

# Package ‘glmertree’

November 19, 2019

**Title** Generalized Linear Mixed Model Trees

**Date** 2019-11-19

**Version** 0.2-0

**Description** Recursive partitioning based on (generalized) linear mixed models (GLMMs) combining lmer()/glmer() from 'lme4' and lmtree()/glmertree() from 'partykit'. The fitting algorithm is described in more detail in Fokkema, Smits, Zeileis, Hothorn & Kelderman (2018; <DOI:10.3758/s13428-017-0971-x>).

**Depends** R (>= 3.1.0), lme4, partykit (>= 1.0-4)

**Imports** graphics, stats, utils, Formula

**Suggests** vcd, lattice

**LazyData** yes

**License** GPL-2 | GPL-3

**RoxygenNote** 6.1.1

**NeedsCompilation** no

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**Repository** CRAN

**Date/Publication** 2019-11-19 18:30:05 UTC

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coef.glmertree	<i>Obtaining Fixed-Effects Coefficient Estimates of (Generalized) Linear Mixed Model Trees</i>
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### Description

coef and fixef methods for (g)lmertree objects.

### Usage

```
## S3 method for class 'lmertree'
coef(object, which = "tree", drop = FALSE, ...)
## S3 method for class 'lmertree'
fixef(object, which = "tree", drop = FALSE, ...)
## S3 method for class 'glmertree'
coef(object, which = "tree", drop = FALSE, ...)
## S3 method for class 'glmertree'
fixef(object, which = "tree", drop = FALSE, ...)
```

### Arguments

object	an object of class lmertree or glmertree.
which	character; "tree" (default) or "global". Specifies whether local (tree) or global fixed-effects estimates should be returned.
drop	logical. Only used when which = "tree"; delete the dimensions of the resulting array if it has only one level?
...	Additional arguments, currently not used.

### Details

The code is still under development and might change in future versions.

### Value

If type = "local", returns a matrix of estimated local fixed-effects coefficients, with a row for every terminal node and a column for every fixed effect. If type = "global", returns a numeric vector of estimated global fixed-effects coefficients.

### References

Fokkema M, Smits N, Zeileis A, Hothorn T, Kelderman H (2018). "Detecting Treatment-Subgroup Interactions in Clustered Data with Generalized Linear Mixed-Effects Model Trees". Behavior Research Methods, 50(5), 2016-2034. <https://doi.org/10.3758/s13428-017-0971-x>

### See Also

[lmertree](#), [glmertree](#), [party-plot](#).

## Examples

```
## load artificial example data
data("DepressionDemo", package = "glmertree")

## fit LMM tree with local fixed effects only
lt <- lmertree(depression ~ treatment + age | cluster | anxiety + duration,
  data = DepressionDemo)
coef(lt)

## fit LMM tree including both local and global fixed effect
lt <- lmertree(depression ~ treatment | (age + (1|cluster)) | anxiety + duration,
  data = DepressionDemo)
coef(lt, which = "tree") # default behaviour
coef(lt, which = "global")

## fit GLMM tree with local fixed effects only
gt <- glmertree(depression_bin ~ treatment | cluster |
  age + anxiety + duration, data = DepressionDemo)
coef(gt)

## fit GLMM tree including both local and global fixed effect
gt <- glmertree(depression_bin ~ treatment | (age + (1|cluster)) |
  anxiety + duration, data = DepressionDemo)
coef(gt, which = "tree") # default behaviour
coef(gt, which = "global")
```

---

DepressionDemo

*Artificial depression treatment dataset*

---

## Description

Simulated dataset of a randomized clinical trial (N = 150) to illustrate fitting of (G)LMM trees.

## Usage

```
data("DepressionDemo")
```

## Format

A data frame containing 150 observations on 6 variables:

**depression** numeric. Continuous treatment outcome variable (range: 3-16, M = 9.12, SD = 2.66).

**treatment** factor. Binary treatment variable.

**cluster** factor. Indicator for cluster with 10 levels.

**age** numeric. Continuous partitioning variable (range: 18-69, M = 45, SD = 9.56).

**anxiety** numeric. Continuous partitioning variable (range: 3-18, M = 10.26, SD = 3.05).

**duration** numeric. Continuous partitioning variable (range: 1-17, M = 6.97, SD = 2.90).

**depression\_bin** factor. Binarized treatment outcome variable (0 = recovered, 1 = not recovered).

### Details

The data were generated such that the duration and anxiety covariates characterized three subgroups with differences in treatment effects. The `cluster` variable was used to introduce a random intercept that should be accounted for. The treatment outcome is an index of depressive symptomatology.

