

# Package ‘spaMM’

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**Type** Package

**Title** Mixed-Effect Models, with or without Spatial Random Effects

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**Imports** methods, stats, graphics, Matrix, MASS, proxy, Rcpp (>= 0.12.10), nlme, nloptr, minqa, pbapply, crayon, gmp (>= 0.6.0), ROI, boot

**LinkingTo** Rcpp, RcppEigen (>= 0.3.3.5.0)

**Depends** R (>= 3.2.0)

**Suggests** maps, testthat, lme4, rsae, rcdd, pedigreemm, foreach, future, future.apply, multilevel, Infusion (>= 1.3.0), IsoriX (>= 0.8.1), blackbox (>= 1.1.25), RSpectra, ROI.plugin.glpk, memoise

**Enhances** multcomp, RLRsim

**NeedsCompilation** yes

**Description** Inference based on models with or without spatially-correlated random effects, multivariate responses, or non-Gaussian random effects (e.g., Beta). Variation in residual variance (heteroscedasticity) can itself be represented by a mixed-effect model. Both classical geostatistical models, and Markov random field models on irregular grids (as considered in the 'INLA' package, <<https://www.r-inla.org>>), can be fitted, with distinct computational procedures exploiting the sparse matrix representations for the latter case and other autoregressive models. Laplace approximations are used for likelihood or restricted likelihood. Penalized quasi-likelihood and other variants discussed in the h-likelihood literature (Lee and Nelder 2001 <[doi:10.1093/biomet/88.4.987](https://doi.org/10.1093/biomet/88.4.987)>) are also implemented.

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**URL** <https://www.r-project.org>,  
<https://gitlab.mbb.univ-montp2.fr/francois/spamm-ref>

**RoxygenNote** 7.1.1

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## R topics documented:

adjlg . . . . .	4
AIC . . . . .	5
algebra . . . . .	8
arabidopsis . . . . .	10
autoregressive . . . . .	11
blackcap . . . . .	13
CauchyCorr . . . . .	14
COMPoisson . . . . .	15
composite-ranef . . . . .	18
confint.HLfit . . . . .	20
convergence . . . . .	22
corMatern . . . . .	23
corrHLfit . . . . .	25
corrMatrix . . . . .	27
corr_family . . . . .	28
covStruct . . . . .	29
div_info . . . . .	31
dofuture . . . . .	32
dopar . . . . .	33
eval_replicate . . . . .	35
external-libraries . . . . .	36
extractors . . . . .	37
fitme . . . . .	39
fitmv . . . . .	42
fixed . . . . .	45
fixedLRT . . . . .	47
fix_predVar . . . . .	50
freight . . . . .	51
get_cPredVar . . . . .	52
get_inits_from_fit . . . . .	54
get_matrix . . . . .	55
get_ranPars . . . . .	56
get_RLRsim_args . . . . .	58
good-practice . . . . .	60
Gryphon . . . . .	61
hatvalues.HLfit . . . . .	62

HLCor . . . . .	64
HLfit . . . . .	67
how . . . . .	72
inits . . . . .	73
inverse.Gamma . . . . .	74
is_separated . . . . .	74
Loaloa . . . . .	76
LRT . . . . .	78
make_scaled_dist . . . . .	81
mapMM . . . . .	82
MaternCorr . . . . .	87
mat_sqrt . . . . .	89
method . . . . .	90
MSFDR . . . . .	91
multiIMRF . . . . .	92
multinomial . . . . .	95
mv . . . . .	98
negbin . . . . .	100
options . . . . .	101
pedigree . . . . .	104
phiHGLM . . . . .	105
plot.HLfit . . . . .	106
plot_effects . . . . .	108
Poisson . . . . .	110
post-fit . . . . .	111
predict . . . . .	112
predVar . . . . .	116
random-effects . . . . .	118
rankinfo . . . . .	119
residuals.HLfit . . . . .	120
residVar . . . . .	121
salamander . . . . .	122
scotlip . . . . .	124
seaMask . . . . .	125
seeds . . . . .	126
simulate.HLfit . . . . .	127
spaMM . . . . .	130
spaMM-conventions . . . . .	134
spaMM.colors . . . . .	135
spaMM.filled.contour . . . . .	135
spaMM_boot . . . . .	138
spaMM_glm.fit . . . . .	140
stripHLfit . . . . .	143
summary.HLfit . . . . .	144
update.HLfit . . . . .	145
vcov . . . . .	147
wafers . . . . .	148
welding . . . . .	150

wrap_parallel . . . . .	151
ZAXlist . . . . .	151

<b>Index</b>	<b>152</b>
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adjlg	<i>Simulated data set for testing sparse-precision code</i>
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### Description

This is used in tests/test-adjacency-long.R

### Usage

```
data("adjlg")
```

### Format

Includes an adjacency matrix `adjlgMat`. and a data frame `adjlg` with 5474 observations on the following 8 variables.

ID a factor with levels 1 to 1000

months a numeric vector

GENDER a character vector

AGE a numeric vector

X1 a numeric vector

X2 a numeric vector

month a numeric vector

BUY a numeric vector

### Source

The simulation code shown below is derived from an example produced by Jeroen van den Ochtend. Following a change incorporated in `spaMM` version 3.8.0, that implied stricter checks of the input matrix, it appeared that the precision matrix generated by this example had inappropriate (repeated) dimnames. This example was then updated to reproduce past fitting results with a correctly formatted matrix. Note that changing the names of an adjacency matrix (as below) is generally unwise as it generally changes the statistical model because these names are matched whenever possible to levels of the grouping factor in the data.

The code was also modified to compensate for changes in R's default random number generator.

## Examples

```

data(adjlg)
## See further usage in tests/test-adjacency-long.R
## Not run:
# as produced by:
library(data.table) ## Included data produced using version 1.10.4.3
library(igraph) ## Included data produced using version 1.2.1

rsample <- function(N=100, ## size of implied adjacency matrix
                    month_max=10,seed) {
  if (is.integer(seed)) set.seed(seed)
  dt <- data.table(ID=factor(1:N))
  dt$months <- sample(1:month_max,N,replace=T) ## # of liens for each level of ID
  dt$GENDER <- sample(c("MALE","FEMALE"),N,replace=TRUE)
  dt$AGE <- sample(18:99,N,replace=T)
  dt$X1 <- sample(1000:9900,N,replace=T)
  dt$X2 <- runif(N)

  dt <- dt[, c(.SD, month=data.table(seq(from=1, to=months, by = 1))), by = ID]
  dt[,BUY := 0]
  dt[month.V1==months,BUY := sample(c(0,1),1),by=ID]
  setnames(dt,"month.V1","month")

  ##### create adjacency matrix
  Network <- data.table(OUT=sample(dt$ID,N*month_max*4/10))
  Network$IN <- sample(dt$ID,N*month_max*4/10)
  Network <- Network[IN != OUT]
  Network <- unique(Network)
  g <- graph.data.frame(Network,directed=F)
  g <- add_vertices(g,sum(!unique(dt$ID) %in% V(g)),
                  name=unique(dt[!dt$ID %in% V(g),list(ID)])) # => improper names
  Network <- as_adjacency_matrix(g,sparse = TRUE,type="both")
  colnames(Network) <- rownames(Network) <- seq(nrow(Network)) # post-v3.8.0 names
  return(list(data=dt,adjMatrix=Network))
}

RNGkind("Mersenne-Twister", "Inversion", "Rounding" )
set.seed(123)
adjlg_sam <- rsample(N=1000,seed=NULL)
RNGkind("Mersenne-Twister", "Inversion", "Rejection" )
#
adjlg <- as.data.frame(adjlg_sam$data)
adjlgMat <- adjlg_sam$adjMatrix

## End(Not run)

```

### Description

`get_any_IC` computes model selection/information criteria such as AIC. See Details for more information about these criteria. The other extractors `AIC` and `extractAIC` are methods for `HLfit` objects of generic functions defined in other packages: `AIC` is equivalent to `get_any_IC`, and `extractAIC` returns the marginal AIC and the number of degrees of freedom for the fixed effects.

