names, one per ... argument. A maihda_analysis argument's null/adjusted rows are suffixed from its name.

Details

REML vs ML. lmer fits Gaussian models by REML by default, and a REML log-likelihood (hence its AIC/BIC) is *not* comparable across models with different fixed effects – exactly the canonical MAIHDA null-vs-adjusted comparison. When more than one model is supplied, maihda_ic() therefore refits any REML lmer model with maximum likelihood ([refitML](#)) before computing AIC/BIC, matching the behaviour of anova() on lme4 models; the estimator column records when this happened. For a single model the criterion is reported as fitted (the estimator column then reads "REML").

Comparability. Like the VPC, information criteria are only comparable across models fitted to the *same* analytic sample (same rows and outcome). AIC/BIC additionally require the same response distribution – they are not comparable across families (e.g. a Gaussian vs a Poisson fit), nor between the likelihood engines and brms (AIC/BIC vs WAIC/LOOIC are different scales). maihda_ic() does not enforce this; [compare_maihda](#) warns when the supplied models differ in outcome, sample, or family.

Design-weighted fits. For the wemix (design-weighted) engine the criteria are reported as NA: a pseudo-likelihood with sampling weights does not define a standard AIC/BIC.

Value

A data.frame of class maihda_ic with one row per model and the columns that apply: model, n (analytic sample size), estimator, df (number of parameters; likelihood engines), logLik, AIC, BIC (likelihood engines), WAIC, LOOIC (brms), and – when more than one model is supplied – delta (the difference from the best model on the primary criterion: AIC for the likelihood engines, LOOIC for brms). Columns that are entirely NA across the supplied models are dropped.

See Also

[compare_maihda](#), which reports these criteria alongside the VPC/ICC, and [calculate_pcv](#) for the variance decomposition.

Examples

```
strata <- make_strata(maihda_sim_data, vars = c("gender", "race"))
null_model <- fit_maihda(health_outcome ~ 1 + (1 | stratum), data = strata$data)
adj_model <- fit_maihda(health_outcome ~ age + (1 | stratum), data = strata$data)

# AIC/BIC for two nested structures (REML lmer fits are ML-refitted first)
maihda_ic(null_model, adj_model, model_names = c("Null", "Adjusted"))

# Or straight from a one-call maihda() analysis (null + adjusted rows)
a <- maihda(health_outcome ~ age + gender + race + (1 | gender:race),
            data = maihda_sim_data)
maihda_ic(a)
```

maihda_interactions *Flag strata with credibly non-zero intersectional interaction*

Description

Reports, for each intersectional stratum, the **interaction** component of its outcome – the stratum random effect (BLUP) of an *adjusted* MAIHDA model, i.e. how far the stratum departs from the additive main-effects prediction of its defining dimensions – and **flags** the strata whose interaction is credibly different from zero. This is the heart of "where is there genuine intersectionality": a flagged stratum is one whose joint identity produces an outcome the additive parts do not.

Usage

```
maihda_interactions(object, conf_level = 0.95, adjust = "BH", rope = NULL, ...)
```

Arguments

object	A <code>maihda_analysis</code> from maihda (preferred – its adjusted / crossed-dimensions model is used automatically) or a <code>maihda_model</code> from fit_maihda (which should be the <i>adjusted</i> model; a null model is accepted but warned about).
conf_level	Confidence / credible level for the interval and the flag. Default 0.95.
adjust	Multiple-comparison adjustment for the per-stratum p-values (frequentist engines only): "BH" (default; false-discovery rate) or any method accepted by p.adjust , including "none" for the uncorrected, per-stratum individual-testing view. Ignored for brms (which uses the posterior tail directly; a message is shown only if you set it explicitly).
rope	Optional equivalence region (a "smallest interaction of interest") for an "is the interaction <i>negligible</i> ?" reading (Schuirmann 1987; Kruschke 2018), on the link (latent) scale. NULL (default) gives only the usual zero-centred flag. A single positive number <i>d</i> means the symmetric region <code>c(-d, d)</code> ; or supply <code>c(lower, upper)</code> . When set, the result gains a decision column classifying each stratum from its <code>conf_level</code> interval relative to the region: "relevant" (interval entirely outside it), "negligible" (entirely inside it), or "inconclusive" (straddling a bound).
...	Currently unused.

Details

It must be read off the adjusted model. Only when the dimensions' additive main effects are in the model (the *adjusted* model of the two-model decomposition, or the crossed-dimensions model) does the stratum random effect isolate the *pure interaction*. On a null model the stratum random effect is the total between-stratum deviation (additive + interaction), so passing one is flagged with a warning. The opposite mis-specification is flagged too: a model that adds a *fixed* interaction among the dimensions (e.g. `var1 * var2`) absorbs the intersectional effect into fixed cell means, so the stratum random effect is no longer the pure interaction. Passing a [maihda](#) result uses the right model automatically.

Frequentist vs. Bayesian evidence. For the frequentist engines (lme4, wemix, ordinal) the flag comes from the BLUP's conditional standard error: a Wald interval at `conf_level` and a two-sided p-value, with an optional multiplicity correction (`adjust`). For brms the full posterior is already available, so the *exact* posterior tail is used – a credible interval at `conf_level` and the probability of direction $pd = \max(P(BLUP > 0), P(BLUP < 0))$ (in $[0.5, 1]$; the sign is in `direction`) – and `adjust` is not applied (the Bayesian answer is multiplicity-free).

Multiplicity: partial pooling and a correction are different things, and the experts disagree.

- *Shrinkage (magnitude/sign).* The stratum BLUP is partially pooled, so extreme values are regularised toward the grand mean, attenuating exaggerated-magnitude and wrong-sign (Type M/S) error (Gelman & Carlin 2014). Gelman, Hill & Yajima (2012) argue this shrinkage *usually substitutes* for a classical multiple-comparisons correction (the problem can "disappear entirely" in the hierarchical model); on that view the flag/no-flag step itself is what to avoid – the null of an *exactly* zero interaction is rarely the question (McShane, Gelman et al. 2019) – so report the estimate and its interval.
- *Whether to correct.* If you do want an error-rate screen, whether a correction is warranted depends on the *inferential structure* of the claim – the joint hypothesis, not the number of strata (Rubin 2021). Each stratum as its own pre-specified hypothesis ("does *this* stratum interact?") is *individual* testing and needs none – **only** if you do not also read the flags collectively. Once the question is "is there an interaction *somewhere*?" – which an automated all-strata scan effectively is – it is *disjunction* testing and a correction applies.

`adjust = "BH"` **is the default:** fitting and flagging every stratum in one call is the disjunction/screening case, where controlling the expected *proportion* of false discoveries (FDR) is the appropriate goal. Pass `adjust = "none"` only when each stratum is a genuine, pre-specified individual hypothesis. The FDR choice (over family-wise "bonferroni"/"holm") is this package's, matching that screening goal; it is not a recommendation of Rubin (2021), who raises FDR only to distinguish it from the family-wise rate. The flag itself is a Wald test on a shrunken BLUP whose conditional SE treats the variance components as known, so it (and any `adjust` on it) is an explicit, approximate *screen*, not a procedure inheriting an exact guarantee from the model. Lead with the interval (and, for brms, the probability of direction); the substantive question is often not whether an interaction differs from zero but whether it exceeds a smallest interaction of interest (an equivalence reading; Schuirmann 1987; Kruschke 2018), read from the interval.

The interaction is reported on the model's link (latent) scale – a log-odds deviation for a logistic model, etc. – because the additive/interaction split is only exact there.

Value

An object of class `maihda_interactions` (a data frame), one row per stratum, sorted flagged-first then by `abs(interaction)`. Columns common to every engine: `stratum`, `label`, `n` (stratum size), `interaction` (the BLUP), `lower/upper` (the interval), `flagged` (logical), and `direction` ("above"/"below" the additive expectation). Frequentist fits add `se` and `p_value` (and `p_adjusted` when `adjust != "none"`); brms adds `pd` (probability of direction, $\max(P(>0), P(<0))$ in $[0.5, 1]$). When `rope` is set, a decision column ("relevant"/"negligible"/"inconclusive") is added. Attributes record `conf_level`, `adjust`, `rope`, `engine`, `model_type`, `n_strata`, `n_flagged`, `scale` and `singular`.