### See Also

[lmertree](#), [glmertree](#)

### Examples

```
data("DepressionDemo", package = "glmertree")
summary(DepressionDemo)
lt <- lmertree(depression ~ treatment | cluster | anxiety + duration + age,
              data = DepressionDemo)
plot(lt)
gt <- glmertree(depression_bin ~ treatment | cluster | anxiety + duration + age,
               data = DepressionDemo)
plot(gt)
```

---

glmertree

*(Generalized) Linear Mixed Model Trees*

---

### Description

Model-based recursive partitioning based on (generalized) linear mixed models.

### Usage

```
lmertree(formula, data, weights = NULL, cluster = NULL,
         ranefstart = NULL, offset = NULL, joint = TRUE,
         abstol = 0.001, maxit = 100, dfsplit = TRUE, verbose = FALSE,
         plot = FALSE, REML = TRUE, lmer.control = lmerControl(), ...)

glmertree(formula, data, family = "binomial", weights = NULL,
          cluster = NULL, ranefstart = NULL, offset = NULL, joint = TRUE,
          abstol = 0.001, maxit = 100, dfsplit = TRUE, verbose = FALSE,
          plot = FALSE, nAGQ = 1L, glmer.control = glmerControl(), ...)
```

**Arguments**

formula	formula specifying the response variable and a three-part right-hand-side describing the regressors, random effects, and partitioning variables, respectively. For details see below.
data	data.frame to be used for estimating the model tree.
family	family specification for glmtree and glmer. See <a href="#">glm</a> documentation for families.
weights	numeric. An optional numeric vector of weights. Can be a name of a column in data or a vector of length nrow(data).
cluster	optional vector of cluster IDs to be employed for clustered covariances in the parameter stability tests. Can be a name of a column in data or a vector of length nrow(data). If cluster = NULL (the default), observation-level covariances are employed in the parameter stability tests. If partitioning variables are measured on the cluster level, this will likely yield spurious splits, which can be mitigated by specification of the cluster argument, which results in cluster-level covariances being employed in the parameter stability tests.
ranefstart	NULL (the default), TRUE, or a numeric vector of length nrow(data). Specifies the offset to be used in estimation of the first tree. NULL by default, yielding a zero offset initialization. If ranefstart = TRUE is specified, the random effects will be estimated first and the first tree will be grown using the random-effects predictions as an offset.
offset	optional numeric vector to be included in the linear predictor with a coefficient of one. Note that offset can be a name of a column in data or a numeric vector of length nrow(data).
joint	logical. Should the fixed effects from the tree be (re-)estimated jointly along with the random effects?
abstol	numeric. The convergence criterion used for estimation of the model. When the difference in log-likelihoods of the random-effects model from two consecutive iterations is smaller than abstol, estimation of the model tree has converged.
maxit	numeric. The maximum number of iterations to be performed in estimation of the model tree.
dfsplitt	logical or numeric. as.integer(dfsplitt) is the degrees of freedom per selected split employed when extracting the log-likelihood.
verbose	Should the log-likelihood value of the estimated random-effects model be printed for every iteration of the estimation?
plot	Should the tree be plotted at every iteration of the estimation? Note that selecting this option slows down execution of the function.
REML	logical scalar. Should the fixed-effects estimates be chosen to optimize the REML criterion (as opposed to the log-likelihood)? Will be passed to function lmer(). See <a href="#">lmer</a> for details.
nAGQ	integer scalar. Specifies the number of points per axis for evaluating the adaptive Gauss-Hermite approximation to the log-likelihood, to be passed to function glmer(). See <a href="#">glmer</a> for details.

`lmer.control`, `glmer.control`  
 list. An optional list with control parameters to be passed to `lmer()` and `glmer()`, respectively. See [lmerControl](#) for details.

... Additional arguments to be passed to `lmtree()` or `glmtree()`. See [mob\\_control](#) documentation for details.

## Details

(G)LMM trees learn a tree where each terminal node is associated with different fixed-effects regression coefficients while adjusting for global random effects (such as a random intercept). This allows for detection of subgroups with different fixed-effects parameter estimates, keeping the random effects constant throughout the tree (i.e., random effects are estimated globally). The estimation algorithm iterates between (1) estimation of the tree given an offset of random effects, and (2) estimation of the random effects given the tree structure. See Fokkema et al. (2018) for a detailed introduction.

