

Package ‘mlmoderator’

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Type Package

Title Probing, Plotting, and Interpreting Multilevel Interaction Effects

Version 0.2.0

Description Provides a unified workflow for probing, plotting, and assessing the robustness of cross-level interaction effects in two-level mixed-effects models fitted with 'lme4' (Bates et al., 2015) [<doi:10.18637/jss.v067.i01>](https://doi.org/10.18637/jss.v067.i01). Implements simple slopes analysis following Aiken and West (1991, ISBN:9780761907121), Johnson-Neyman intervals following Johnson and Fay (1950) [<doi:10.1007/BF02288864>](https://doi.org/10.1007/BF02288864) and Bauer and Curran (2005) [<doi:10.1207/s15327906mbr4003_5>](https://doi.org/10.1207/s15327906mbr4003_5), and grand- or group-mean centering as described in Enders and Tofighi (2007) [<doi:10.1037/1082-989X.12.2.121>](https://doi.org/10.1037/1082-989X.12.2.121). Includes a slope variance decomposition that separates fixed-effect uncertainty from random-slope variance (τ_{11}), a contour surface plot of predicted outcomes over the full predictor-by-moderator space, and robustness diagnostics comprising intraclass correlation coefficient shift analysis and leave-one-cluster-out (LOCO) stability checks. Designed for researchers in education, psychology, biostatistics, epidemiology, organizational science, and other fields where outcomes are clustered within higher-level units.

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mlm_center	<i>Center variables for multilevel modeling</i>
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Description

Performs grand-mean centering, group-mean centering, or both (within-between decomposition) on one or more variables in a data frame. Group-mean centering is the standard preparation for cross-level interaction models.

Usage

```
mlm_center(
  data,
  vars,
  cluster = NULL,
  type = c("grand", "group", "both"),
  suffix_within = "_within",
  suffix_between = "_between"
)
```

Arguments

<code>data</code>	A data frame.
<code>vars</code>	Character vector of variable names to center.
<code>cluster</code>	Character scalar: name of the clustering variable (required when type is "group" or "both").
<code>type</code>	One of "grand", "group", or "both". <ul style="list-style-type: none"> "grand": subtract the overall mean. "group": subtract the cluster mean (within-person / within-school centering). "both": return both the within-cluster-centered value <i>and</i> the cluster mean (between component), appended as new columns.
<code>suffix_within</code>	Suffix appended to within-centered variable names when type = "both". Default is "_within".
<code>suffix_between</code>	Suffix appended to between (cluster mean) variable names when type = "both". Default is "_between".

Value

The input data frame with new centered columns appended. Original columns are not modified.

Examples

```
data(school_data)

# Grand-mean center SES
d1 <- mlm_center(school_data, vars = "ses", type = "grand")
head(d1[, c("ses", "ses_c")])

# Group-mean center SES within schools
d2 <- mlm_center(school_data, vars = "ses", cluster = "school", type = "group")
head(d2[, c("ses", "ses_c")])

# Within-between decomposition
d3 <- mlm_center(school_data, vars = "ses", cluster = "school", type = "both")
head(d3[, c("ses", "ses_within", "ses_between")])
```

mlm_jn

Johnson—Neyman interval for multilevel two-way interactions

Description

Computes the Johnson—Neyman (JN) interval: the region(s) of the moderator (modx) where the simple slope of pred transitions between statistical significance and non-significance. Useful for identifying *exactly* at which moderator values an effect becomes significant.

Usage

```
mlm_jn(model, pred, modx, alpha = 0.05, modx.range = NULL, grid = 200L)
```

Arguments

model	An lmerMod object with a two-way interaction between pred and modx in the fixed-effects structure.
pred	Character scalar. Focal predictor name.
modx	Character scalar. Moderator name.
alpha	Significance level. Default 0.05.
modx.range	Numeric vector of length 2 giving the range over which to evaluate the slope. Defaults to the observed range of modx.
grid	Integer. Number of points at which to evaluate the slope across the moderator range. Default 200.