### Usage

```
get_any_IC(object, nsim=0L, ..., verbose=interactive(),
           also_cAIC=TRUE, short.names=NULL)
## S3 method for class 'HLfit'
AIC(object, nsim=0L, ..., k, verbose=interactive(),
     also_cAIC=TRUE, short.names=NULL)
## S3 method for class 'HLfit'
extractAIC(fit, scale, k, ..., verbose=FALSE)
```

### Arguments

<code>object, fit</code>	A object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
<code>scale, k</code>	Currently ignored, but are required in the definitions for consistency with the generic.
<code>verbose</code>	Whether to print the model selection criteria or not.
<code>also_cAIC</code>	Whether to include the plug-in estimate of conditional AIC in the result (its computation may be slow).
<code>nsim</code>	Controls whether to include the bootstrap estimate of conditional AIC (see Details) in the result. If positive, <code>nsim</code> gives the number of bootstrap replicates.
<code>short.names</code>	NULL, or boolean; controls whether the return value uses short names ( <code>mAIC</code> , etc., as shown by screen output if <code>verbose</code> is <code>TRUE</code> ), or the descriptive names ("marginal AIC:", etc.) also shown in the screen output. Short names are more appropriate for programming but descriptive names may be needed for back-compatibility. The default (NULL) ensures back-compatibility by using descriptive names unless the bootstrap estimate of conditional AIC is reported.
<code>...</code>	Other arguments that may be needed by some method. If <code>nsim</code> is positive, a <code>seed</code> argument may be passed to <code>simulate</code> , and the other " <code>...</code> " will be used in a call to <code>dopar</code> to control the optional parallel execution of the bootstrap computations.

### Details

The AIC is a measure (by Kullback-Leibler directed distance, up to an additive constant) of quality of prediction of new data by a fitted model. Comparing information criteria may be viewed as a fast alternative to a comparison of the predictive accuracy of different models by cross-validation. Further procedures for model choice may also be useful (e.g. Williams, 1970; Lewis et al. 2010).

The **conditional AIC** (Vaida and Blanchard 2005) applies the AIC concept to new realizations of a mixed model, conditional on the realized values of the random effects. Lee et al. (2006) and Ha et al (2007) defined a corrected AIC [i.e.,  $AIC(D^*)$  in their eq. 7] which is here interpreted as the conditional AIC.

Such Kullback-Leibler relative distances cannot generally be evaluated exactly and various estimates have been discussed. `get_any_IC` computes, optionally prints, and returns invisibly one or more of the following quantities: (1) Akaike's classical AIC (**marginal AIC**, mAIC); (2) a plug-in estimate (cAIC) and/or a bootstrap estimate (b\_cAIC) of the conditional AIC; and (3) a focussed AIC for dispersion parameters (**dispersion AIC**, dAIC).

For the **conditional AIC**, Vaida and Blanchard's plug-in estimator involves the conditional likelihood, and degrees of freedom for (i) estimated residual error parameters and (ii) the overall linear predictor characterized by the **Effective degrees of freedom** already discussed by previous authors including Lee and Nelder (1996), which gave a plug-in estimator ( $p_D$ ) for it in HGLMs. By default, the plug-in estimate of both the conditional AIC and of  $n - p_D$  (GoFdf, where  $n$  is the length of the response vector) are returned by `get_any_IC`. But these are biased estimates of conditional AIC and effective df, and an alternative procedure is available if a non-default positive `nsim` value is used. In that case, the conditional AIC is estimated by a bootstrap version of Saefken et al. (2014)'s equation 2.5; this involves refitting the model to each bootstrap samples, so it may take time, and a full cross-validation procedure might as well be considered for model selection.

The dispersion AIC has been defined from restricted likelihood by Ha et al (2007; eq.10). The present implementation will use restricted likelihood only if made available by an REML fit, otherwise marginal likelihood is used.

### Value

For AIC and `get_any_IC`, a numeric vector whose possible elements are described in the Details, and whose names are controlled by the `short.names` argument. Note that the bootstrap computation actually makes sense and works also for fixed-effect models (although it is not clear how useful it is in that case). The return value will still refer to its results as conditional AIC.

For `extractAIC`, a numeric vector of length 2, with first and second elements giving

edf	the degree of freedom of the fixed-effect terms of the model for the fitted model <code>fit</code> .
AIC	the (marginal) Akaike Information Criterion for <code>fit</code> .

This output aims to be equivalent (except for the explicit names) to the one from `stats::extractAIC`, despite the obscurities of the latter's documentation, and is indeed equivalent in value for GLMs (see Examples).

### References

- Ha, I. D., Lee, Y. and MacKenzie, G. (2007) Model selection for multi-component frailty models. *Statistics in Medicine* 26: 4790-4807.
- Lee Y. and Nelder. J. A. 1996. Hierarchical generalized linear models (with discussion). *J. R. Statist. Soc. B*, 58: 619-678.
- Lewis, F., Butler, A. and Gilbert, L. (2011), A unified approach to model selection using the likelihood ratio test. *Methods in Ecology and Evolution*, 2: 155-162. doi: [10.1111/j.2041210X.2010.00063.x](https://doi.org/10.1111/j.2041210X.2010.00063.x)
- Saefken B., Kneib T., van Waveren C.-S., Greven S. (2014) A unifying approach to the estimation of the conditional Akaike information in generalized linear mixed models. *Electron. J. Statist.* 8, 201-225.

Vaida, F., and Blanchard, S. (2005) Conditional Akaike information for mixed-effects models. *Biometrika* 92, 351-370.

Williams D.A. (1970) Discrimination between regression models to determine the pattern of enzyme synthesis in synchronous cell cultures. *Biometrics* 26: 23-32.

### Examples

```
data("wafers")
m1 <- fitme(y ~ X1+X2+X3+X1*X3+X2*X3+I(X2^2)+(1|batch), data=wafers,
           family=Gamma(log))

get_any_IC(m1)
# => The plug-in estimate is stored in the 'm1' object
#   as a result of the previous computation, and is now returned even by:
get_any_IC(m1, also_cAIC=FALSE)

if (spaMM.getOption("example_maxtime")>4) {
  get_any_IC(m1, nsim=100L, seed=123) # provides bootstrap estimate of cAIC.
  # (parallelisation options could be used, e.g. nb_cores=detectCores()-1L)
}

extractAIC(m1)

## Not run:
# Checking consistency with glm example from help("stats::extractAIC"):
utils::example(glm)
dataf <- data.frame(counts=counts, outcome=outcome, treatment=treatment)
extractAIC(glm.D93)
extractAIC(fitme(counts ~ outcome + treatment, family = poisson(), data=dataf))
lm.D93 <- glm(counts ~ outcome + treatment)
extractAIC(lm.D93)
extractAIC(fitme(counts ~ outcome + treatment, data=dataf))

## End(Not run)
```

---

algebra

*Control of matrix-algebraic methods*

---

### Description

Autocorrelated gaussian random effects can be specified in terms of their covariance matrix, or in terms of the precision matrix (i.e. inverse covariance matrix). In a pre-processing step, spaMM may assess whether such precision matrices are sparse but the correlation matrix is dense, and if so, it may use “sparse-precision” algorithms efficient for this case. If the precision matrix does not appear sufficiently sparser than the correlation matrix, correlation matrices are used, and they can themselves be sparse or dense, with distinct algebraic methods used in each case.

For example, when the model includes a `corrMatrix` term specified by a covariance matrix, the precision matrix may be computed to assess its sparseness. The Example below illustrates a case

where detecting sparsity of the precision matrix allows a faster fit. However, such a comparison of correlation and precision matrices takes time and is not performed for all types of random-effect structures. Instead, some fast heuristics may be used (see Details). The default selection of methods may not always be optimal, and may be overcome by using the `control.HLfit` argument of the fitting function (or by `spaMM.options()`, see Details). In particular one can use either `control.HLfit=list(sparse_precision= <TRUE|FALSE>)` or `control.HLfit=list(algebra= <"spprec"|"spcorr"|"decorr">)` with the obvious expected effects.

Such control may be useful when you already know that the precision matrix is sparse (as `spaMM` may even kindly remind you of, see Example below). In that case, it is also efficient to specify the precision matrix directly (see Example in [Gryphon](#)), as `spaMM` then assumes that sparse-precision methods are better without checking the correlation matrix.

Such control may also be useful when the correlation matrix is nearly singular so that computation of its inverse fails. This may occur if the model is poorly specified, but also occurs sometimes for valid correlation models because inversion of large matrices though Cholesky methods is not numerically accurate enough. In the latter case, you may be directed to this documentation by an error message, and specifying `sparse_precision= FALSE` may be useful.