To specify all variables in the model a formula such as  $y \sim x1 + x2 \mid \text{random} \mid z1 + z2 + z3$  is used, where  $y$  is the response,  $x1$  and  $x2$  are the regressors in every node of the tree, `random` is the random effects, and  $z1$  to  $z3$  are the partitioning variables considered for growing the tree. If `random` is only a single variable such as `id` a random intercept with respect to `id` is used. Alternatively, it may be an explicit random-effects formula such as  $(1 \mid \text{id})$  or a more complicated formula such as  $((1 + \text{time}) \mid \text{id})$ . (Note that in the latter two formulas, the brackets are necessary to protect the pipes in the random-effects formulation.)

In the random-effects model from step (2), two strategies are available: Either the fitted values from the tree can be supplied as an offset (`joint = FALSE`) so that only the random effects are estimated. Or the fixed effects are (re-)estimated along with the random effects using a nesting factor with nodes from the tree (`joint = TRUE`). In the former case, the estimation of each random-effects model is typically faster, but more iterations are required.

The code is still under development and might change in future versions.

## Value

The function returns a list with the following objects:

<code>tree</code>	The final <code>lmtree</code> / <code>glmtree</code> .
<code>lmer</code>	The final <code>lmer</code> random-effects model.
<code>ranef</code>	The corresponding random effects of <code>lmer</code> .
<code>varcorr</code>	The corresponding <code>VarCorr(lmer)</code> .
<code>variance</code>	The corresponding <code>attr(VarCorr(lmer), "sc")^2</code> .
<code>data</code>	The dataset specified with the <code>data</code> argument including added auxiliary variables <code>.ranef</code> and <code>.tree</code> from the last iteration.
<code>loglik</code>	The log-likelihood value of the last iteration.
<code>iterations</code>	The number of iterations used to estimate the <code>lmtree</code> .
<code>maxit</code>	The maximum number of iterations specified with the <code>maxit</code> argument.
<code>ranefstart</code>	The random effects used as an offset, as specified with the <code>ranefstart</code> argument.

formula	The formula as specified with the formula argument.
randomformula	The formula as specified with the randomformula argument.
abstol	The prespecified value for the change in log-likelihood to evaluate convergence, as specified with the abstol argument.
mob.control	A list containing control parameters passed to lmtree(), as specified with ...
lmer.control	A list containing control parameters passed to lmer(), as specified in the lmer.control argument.
joint	Whether the fixed effects from the tree were (re-)estimated jointly along with the random effects, specified with the joint argument.

## References

Fokkema M, Smits N, Zeileis A, Hothorn T, Kelderman H (2018). “Detecting Treatment-Subgroup Interactions in Clustered Data with Generalized Linear Mixed-Effects Model Trees”. *Behavior Research Methods*, 50(5), 2016-2034. <https://doi.org/10.3758/s13428-017-0971-x>

## See Also

[lmer](#), [glmer](#), [lmtree](#), [glmtree](#), [plot.lmtree](#), [plot.glmtree](#)

## Examples

```
## artificial example data
data("DepressionDemo", package = "glmtree")

## fit normal linear regression LMM tree for continuous outcome
lt <- lmtree(depression ~ treatment | cluster | age + anxiety + duration,
  data = DepressionDemo)
print(lt)
plot(lt, which = "all") # default behavior, may also be "tree" or "ranef"
coef(lt)
ranef(lt)
predict(lt, type = "response") # default behavior, may also be "node"
predict(lt, re.form = NA) # excludes random effects, see ?lme4::predict.merMod
residuals(lt)
VarCorr(lt) # see lme4::VarCorr

## fit logistic regression GLMM tree for binary outcome
gt <- glmtree(depression_bin ~ treatment | cluster | age + anxiety + duration,
  data = DepressionDemo)
print(gt)
plot(gt, which = "all") # default behavior, may also be "tree" or "ranef"
coef(gt)
ranef(gt)
predict(gt, type = "response") # default behavior, may also be "node" or "link"
predict(gt, re.form = NA) # excludes random effects, see ?lme4::predict.merMod
residuals(gt)
VarCorr(gt) # see lme4::VarCorr
```

---

GrowthCurveDemo

*Artificial dataset for partitioning of linear growth curve models*

---

### Description

Artificial dataset to illustrate fitting of LMM trees with growth curve models in the terminal nodes.