Value

An object of class `mlm_jn` with components:

- `jn_bounds`: numeric vector of moderator values where the slope crosses the significance threshold. NA if no finite region exists.
- `slopes_df`: data frame of slope estimates and significance across the grid.
- `pred`, `modx`, `alpha`, `modx.range`.

Examples

```
set.seed(1)
dat <- data.frame(
  y = rnorm(200), x = rnorm(200),
  m = rep(rnorm(20), each = 10),
  grp = factor(rep(1:20, each = 10))
)
dat$y <- dat$y + dat$x * dat$m
mod <- lme4::lmer(y ~ x * m + (1 | grp), data = dat,
  control = lme4::lmerControl(optimizer = "bobyqa"))
jn <- mlm_jn(mod, pred = "x", modx = "m")
print(jn)
```

mlm_plot

*Publication-ready interaction plot for multilevel models***Description**

Creates a ggplot2-based interaction plot showing predicted values of the outcome across levels of pred, with separate lines for each selected value of modx. Confidence bands and raw data overlay are optional.

Usage

```
mlm_plot(
  model,
  pred,
  modx,
  modx.values = c("mean-sd", "quartiles", "tertiles", "custom"),
  at = NULL,
  interval = TRUE,
  conf.level = 0.95,
  points = FALSE,
  point_alpha = 0.3,
  colors = NULL,
  line_size = 1,
  x_label = NULL,
  y_label = NULL,
  legend_title = NULL
)
```

Arguments

model	An lmerMod object with a two-way interaction between pred and modx in the fixed-effects.
pred	Character scalar. Focal predictor (x-axis).
modx	Character scalar. Moderator (separate lines).
modx.values	Strategy for moderator values. Same options as mlm_probe(): "mean-sd", "quartiles", "tertiles", "custom".
at	Numeric vector of custom moderator values (used when modx.values = "custom").
interval	Logical. Draw confidence bands? Default TRUE.
conf.level	Confidence level for bands. Default 0.95.
points	Logical. Overlay raw data points? Default FALSE.
point_alpha	Transparency for raw data points. Default 0.3.
colors	Character vector of colours for moderator lines. If NULL, uses a accessible default palette.
line_size	Line width for predicted lines. Default 1.

x_label Label for x-axis. Defaults to pred.
 y_label Label for y-axis. Defaults to response variable name.
 legend_title Label for the legend. Defaults to modx.

Value

A ggplot object.

Examples

```
set.seed(1)
dat <- data.frame(
  y = rnorm(200),
  x = rnorm(200),
  m = rep(rnorm(20), each = 10),
  grp = factor(rep(1:20, each = 10))
)
dat$y <- dat$y + dat$x * dat$m
mod <- lme4::lmer(y ~ x * m + (1 | grp), data = dat,
  control = lme4::lmerControl(optimizer = "bobyqa"))
mlm_plot(mod, pred = "x", modx = "m")
mlm_plot(mod, pred = "x", modx = "m", modx.values = "quartiles")
```

mlm_probe

Probe simple slopes from a multilevel interaction

Description

Computes simple slopes of a focal predictor (pred) at selected values of a moderator (modx) from a two-level mixed-effects model fitted with `lme4::lmer()`. Returns estimates, standard errors, *t*-values, *p*-values, and confidence intervals in a tidy data frame.

Usage

```
mlm_probe(
  model,
  pred,
  modx,
  modx.values = c("mean-sd", "quartiles", "tertiles", "custom"),
  at = NULL,
  conf.level = 0.95
)
```

Arguments

model	An lmerMod object containing a two-way interaction between pred and modx in the fixed-effects structure.
pred	Character scalar. Name of the focal predictor variable.
modx	Character scalar. Name of the moderator variable.
modx.values	Strategy for selecting moderator values. One of: <ul style="list-style-type: none"> • "mean-sd" (default): mean — 1 SD, mean, mean + 1 SD. • "quartiles": 25th, 50th, 75th percentiles. • "tertiles": 33rd and 67th percentiles. • "custom": use values supplied via at.
at	Numeric vector of custom moderator values. Used when modx.values = "custom", or to override any strategy.
conf.level	Confidence level for intervals. Default 0.95.