## Details

Currently the sparse-precision methods are selected by default in two cases (with possible exceptions indicated by specific messages): (1) for models including [IMRF](#) random effects; and (2) when the `corrMatrix` (or `covStruct`) syntax is used to provide a fixed precision matrix. Further, for models including autoregressive terms other than [IMRF](#) (i.e., adjacency, [AR1](#)), sparse-precision methods may or may not be selected on a simple heuristic based on the likely structure of the correlation matrix.

Algebraic methods can be controlled globally over all further fits by using `spaMM.options(sparse_precision= <TRUE|FALSE>)` and, among the correlation-based methods, `spaMM.options(QRmethod= <"sparse"|"dense">)` to select "spcorr" vs. "decorr" methods. Fit-specific controls (by `control.HLfit`) override these global ones.

## See Also

[pedigree](#)

## Examples

```
if (spaMM.getOption("example_maxtime")>6) {
  data("Gryphon")

  gry_df <- fitme(BWT ~ 1 + corrMatrix(1|ID), corrMatrix = Gryphon_A,
                 data = Gryphon_df, method = "REML")
  how(gry_df)

  # => Note the message about 'Choosing matrix methods...'.
  # Using control.HLfit=list(algebra="spprec") would indeed
  # save the time used to select this method.

  # Conversely, using a correlation-based method would be a waste of time:
```

```

gry_dn <- fitme(BWT ~ 1 + corrMatrix(1|ID), corrMatrix = Gryphon_A,
               data = Gryphon_df, method = "REML",
               control.HLfit=list(sparse_precision=FALSE))
how(gry_dn) # forced dense-correlation methods, which is slower here.
}

```

---

arabidopsis

*Arabidopsis genetic and climatic data*


---

### Description

For 948 “accessions” from European *Arabidopsis thaliana* populations, this data set merges the genotypic information at four single nucleotide polymorphisms (SNP) putatively involved in adaptation to climate (Fournier-Level et al, 2011, Table 1), with 13 climatic variables from Hancock et al. (2011).

### Usage

```
data("arabidopsis")
```

### Format

The data frame includes 948 observations on the following variables:

**pos1046738, pos5510910, pos6235221, pos8132698** Genotypes at four SNP loci

**LAT** latitude

**LONG** longitude

**seasonal, tempWarmest, tempColdest, preciWettest, preciDriest, preciCV, PAR\_SPRING,**

**growingL, conseqCold, conseqFrFree, RelHumidSp, dayLSp, aridity** Thirteen climatic variables.

See Hancock et al. (2011) for details about these variables.

### Details

The response is binary so method="PQL/L" seems warranted (see Rousset and Ferdy, 2014).

### Source

The data were retrieved from <http://bergelson.uchicago.edu/regmap-data/climate-genome-scan> on 22 February 2013 (they may no longer be available from there).

## References

- Fournier-Level A, Korte A., Cooper M. D., Nordborg M., Schmitt J., Wilczek AM (2011). A map of local adaptation in *Arabidopsis thaliana*. *Science* 334: 86-89.
- Hancock, A. M., Brachi, B., Faure, N., Horton, M. W., Jarymowycz, L. B., Sperone, F. G., Toomajian, C., Roux, F., and Bergelson, J. 2011. Adaptation to climate across the *Arabidopsis thaliana* genome, *Science* 334: 83-86.
- Rousset F., Ferdy, J.-B. (2014) Testing environmental and genetic effects in the presence of spatial autocorrelation. *Ecography*, 37: 781-790. doi: [10.1111/ecog.00566](https://doi.org/10.1111/ecog.00566)

## Examples

```
data("arabidopsis")
if (spaMM.getOption("example_maxtime")>2.5) {
  fitme(cbind(pos1046738,1-pos1046738)~seasonal+Matern(1|LAT+LONG),
        fixed=list(rho=0.119278,nu=0.236990,lambda=8.599),
        family=binomial(),method="PQL/L",data=arabidopsis)
}
## The above 'fixed' values are deduced from the following fit:
if (spaMM.getOption("example_maxtime")>46) {
  SNPfit <- fitme(cbind(pos1046738,1-pos1046738)~seasonal+Matern(1|LAT+LONG),
                 verbose=c(TRACE=TRUE),
                 family=binomial(),method="PQL/L",data=arabidopsis)
  summary(SNPfit) # p_v=-125.0392
}
```

---

autoregressive

*Fitting autoregressive models*

---

## Description

Two autoregressive(AR) models are currently implemented: the adjacency model (a conditional AR, i.e., CAR), and the AR1 model for time series.

An AR1 random effect is specified as `AR1(1|<grouping factor>)`. It describes correlations between realizations of the random effect for (typically) successive time-steps by a correlation  $\phi$ , denoted `ARphi` in function calls. Nested AR1 effects can be specified by a nested grouping factor, as in `AR1(1|<time index>%in%<nesting factor>)`.

A CAR random effect is specified as `adjacency(1|<grouping factor>)`. The correlations among levels of the random effect form a matrix  $(\mathbf{I}-\rho \text{adjMatrix})^{-1}$ , in terms of an `adjMatrix` matrix which must be provided, and of the scalar  $\rho$ , denoted `rho` in function calls. The rows and columns of `adjMatrix` must have names matching those of levels of the random effect **or else** be ordered as increasing values of the levels of the geographic location index specifying the spatial random effect. For example, if the model formula is `y ~ adjacency(1|geo.loc)` and `<data>$geo.loc` is `2,4,3,1,...` the first row/column of the matrix refers to `geo.loc=1`, i.e. to the fourth row of the data.

## Details

Efficient algorithms for CAR models have been widely discussed in particular in the econometric literature (e.g., LeSage and Pace 2009), but these models are not necessarily recommended for irregular lattices (see Wall, 2004 and Martellosio, 2012 for some insights on the implications of autoregressive models).

In **CAR** models, the covariance matrix of random effects  $\mathbf{u}$  can be described as  $\lambda(\mathbf{I}-\rho\mathbf{W})^{-1}$  where  $\mathbf{W}$  is the (symmetric) adjacency matrix. HLCor uses the spectral decomposition of the adjacency matrix, written as  $\mathbf{W}=\mathbf{V}\mathbf{D}\mathbf{V}'$  where  $\mathbf{D}$  is a diagonal matrix of eigenvalues  $d_i$ . The covariance of  $\mathbf{V}'\mathbf{u}$  is  $\lambda(\mathbf{I}-\rho\mathbf{D})^{-1}$ , which is a diagonal matrix with elements  $\lambda_i=\lambda/(1-\rho d_i)$ . Hence  $1/\lambda_i$  is in the linear predictor form  $\alpha+\beta d_i$ . This can be used to fit  $\lambda$  and  $\rho$  efficiently. A call to `corrHLfit` with the additional argument `init.HLfit=list(rho=0)` should be equivalent in speed and result to the HLCor call.

This is fast for small datasets (as in the example below) but more generic maximization algorithms may be preferable for large ones. It is suggested to use `fitme` generally unless one has a large number of small data sets to analyze. A call to `fitme` or `corrHLfit` without that initial value does not use the spectral decomposition. It performs numerical maximization of the likelihood (or restricted likelihood) as function of the correlation parameter  $\rho$ . The choice of fitting function may slightly impact the results. The ML fits by `corrHLfit` and HLCor should be practically equivalent. The REML fits should slightly differ from each other, due to the fact that the REML approximation for GLMMs does not maximize a single likelihood function.

If HLCor is used, the results are reported as the coefficients  $\alpha$  ((Intercept)) and  $\beta$  (adjd) of the predictor for  $1/\lambda_i$ , in addition to the resulting values of  $\rho$  and of the common  $\lambda$  factor.

Different fits may also differ in using or not algorithms that exploit the sparsity of the precision matrix of the autoregressive random effect. By default, `spaMM` tends to select sparse-precision algorithms for large datasets and large (i.e. many-level) random effects (details are complex). However, for **ARI** models, the dimension of the implied precision matrix is determined by the extreme values of grouping factor (typically interpreted as a time index), as all intermediate values must be considered. Then, the correlation-based algorithms may be more efficient if only a few levels are present in the data, as only a small correlation matrix is required in that case.

## References

- LeSage, J., Pace, R.K. (2009) Introduction to Spatial Econometrics. Chapman & Hall/CRC.
- Martellosio, F. (2012) The correlation structure of spatial autoregressions, *Econometric Theory* 28, 1373-1391.
- Wall M.M. (2004) A close look at the spatial structure implied by the CAR and SAR models: *Journal of Statistical Planning and Inference* 121: 311-324.