References

- Evans, C. R., Williams, D. R., Onnela, J. P., & Subramanian, S. V. (2018). A multilevel approach to modeling health inequalities at the intersection of multiple social identities. *Social Science & Medicine*, 203, 64-73.
- Merlo, J. (2018). Multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) within an intersectional framework. *Social Science & Medicine*, 203, 74-80.
- Gelman, A., Hill, J., & Yajima, M. (2012). Why we (usually) don't have to worry about multiple comparisons. *Journal of Research on Educational Effectiveness*, 5(2), 189-211.
- Gelman, A., & Carlin, J. (2014). Beyond power calculations: assessing Type S (sign) and Type M (magnitude) errors. *Perspectives on Psychological Science*, 9(6), 641-651.
- Rubin, M. (2021). When to adjust alpha during multiple testing: a consideration of disjunction, conjunction, and individual testing. *Synthese*, 199(3-4), 10969-11000. doi:10.1007/s11229021-032764
- McShane, B. B., Gal, D., Gelman, A., Robert, C., & Tackett, J. L. (2019). Abandon statistical significance. *The American Statistician*, 73(sup1), 235-245.
- Schuirman, D. J. (1987). A comparison of the two one-sided tests procedure and the power approach for assessing the equivalence of average bioavailability. *Journal of Pharmacokinetics and Biopharmaceutics*, 15(6), 657-680.
- Kruschke, J. K. (2018). Rejecting or accepting parameter values in Bayesian estimation. *Advances in Methods and Practices in Psychological Science*, 1(2), 270-280.

See Also

`maihda`, `calculate_pcv`, `summary.maihda_model`; and `plot(..., highlight_interactions = TRUE)` to mark the flagged strata on the effect-decomposition / predicted / shrinkage plots.

Examples

```
data(maihda_health_data)
a <- maihda(BMI ~ Age + Gender + Race + (1 | Gender:Race),
            data = maihda_health_data)
maihda_interactions(a) # FDR-screened (default adjust = "BH")
maihda_interactions(a, adjust = "none") # uncorrected per-stratum individual view
maihda_interactions(a, rope = 0.1) # equivalence: |interaction| within 0.1?
```

Description

A simulated long-format (one row per person-occasion) panel for demonstrating **longitudinal / growth-curve MAIHDA** (`fit_maihda(id =, time =)` and `maihda(decomposition = "longitudinal")`). 600 individuals are each measured over five waves on a continuous wellbeing score, within 12 intersectional strata defined by gender x ethnicity x education. The between-stratum *trajectory* differences are constructed to be mostly additive (each dimension's main effect on the baseline level and on the rate of change) with one genuine multiplicative interaction, so the longitudinal PCV – a high but sub-1 PCV_slope – is demonstrable.

Usage

```
maihda_long_data
```

Format

A data frame with 3000 rows (600 persons x 5 waves) and 8 variables:

id Person identifier (level 2); repeated across waves.

wave Measurement occasion, 0 to 4 (the numeric time variable).

gender Gender (Women/Men); a stratum dimension.

ethnicity Ethnicity (EthA/EthB/EthC); a stratum dimension.

education Education (Low/High); a stratum dimension.

age Baseline age in years, a time-invariant covariate.

wellbeing Continuous wellbeing outcome (the growth-curve response).

low_wellbeing Binary companion outcome (1 = bottom 40% of wellbeing), for the logistic longitudinal path.

Source

Simulated for the purpose of the MAIHDA package. The growth structure follows the longitudinal MAIHDA of Bell, Evans, Holman & Leckie (2024) [doi:10.1016/j.socscimed.2024.116955](https://doi.org/10.1016/j.socscimed.2024.116955).

Examples

```
data(maihda_long_data)

# Time-varying VPC from a 3-level growth model:
m <- fit_maihda(wellbeing ~ wave + (1 | gender:ethnicity:education),
               data = maihda_long_data, id = "id", time = "wave")
summary(m)

# Additive-vs-multiplicative PCV (null vs adjusted growth model):
a <- maihda(wellbeing ~ wave + (1 | gender:ethnicity:education),
            data = maihda_long_data, id = "id", time = "wave",
            decomposition = "longitudinal")
a$pcv
```


maihda_mor

*Median Odds Ratio (MOR) for a logistic MAIHDA model***Description**

The Median Odds Ratio translates the between-stratum variance of a logistic MAIHDA model onto the odds-ratio scale: the median relative change in the odds of the outcome when comparing two individuals from randomly chosen strata (higher- vs lower-risk). $MOR = \exp(\sqrt{2 * V_A} * qnorm(0.75))$, where V_A is the between-stratum (latent, logit-scale) variance. An MOR of 1 indicates no between-stratum heterogeneity. The MOR is defined only for the **logit** link (it is the median *odds* ratio); a non-logit binomial fit such as probit is rejected, because its latent variance is on a different scale and the $\exp(\dots)$ above would not be an odds ratio.

For a **cumulative-logit** (ordinal) MAIHDA model the same formula applies to the latent logit-scale between-stratum variance and is the *median cumulative odds ratio*: the median relative change in the odds of being at or below any given outcome category between two randomly chosen strata (under the model's proportional-odds assumption it is the same for every category split).

Usage

```
maihda_mor(model)
```

Arguments

model A maihda_model from [fit_maihda](#) fitted with a binomial (lme4), bernoulli (brms), or cumulative (ordinal) family and a **logit** link.

Value

A single number (the MOR, ≥ 1), or NA_real_ if the between-stratum variance is unavailable.

References

Larsen, K., & Merlo, J. (2005). Appropriate assessment of neighborhood effects on individual health: integrating random and fixed effects in multilevel logistic regression. *American Journal of Epidemiology*, 161(1), 81-88.

See Also

[maihda_discriminatory_accuracy](#)

maihda_sim_data	<i>Simulated Health Data for MAIHDA Use</i>
-----------------	---

Description

A simulated dataset for demonstrating Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA).

Usage

```
maihda_sim_data
```

Format

A data frame with 500 rows and 7 variables:

id Unique participant identifier.
gender Gender of the participant.
race Simulated race/ethnicity category.
education Educational attainment level.
age Age in years, a continuous covariate.
health_outcome A continuous simulated health outcome.
binary_outcome A binary version of the health outcome.

Source

Simulated for the purpose of the MAIHDA package.

Examples

```
data(maihda_sim_data)
strata_result <- make_strata(maihda_sim_data, vars = c("gender", "race", "education"))
```

maihda_sparse_data	<i>Sparse Intersectional Data for Bayesian MAIHDA</i>
--------------------	---

Description

A simulated cross-sectional dataset built to showcase **Bayesian (brms) MAIHDA for sparse intersections** – the regime where many intersectional strata each hold only a handful of individuals. There the maximum-likelihood (lme4) estimate of the **interaction** between-stratum variance collapses to a singular fit with no uncertainty, so the additive-vs-interaction split is both unstable and falsely precise; weakly-informative priors (`engine = "brms"`) regularise the variance off the boundary and return a calibrated credible interval.

Usage

```
maihda_sparse_data
```

Format

A data frame with 240 rows and 6 variables:

gender Strata dimension (Women/Men).

ethnicity Strata dimension (White/Black/Asian).

education Strata dimension (Low/High).

age_group Strata dimension (Young/Mid/Older).

y A continuous (Gaussian) outcome. True between-stratum VPC 0.26, of which 40% is the interaction.

event A binary outcome (No/Yes), ~46% "Yes". Its latent-scale between-stratum VPC is 0.31, again 40% interaction.

The exact generative truth is also attached as `attr(maihda_sparse_data, "truth")` (additive/interaction variances, shares, and VPCs for each outcome).

Details

The data carry a **known, non-trivial interaction** so the vignette can claim *recovery* rather than merely report numbers: 4 dimensions form 36 intersectional strata with deliberately skewed sizes (median 6 individuals, 12 of 36 cells below 5, two singletons), and the true interaction accounts for **40 between-stratum variance** on both outcomes. On the binary outcome a genuine 40 interaction is read by lme4 as roughly 3 that is purely a small-cell artifact.

Note

A purely illustrative dataset. The dimension labels are arbitrary and the interaction is constructed, not estimated from any real population – its only purpose is to make the sparse-cell behaviour of the ML and Bayesian estimators visible against a known answer.

Source

Simulated; see `data-raw/maihda_sparse_data.R`.

Examples

```
data(maihda_sparse_data)
attr(maihda_sparse_data, "truth")$gaussian$interaction_share # 0.40

# ML over-shrinks the interaction under sparse cells (a singular fit):
# m_lme4 <- maihda(y ~ 1 + (1 | gender:ethnicity:education:age_group),
#               data = maihda_sparse_data, decomposition = "crossed-dimensions")
#
# Weakly-informative priors regularise it and report honest uncertainty:
# m_brms <- maihda(y ~ 1 + (1 | gender:ethnicity:education:age_group),
#               data = maihda_sparse_data, decomposition = "crossed-dimensions",
```

```
#           engine = "brms",
#           prior = brms::set_prior("normal(0, 0.5)", class = "sd"))
# See vignette("bayesian_sparse_maihda").
```

maihda_table

Canonical MAIHDA results table and ranked-strata table

Description

Assembles the two standard MAIHDA write-up deliverables from a fitted analysis in one call: (a) a **model-results table** contrasting the null and adjusted models (intercept, between-stratum variance and SD, VPC/ICC, the PCV, and – for a binary outcome – the AUC and Median Odds Ratio), and (b) a **ranked-strata table** ordering the intersectional strata by their predicted outcome, so the best- and worst-off strata can be read directly. It introduces no new estimator: the model-results table reuses the quantities from `summary()` (calling `summary()` itself for a bare `fit_maihda` model), and the ranked-strata table reuses the same stratum predictions as `plot(type = "predicted")`, so the table agrees exactly with `summary()` and `plot()`.