Value

An object of class `mlm_probe` (a list) with components:

- `slopes`: a data frame with columns `modx_value`, `slope`, `se`, `t`, `df`, `p`, `ci_lower`, `ci_upper`.
- `pred`, `modx`: names of the predictor and moderator.
- `modx.values`: the strategy used.
- `conf.level`: the confidence level.
- `model`: the original model (stored for downstream use).

Examples

```
set.seed(1)
dat <- data.frame(
  y = rnorm(200), x = rnorm(200),
  m = rep(rnorm(20), each = 10),
  grp = factor(rep(1:20, each = 10))
)
dat$y <- dat$y + dat$x * dat$m
mod <- lme4::lmer(y ~ x * m + (1 | grp), data = dat,
  control = lme4::lmerControl(optimizer = "bobyqa"))
mlm_probe(mod, pred = "x", modx = "m")
mlm_probe(mod, pred = "x", modx = "m", modx.values = "quartiles")
mlm_probe(mod, pred = "x", modx = "m", modx.values = "custom", at = c(-1, 0, 1))
```

mlm_sensitivity *Robustness diagnostics for cross-level interaction effects*

Description

Assesses the stability of a cross-level interaction effect using two MLM-appropriate diagnostics:

Usage

```
mlm_sensitivity(
  model,
  pred,
  modx,
  alpha = 0.05,
  icc_range = c(0.01, 0.4),
  icc_grid = 50L,
  loco = TRUE,
  conf.level = 0.95,
  verbose = FALSE
)
```

Arguments

model	An lmerMod object with a two-way interaction between pred and modx.
pred	Character scalar. Focal predictor name.
modx	Character scalar. Moderator name.
alpha	Significance level. Default 0.05.
icc_range	Numeric vector of length 2. Range of ICC values to evaluate. Default c(0.01, 0.40).
icc_grid	Integer. Number of ICC values in the grid. Default 50.
loco	Logical. Run leave-one-cluster-out analysis? Default TRUE. Set to FALSE for large datasets where refitting is slow.
conf.level	Confidence level. Default 0.95.
verbose	Logical. Print progress during LOCO refitting? Default FALSE.

Details

1. **ICC-shift robustness** – how do the interaction SE and Johnson-Neyman boundary change if the intraclass correlation were different from what was observed? This is relevant because the ICC determines the effective sample size at level 2, which directly governs precision of cross-level interaction estimates.
2. **Leave-one-cluster-out (LOCO) stability** – refit the model dropping one cluster at a time and track how the interaction coefficient moves. This is nonparametric, makes no distributional assumptions, and directly answers: "Is this finding driven by a small number of influential clusters?"

Value

An object of class `mlm_sensitivity` with components:

- `icc_shift`: data frame of interaction SE, t, p, significance, and approximate JN boundary across the ICC grid.
- `loco`: data frame with one row per cluster giving the interaction coefficient, SE, t, p, and Cook's-distance-style influence measure when that cluster is omitted. NULL if `loco = FALSE`.
- `robustness_index`: proportion of the ICC range where the interaction remains significant.
- `observed`: list of observed model statistics.
- `Metadata`: `pred`, `modx`, `alpha`, `icc_range`, `int_term`.

Scope

These are **robustness diagnostics**, not a full causal sensitivity analysis. They do not quantify the strength of unmeasured confounding needed to explain away the interaction – that requires a level-2-aware omitted variable bound that is currently under development as a separate methodological contribution. See `vignette("robustness-diagnostics")` for interpretation guidance.

Examples

```
# Use a small dataset for fast execution
set.seed(42)
n_j <- 20; n_i <- 10
dat_small <- data.frame(
  y = rnorm(n_j * n_i),
  x = rnorm(n_j * n_i),
  m = rep(rnorm(n_j), each = n_i),
  grp = factor(rep(seq_len(n_j), each = n_i))
)
dat_small$y <- dat_small$y + 0.5 * dat_small$x * dat_small$m
mod_small <- lme4::lmer(y ~ x * m + (1 + x | grp), data = dat_small,
  control = lme4::lmerControl(optimizer = "bobyqa"))

# ICC-shift only (fast)
sens <- mlm_sensitivity(mod_small, pred = "x", modx = "m", loco = FALSE)
print(sens)

# Full diagnostics including LOCO (20 clusters - fast)

sens_full <- mlm_sensitivity(mod_small, pred = "x", modx = "m")
plot(sens_full)
```

mlm_summary

*Summary table for a multilevel moderation effect***Description**

Returns a consolidated summary of the moderation effect: the focal interaction coefficient, simple slopes at selected moderator values, and (optionally) the Johnson—Neyman interval. Designed for quick reporting and results sections.