## Examples

```
##### AR1 random effect:
ts <- data.frame(lh=lh,time=seq(48)) ## using 'lh' data from stats package
fitme(lh ~ 1 +AR1(1|time), data=ts, method="REML")
# With fixed parameters:
# HLCor(lh ~ 1 +AR1(1|time), data=ts, ranPars=list(ARphi=0.5,lambda=0.25,phi=0.001))

##### CAR random effect:
```

```

data("scotlip")
# CAR by Laplace with 'outer' estimation of rho
if (spaMM.getOption("example_maxtime")>0.8) {
  fitme(cases ~ I(prop.ag/10)+adjacency(1|gridcode)+offset(log(expec)),
        adjMatrix=Nmatrix, family=poisson(), data=scotlip)
}

# CAR by Laplace with 'inner' estimation of rho
HLCor(cases ~ I(prop.ag/10)+adjacency(1|gridcode)+offset(log(expec)),
      adjMatrix=Nmatrix, family=poisson(), data=scotlip, method="ML")

```

---

blackcap

*Genetic polymorphism in relation to migration in the blackcap*


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## Description

This data set is extracted from a study of genetic polymorphisms potentially associated to migration behaviour in the blackcap (*Sylvia atricapilla*). Across different populations in Europe and Africa, the average migration behaviour was found to correlate with average allele size (dependent on the number of repeats of a small DNA motif) at the locus ADCYAP1, encoding a neuropeptide. This data set is quite small and ill-suited for separating random-effect variance from residual variance. The likelihood surface for the Matérn model actually has local maxima.

## Usage

```
data("blackcap")
```

## Format

The data frame includes 14 observations on the following variables:

**latitude** latitude, indeed.

**longitude** longitude, indeed.

**migStatus** migration status as determined by Mueller et al, from 0 (resident populations) to 2.5 (long-distance migratory populations)

**means** Mean allele sizes in each population

**pos** Numerical index for the populations

## Details

Migration status was coded as : pure resident populations as '0', resident populations with some migratory restlessness as '0.5', partial migratory populations as '1', completely migratory populations migrating short-distances as '1.5', intermediate-distance migratory populations as '2' and distinct long-distance migratory populations as '2.5'.

## Source

Data from Mueller et al. (2011), including supplementary material now available from doi: [10.1098/rspb.2010.2567](https://doi.org/10.1098/rspb.2010.2567).

## References

Mueller, J. C., Pulido, F., and Kempnaers, B. 2011. Identification of a gene associated with avian migratory behaviour, Proc. Roy. Soc. (Lond.) B 278, 2848-2856.

## Examples

```
## see 'fitme', 'corrHLfit' and 'fixedLRT' for examples involving these data
```

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CauchyCorr

*Cauchy correlation function and Cauchy formula term*

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## Description

The Cauchy family of correlation functions is useful to describe spatial processes with power-law decrease of correlation at long distance. It is valid for Euclidean distances in spaces of any dimension, and for great-circle distances on spheres of any dimension. It has a scale parameter ( $\rho$ , as in the Matérn correlation function), a shape (or “smoothness”, Gneiting 2013) parameter, and a long-memory dependence (or, more abstractly, “shape”; Gneiting 2013) parameter (Gneiting and Schlater 2004). The present implementation also accepts a Nugget parameter. The family can be invoked in two ways. First, the `CauchyCorr` function evaluates correlations, using distances as input. Second, a term of the form `Cauchy(1|<...>)` in a formula specifies a random effect with Cauchy correlation function, using coordinates found in a data frame as input. In the latter case, the correlations between realizations of the random effect for any two observations in the data will be the value of the Cauchy function at the scaled distance between coordinates specified in `<...>`, using “+” as separator (e.g., `Cauchy(1|longitude+latitude)`). A syntax of the form `Cauchy(1|longitude+latitude %in% grp)` can be used to specify a Cauchy random effect with independent realizations for each level of the grouping variable `grp`.

## Usage

```
## Default S3 method:
CauchyCorr(d, rho=1, shape, longdep, Nugget=NULL)
# Cauchy(1|...)
```

## Arguments

<code>d</code>	Euclidean or great-circle distance
<code>rho</code>	The scaling factor for distance, a real $>0$ .
<code>shape</code>	The shape (smoothness) parameter, a real $0 < \leq 2$ for Euclidean distances and $0 < \leq 1$ for great-circle distances. Smoothness increases, and fractal dimension decreases, with increasing shape (the fractal dimension of realizations in spaces of dimension $d$ being $d+1-\text{shape}/2$ ).
<code>longdep</code>	The long-memory dependence parameter, a real $>0$ . It gives the exponent of the asymptotic decrease of correlation with distance: the <b>smaller</b> <code>longdep</code> is, the longer the dependence.

Nugget (Following the jargon of Kriging) a parameter describing a discontinuous decrease in correlation at zero distance. Correlation will always be 1 at  $d = 0$ , and from which it immediately drops to  $(1-\text{Nugget})$ . Defaults to zero.

... Names of coordinates, using “+” as separator (e.g., `Matern(1|longitude+latitude)`)

### Details

The correlation at distance  $d > 0$  is

$$(1 - \text{Nugget})(1 + (\rho d)^{\text{extrmshape}})^{-\text{extrmlongdep}/\text{shape}}$$

### Value

Scalar/vector/matrix depending on input.

### References

Gneiting, T. and Schlater M. (2004) Stochastic models that separate fractal dimension and the Hurst effect. *SIAM Rev.* 46: 269–282.

Gneiting T. (2013) Strictly and non-strictly positive definite functions on spheres. *Bernoulli* 19: 1327-1349.

### Examples

```
data("blackcap")
fitme(migStatus ~ means+ Cauchy(1|longitude+latitude),data=blackcap,
      fixed=list(longdep=0.5,shape=0.5,rho=0.05))
## The Cauchy family can be used in Euclidean spaces of any dimension:
set.seed(123)
randpts <- matrix(rnorm(20),nrow=5)
distMatrix <- as.matrix(proxy::dist(randpts))
CauchyCorr(distMatrix,rho=0.1,shape=1,longdep=10)

# See ?MaternCorr for examples of syntaxes for group-specific random effects,
# also handled by Cauchy().
```

---

COM $\text{Poisson}$

*Conway-Maxwell-Poisson (COM-Poisson) GLM family*

---

### Description

The COM-Poisson family is a generalization of the Poisson family which can describe over-dispersed as well as under-dispersed count data. It is indexed by a parameter  $\nu$  that quantifies such dispersion. For  $\nu > 1$ , the distribution is under-dispersed relative to the Poisson distribution with same mean. It includes the Poisson, geometric and Bernoulli as special (or limit) cases (see Details). The COM-Poisson family is here implemented as a `family` object, so that it can be fitted by `glm`, and further used to model conditional responses in mixed models fitted by this package’s functions

(see Examples). `nu` is distinct from the dispersion parameter  $\nu = 1/\phi$  considered elsewhere in this package and in the GLM literature, as  $\nu$  affects in a more specific way the log-likelihood.

Several links are now allowed for this family, corresponding to different versions of the COMPoisson described in the literature (e.g., Sellers & Shmueli 2010; Huang 2017).

### Usage

```
COMPoisson(nu = stop("COMPoisson's 'nu' must be specified"),
           link = "loglambda")
```

### Arguments

<code>link</code>	GLM link function. The default is the canonical link "loglambda" (see Details), but other links are allowed (currently log, sqrt or identity links as commonly handled for the Poisson family).
<code>nu</code>	Under-dispersion parameter. The <code>fitme</code> and <code>corrHLfit</code> functions called with <code>family=COMPoisson()</code> (no given <code>nu</code> value) will estimate this parameter. In other usage of this family, <code>nu</code> must be specified. <code>COMPoisson(nu=1)</code> is the Poisson family.

### Details

The  $i$ th term of the distribution can be written  $q_i/Z$  where  $q_i = \lambda^i/(i!)^\nu$  and  $Z = \sum_{i=0}^{\infty} q_i$ , for  $\lambda = \lambda(\mu)$  implied by its inverse relationship, the expectation formula  $\mu = \mu(\lambda) = \sum_{i=0}^{\infty} i q_i(\lambda)/Z$ . The case `nu=0` is the geometric distribution with parameter  $\lambda$ ; `nu=1` is the Poisson distribution with mean  $\lambda$ ; and the limit as `nu`  $\rightarrow \infty$  is the Bernoulli distribution with expectation  $\lambda/(1 + \lambda)$ .