### Usage

```
data("GrowthCurveDemo")
```

### Format

A data frame containing 1250 repeated observations on 250 persons. x1 - x8 are time-invariant partitioning variables. Thus, they are measurements on the person (i.e., cluster) level, not on the individual observation level.

**person** numeric. Indicator linking repeated measurements to persons.

**time** factor. Indicator for timepoint.

**y** numeric. Response variable.

**x1** numeric. Potential partitioning variable.

**x2** numeric. Potential partitioning variable.

**x3** numeric. Potential partitioning variable.

**x4** numeric. Potential partitioning variable.

**x5** numeric. Potential partitioning variable.

**x6** numeric. Potential partitioning variable.

**x7** numeric. Potential partitioning variable.

**x8** numeric. Potential partitioning variable.

### Details

Data were generated so that x1, x2 and x3 are true partitioning variables, x4 through x8 are noise variables. The (potential) partitioning variables are time invariant. Time-varying covariates can also be included in the model. For partitioning growth curves these should probably not be potential partitioning variables, as this could result in observations from the same person ending up in different terminal nodes. Thus, time-varying covariates are probably best included as predictors in the node-specific regression model. E.g.:  $y \sim \text{time} + \text{timevarying\_cov} \mid \text{person} \mid x1 + x2 + x3 + x4$ .

### See Also

[lmertree](#), [glmertree](#)



## Examples

```

data("GrowthCurveDemo", package = "glmtree")
head(GrowthCurveDemo)

## Fit LMM tree with a random intercept w.r.t. person:
form <- y ~ time | person | x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8
lt.default <- lmtree(form, data = GrowthCurveDemo)
plot(lt.default, which = "tree") ## yields too large tree
VarCorr(lt.default)

## Account for measurement level of the partitioning variables:
lt.cluster <- lmtree(form, cluster = person, data = GrowthCurveDemo)
plot(lt.cluster, which = "tree") ## yields correct tree
VarCorr(lt.cluster) ## yields slightly larger ranef variance

## Fit LMM tree with random intercept and random slope of time w.r.t. person:
form.s <- y ~ time | (1 + time | person) | x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8
lt.s.cluster <- lmtree(form.s, cluster = person, data = GrowthCurveDemo)
plot(lt.s.cluster, which = "tree") ## same tree as before
VarCorr(lt.s.cluster)

```

---

MHserviceDemo

*Artificial mental-health service outcomes dataset*

---

## Description

Artificial dataset of treatment outcomes (N = 3739) of 13 mental-health services to illustrate fitting of (G)LMM trees with constant fits in terminal nodes.

## Usage

```
data("MHserviceDemo")
```

## Format

A data frame containing 3739 observations on 8 variables:

**age** numeric. Variable representing age in years (range: 4.8 - 23.6, M = 11.46).

**impact** numeric. Continuous variable representing severity of and impairment due to mental-health problems at baseline. Higher values indicate higher severity and impairment.

**gender** factor. Indicator for gender.

**emotional** factor. Indicator for presence of emotional disorder at baseline.

**autism** factor. Indicator for presence of autistic disorder at baseline.

**conduct** factor. Indicator for mental-health service provider.

**cluster\_id** factor. Binarized treatment outcome variable (0 = recovered, 1 = not recovered).

**outcome** numeric. Variable representing treatment outcome as measured by a total mental-health difficulties score assessed about 6 months after baseline, corrected for the baseline assessment. Higher values indicate poorer outcome.

### Details

Dataset was modelled after Edbrooke-Childs et al. (2017), who analyzed a sample of  $N = 3,739$  young people who received treatment at one of 13 mental-health service providers in the UK. Note that the data were artificially generated and do not reflect actual empirical findings.

### See Also

[lmertree](#), [glmertree](#)

### Examples

```
data("MHserviceDemo", package = "glmertree")
summary(MHserviceDemo)
lt <- lmertree(outcome ~ 1 | cluster_id | age + gender + emotional +
              autism + impact + conduct, data = MHserviceDemo)
plot(lt)

MHserviceDemo$outcome_bin <- factor(MHserviceDemo$outcome > 0)
gt <- glmertree(outcome_bin ~ 1 | cluster_id | age + gender +
               emotional + autism + impact + conduct,
               data = MHserviceDemo, family = "binomial")
plot(gt)
```

---

plot.glmertree

*Plotting (Generalized) Linear Mixed Model Trees*

---

### Description

plot method for (g)lmertree objects.