Usage

```
mlm_summary(
  model,
  pred,
  modx,
  modx.values = c("mean-sd", "quartiles", "tertiles", "custom"),
  at = NULL,
  conf.level = 0.95,
  jn = TRUE,
  alpha = 0.05
)
```

Arguments

model	An lmerMod object with a two-way interaction between pred and modx.
pred	Character scalar. Focal predictor name.
modx	Character scalar. Moderator name.
modx.values	Moderator value strategy. See <code>mlm_probe()</code> .
at	Optional numeric vector of custom moderator values.
conf.level	Confidence level. Default 0.95.
jn	Logical. Include Johnson-Neyman region? Default TRUE.
alpha	Alpha for JN interval. Default 0.05.

Value

An object of class `mlm_summary` (a list) with components:

- `interaction`: one-row data frame for the interaction term.
- `simple_slopes`: data frame from `mlm_probe()`.
- `jn`: output of `mlm_jn()` (or NULL if `jn = FALSE`).
- Other metadata.

Examples

```

set.seed(1)
dat <- data.frame(
  y = rnorm(200), x = rnorm(200),
  m = rep(rnorm(20), each = 10),
  grp = factor(rep(1:20, each = 10))
)
dat$y <- dat$y + dat$x * dat$m
mod <- lme4::lmer(y ~ x * m + (1 | grp), data = dat,
  control = lme4::lmerControl(optimizer = "bobyqa"))
mlm_summary(mod, pred = "x", modx = "m")

```

mlm_surface	<i>Contour plot of predicted outcomes over the predictor x moderator space</i>
-------------	--

Description

Plots iso-outcome contour lines of $\hat{Y}(x, w)$ over the full joint space of pred (x-axis) and modx (y-axis). This is the most direct geometric representation of a two-way interaction:

Usage

```

mlm_surface(
  model,
  pred,
  modx,
  grid = 80L,
  n_contours = 10L,
  fill = TRUE,
  probe_lines = TRUE,
  x_label = NULL,
  y_label = NULL,
  legend_title = NULL
)

```

Arguments

model	An lmerMod object with a two-way interaction between pred and modx in the fixed effects.
pred	Character scalar. Focal predictor (x-axis).
modx	Character scalar. Moderator (y-axis).
grid	Integer. Grid resolution (points per axis). Default 80.
n_contours	Integer. Number of contour levels to draw. Default 10.
fill	Logical. Fill contour bands with colour? Default TRUE.

probe_lines	Logical. Overlay horizontal lines at mean – 1 SD of modx? Default TRUE.
x_label	x-axis label. Defaults to pred.
y_label	y-axis label. Defaults to modx.
legend_title	Legend title. Defaults to the outcome variable name.

Details

- **No interaction:** contour lines are perfectly straight and parallel — the effect of pred does not depend on modx.
- **Positive interaction:** contour lines fan outward (rotate clockwise) — higher modx steepens the pred slope.
- **Negative interaction:** contour lines fan inward (rotate counter-clockwise).

The degree of non-parallelism among contours is a direct visual index of interaction strength: the larger β_3 , the more the lines rotate.

An optional overlay draws the three standard simple-slope evaluation lines (mean – 1 SD of modx) as horizontal reference lines, connecting the plot to `mlm_probe()` output.

Predicted values are computed from fixed effects only (*re. form = NA*), with all covariates held at their means or reference levels. The surface therefore represents the population-average predicted outcome, not any specific cluster.