Usage

```
maihda_table(
  x,
  n_strata = 10L,
  scale = c("response", "link"),
  which = c("null", "adjusted"),
  digits = 3,
  ...
)
```

Arguments

<code>x</code>	A <code>maihda_analysis</code> from <code>maihda</code> (the usual input), or a single <code>maihda_model</code> from <code>fit_maihda</code> .
<code>n_strata</code>	Number of strata to show at each end (top and bottom) in the printed ranked-strata table. The returned <code>\$strata</code> holds all strata (NULL for a longitudinal fit, whose strata are trajectories rather than single ranked values – see <code>\$strata</code> in <code>Value</code>). Default 10.
<code>scale</code>	Scale for the predicted stratum values: "response" (default) or "link". For a cumulative (ordinal) model the response scale is the expected category score.
<code>which</code>	For a two-model analysis, which model's predictions to rank the strata by: "null" (default) or "adjusted". Ignored for a crossed-dimensions analysis or a single model.
<code>digits</code>	Number of decimal places for the <code>print()</code> method. Default 3.
<code>...</code>	For a <code>maihda_model</code> input, additional arguments passed to <code>summary.maihda_model</code> (e.g. <code>bootstrap = TRUE</code>); ignored for a <code>maihda_analysis</code> input, whose summaries are already computed.

Details

The model-results table is mostly numeric and export-ready (e.g. `write.csv(maihda_table(a)$models, ...)` or pass it to `knitr::kable()`): statistics are rows, models are columns, and each estimate has accompanying `*_lower/*_upper` columns that hold the confidence/credible interval when one is available (the VPC bootstrap or posterior interval, and the bootstrap PCV interval) and NA otherwise. The intercept and the variance/SD rows are point estimates. The `print()` method renders the same table in the familiar “estimate [low, high]” layout.

For a “crossed-dimensions” analysis (one model, no null/adjusted pair) the results table has a single estimate column and gains “Additive share” / “Interaction share” rows instead of the PCV. For a contextual cross-classified analysis (`maihda(context = )`) it gains a “Context share (VPC)” row. A bare `fit_maihda` model is also accepted and yields a single-model table (no PCV).

The ranked-strata table ranks every stratum by its model-predicted outcome (on the scale requested), using the same stratum predictions as `plot(type = "predicted")`: the predicted value carries the conditional (random-effect) interval, and the stratum random effect (BLUP) is reported alongside it. By default the ranking uses the **null** model – the headline intersectional inequality (which strata fare best/worst overall); set `which = "adjusted"` to rank by the adjusted model instead. The full ranked table is returned in `$strata`; `print()` shows the top and bottom `n_strata`.

Value

An object of class `maihda_table`: a list with

<code>models</code>	a data frame of the model-results table (statistics in rows; one estimate column per model, each with <code>*_lower/*_upper</code> interval columns)
<code>strata</code>	a data frame of all strata ranked by predicted outcome, with rank, stratum, label, n, the predicted value and its conditional interval, and the stratum random effect and its interval. NULL when a single ranked value per stratum is not defined – in particular for a longitudinal (growth-curve) fit, whose strata are trajectories (see <code>strata_note</code>) – or if the stratum predictions could not otherwise be computed
<code>strata_note</code>	a character note explaining why <code>strata</code> is NULL (e.g. a longitudinal fit), or NULL when a ranked-strata table was produced
<code>models_note</code>	a character note (or NULL) flagging that the PCV was computed from maximum-likelihood-refitted between-stratum variances while the variance/VPC rows are each model’s own (REML) estimate, so the PCV need not equal the reduction implied by the displayed variance rows; see calculate_pcv
<code>model_keys, model_labels</code>	the estimate-column keys and their display labels
<code>family, engine, mode, scale, ranked_by, n_obs, n_strata_total, context_vars</code>	metadata used by <code>print()</code>

See Also

[maihda](#), [summary.maihda_model](#), [calculate_pcv](#), [maihda_discriminatory_accuracy](#).

Examples

```
data(maihda_health_data)
a <- maihda(BMI ~ Age + Gender + Race + (1 | Gender:Race), data = maihda_health_data)

tab <- maihda_table(a)
tab          # printed: model-results table + top/bottom strata
tab$models   # the numeric, export-ready results table
tab$strata   # all strata ranked by predicted BMI

# write.csv(tab$models, "results.csv", row.names = FALSE)
```

maihda_tidiers	<i>Tidy a MAIHDA summary, model, or analysis</i>
----------------	--

Description

[tidy](#) methods that return the MAIHDA estimates as a tidy tibble, ready for downstream tables (gt, flextable) and ggplot2. They read the slots that [summary.maihda_model](#) already computes and add no new statistics.

Usage

```
## S3 method for class 'maihda_summary'
tidy(x, component = c("strata", "variance", "fixed"), ...)

## S3 method for class 'maihda_model'
tidy(x, component = c("strata", "variance", "fixed"), ...)

## S3 method for class 'maihda_analysis'
tidy(
  x,
  component = c("strata", "variance", "fixed"),
  which = c("null", "adjusted"),
  ...
)
```

Arguments

x	A maihda_summary (from summary), a maihda_model (from fit_maihda), or a maihda_analysis (from maihda).
component	Which estimates to return: "strata" (default) the stratum (intersection) random-effect estimates – one row per stratum, with estimate, std.error and conf.low/conf.high, plus the human-readable intersectional label when available.

	"variance" the variance-components table (between-stratum, any other random effects, residual, and total) with each component's variance, SD and proportion.
	"fixed" the fixed-effect estimates, in broom's term/estimate/std.error shape (with conf.low/conf.high for the brms engine).
...	Unused, for S3 consistency.
which	For a maihda_analysis, whether to tidy the "null" (default) or "adjusted" model's summary.

Value

A tibble. For component = "strata": columns stratum, label, estimate, std.error, conf.low, conf.high. For "variance": component, variance, sd, proportion. For "fixed": term, estimate, std.error, conf.low, conf.high.

See Also

[glance.maihda_analysis](#) for the one-row model summary.

Examples

```
data("maihda_health_data")
m <- fit_maihda(BMI ~ Age + (1 | Gender:Race:Education), data = maihda_health_data)
tidy(m) # stratum estimates
tidy(m, component = "variance")
tidy(m, component = "fixed")
```

maihda_upset_size	<i>Recommended Figure Size for the UpSet Stratum Plot</i>
-------------------	---

Description

Computes sensible width and height (in inches) for plot(object, type = "upset"), so a knitr chunk or [ggsave\(\)](#) call can size the figure to its content. The UpSet composite grows *taller* with the number of matrix rows (one per binary 0/1 dimension, one per level of a multi-level factor) and *wider* with the number of strata columns shown, so a single fixed size tends to crop or stretch it – particularly for multi-level designs (many rows) or a large n_strata (many columns; UpSet is an inherently wide format).

Usage

```
maihda_upset_size(object, n_strata = 50)
```

Arguments

object	A maihda_model from fit_maihda or a maihda analysis from maihda ; it must carry the per-dimension stratum table from make_strata .
n_strata	Maximum number of strata the plot will show – pass the same value you give <code>plot()</code> . NULL means all strata. Default 50.

Value

A list with numeric width and height (inches) plus the rows (matrix rows) and cols (strata shown) they derive from.

See Also

[plot.maihda_model](#)

Examples

```
strata <- make_strata(maihda_sim_data, vars = c("gender", "race"))
model <- fit_maihda(health_outcome ~ (1 | stratum), data = strata$data)
sz <- maihda_upset_size(model, n_strata = 30)
ggplot2::ggsave(
  tempfile(fileext = ".png"),
  plot(model, type = "upset", n_strata = 30),
  width = sz$width, height = sz$height)
```

maihda_vpc_response	<i>Response-scale VPC for a binomial MAIHDA model</i>
---------------------	---

Description

Computes the variance partition coefficient on the response (probability) scale for a binomial MAIHDA model, using the simulation method of Goldstein, Browne & Rasbash (2002). Stratum random effects $u \sim N(0, \sigma_u^2)$ are simulated and converted to predicted probabilities $p = g^{-1}(\eta + u)$ (with η the fixed-part linear predictor); the VPC is then the between-stratum variance of p as a share of the total (between + the binomial within-stratum variance $\overline{p(1-p)}$).