### Usage

```
## S3 method for class 'lmertree'
plot(x, which = "all", ask = TRUE, type = "extended",
     observed = TRUE, fitted = "combined", tp_args = list(),
     drop_terminal = TRUE, terminal_panel = NULL, ...)
## S3 method for class 'glmertree'
plot(x, which = "all", ask = TRUE, type = "extended",
     observed = TRUE, fitted = "combined", tp_args = list(),
     drop_terminal = TRUE, terminal_panel = NULL, ...)
```

**Arguments**

x	an object of class <code>lmtree</code> or <code>glmertree</code> .
which	character; "all" (default), "tree", "random" or "tree.coef". Specifies whether, tree, random effects, or both should be plotted. Alternatively, "tree.coef" yields caterpillar plots of the estimated fixed-effects coefficients in every terminal node of the tree, but omits the tree structure (see Details).
ask	logical. Should user be asked for input, before a new figure is drawn?
type	character; "extended" (default) or "simple". <code>type = "extended"</code> yields a plotted tree with observed data and/or fitted means plotted in the terminal nodes; "simple" yields a plotted tree with the value of fixed and/or random effects coefficients reported in the terminal nodes.
observed	logical. Should observed datapoints be plotted in the tree? Defaults to TRUE, FALSE is only supported for objects of class <code>lmtree</code> , not of class <code>glmertree</code> .
fitted	character. "combined" (default), "marginal" or "none". Specifies whether and how fitted values should be computed and visualized. Only used when predictor variables for the node-specific (G)LMs were specified. If "combined", fitted values will be computed, based on the observed values of the remaining (random and fixed-effects) predictor variables, and their estimated effects. If "marginal", fitted values will be calculated, keeping all remaining variables (with random and/or fixed effects) fixed at their (population and sample) means (or majority class).
tp_args	list of arguments to be passed to panel generating function <code>node_glmertree</code> . See arguments <code>node_bivplot</code> in <a href="#">panelfunctions</a> .
drop_terminal	logical. Should all terminal nodes be plotted at the bottom of the plot?
terminal_panel	an optional panel function to be passed to <code>plot.party()</code> . See <a href="#">party-plot</a> documentation for details.
...	Additional arguments to be passed to <code>plot.party()</code> . See <a href="#">party-plot</a> documentation for details.

**Details**

The caterpillar plot(s) for the local (node-specific) fixed effects (created when `which = "tree.coef"`) depict the estimated fixed-effects coefficients with 95% confidence intervals, but these CIs do not account for the searching of the tree structure and are therefore likely too narrow. There is currently no way to adjust CIs for searching of the tree structure, but the CIs can be useful to obtain an indication of the variability of the coefficient estimates, not for statistical significance testing.

The caterpillar plot(s) for the random effect (created if `which = "ranef"` or "all") depict the predicted random effects with 95% confidence intervals. See also [ranef](#).

The code is still under development and might change in future versions.

**References**

Fokkema M, Smits N, Zeileis A, Hothorn T, Kelderman H (2018). "Detecting Treatment-Subgroup Interactions in Clustered Data with Generalized Linear Mixed-Effects Model Trees". *Behavior Research Methods*, 50(5), 2016-2034. <https://doi.org/10.3758/s13428-017-0971-x>

**See Also**

[lmertree](#), [glmertree](#), [party-plot](#).

**Examples**

```
## load artificial example data
data("DepressionDemo", package = "glmertree")

## fit linear regression LMM tree for continuous outcome
lt <- lmertree(depression ~ treatment + age | cluster | anxiety + duration,
  data = DepressionDemo)
plot(lt)
plot(lt, type = "simple")
plot(lt, which = "tree", fitted = "combined")
plot(lt, which = "tree", fitted = "none")
plot(lt, which = "tree", observed = FALSE)
plot(lt, which = "tree.coef")
plot(lt, which = "ranef")

## fit logistic regression GLMM tree for binary outcome
gt <- glmertree(depression_bin ~ treatment + age | cluster |
  anxiety + duration, data = DepressionDemo)
plot(gt)
plot(gt, type = "simple")
plot(gt, which = "tree", fitted = "combined")
plot(gt, which = "tree", fitted = "none")
plot(gt, which = "tree.coef")
plot(gt, which = "ranef")
```

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