Reading the plot: Pick any contour line. Its slope in the pred direction tells you how fast the outcome changes with pred at that modx value. If the contour slopes steeply up-right, pred has a strong positive effect there. If contours become more horizontal as modx increases, the pred effect is weakening. If they rotate from positive to flat to negative, you have a sign-changing interaction — and the modx value where they are perfectly horizontal is the Johnson-Neyman boundary.

Value

A ggplot object.

Examples

```
set.seed(1)
dat <- data.frame(
  y = rnorm(200), x = rnorm(200),
  m = rep(rnorm(20), each = 10),
  grp = factor(rep(1:20, each = 10))
)
dat$y <- dat$y + dat$x * dat$m
mod <- lme4::lmer(y ~ x * m + (1 | grp), data = dat,
  control = lme4::lmerControl(optimizer = "bobyqa"))
mlm_surface(mod, pred = "x", modx = "m")
mlm_surface(mod, pred = "x", modx = "m", fill = FALSE, n_contours = 15)
```

mlm_variance_decomp *Decompose uncertainty in the simple slope of a multilevel interaction*

Description

In a random-slope model, the uncertainty around a simple slope has two distinct sources that standard `mlm_probe()` collapses into one SE:

Usage

```
mlm_variance_decomp(
  model,
  pred,
  modx,
  modx.values = c("mean-sd", "quartiles", "tertiles", "custom"),
  at = NULL,
  conf.level = 0.95
)
```

Arguments

<code>model</code>	An <code>lmerMod</code> object with a random slope for <code>pred</code> and a two-way interaction between <code>pred</code> and <code>modx</code> .
<code>pred</code>	Character scalar. Focal predictor name.
<code>modx</code>	Character scalar. Moderator name.
<code>modx.values</code>	Strategy for moderator values. See <code>mlm_probe()</code> .
<code>at</code>	Optional numeric vector of custom moderator values.
<code>conf.level</code>	Confidence level for fixed-effect CIs. Default 0.95.

Details

1. **Fixed-effect uncertainty** – imprecision in the estimated average slope ($\beta_1 + \beta_3 \cdot w$), captured by the fixed-effect variance-covariance matrix.
2. **Random-slope variance** – genuine between-cluster heterogeneity in the slope of `pred` (τ_{11}), which is *not* estimation error but real variation in effects across clusters.

These answer different questions:

- Fixed-effect uncertainty: "How precisely do we know the *average* slope at this moderator value?"
- Random-slope variance: "How much does the slope *actually vary* across clusters, regardless of what the moderator does?"

The function also reports a **prediction interval** for the slope in a new (unobserved) cluster, which combines both sources and is the appropriate uncertainty interval for making cluster-level predictions.

Random-slope variance (τ_{11}) interpretation: If τ_{11} is large relative to the fixed slope, the effect of pred varies substantially across clusters even *after* accounting for the moderator. This is important: a significant interaction does not mean the moderator fully explains between-cluster slope heterogeneity.

Prediction interval interpretation: The prediction interval answers: "For a randomly sampled new cluster at this moderator value, what range of slopes should we expect?" It will always be wider than the confidence interval because it incorporates τ_{11} .

Percentage of variance from random effects: $\%random = \frac{\tau_{11}}{\tau_{11} + \text{Var}(\hat{\beta}_{\text{simple slope}})} \times 100$

Value

An object of class `mlm_variance_decomp` (a list) with:

- `decomp`: data frame with columns `modx_value`, `slope`, `se_fixed` (SE from fixed-effect vcov only), `tau11` (random-slope SD, if estimable), `se_total` (combined SE for prediction in new cluster), `ci_lower`, `ci_upper` (fixed-effect CI), `pi_lower`, `pi_upper` (prediction interval for new cluster), `pct_random` (% of total slope variance from random effects).
- `tau11`: the random-slope variance (τ_{11}).
- `has_random_slope`: logical – does the model include a random slope for pred?
- `Metadata`: `pred`, `modx`, `conf.level`.