Unlike the latent-scale VPC (fixed level-1 variance $\pi^2/3$ for the logit), the response-scale VPC depends on the overall outcome prevalence, so report it as a complement to – not a replacement for – the latent-scale value.

Usage

```
maihda_vpc_response(model, n_sim = 10000, seed = NULL)
```


Arguments

model	A binomial maihda_model (lme4 engine) from fit_maihda .
n_sim	Number of Monte-Carlo draws of the stratum random effect (≥ 100). Default 10000.
seed	Optional integer seed for reproducibility.

Details

The fixed part η is collapsed to a single value – the mean linear predictor $\bar{\eta}$ over the analytic sample – before the random effect is simulated around it. The result is therefore a VPC *evaluated at the mean covariate profile* (a conditional-at-mean estimate), not one marginalised over the empirical covariate distribution. For the canonical strata-only (null) model η is constant (the intercept), so the two coincide and the value is exact. For an *adjusted* model (one with covariates) they can differ, because the inverse link is nonlinear and $g^{-1}(\bar{\eta}) \neq \overline{g^{-1}(\eta)}$: read the response-scale VPC from the null model, or interpret an adjusted value as conditional on the average covariate profile rather than as a covariate-averaged (marginal) VPC.

The method is binomial-link agnostic: it maps the simulated stratum effects through whichever inverse link the model uses (logit, probit, cloglog, ...), so a non-logit binomial fit is computed on its own scale rather than rejected. Only the family is required to be binomial.

Value

An object of class maihda_vpc_response: a list with estimate, scale = "response", method = "simulation", n_sim, var_between (the latent-scale between-stratum variance) and lp_fixed (the mean fixed-part linear predictor).

References

Goldstein, H., Browne, W., & Rasbash, J. (2002). Partitioning variation in multilevel models. *Understanding Statistics*, 1(4), 223-231.

See Also

[maihda_discriminatory_accuracy](#), [summary.maihda_model](#)

Examples

```
strata <- make_strata(maihda_health_data, vars = c("Gender", "Race"))
d <- maihda_health_data
d$stratum <- strata$data$stratum
m <- fit_maihda(Obese ~ (1 | stratum), data = d, family = "binomial")
maihda_vpc_response(m, seed = 1)
```

make_strata

*Create Strata from Multiple Variables***Description**

This function creates strata (intersectional categories) from multiple categorical variables in a dataset.

Usage

```
make_strata(data, vars, sep = " × ", min_n = 1, autobin = TRUE)
```

Arguments

data	A data frame containing the variables to create strata from.
vars	Character vector of variable names to use for creating strata.
sep	Separator to use between variable values when creating stratum labels. Default is " \u00d7 " (a mathematical multiplication sign).
min_n	Minimum number of observations required for a stratum to be included. Strata with fewer observations will be coded as NA. Default is 1.
autobin	Logical indicating whether to automatically bin numeric grouping variables with more than 10 unique values into 3 categories (tertiles). Default is TRUE. When this happens a message() is emitted, because the resulting strata are data-dependent (tertile cut-points depend on the sample) and a continuous variable placed in the grouping term is usually unintended. Set autobin = FALSE to disable, or bin the variable yourself for explicit, reproducible cut-points.

Details

If any of the specified variables has a missing value (NA) for a given observation, that observation will be assigned to the NA stratum (stratum = NA), rather than creating a stratum that includes the missing value.

The strata_info data frame is also attached as an attribute to the data, which allows fit_maihda() to automatically capture stratum labels for use in plots and summaries.

When autobin discretises a numeric grouping variable *v*, the adjusted-model and prediction machinery later add an internal factor column named .maihda_dim_<*v*>; the .maihda_dim_ prefix is therefore reserved. make_strata() errors if data already holds the .maihda_dim_<*v*> column for a variable it is about to auto-bin, so an existing user column is never silently overwritten (rename it, or pass autobin = FALSE).

A numeric grouping variable with 10 or fewer unique values (or any numeric when autobin = FALSE) is kept as its raw values: distinct values still define distinct strata, but the variable is *not* binned. If such a variable is then used to build an adjusted MAIHDA ([maihda](#)), it enters the adjusted model as a linear fixed effect rather than categorical main effects, and maihda() warns (when it has three or more distinct values). Wrap category codes in factor() before creating strata if you want them treated categorically.

Value

A list with two elements:

data	The original data frame with an added 'stratum' column. The strata_info is also attached as an attribute for use by fit_maihda()
strata_info	A data frame with information about each stratum including counts and the combination of variable values

Examples

```
# Create strata from gender and race variables
result <- make_strata(maihda_sim_data, vars = c("gender", "race"))
print(result$strata_info)
```

plot.maihda_analysis *Plot a MAIHDA Analysis*

Description

Dispatches each type to the model it is valid on. The VPC and shrinkage views ("vpc", "obs_vs_shrunken", "predicted") use the **null** model by default; for type = "vpc" the model argument selects the null model, the adjusted model, or "both" – one combined plot that shows the null-to-adjusted change with the PCV annotated. The additive-vs-intersectional views ("effect_decomp", "prediction_deviation") use the **adjusted** model, whose fixed effects carry the dimensions' additive part so the stratum random effect is the pure interaction; with fewer than two dimensions (no adjusted model) they fall back to the null model. Group types ("group_vpc", "group_components", "group_between_variance", "group_pcv", "group_additive_share") use the group comparison when **maihda** was called with a group.

Usage

```
## S3 method for class 'maihda_analysis'
plot(
  x,
  type = "all",
  highlight_interactions = FALSE,
  only_flagged = FALSE,
  highlight_by = c("flag", "rope"),
  rope = NULL,
  select = c("order", "deviation"),
  order_by = c("predicted_desc", "stratum", "predicted_asc", "deviation"),
  model = c("null", "adjusted", "both"),
  ...
)
```

Arguments

x	A maihda_analysis object from maihda .
type	One of the model types ("all", "vpc", "obs_vs_shrunken", "predicted", "upset" (the UpSet-style alternative to "predicted"; forwards quantity via ...), "effect_decomp", "prediction_deviation"), the contextual type ("context_vpc", a stratum-vs-context variance bar; requires maihda(context =)), a longitudinal type ("vpc_trajectory", "trajectories", "pcv_trajectory"; requires decomposition = "longitudinal"), or a group type ("group_vpc", "group_components", "group_between_variance", "group_pcv", "group_additive_share"). Default "all". For a longitudinal analysis "all" shows the VPC-over-time, the stratum trajectories, and the time-specific PCV.
highlight_interactions	Highlight strata with a credibly non-zero intersectional interaction on the BLUP-based views (see maihda_interactions and plot). FALSE (default), TRUE (computed from this analysis's adjusted / crossed-dimensions model), a multiple-testing method such as "BH", or a maihda_interactions object. The flags are computed once from the correct (adjusted) model and reused across views.
only_flagged	Show only the highlighted strata on the "predicted" and "obs_vs_shrunken" views instead of dimming the rest (see plot). FALSE (default) keeps every stratum; TRUE restricts those views to the highlighted strata (those carrying a credibly non-zero interaction, or – under highlight_by = "rope" – those classified ROPE-"relevant") and, when highlight_interactions is left FALSE, turns the highlight on with this analysis's stored diagnostic. "effect_decomp" ignores it (it stays highlighted in context).
highlight_by	Which interaction-screen column defines the highlighted strata: "flag" (default, the zero-centred flagged column) or "rope" (the equivalence decision column, highlighting the strata classified "relevant"). See plot . "rope" requires rope (or a highlight_interactions object built with one).
rope	Equivalence region forwarded to maihda_interactions when computing the screen, so highlight_by = "rope" has a decision column to read: a single positive d for the symmetric region c(-d, d) on the latent (link) scale, or c(lower, upper). NULL (default) adds no equivalence classification.
select	When the n_strata cap drops strata on the "predicted" (or longitudinal "trajectories") view, which to keep: "order" (default, first n_strata in stratum order) or "deviation" (the n_strata furthest from the reference, both tails). See plot .
order_by	Display order of the strata on the "predicted" view (display-only; does not change which strata are shown, nor any value): "predicted_desc" (default) highest predicted first, "stratum" native order, "predicted_asc" lowest first, or "deviation" largest predicted - reference first. See plot .
model	For type = "vpc", which model's variance partition to show: "null" (default) the total between-stratum heterogeneity (the previous, backward-compatible behaviour), "adjusted" the between-stratum heterogeneity remaining after the dimensions' additive main effects (closer to the pure intersectional component), or "both" – a single plot placing the two partitions together and annotating the PCV, so the null-to-adjusted change is visible in one figure. The null and adjusted single views are labelled with a "Null model" / "Adjusted model" sub-

title. For a **longitudinal** analysis the VPC view is the time-varying VPC trajectory, and "both" overlays the null and adjusted curves. A "crossed-dimensions" analysis fits a single model (no null/adjusted pair), so only "null" is valid there; "adjusted"/"both" error. model applies to the VPC view only – combining a non-default model with another type is an error.