From this definition, this is an exponential family model with canonical parameters  $\log(\lambda)$  and  $\nu$ . When the linear predictor  $\eta$  specifies  $\log(\lambda(\mu))$ , the canonical link is used (e.g., Sellers & Shmueli 2010). It is here nicknamed "loglambda" and does not have a known expression in terms of elementary functions. To obtain  $\mu$  as the link inverse of the linear predictor  $\eta$ , one then first computes  $\lambda = e^\eta$  and then  $\mu(\lambda)$  by the expectation formula. For other links (Huang 2017), one directly computes  $\mu$  by the link inverse (e.g.,  $\mu = e^\eta$  for link "log"), and then one may solve for  $\lambda = \lambda(\mu)$  to obtain other features of the distribution.

The relationships between  $\lambda$  and  $\mu$  or other moments of the distribution involve infinite summations. These sums can be easily approximated by a finite number of terms for large `nu` but not when `nu` approaches zero. For this reason, the code may fail to fit distributions with `nu` approaching 0 (strong residual over-dispersion). The case `nu=0` (the geometric distribution) is fitted by an ad hoc algorithm devoid of such problems. Otherwise, `spaMM` truncates the sum, and uses numerical integrals to approximate missing terms (which slows down the fitting operation). In addition, it applies an ad hoc continuity correction to ensure continuity of the result in `nu=1` (Poisson case). These corrections affect numerical results for the case of residual overdispersion but are negligible for the case of residual underdispersion. Alternatively, `spaMM` uses Gaunt et al.'s (2017) approximations when the condition defined in `spaMM.getOption("CMP_asympto_cond")` is satisfied. All approximations reduces the accuracy of computations, in a way that can impede the extended Levenberg-Marquardt algorithm sometimes needed by `spaMM`.

The name COMP\_nu should be used to set initial values or bounds on nu in control arguments of the fitting functions (e.g., `fitme(., init=list(COMP_nu=1))`). Fixed values should be set by the family argument (`COMPoisson(nu=.)`).

### Value

A family object.

### References

Gaunt, Robert E. and Iyengar, Satish and Olde Daalhuis, Adri B. and Simsek, Burcin. (2017) An asymptotic expansion for the normalizing constant of the Conway–Maxwell–Poisson distribution. *Ann Inst Stat Math* doi: [10.1007/s1046301706296](https://doi.org/10.1007/s1046301706296).

Huang, Alan (2017) Mean-parametrized Conway-Maxwell-Poisson regression models for dispersed counts. *Stat. Modelling* doi: [10.1177/1471082X17697749](https://doi.org/10.1177/1471082X17697749)

G. Shmueli, T. P. Minka, J. B. Kadane, S. Borle and P. Boatwright (2005) A useful distribution for fitting discrete data: revival of the Conway-Maxwell-Poisson distribution. *Appl. Statist.* 54: 127-142.

Sellers KF, Shmueli G (2010) A Flexible Regression Model for Count Data. *Ann. Appl. Stat.* 4: 943–961

### Examples

```
if (spaMM.getOption("example_maxtime")>0.9) {
  # Fitting COMPoisson model with estimated nu parameter:
  #
  data("freight") ## example from Sellers & Shmueli, Ann. Appl. Stat. 4: 943961 (2010)
  fitme(broken ~ transfers, data=freight, family = COMPoisson())
  fitme(broken ~ transfers, data=freight, family = COMPoisson(link="log"))

  # glm(), HLCor() and HLfit() handle spaMM::COMPoisson() with fixed overdispersion:
  #
  glm(broken ~ transfers, data=freight, family = COMPoisson(nu=10))
  HLfit(broken ~ transfers+(1|id), data=freight, family = COMPoisson(nu=10),method="ML")

  # Equivalence of poisson() and COMPoisson(nu=1):
  #
  COMPglm <- glm(broken ~ transfers, data=freight, family = poisson())
  coef(COMPglm)
  logLik(COMPglm)
  COMPglm <- glm(broken ~ transfers, data=freight, family = COMPoisson(nu=1))
  coef(COMPglm)
  logLik(COMPglm)
  HLfit(broken ~ transfers, data=freight, family = COMPoisson(nu=1))
}
```

## Description

An example of a composite random effect is `corrMatrix(sex|pair)`. It combines features of a random-coefficient model (`sex|pair`) and of a random effect `corrMatrix(1|pair)`. The random-coefficient model is characterized by a  $2 \times 2$  covariance matrix **C** for the random effects  $u_{1,pair}$  and  $u_{2,pair}$  both affecting each of the two sexes for each pair, and the `corrMatrix` random effect assumes that elements of each of the two vectors  $u_i = (u_{i,pair})$  for  $pair=1,\dots,P$  are correlated according to a given  $P \times P$  correlation matrix **A**. Then the composite random effect is defined as the one with  $2P \times 2P$  covariance matrix `kronecker(C,A)`.

Composite random effects can also be fitted for multivariate-response models, e.g. `corrMatrix(mv(1,2)|ID)` for two response variables for each individual ID.

The definition of composite random effects through the kronecker product may be motivated and understood in light of a quantitative-genetics application (see `help("Gryphon")` for an example). In this context the two response variables are typically two individual traits. Each trait is affected by two sets of genes, the effect of each set being represented by a gaussian random effect ( $u_1$  or  $u_2$ ). The effect of genetic relatedness on the correlation of random effects  $u_i, ID$  among individuals ID within each set  $i$  of genes is described by the `corrMatrix` **A**. The effects on the two traits for each individual are interpreted as different linear combinations of these two random effects (the coefficients of these linear combinations determining the **C** matrix). Under these assumptions the correlation matrix of the responses (in order (trait, individual)=(1,1)...(1,ID)... (2,1)...(2,ID)...) is indeed `kronecker(C,A)`.

The summary of the model provides a description of the **C** matrix in terms of its variances and its correlation coefficient(s) when **C** is viewed as a covariance matrix. In a standard random-coefficient model these variances are those of the correlated random effects (see `summary.HLfit`). In the composite random-effect model this is not necessarily so as the variance of the correlated random effects also depend on the variances implied by the **A** matrix, which are not necessarily 1 if **A** is a covariance matrix rather than simply a correlation matrix.

In a `corrMatrix(<LHS>|<RHS>)` term the type (logical, factor...) of the `<LHS>` has an effect identical to its effect in a non-composite (`<LHS>|<RHS>`) term, as described in `spaMM`. In particular, in some cases no random-coefficient correlation matrix **C** is implied: see the Examples below.

## Examples

```
if (spaMM.getOption("example_maxtime")>1.8) {
  ## Toy data preparation

  data("blackcap")
  toy <- blackcap
  toy$ID <- gl(7,2)
  grp <- rep(1:2,7)
  toy$migStatus <- toy$migStatus +(grp==2)
  toy$loc <- rownames(toy) # to use as levels matching the corrMatrix dimnames
```

```

toy$grp <- factor(grp)
toy$bool <- toy$grp==1L
toy$boolfac <- factor(toy$bool)
toy$num <- seq(from=1, to=2, length.out=14)

## Build a toy corrMatrix as perturbation of identity matrix:
n_rhs <- 14L
eps <- 0.1
set.seed(123)
rcov <- ((1-eps)*diag(n_rhs)+eps*rWishart(1,n_rhs,diag(n_rhs)/n_rhs)[, ,1])
# eigen(rcov)$values
colnames(rcov) <- rownames(rcov) <- toy$loc # DON'T FORGET NAMES

##### Illustrating the different LHS types

### <LHS> is logical (TRUE/FALSE) => No induced random-coefficient C matrix;
# corrMatrix affects only responses for which <LHS> is TRUE:
#
(fit1 <- fitme(migStatus ~ bool + corrMatrix(bool|loc), data=toy, corrMatrix=rcov))
#
# Matrix::image(get_ZALMatrix(fit1))

### <RHS> is a factor built from a logical => same a 'logical' case above:
#
(fit2 <- fitme(migStatus ~ boolfac + corrMatrix(boolfac|loc), data=toy, corrMatrix=rcov))
#
# Matrix::image(get_ZALMatrix(fit2))

### <RHS> is a factor not built from a logical:
# (grp|. ) and (0+grp|. ) lead to equivalent fits of the same composite model,
# but contrasts are not used in the second case and the C matrices differ,
# as for standard random-coefficient models.
#
(fit1 <- fitme(migStatus ~ grp + corrMatrix(grp|loc), data=toy, corrMatrix=rcov))
(fit2 <- fitme(migStatus ~ grp + corrMatrix(0+grp|loc), data=toy, corrMatrix=rcov))
#
# => same fits, but different internal structures:
Matrix::image(fit1$ZAList[[1]]) # (contrasts used)
Matrix::image(fit2$ZAList[[1]]) # (contrasts not used)
# Also compare ranef(fit1) versus ranef(fit2)
#
## One can fix the C matrix, as for standard random-coefficient terms
#
(fit1 <- fitme(migStatus ~ grp + corrMatrix(0+grp|loc),data=toy, corrMatrix=rcov,
              fixed=list(ranCoefs=list("1"=c(1,0.5,1))))))
#
# same result without contrasts hence different 'ranCoefs':
#
(fit2 <- fitme(migStatus ~ grp + corrMatrix(grp|loc), data=toy, corrMatrix=rcov,