Examples

```
set.seed(1)
dat <- data.frame(
  y = rnorm(200), x = rnorm(200),
  m = rep(rnorm(20), each = 10),
  grp = factor(rep(1:20, each = 10))
)
dat$y <- dat$y + dat$x * dat$m
mod <- lme4::lmer(y ~ x * m + (1 + x | grp), data = dat,
  control = lme4::lmerControl(optimizer = "bobyqa"))
vd <- mlm_variance_decomp(mod, pred = "x", modx = "m")
print(vd)
```

Description

Creates a `ggplot2` figure showing the simple slope of `pred` across the full range of `modx`, with shading indicating regions of significance. A vertical dashed line marks each Johnson-Neyman boundary.

Usage

```
## S3 method for class 'mlm_jn'
plot(
  x,
  x_label = NULL,
  y_label = NULL,
  sig_color = "#2166AC",
  nonsig_color = "#D6604D",
  ...
)
```

Arguments

x	An <code>mlm_jn</code> object from <code>mlm_jn()</code> .
x_label	Label for the x-axis. Defaults to the moderator name.
y_label	Label for the y-axis. Defaults to "Simple slope of pred".
sig_color	Fill colour for the significant region. Default "#2166AC".
nonsig_color	Fill colour for the non-significant region. Default "#D6604D".
...	Ignored.

Value

A ggplot object.

Examples

```
set.seed(1)
dat <- data.frame(
  y = rnorm(200), x = rnorm(200),
  m = rep(rnorm(20), each = 10),
  grp = factor(rep(1:20, each = 10))
)
dat$y <- dat$y + dat$x * dat$m
mod <- lme4::lmer(y ~ x * m + (1 | grp), data = dat,
  control = lme4::lmerControl(optimizer = "bobyqa"))
jn <- mlm_jn(mod, pred = "x", modx = "m")
plot(jn)
```

plot.mlm_sensitivity *Plot robustness diagnostics for a cross-level interaction*

Description

Produces up to three panels: (1) interaction SE across the ICC range, (2) JN boundary shift across the ICC range, and (3) LOCO coefficient stability plot showing the interaction estimate when each cluster is omitted, with influential clusters flagged.

Usage

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

Arguments

x	An <code>mlm_sensitivity</code> object.
...	Ignored.

Value

A ggplot object.

```
plot.mlm_variance_decomp
```

Plot the variance decomposition of simple slopes

Description

Shows the simple slope at each moderator value as a point with two interval layers: an inner confidence interval (fixed-effect uncertainty only) and an outer prediction interval (fixed + random-slope variance). The gap between the two intervals is the contribution of random-slope heterogeneity.

Usage

```
## S3 method for class 'mlm_variance_decomp'  
plot(x, x_label = NULL, y_label = NULL, ...)
```

Arguments

x	An <code>mlm_variance_decomp</code> object.
x_label	x-axis label. Defaults to moderator name.
y_label	y-axis label. Defaults to "Simple slope of pred".
...	Ignored.

Value

A ggplot object.

 school_data

Simulated school achievement dataset

Description

A simulated two-level dataset with students nested within schools, designed to illustrate multilevel moderation analysis. The true data-generating model includes a cross-level interaction between student socioeconomic status and school climate.

Usage

```
school_data
```

Format

A data frame with 3,000 rows and 6 variables:

school A factor indicating the school identifier (1–100).

student An integer indicating the student identifier (1–3000).

math A numeric mathematics achievement score.

ses A numeric student socioeconomic status variable (standardized).

climate A numeric school climate rating (standardized level-2 variable).

gender A factor indicating student gender with levels "female" and "male".

Details

The data were generated from the model

$$math_{ij} = 50 + 1.5 ses_{ij} + 0.8 climate_j + 0.5 ses_{ij}climate_j + u_{0j} + u_{1j}ses_{ij} + e_{ij}.$$

The level-2 random effects were generated as $u_{0j} \sim N(0, 9)$ and $u_{1j} \sim N(0, 0.25)$, and the level-1 residuals were generated as $e_{ij} \sim N(0, 25)$.

Examples

```
data(school_data)
head(school_data)
str(school_data)
```

```
library(lme4)
mod <- lmer(math ~ ses * climate + gender + (1 + ses | school),
            data = school_data)
mlm_probe(mod, pred = "ses", modx = "climate")
```

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