... Additional arguments passed to the underlying plot method.

Value

A ggplot2 object – including type = "vpc", model = "both", which is a single combined change plot – or (for type = "all") an invisible list of them.

```
plot.maihda_comparison
```

Plot a MAIHDA Model Comparison

Description

Plots VPC/ICC across the models compared by [compare_maihda](#). Dispatched via plot() on the classed result.

Usage

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

Arguments

x A maihda_comparison object from [compare_maihda](#).
 ... Additional arguments (not used).

Value

A ggplot2 object.

Examples

```
strata <- make_strata(maihda_sim_data, vars = c("gender", "race"))

null_model <- fit_maihda(health_outcome ~ 1 + (1 | stratum), data = strata$data)
adj_model <- fit_maihda(health_outcome ~ age + (1 | stratum), data = strata$data)

comparison <- compare_maihda(null_model, adj_model, bootstrap = TRUE)
plot(comparison)
```

plot.maihda_group_comparison

Plot a MAIHDA Group Comparison

Description

Visualises the output of [compare_maihda_groups](#) as a point/forest plot of the VPC/ICC by group, as stacked variance-composition bars (between- vs within-stratum share) by group, as bars of the absolute between-stratum (intersectional) variance by group, or as bars of the additive share (PCV) by group. Dispatched via `plot()` on the classed result.

Usage

```
## S3 method for class 'maihda_group_comparison'
plot(
  x,
  type = c("vpc", "components", "between_variance", "pcv", "additive_share"),
  ...
)
```

Arguments

x	A <code>maihda_group_comparison</code> object from compare_maihda_groups .
type	One of "vpc" (default) for VPC by group with optional bootstrap confidence intervals, "components" for stacked variance proportions (additive / interaction / residual for a crossed-dimensions comparison, between / other / residual otherwise, with a separate context slice for a contextual comparison), "between_variance" for the absolute between-stratum variance by group, "pcv" for the two-model additive share (null -> adjusted proportional change in between-stratum variance) by group, or "additive_share" for the crossed-dimensions additive share by group. The VPC is a <i>share</i> of the unexplained variance; "between_variance" shows the <i>magnitude</i> the ratio cannot convey (two groups with very different VPCs can share a between-stratum variance, and vice versa); "pcv" requires strata defined by at least two dimensions.
...	Additional arguments (not used).

Value

A `ggplot2` object.

Examples

```
data(maihda_health_data)
cmp <- compare_maihda_groups(BMI ~ Age + (1 | Gender:Race),
                             data = maihda_health_data, group = "Education")
plot(cmp, type = "vpc")
plot(cmp, type = "components")
```

```
plot(cmp, type = "between_variance")
```

plot.maihda_model	<i>Plot MAIHDA Model Results</i>
-------------------	----------------------------------

Description

Creates various plots for visualizing MAIHDA model results including variance partition coefficient comparisons, observed vs. shrunk estimates, and predicted subgroup values with confidence intervals.

Usage

```
## S3 method for class 'maihda_model'
plot(
  x,
  type = c("all", "vpc", "obs_vs_shrunken", "predicted", "upset", "effect_decomp",
    "prediction_deviation", "context_vpc", "vpc_trajectory", "trajectories"),
  summary_obj = NULL,
  n_strata = 50,
  highlight_interactions = FALSE,
  only_flagged = FALSE,
  highlight_by = c("flag", "rope"),
  rope = NULL,
  select = c("order", "deviation"),
  order_by = c("predicted_desc", "stratum", "predicted_asc", "deviation"),
  quantity = c("predicted", "interaction"),
  ...
)
```

Arguments

- | | |
|------|---|
| x | A maihda_model object from fit_maihda(). |
| type | Character string specifying plot type: <ul style="list-style-type: none"> "vpc": Variance partition coefficient visualization "obs_vs_shrunken": Observed vs. shrunk stratum means. The y-axis (model-based estimate) includes the fixed effects, so for a covariate-adjusted model the distance from the diagonal reflects both shrinkage <i>and</i> covariate adjustment, not shrinkage alone; it is a pure shrinkage view only for an intercept-only (null) model "predicted": Predicted values for each stratum with confidence intervals. By default the strata are ordered highest-to-lowest predicted value (a ranked caterpillar plot); see order_by to change or disable the ordering |

	• "upset": UpSet-style alternative to "predicted" – an intersection-size bar, a category matrix encoding each stratum's level on every dimension, and the predicted-value panel, all sharing one column order. Replaces the long intersectional axis labels with the matrix. Binary 0/1 dimensions show as a single present/absent row; multi-level factors get one row per level • "effect_decomp": Visualizes additive vs intersectional deviation from global mean • "prediction_deviation": Detailed deviation panels for individuals or strata • "context_vpc": Stratum vs. context variance bars for a contextual cross-classified fit (<code>fit_maihda(context =)</code>); errors otherwise • "vpc_trajectory": Time-varying VPC/ICC curve for a longitudinal fit (<code>fit_maihda(id = , time =)</code>); errors otherwise. For a longitudinal model "vpc" and "all" also route here • "trajectories": Predicted per-stratum mean trajectories over time (longitudinal fits only) • "all": Generate all available plots (default if not specified)
summary_obj	Optional maihda_summary object from <code>summary()</code> . If NULL, will be computed.
n_strata	Maximum number of strata to display in the predicted plot. When there are more strata than this, the first n_strata (in stratum order) are shown and the plot caption notes how many were omitted. Default is 50. Use NULL for all strata.
highlight_interactions	Highlight the strata that carry a credibly non-zero intersectional interaction (from maihda_interactions) on the BLUP-based views ("effect_decomp", "predicted", "obs_vs_shrunken"); other views ignore it. FALSE (default) off; TRUE computes the flags with <code>maihda_interactions()</code> defaults; or pass a multiple-testing method such as "BH" or a maihda_interactions object to reuse a specific <code>conf_level/adjust</code> . For the pure-interaction reading the model should be the adjusted (or crossed-dimensions) model – e.g. via <code>plot()</code> on a maihda analysis, which routes these views to the adjusted model automatically. Which column of the screen drives the highlight set is governed by <code>highlight_by</code> .
only_flagged	Show <i>only</i> the flagged strata rather than dimming the rest. FALSE (default) keeps every stratum (flagged ones highlighted); TRUE restricts the "predicted" and "obs_vs_shrunken" views to the highlighted strata (those carrying a credibly non-zero interaction, or – under <code>highlight_by = "rope"</code> – those classified ROPE-"relevant"), so a highlighted stratum is never hidden by the n_strata cap. When TRUE and <code>highlight_interactions</code> is left FALSE, the flags are computed with maihda_interactions defaults; pass <code>highlight_interactions</code> to choose the <code>conf_level/adjust</code> . A captioned empty panel is returned when no stratum is flagged. It does not apply to "effect_decomp" (whose waterfall exists to show each flagged stratum's place in the <i>full</i> distribution); that view stays highlighted. Independently of this argument, whenever interactions are highlighted the n_strata cap on "predicted" becomes flag-aware: every flagged stratum is kept and the remaining slots are filled according to <code>select</code> .
highlight_by	Which interaction-screen column defines the highlighted strata: "flag" (default) uses the zero-centred flagged column (credibly non-zero interaction),

preserving the historical behaviour; "rope" uses the equivalence decision column, highlighting the strata classified "relevant" (interaction interval entirely outside the region of practical equivalence). "rope" requires a screen carrying a decision column: either pass rope, or supply a maihda_interactions object built with rope; otherwise it errors.

rope	Equivalence region (a "smallest interaction of interest") forwarded to maihda_interactions when the screen is computed here (i.e. when highlight_interactions is TRUE or a p.adjust method name). NULL (default) adds no equivalence classification; a single positive d means the symmetric region c(-d, d) on the latent (link) scale, or supply c(lower, upper). Needed for highlight_by = "rope" unless the supplied maihda_interactions object already carries a decision column. Ignored when a precomputed maihda_interactions object is passed (its own rope is used).
select	When the n_strata cap must drop strata, which to keep: "order" (default; the first n_strata in stratum order, the historical behaviour) or "deviation" (the n_strata furthest from the reference line – largest predicted - reference , so the most extreme strata in <i>both</i> directions). Applies to "predicted" and, for a longitudinal fit, "trajectories" (where it keeps the strata whose trajectories swing furthest from the population curve). Flagged strata are always kept; this governs the fill and the unflagged case. select changes <i>which</i> strata appear; their left-to-right display order is a separate choice governed by order_by.
order_by	For type = "predicted", how to order the strata that are displayed (display-only – it does not change <i>which</i> strata are shown, that is n_strata/select, nor the predicted values, intervals, reference line, or highlighted set): "predicted_desc" (default) orders labels from the highest predicted value to the lowest, "stratum" keeps the native stratum order (the previous behaviour), "predicted_asc" orders from lowest to highest, and "deviation" orders by largest absolute deviation from the reference line (predicted - reference). Ignored by the other plot types ("upset" orders by intersection size).
quantity	For type = "upset", which quantity the bottom panel shows: "predicted" (default) the stratum's predicted value (fixed + random effect) against the across-strata reference line, or "interaction" the stratum random effect (the BLUP) against zero – the deviation from the model's fixed prediction, which is the <i>pure</i> intersectional interaction when the dimension main effects are in the model (the adjusted model). Ignored by the other plot types.
...	Additional arguments (not currently used).