```

```

fixed=list(ranCoefs=list("1"=c(1,-0.5,1))))

### <LHS> is numeric (but not '0+numeric'):
# composite model with C being 2*2 for Intercept and numeric variable
#
(fitme(migStatus ~ num + corrMatrix(num|loc), data=toy, corrMatrix=rcov))

### <LHS> is 0+numeric: no random-coefficient C matrix
# as the Intercept is removed, but the correlated random effects
# arising from the corrMatrix are multiplied by sqrt(<numeric variable>)
#
(fitme(migStatus ~ num + corrMatrix(0+num|loc), data=toy, corrMatrix=rcov))

### <LHS> for multivariate response (see help("Gryphon") for more typical example)
## More toy data preparation for multivariate response
ch <- chol(rcov)
set.seed(123)
v1 <- tcrossprod(ch,t(rnorm(14,sd=1)))
v2 <- tcrossprod(ch,t(rnorm(14,sd=1)))
toy$status <- 2*v1+v2
toy$status2 <- 2*v1-v2

## Fit:
fitmv(submodels=list(mod1=list(status ~ 1+ corrMatrix(0+mv(1,2)|loc)),
                    mod2=list(status2 ~ 1+ corrMatrix(0+mv(1,2)|loc))),
      data=toy, corrMatrix=rcov)

}

```

---

confint.HLfit

*Confidence intervals*

---

## Description

This computes confidence intervals for given parameter(s), based either on parametric bootstrap or, for **fixed-effect** parameters, on the  $p_v$ -based approximation of the profile likelihood ratio for this parameter. The profiling is over all other fitted parameters, including fixed effects, as well as variances of random effects and spatial correlations if these were fitted. The bootstrap is performed if the `parm` argument is a function or a quoted expression or if the `boot_args` argument is a list. The profile confidence interval is computed if neither of these conditions is true; in that case `parm` must be the name(s) of some **fixed-effect** coefficient.

## Usage

```

## S3 method for class 'HLfit'
confint(object, parm, level=0.95, verbose=TRUE,
        boot_args=NULL, format="default", ...)

```

**Arguments**

object	An object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
parm	character vector, integer vector, or function, or a quoted expression. If <b>character</b> , the name(s) of parameter(s) to be fitted; if <b>integer</b> , their position in the <code>fixef(object)</code> vector. Valid names are those of this vector. If a <b>function</b> , it must return a (vector of) parameter estimate(s) from a fit object. If a <b>quoted expression</b> , it must likewise extract parameter estimate(s) from a fit object; this expression must refer to the fitted object as ‘ <code>hlfit</code> ’ (see Examples).
level	The coverage of the interval.
verbose	whether to print the interval or not. As the function returns its more extensive results invisibly, this printing is the only visible output.
boot_args	NULL or a list of arguments passed to functions <code>spaMM_boot</code> and <code>boot.ci</code> . It must contain element <code>nsim</code> (for <code>spaMM_boot</code> ). The <code>type</code> argument of <code>boot.ci</code> can only be given as element <code>ci_type</code> , to avoid conflict with the <code>type</code> argument of <code>spaMM_boot</code> .
format	Only effective non-default value is “ <code>stats</code> ” to return results in the format of the <code>stats::confint</code> result (see Value).
...	Additional arguments (maybe not used, but conforming to the generic definition of <code>confint</code> ).

**Value**

The format of the value varies, but in all cases distinguished below, one or more tables are included, as a table attribute, in the format of the `stats::confint` result, to facilitate consistent extraction of results. By default `confint` returns invisibly the full values described below, but if `format="stats"`, only the table attribute is returned.

If a profile CI has been computed for a single parameter, a list is returned including the confidence interval as shown by `verbose=TRUE`, and the fits `lowerfit` and `upperfit` giving the profile fits at the confidence bounds. This list bears the `table` attribute.

If a profile CI has been computed for several parameters, a structured list, named according to the parameter names, of such single-parameter results is returned, and a single `table` attribute for all parameters is attached to the upper level of the list.

If a bootstrap was performed, for a single parameter the result of the `boot.ci` call is returned, to which a `table` attribute is added. This `table` is now a list of tables for the different bootstrap CI types (default being `normal`, `percent`, and `basic`), each such table in the format of the `stats::confint` results. For several parameters, a named list of `boot.ci` results is returned, its names being the parameter names, and the `table` attribute is attached to the upper level of the list.

The `boot.ci` return value for each parameter includes the call to `boot.ci`. This call is typically shown including a long `t` vector, which makes a bulky display. `spaMM` hacks the printing to abbreviate long `ts`.

**Examples**

```
data("wafers")
wfit <- HLfit(y ~X1+(1|batch), family=Gamma(log), data=wafers, method="ML")
```

```

confint(wfit,"X1") # profile CI
if (spaMM.getOption("example_maxtime")>30) {
  # bootstrap CI induced by 'boot_args':
  confint(wfit,names(fixef(wfit)), boot_args=list(nsim=99, seed=123))
  # bootstrap CI induced by 'parm' being a function:
  confint(wfit,parm=function(v) fixef(v),
          boot_args=list(nb_cores=10, nsim=199, seed=123))
  # Same effect if 'parm' is a quoted expression in terms of 'hlfit':
  confint(wfit,parm=quote(fixef(hlfit)),
          boot_args=list(nb_cores=10, nsim=199, seed=123))

  # CI for the variance of the random effect:
  ( ci <- confint(wfit,parm=function(fit){VarCorr(fit)[1,"Variance"]},
                boot_args=list(nb_cores=10, nsim=199, seed=123)) )
  # The distribution of bootstrap replicates:
  plot(ecdf(ci$call$t))
  # We may be far from ideal condition for accuracy of bootstrap intervals;
  # for variances, a log transformation may sometimes help, but not here.
}

```

## Description

spaMM fits may produce convergence warnings coming from `.check_conv_glm_reinit()`. These can generally be ignored (particularly when they show a small criterion,  $<1e-5$ ).

spaMM fits may also produce messages pointing to slow convergence and drawing users here. These do not necessarily mean the fit is incorrect. Rather, they suggest that another fitting strategy could be tried. Keep in mind that several parameters (notably the dispersion parameters: the variance of random effects and the residual variance parameter, if any) can be estimated either by the iterative algorithms, or by generic optimization methods. In my experience, slow convergence happens in certain cases where a large random-effect variance is considered by the algorithm used.

How to know which algorithm has been selected for each parameter? `fitme(., verbose=c(TRACE=TRUE))` shows successive values of the variables estimated by optimization (See Examples; if no value appears, then all are estimated by iterative methods). The first lines of the summary of a fit object should tell which variances are estimated by the “outer” method.

If the iterative algorithm is being used, then it is worth trying to use the generic optimization methods. In particular, if you used `HLfit`, try using `fitme`; if you already use `fitme`, try to enforce generic optimization of the random-effect variance(s) (see [inits](#)). Conversely, if generic optimization is being used, the maximum lambda value could be controlled (say, `upper=list(lambda=c(10, NA))`), or the iterative algorithm can be called (see [inits](#) again).

For the largest datasets, it may be worth comparing the speed of the “`spcorr`” and “`spprec`” choices of the [algebra](#) control, in case spaMM has not selected the most appropriate by default. However, this will not be useful for geostatistical models with many spatial locations.

## Examples

```
# See help("inits") for examples of control by initial values.
```

---

corMatern

*Matern Correlation Structure as a corSpatial object*

---

## Description

This implements the Matérn correlation structure (see [Matern](#)) for use with lme or glmmPQL. Usage is as for others corSpatial objects such as corGaus or corExp, except that the Matérn family has an additional parameter. This function was defined for comparing results obtained with corHLfit to those produced by lme and glmmPQL. There are problems in fitting (G)LMMs in the latter way, so it is not a recommended practice.

## Usage

```
corMatern(value = c(1, 0.5), form = ~1, nugget = FALSE, nuScaled = FALSE,
          metric = c("euclidean", "maximum", "manhattan"), fixed = FALSE)
```

## Arguments

- |        |  |
|--------|--|
| value  | <p>An optional vector of parameter values, which serves as initial values or as fixed values depending on the fixed argument. It has either two or three elements, depending on the nugget argument.</p> <p>If nugget is FALSE, value should have two elements, corresponding to the "range" and the "smoothness" <math>\nu</math> of the Matérn correlation structure. If value has zero length, the default is a range of 90% of the minimum distance and a smoothness of 0.5 (exponential correlation). <b>Warning:</b> the range parameter used in corSpatial objects is the inverse of the scale parameter used in <a href="#">MaternCorr</a> and thus they have opposite meaning despite both being denoted <math>\rho</math> elsewhere in this package or in nlme literature.</p> <p>If nugget is TRUE, meaning that a nugget effect is present, value can contain two or three elements, the first two as above, the third being the "nugget effect" (one minus the correlation between two observations taken arbitrarily close together). If value has length zero or two, the nugget defaults to 0.1. The range and smoothness must be greater than zero and the nugget must be between zero and one.</p> |
| form   | <p>(Pasted from corSpatial) a one sided formula of the form <math>\sim S1 + \dots + Sp</math>, or <math>\sim S1 + \dots + Sp \mid g</math>, specifying spatial covariates <math>S1</math> through <math>Sp</math> and, optionally, a grouping factor <math>g</math>. When a grouping factor is present in form, the correlation structure is assumed to apply only to observations within the same grouping level; observations with different grouping levels are assumed to be uncorrelated. Defaults to <math>\sim 1</math>, which corresponds to using the order of the observations in the data as a covariate, and no groups.</p>  |
| nugget | <p>an optional logical value indicating whether a nugget effect is present. Defaults to FALSE.</p>   |

nuScaled	If nuScaled is set to TRUE the "range" parameter $\rho$ is divided by $2\sqrt{\nu}$ . With this option and for large values of $\nu$ , corMatern reproduces the calculation of corGaus. Defaults to FALSE, in which case the function compares to corGaus with range parameter $2(\sqrt{\nu})\rho$ when $\nu$ is large.
metric	(Pasted from corSpatial) an optional character string specifying the distance metric to be used. The currently available options are "euclidean" for the root sum-of-squares of distances; "maximum" for the maximum difference; and "manhattan" for the sum of the absolute differences. Partial matching of arguments is used, so only the first three characters need to be provided. Defaults to "euclidean".
fixed	an optional logical value indicating whether the coefficients should be allowed to vary in the optimization, or kept fixed at their initial value. Defaults to FALSE, in which case the coefficients are allowed to vary.

### Details

This function is a constructor for the corMatern class, representing a Matérn spatial correlation structure. See [MaternCorr](#) for details on the Matérn family.

### Value

an object of class corMatern, also inheriting from class corSpatial, representing a Matérn spatial correlation structure.

### Note

The R and C code for the methods for corMatern objects builds on code for corSpatial objects, by D.M. Bates, J.C. Pinheiro and S. DebRoy, in a circa-2012 version of nlme.

### References

Mixed-Effects Models in S and S-PLUS, José C. Pinheiro and Douglas M. Bates, Statistics and Computing Series, Springer-Verlag, New York, NY, 2000.

### See Also

[glmPQL](#), [lme](#)

### Examples

```
## LMM
data("blackcap")
blackcapD <- cbind(blackcap,dummy=1) ## obscure, isn't it?
## With method= 'ML' in lme, The correlated random effect is described
## as a correlated residual error and no extra residual variance is fitted:
nlme::lme(fixed = migStatus ~ means, data = blackcapD, random = ~ 1 | dummy,
          correlation = corMatern(form = ~ longitude+latitude | dummy),
          method = "ML", control=nlme::lmeControl(sing.tol=1e-20))

## Binomial GLMM
```

```

if (spaMM.getOption("example_maxtime")>32) {
  data("Loaloe")
  LoaloeD <- cbind(Loaloe,dummy=1)
  MASS::glmPQL(fixed =cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI,
    data = LoaloeD, random = ~ 1 | dummy,family=binomial,
    correlation = corMatern(form = ~ longitude+latitude | dummy))
}

```

corrHLfit

*Fits a mixed model, typically a spatial GLMM.*

### Description

This was the first function for fitting all spatial models in spaMM, and is still fully functional, but it is recommended to use [fitme](#) which has different defaults and generally selects more efficient fitting methods, and will handle all classes of models that spaMM can fit, including non-spatial ones. `corrHLfit` performs the joint estimation of correlation parameters, fixed effect and dispersion parameters.

### Usage

```

corrHLfit(formula, data, init.corrHLfit = list(),
  init.HLfit = list(), ranFix = list(), lower = list(),
  upper = list(),
  objective = NULL, resid.model = ~1,
  control.dist = list(), control.corrHLfit = list(),
  processed = NULL, family = gaussian(), method="REML",
  nb_cores = NULL, ...)

```

### Arguments

- |                             |  |
|-----------------------------|--|
| <code>formula</code>        | Either a linear model <a href="#">formula</a> (as handled by various fitting functions) or a predictor, i.e. a formula with attributes (see <a href="#">Predictor</a> and examples below). See Details in <a href="#">spaMM</a> for allowed terms in the formula.  |
| <code>data</code>           | A data frame containing the variables in the response and the model formula.   |
| <code>init.corrHLfit</code> | An optional list of initial values for correlation and/or dispersion parameters, e.g. <code>list(rho=1,nu=1,lambda=1,phi=1)</code> where <code>rho</code> and <code>nu</code> are parameters of the Matérn family (see <a href="#">Matern</a> ), and <code>lambda</code> and <code>phi</code> are dispersion parameters (see Details in <a href="#">spaMM</a> for the meaning of these parameters). All are optional, but giving values for a dispersion parameter changes the ways it is estimated (see Details). <code>rho</code> may be a vector (see <a href="#">make_scaled_dist</a> ) and, in that case, it is possible that some or all of its elements are NA, for which <code>corrHLfit</code> substitutes automatically determined values. |
| <code>init.HLfit</code>     | See identically named <a href="#">HLfit</a> argument.  |
| <code>ranFix</code>         | A list similar to <code>init.corrHLfit</code> , but specifying fixed values of the parameters not estimated. See <a href="#">ranFix</a> for further information.   |

lower	An optional (sub)list of values of the parameters specified through <code>init.corrHLfit</code> , in the same format as <code>init.corrHLfit</code> , used as lower values in calls to <code>optim</code> . See Details for default values.
upper	Same as lower, but for upper values.
objective	For development purpose, not documented (this had a distinct use in the first version of spaMM, but has been deprecated as such).
resid.model	See identically named <code>HLfit</code> argument.
control.dist	See <code>control.dist</code> in <code>HLCor</code>
control.corrHLfit	This may be used control the optimizer. See <code>spaMM.options</code> for default values.
processed	For programming purposes, not documented.
family	Either a <code>family</code> or a <code>multi</code> value.
method	Character: the fitting method to be used, such as "ML", "REML" or "PQL/L". "REML" is the default. Other possible values of <code>HLfit</code> 's <code>method</code> argument are handled.
nb_cores	<b>Not yet operative</b> , only for development purposes. Number of cores to use for parallel computations.
...	Optional arguments passed to <code>HLCor</code> , <code>HLfit</code> or <code>mat_sqrt</code> , for example the <code>distMatrix</code> argument of <code>HLCor</code> , or the <code>verbose</code> argument of <code>HLfit</code> . Arguments that do not fit within these functions are detected and a warning is issued. In a <code>corrHLfit</code> call, the <code>verbose</code> vector of booleans may include a <code>TRACE=TRUE</code> element, in which case information is displayed for each set of correlation and dispersion parameter values considered by the optimiser. Non-boolean values of <code>TRACE</code> are meaningful, but the source code of <code>spaMM:::do_TRACE</code> should be consulted for their meaning.