Value

For a single type, a **ggplot2** object that you can extend with the usual + grammar (themes, [labs\(\)](#), added layers, or a replacement fill/colour scale). Two types return a richer object: "prediction_deviation" returns a **patchwork** of two panels (theme every panel at once with & theme_*()). type = "all" returns a named list of ggplot2 objects.

Examples

```
strata_result <- make_strata(maihda_sim_data, vars = c("gender", "race"))
model <- fit_maihda(health_outcome ~ age + (1 | stratum), data = strata_result$data)
```

```
# VPC plot
plot(model, type = "vpc")

# Single-type plots are ggplot objects -- restyle them with ggplot2:
plot(model, type = "vpc") +
  ggplot2::theme_classic() +
  ggplot2::labs(title = "Variance partition, restyled")

# Generate all plots (a named list); pick one out to restyle it:
plots <- plot(model)
plots$predicted + ggplot2::theme_bw()
```

plot_prediction_deviation_panels

Plot Prediction Deviation Panels

Description

Creates an advanced, publication-ready two-panel dashboard for visualizing predicted values and highlighting the most notable cases or strata. What "notable" means depends on the model type, and the labelled points are *not* statistical outliers in the regression-diagnostic sense:

- Gaussian and Poisson (and the ordinal "expected_score" mode): the cases/strata whose prediction sits furthest from the mean prediction (largest deviation), ranked by absolute deviation.
- Binomial: the cases/strata with the largest absolute deviance residual, i.e. where the observed 0/1 outcome is least consistent with the fitted probability (worst-fit points), ranked by $|devianceresidual|$.
- Ordinal "surprise" mode: the cases/strata with the highest surprise $-\log P(\text{observed category})$, i.e. the least probable observations under the model.

Usage

```
plot_prediction_deviation_panels(
  model,
  data = NULL,
  type = c("auto", "gaussian", "poisson", "binomial", "ordinal"),
  ordinal_mode = c("surprise", "expected_score"),
  top_n_labels = 5,
  strata_info = NULL
)
```

Arguments

model A fitted model object (e.g., from `lm()`, `glm()`, `MASS::polr()`, or `lme4::glmer()`).

data	The original data frame used to fit the model. If 'NULL', attempts to extract from the model.
type	Model type: "auto" (default), "gaussian", "poisson", "binomial", or "ordinal".
ordinal_mode	For ordinal models: "surprise" (default, based on observation probability) or "expected_score".
top_n_labels	Number of points to label on the plot. The ranking metric depends on the model type (see Description): deviation from the mean prediction for Gaussian/Poisson and the ordinal expected-score mode, absolute deviance residual for binomial, and surprise for the ordinal surprise mode. Default is 5.
strata_info	Optional data frame of strata labels, generally extracted from 'maihda_model' objects.

Value

A 'patchwork' object containing two 'ggplot2' panels.

predict_maihda	<i>Predict from MAIHDA Model</i>
----------------	----------------------------------

Description

Makes predictions from a fitted MAIHDA model, either at the stratum level or individual level.

Usage

```
predict_maihda(
  object,
  newdata = NULL,
  type = c("individual", "strata", "response", "link"),
  scale = c("response", "link"),
  allow_new_levels = FALSE,
  ...
)
```

Arguments

object	A maihda_model object from fit_maihda().
newdata	Optional data frame for making predictions. If NULL, uses the original data from model fitting.
type	Character string specifying prediction type: "individual": Individual-level predictions including random effects "strata": Stratum-level predictions (random effects only). For a longitudinal (growth-curve) fit a stratum is a <i>trajectory</i>, so this returns the per-stratum trajectory parameters (baseline deviation, random intercept and random slope(s)) rather than a single random effect.

	For backward compatibility, "link" or "response" may also be passed here and will be interpreted as individual-level predictions on that scale.
scale	Character string specifying the prediction scale for individual-level predictions: "response" (default) or "link". For a cumulative (ordinal) model the "link" scale is the latent location η and the "response" scale is the <i>expected category score</i> $\sum_k kP(Y = k)$ (categories scored 1..K in their declared order). For an aggregated-binomial fit (an lme4 cbind(success, failure) or a brms success trials(n)) the "response" scale is the per-trial <i>probability</i> on both engines (not the expected success count).
allow_new_levels	Logical. By default (FALSE) a stratum in newdata that the model never saw – whether supplied directly as a stratum column or rebuilt from the grouping variables – is an error, for every engine, matching lme4 's default. Set TRUE to instead predict unseen strata with the stratum random effect dropped (treated as zero), while keeping any <i>other</i> random effect the row participates in (e.g. a contextual (1 school) intercept from fit_maihda(context =), or a longitudinal growth term) – the same behaviour as lme4 's allow.new.levels, which zeroes only the unseen level's effect and keeps seen ones. For the usual single-stratum model the stratum is the only random effect, so this is the <i>population-average</i> (fixed-effects-only) prediction. This affects type = "individual" only: a stratum-level prediction (type = "strata") has no random effect to report for an unseen stratum, so unseen strata remain an error there regardless.
...	Additional arguments passed to predict method of underlying model.

Value

Depending on type:

- For "individual": A numeric vector of predicted values on the requested scale
- For "strata": A data frame with stratum ID and predicted random effect. When newdata is supplied, the result is restricted to the strata present in newdata (and a stratum the model never saw is an error, as for "individual"); when newdata is NULL, every training stratum is returned.

Examples

```
strata_result <- make_strata(maihda_sim_data, vars = c("gender", "race"))
model <- fit_maihda(health_outcome ~ age + (1 | stratum), data = strata_result$data)

# Individual predictions
pred_ind <- predict_maihda(model, type = "individual")

# Stratum predictions
pred_strata <- predict_maihda(model, type = "strata")
```

print.maihda_analysis *Print a MAIHDA Analysis*

Description

Print a MAIHDA Analysis

Usage

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

Arguments

x	A maihda_analysis object from maihda .
...	Additional arguments (not used).

Value

No return value, called for side effects.

print.maihda_group_comparison
Print method for MAIHDA group comparisons

Description

Print method for MAIHDA group comparisons

Usage

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

Arguments

x	A maihda_group_comparison object.
...	Additional arguments (not used).

Value

No return value, called for side effects.

print.maihda_ic	<i>Print MAIHDA information criteria</i>
-----------------	--

Description

Print MAIHDA information criteria

Usage

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

Arguments

x	A maihda_ic object from maihda_ic .
...	Additional arguments (not used).

Value

No return value, called for side effects.

print.maihda_interactions	<i>Print a MAIHDA interaction diagnostic</i>
---------------------------	--

Description

Print a MAIHDA interaction diagnostic

Usage

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

Arguments

x	A maihda_interactions object from maihda_interactions .
...	Additional arguments (not used).

Value

No return value, called for side effects.

print.maihda_long_pcv *Print a longitudinal MAIHDA PCV*

Description

Print a longitudinal MAIHDA PCV

Usage

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

Arguments

x	A maihda_long_pcv object.
...	Unused.

Value

The object, invisibly.

print.maihda_model *Print method for maihda_model*

Description

Print method for maihda_model

Usage

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

Arguments

x	A maihda_model object
...	Additional arguments

Value

No return value, called for side effects.

`print.maihda_stepwise` *Print a stepwise MAIHDA table*

Description

Print a stepwise MAIHDA table

Usage

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

Arguments

<code>x</code>	A <code>maihda_stepwise</code> object from stepwise_pcv .
<code>...</code>	Additional arguments (not used).

Value

Invisibly, `x`.

`print.maihda_strata` *Print method for maihda_strata objects*

Description

Print method for `maihda_strata` objects

Usage

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

Arguments

<code>x</code>	A <code>maihda_strata</code> object
<code>...</code>	Additional arguments (not used)

Value

No return value, called for side effects.

print.maihda_summary *Print method for maihda_summary objects*

Description

Print method for maihda_summary objects

Usage

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

Arguments

x	A maihda_summary object
...	Additional arguments (not used)

Value

No return value, called for side effects.

print.maihda_table *Print a MAIHDA results table*

Description

Print a MAIHDA results table

Usage

```
## S3 method for class 'maihda_table'
print(x, digits = x$digits, ...)
```

Arguments

x	A maihda_table object from maihda_table .
digits	Decimal places (defaults to the value stored on x).
...	Additional arguments (not used).

Value

Invisibly, x.

print.pcv_result	<i>Print method for PCV results</i>
------------------	-------------------------------------

Description

Print method for PCV results

Usage

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

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

Arguments

x	A pcv_result object from calculate_pcv
...	Additional arguments

Value

No return value, called for side effects.

run_maihda_app	<i>Run MAIHDA Shiny Application</i>
----------------	-------------------------------------

Description

Launches a Shiny graphical user interface that exposes core functions of the MAIHDA package, allowing for visual data exploration, model fitting, and performance visualization.

Usage

```
run_maihda_app()
```

Value

No return value, called to launch the shiny app.

Examples

```
## Not run:
run_maihda_app()

## End(Not run)
```

stepwise_pcv

*Stepwise Proportional Change in Variance (PCV)***Description**

Estimates the proportional change in variance (PCV) sequentially by fitting intermediate (partially-adjusted) models, adding each predictor one-by-one. The step-specific PCV is the change in between-stratum variance contributed by a predictor *given the variables already in the model*. Because the steps are sequential it is order-dependent: it reflects each variable's marginal, model-dependent change, not an order-invariant "unique" contribution.

Usage

```
stepwise_pcv(
  data,
  outcome,
  vars,
  engine = "lme4",
  family = "gaussian",
  context = NULL,
  sampling_weights = NULL
)
```

Arguments

data	Data frame with observations. Ensure 'make_strata()' was run first so the 'stratum' variable exists.
outcome	Character string; the dependent variable.
vars	Character vector; predictors (strata groupings & covariates) to add sequentially to the model.
engine	Modeling engine ("lme4", "brms", "wemix", or "ordinal"). Default is "lme4"; switches to "wemix" automatically when <code>sampling_weights</code> is supplied, and to "ordinal" for an ordinal family or ordered-factor outcome.
family	Error distribution and link function. Default is "gaussian".
context	Optional character vector naming one or more higher-level <i>context</i> columns in data (e.g. "school", "region"), forwarded to every step's <code>fit_maihda</code> call so that each model carries a crossed contextual random intercept, (1 context), alongside the intersectional stratum effect – the stepwise analogue of <code>maihda(context =)</code> (the literature's contextual cross-classified MAIHDA). The reported <code>Step_PCV / Total_PCV</code> are then the between-stratum PCV net of the context (the context intercept is held in the null model and every step, so the stratum variance is isolated from it), and an extra <code>Context_Variance</code> column reports the between-context variance held at each step. Context columns join the complete-case filter so every step shares one analytic sample. A context variable may not be a stratum dimension, "stratum" itself, or one of <code>vars</code> . Supported

by the lme4 and brms engines only (wemix and ordinal fit no crossed random effects). See [fit_maihda](#) for the full contextual-model semantics. Default NULL (no context).

sampling_weights

Optional name of a sampling-weight column for design-weighted stepwise fits; see [fit_maihda](#). The weight column joins the complete-case filter so every step uses the same analytic sample.

Details

All models are fit on the complete cases for ‘outcome’, ‘stratum’, and all variables in ‘vars’ so that each sequential variance comparison uses the same analytic sample.

For a binary (or ordinal) outcome the sequential between-stratum variances live on the latent scale, whose level-1 variance is fixed by the link: a step that adds an *individual-level* variable (one varying within strata) rescales the latent metric itself, so its Step_PCV mixes explained variance with rescaling and can be understated or negative on that account – see the “Latent-scale families and rescaling” note in [calculate_pcv](#). Steps that add a stratum-constant dimension are largely unaffected.

For a binary outcome the table additionally tracks discriminatory accuracy (Merlo et al. 2016): AUC is each model’s C-statistic and Step_AUC / Total_AUC are its *absolute* change (delta-AUC), in contrast to the *proportional* Step_PCV / Total_PCV. The MOR is reported for the logit link (NA otherwise) and is a monotone transform of the between-stratum variance already in Variance. For a design-weighted fit (sampling_weights) the AUC is the design-weighted (population) C-statistic. Reuses [maihda_discriminatory_accuracy](#) on each step’s fitted model, so no additional models are fit. Note that adding a *stratum-defining* dimension (one already encoded by the strata) typically leaves the AUC essentially unchanged: it re-partitions the between-stratum variance (so the PCV and MOR move) but not the per-stratum predicted ranking the rank-based AUC depends on. The AUC trajectory is therefore most informative for individual-level covariates that vary *within* strata.

Value

A data.frame (class maihda_stepwise) showing the sequential models, the between-stratum variance at each step, and both the step-specific and total PCV. For a **binary** (binomial/Bernoulli) outcome it also carries the discriminatory-accuracy trajectory: AUC (the C-statistic of each step’s model – step 0 is the strata-only discriminatory accuracy), Step_AUC and Total_AUC (the *absolute* change in AUC, delta-AUC, versus the previous step and versus the null), and MOR (the Median Odds Ratio, logit link only). These columns are absent for non-binary outcomes. When context is supplied, a Context_Variance column reports the between-context variance held at each step, and the discriminatory-accuracy trajectory is omitted even for a binary outcome – the AUC would include the context random effect and so mismatch the net-of-context Step_PCV / Total_PCV, exactly as [summary.maihda_model](#) drops it for a contextual fit.

References

Merlo, J., Wagner, P., Ghith, N., & Leckie, G. (2016). An original stepwise multilevel logistic regression analysis of discriminatory accuracy: the case of neighbourhoods and health. *PLOS ONE*, 11(4), e0153778.

Examples

```
strata_result <- make_strata(maihda_sim_data, c("gender", "race"))
stepwise_pcv(strata_result$data, "health_outcome", c("gender", "race", "age"))

# Contextual cross-classified stepwise PCV: strata crossed with a higher-level
# context (country). Step_PCV / Total_PCV are then net of the country intercept,
# and a Context_Variance column reports the between-country variance per step.
cc <- make_strata(maihda_country_data, c("gender", "ses"))
stepwise_pcv(cc$data, "math", c("gender", "ses"), context = "country")
```

summary.maihda_analysis

Summarize a MAIHDA Analysis

Description

Returns the variance summary (VPC/ICC, variance components, stratum estimates) of the fitted model. The per-group comparison, when present, is attached as the "groups" attribute.

Usage

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

Arguments

object	A maihda_analysis object from maihda .
...	Additional arguments (not used).

Value

The maihda_summary for the fitted model.

summary.maihda_model *Summarize MAIHDA Model*

Description

Provides a summary of a MAIHDA model including variance partition coefficients (VPC/ICC) and stratum-specific estimates.

Usage

```
## S3 method for class 'maihda_model'
summary(
  object,
  bootstrap = FALSE,
  n_boot = 1000,
  conf_level = 0.95,
  response_vpc = FALSE,
  seed = NULL,
  ...
)
```

Arguments

object	A maihda_model object from fit_maihda().
bootstrap	Logical indicating whether to compute parametric bootstrap confidence intervals for VPC/ICC. Default is FALSE. Supported for lme4 models only; brms models always return a posterior credible interval (see Details), so bootstrap = TRUE is rejected for them. For a negative-binomial model (glmer.nb) the bootstrap refits via lme4::refit(), which holds the dispersion parameter theta fixed at its original estimate, so the interval is conditional on the estimated theta (theta's own sampling uncertainty is not propagated). The ordinal (clmm) engine has no simulate/refit machinery, so bootstrap = TRUE is rejected there (use engine = "brms" for interval estimates).
n_boot	Number of bootstrap samples if bootstrap = TRUE. Default is 1000.
conf_level	Confidence level for the VPC/ICC interval – the lme4 bootstrap CI or the brms posterior credible interval. Default is 0.95.
response_vpc	Logical; for a binomial (lme4) model, also compute the response-scale VPC (maihda_vpc_response) and attach it as the vpc_response slot. It is estimated by simulation, so it is opt-in (default FALSE) and uses seed for reproducibility. Ignored for other families/engines.
seed	Optional integer seed for the response-scale VPC simulation when response_vpc = TRUE.
...	Additional arguments (not currently used).

Value

A maihda_summary object containing:

vpc	Variance Partition Coefficient (ICC); for lme4 with bootstrap = TRUE and for all brms models this includes ci_lower/ci_upper/conf_level. For a contextual cross-classified fit this is the <i>between-stratum</i> share of all unexplained variance (net of the context)
variance_components	Data frame of variance components. For a contextual cross-classified fit (fit_maihda(context =)) each context appears as its own Context: <name> row

context	For a contextual cross-classified fit, the stratum vs. context partition: per-context variances and shares, the contexts' total share (vpc_context_total, with an interval when bootstrapped or for brms), and the between-stratum share (vpc_stratum); NULL otherwise
discriminatory_accuracy	For a binomial/Bernoulli outcome, the maihda_da object (AUC + MOR) from <code>maihda_discriminatory_accuracy</code> ; NULL otherwise. Also NULL for a crossed-dimensions fit (whose single-stratum between-variance the MOR needs is not defined across crossed random effects) and for a contextual cross-classified fit (<code>fit_maihda(context =)</code>), where the AUC would be built from predictions that include the context random effects – a mismatch with the stratum-vs-context partition the summary reports
vpc_response	The response-scale VPC (<code>maihda_vpc_response</code>) when <code>response_vpc = TRUE</code> for a single-stratum binomial lme4 model; NULL otherwise (including for crossed-dimensions and contextual fits, whose partition the stratum-only simulation does not match)
stratum_estimates	Data frame of stratum-specific random effects with labels if available
fixed_effects	Fixed effects estimates
thresholds	For a cumulative (ordinal) clmm fit, the threshold (cut point) estimates with standard errors – the cumulative model's "intercepts"; NULL otherwise
model_summary	Original model summary
diagnostics	Fit-quality diagnostics (singular fit / convergence) carried over from the fitted model and reported by the print method

Interpreting the VPC/ICC

The VPC is the between-stratum variance divided by the total *unexplained* variance. For the canonical single-stratum model that denominator is between-stratum + residual, but if the model includes additional random effects (e.g. $(1 \mid \text{site})$) their variance is included in the denominator too (between-stratum + other random effects + residual), so the VPC is the between-stratum *share* of all unexplained variance. It is a conditional/residual ICC that excludes variance captured by the fixed effects, so for models with covariates it is conditional on them. It is most commonly read from the null model outcome $\sim 1 + (1 \mid \text{stratum})$, where it is the total between-stratum share. For non-Gaussian families the level-1 (residual) variance uses a latent/distributional approximation ($\pi^2/3$ for logistic; $\log(1 + 1/\lambda)$ for Poisson per Stryhn et al. 2006 and $\log(1 + 1/\lambda + 1/\theta)$ for the negative binomial per Nakagawa, Johnson & Schielzeth 2017, each evaluated at the *marginal* expected count $\lambda_i = \exp(x_i'\beta + v_i/2)$ – the fixed-part prediction with the log-normal correction for the row's total random-effect variance v_i , which reduces to Nakagawa et al.'s $\lambda = \exp(\beta_0 + \sigma^2/2)$ in the null model – and averaged over the analytic sample, *not* at the conditional fitted means, whose BLUPs would tie the level-1 variance to the realized random effects), so the VPC is on that latent scale; for a *weighted* Gaussian model the level-1 variance is the mean conditional residual variance, σ^2/w_i , since the per-observation residual variance is σ^2/w_i . The stratum random effects represent the total between-stratum deviation; they equal the *pure* intersectional (interaction) component only when the additive main effects of the strata variables are included in the model.

Note

For lme4 models a VPC/ICC interval is obtained from a parametric bootstrap (bootstrap = TRUE). For brms models the VPC/ICC is summarised directly from the posterior draws: the reported estimate is the posterior median of the per-draw VPC ($E[\sigma^2]$ -based, not the biased $E[\sigma]^2$) and the interval is a central credible interval at conf_level (default 95%), so no bootstrap argument is needed. The variance-components table reports the posterior-mean variance components, so the stratum proportion shown there may differ slightly from the headline VPC because the median of a ratio is not the ratio of means. For non-Gaussian brms families the level-1 (residual) variance uses the usual latent-scale approximation; for the count families the marginal expected counts are built from the posterior-mean fixed effects and random-effect variances rather than per draw, to avoid an expensive $ndraws \times nob$ s computation (the negative-binomial shape draws are still propagated).

Examples

```
strata_result <- make_strata(maihda_sim_data, vars = c("gender", "race"))
model <- fit_maihda(health_outcome ~ age + (1 | stratum), data = strata_result$data)
summary_result <- summary(model)

# With bootstrap CI
# summary_boot <- summary(model, bootstrap = TRUE, n_boot = 50)
```

 theme_maihda

MAIHDA plot theme

Description

A **ggplot2** theme that applies the MAIHDA brand identity to plot *chrome* only – navy titles and axis labels and soft slate gridlines. It encodes no data: the colourblind-safe data palettes used by the package’s plotting functions are left untouched.

Usage

```
theme_maihda(base_size = 11, base_family = NULL)
```

Arguments

base_size	Base font size in points. Default ‘11’.
base_family	Base font family. Defaults to ‘getOption("maihda.font", "")’, i.e. the graphics device default unless you have opted into a brand font globally. Pass a string to force a family for a single plot.

Details

Built on [ggplot2::theme_minimal()], so it composes with additional ‘+ theme()’ calls in the usual way (later settings win).

Value

A **ggplot2** theme object that can be added to a plot with `'+'`.

Fonts

By default the theme uses the graphics device's default font, which is safe on every device (including the PostScript/PDF devices used by 'R CMD check' and many rendering back-ends). To render figures in the brand font (Montserrat) – matching the hex logo – set `'options(maihda.font = "Montserrat")'` or pass `'base_family = "Montserrat"'`, and use a graphics device that can resolve that family (e.g. **ragg** or **showtext**). Forcing a font that the active device cannot find produces "invalid font type" errors, which is why it is opt-in rather than automatic.

Examples

```
library(ggplot2)
ggplot(mtcars, aes(mpg, wt)) +
  geom_point(colour = "#0072B2") +
  labs(title = "MAIHDA brand theme", x = "MPG", y = "Weight") +
  theme_maihda()
```

Index

* datasets

- maihda_country_data, 22
- maihda_health_data, 26
- maihda_long_data, 31
- maihda_sim_data, 34
- maihda_sparse_data, 34
- calculate_pcv, 3, 5, 6, 10, 17, 19, 28, 31, 37, 58, 60
- calculate_pvc, 5
- compare_maihda, 6, 11, 28, 45
- compare_maihda_groups, 7, 16, 18–20, 22, 46
- fit_maihda, 8, 9, 11, 16–20, 23, 24, 27, 29, 33, 36–38, 40, 41, 59, 60
- ggsave, 39
- glance, 25
- glance.maihda_analysis, 39
- glance.maihda_analysis (maihda_glance), 25
- glance.maihda_model (maihda_glance), 25
- glance.maihda_summary (maihda_glance), 25
- labs, 49
- maihda, 5, 9, 14, 15, 22, 23, 27, 29, 31, 36–38, 40, 42–44, 48, 53, 61
- maihda_adjusted_terms, 9
- maihda_auc, 21, 25
- maihda_country_data, 22
- maihda_cumulative, 12, 23
- maihda_discriminatory_accuracy, 24, 33, 37, 41, 60, 63
- maihda_glance, 25
- maihda_health_data, 26
- maihda_ic, 3, 6, 7, 27, 54
- maihda_interactions, 14, 18, 19, 29, 44, 48, 49, 54
- maihda_long_data, 31
- maihda_mor, 25, 33
- maihda_sim_data, 34
- maihda_sparse_data, 34
- maihda_table, 36, 57
- maihda_tidiers, 26, 38
- maihda_upset_size, 39
- maihda_vpc_response, 18, 40, 62
- make_strata, 8, 9, 12, 13, 16, 17, 19, 20, 40, 42
- p.adjust, 14, 18, 29
- plot, 44
- plot.maihda_analysis, 43
- plot.maihda_comparison, 45
- plot.maihda_group_comparison, 11, 46
- plot.maihda_model, 40, 47
- plot_prediction_deviation_panels, 50
- predict_maihda, 51
- print.maihda_analysis, 53
- print.maihda_group_comparison, 53
- print.maihda_ic, 54
- print.maihda_interactions, 54
- print.maihda_long_pcv, 55
- print.maihda_model, 55
- print.maihda_stepwise, 56
- print.maihda_strata, 56
- print.maihda_summary, 57
- print.maihda_table, 57
- print.pcv_result, 58
- print.pvc_result (print.pcv_result), 58
- refitML, 3, 28
- run_maihda_app, 58
- stepwise_pcv, 4, 5, 56, 59
- summary, 38
- summary.maihda_analysis, 61
- summary.maihda_model, 4, 12–14, 19, 20, 31, 36–38, 41, 60, 61

theme_maihda, [64](#)
tidy, [38](#)
tidy.maihda_analysis(maihda_tidiers),
 [38](#)
tidy.maihda_model(maihda_tidiers), [38](#)
tidy.maihda_summary(maihda_tidiers), [38](#)