## Details

For approximations of likelihood, see `method`. For the possible structures of random effects, see `random-effects`,

By default `corrHLfit` will estimate correlation parameters by maximizing the objective value returned by `HLCor` calls wherein the dispersion parameters are estimated jointly with fixed effects for given correlation parameters. If dispersion parameters are specified in `init.corrHLfit`, they will also be estimated by maximizing the objective value, and `HLCor` calls will not estimate them jointly with fixed effects. This means that in general the fixed effect estimates may vary depending on `init.corrHLfit` when any form of REML correction is applied.

Correctly using `corrHLfit` for likelihood ratio tests of fixed effects may then be tricky. It is safe to perform full ML fits of all parameters (using `method="ML"`) for such tests (see Examples). The higher level function `fixedLRT` is a safe interface for likelihood ratio tests using some form of REML estimation in `corrHLfit`.

`attr(<fitted object>, "optimInfo")$lower` and `...$upper` gives the lower and upper bounds for optimization of correlation parameters. These are the default values if the user did not provide explicit values. For the adjacency model, the default values are the inverse of the maximum and minimum eigenvalues of the `adjMatrix`. For the Matérn model, the default values are not so easily summarized: they are intended to cover the range of values for which there is statistical information to distinguish among them.

**Value**

The return value of an HLCor call, with additional attributes. The HLCor call is evaluated at the estimated correlation parameter values. These values are included in the return object as its \$corrPars member. The attributes added by corrHLfit include the original call of the function (which can be retrieved by getCall(<fitted object>), and information about the optimization call within corrHLfit.

**See Also**

See more examples on data set [Loaloo](#), to compare fit times by corrHLfit and fitme. See [fixedLRT](#) for likelihood ratio tests.

**Examples**

```
# Example with an adjacency matrix (autoregressive model):
if (spaMM.getOption("example_maxtime")>0.7) {
  corrHLfit(cases~I(prop.ag/10) +adjacency(1|gridcode)+offset(log(expec)),
            adjMatrix=Nmatrix,family=poisson(),data=scotlip,method="ML")
}

#### Examples with Matern correlations
## A likelihood ratio test based on the ML fits of a full and of a null model.
if (spaMM.getOption("example_maxtime")>1.4) {
  data("blackcap")
  (fullfit <- corrHLfit(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
                      method="ML" )
  (nullfit <- corrHLfit(migStatus ~ 1 + Matern(1|longitude+latitude),data=blackcap,
                      method="ML",init.corrHLfit=list(phi=1e-6)))
  ## p-value:
  1-pchisq(2*(logLik(fullfit)-logLik(nullfit)),df=1)
}
```

---

 corrMatrix

*Using a corrMatrix argument*


---

**Description**

corrMatrix is an argument of HLCor, of class `dist` or `matrix`, with is used if the model formula contains a term of the form `corrMatrix(1|<...>)`. It describes a correlation matrix, possibly as a `dist` object. A covariance matrix can actually be passed through this argument, but then it must be a full matrix, not a `dist` object. The way the rows and columns of the matrix are matched to the rows of the data depends on the nature of the grouping term `<...>`.

**Details**

The simplest case is illustrated in the first two examples below: the grouping term is identical to a single variable which is present in the data, whose levels match the rownames of the `corrMatrix`. As illustrated by the second example, the order of the data does not matter in that case, because the

factor levels are used to match the data rows to the appropriate row and columns of the `corrMatrix`. The `corrMatrix` may even contain rows (and columns) in excess of the levels of the grouping term, in which case these rows are ignored.

These convenient properties no longer hold when the grouping term is not a single variable from the data (third example below), or when its levels do not correspond to row names of the matrix. In these cases, (1) no attempt is made to match the data rows to the row and column names of the `corrMatrix`. Such attempt could succeed only if the user had given names to the matrix matching those that the called function could create from the information in the data, in which case the user should find easier to specify a single variable that can be matched; (2) the order of data and `corrMatrix` matter; Internally, a single factor variable is constructed from all levels of the variables in the grouping term (i.e., from all levels of `latitude` and `longitude`, in the third example), with levels 1,2,3... that are matched to rows 1,2,3... of the `corrMatrix`. Thus the first row of the data is always associated to the first row of the matrix; (3) further, the dimension of the matrix must match the number of levels implied by the grouping term. For example, one might consider the case of 14 response values but of correlations between only 7 levels of a random effect, with two responses for each level. Then the matrix must be of dimension 7x7.

## Examples

```
data("blackcap")
## Here we manually reconstruct the correlation matrix
## of the ML fit produced by corrHLfit:
MLcorMat <- MaternCorr(proxy::dist(blackcap[,c("longitude", "latitude")] ),
                      nu=0.6285603, rho=0.0544659)
blackcap$name <- as.factor(rownames(blackcap))
## (1) Single variable present in the data
HLCor(migStatus ~ means+ corrMatrix(1|name), data=blackcap,
      corrMatrix=MLcorMat, method="ML")
## (2) Same, permuted: still gives correct result
perm <- sample(14)
# Permuted matrix (with permuted names)
pmat <- as.matrix(MLcorMat)[perm, perm]
HLCor(migStatus ~ means+ corrMatrix(1|name), data=blackcap,
      corrMatrix=as.dist(pmat), method="ML")
## (3) Other grouping terms (note the messages):
HLCor(migStatus ~ means+ corrMatrix(1|longitude+latitude), data=blackcap,
      corrMatrix=MLcorMat, method="ML")
```

---

corr\_family

corr\_family objects

---

## Description

`corr_family` objects provide a convenient way to implement correlation models handled by `spaMM`, analogous to `family` objects. These objects are undocumented (but there are documentation pages for each of the models implemented).

**Usage**

```
# Matern(...)          # see help(Matern)
# Cauchy(...)          # see help(Cauchy)
# corrMatrix(...)     # see help(corrMatrix)
# AR1(...)            # see help(AR1)
# adjacency(...)      # see help(adjacency)
# IMRF(...)           # see help(IMRF)
## S3 method for class 'corr_family'
print(x,...)
```

**Arguments**

```
x          corr_family object.
...        arguments that may be needed by some corr_family object or some print
           method.
```

---

covStruct	<i>Specifying correlation structures</i>
-----------	--

---

**Description**

covStruct is a formal argument of HLCor, also handled by fitme and corrHLfit, that allows one to specify the correlation structure for different types of random effects, It is an alternative to other ad hoc formal arguments such as corrMatrix or adjMatrix. It replaces the deprecated function Predictor(...) which has served as an interface for specifying the design matrices for random effects in early versions of spaMM.

The main use of covStruct is to specify the correlation matrix of levels of a given random effect term, or its inverse (a precision matrix). Assuming that the design matrix of each random effect term follows the structure **ZAL** described in [random-effects](#), it is thus an indirect way of specifying the “square root” **L** of the correlation matrix. The optional **A** factor can also be given by the optional “AMatrices” attribute of covStruct.

covStruct is a list of matrices with names specifying the type of matrix considered: covStruct=list(corrMatrix=<some matrix>) or covStruct=list(adjMatrix=<some matrix>), where the “corrMatrix” or “adjMatrix” labels are used to specify the type of information provided (accordingly, the names can be repeated: covStruct=list(corrMatrix=<.>,corrMatrix=<.>)). NULL list members may be necessary, e.g.

```
covStruct=list(corrMatrix=<.>,"2"=NULL,corrMatrix=<.>)
```

when correlations matrices are required only for the first and third random effect.

The covariance structure of a corrMatrix(1|<grouping factor>) formula term can be specified in two ways (see Examples): either by a correlation matrix factor (covStruct=list(corrMatrix=<some matrix>)), or by a precision matrix factor **Q** such that the covariance factor is  $\lambda\mathbf{Q}^{-1}$ , using the type name “precision”: covStruct=list(precision=<some matrix>). The function as\_precision can be used to perform the conversion from correlation information to precision factor (using a crude solve() that may not always be efficient), but fitting functions may also perform such conversions automatically.

"AMatrices" is a list of matrices. The names of elements of the list does not matter, but the  $i$ th A matrix, and its row names, should match the  $i$ th  $Z$  matrix, and its column names. This implies that NULL list members may be necessary, as for the covStruct list.

### Usage

```
as_precision(corrMatrix)
```

### Arguments

corrMatrix      Correlation matrix, specified as matrix or as dist object

### Details

covStruct can also be specified as a list with an optional "types" attribute, e.g. `structure(list(<some matrix>, types="corrMatrix"))`.

### Value

as\_precision returns a list with additional class precision and with single element a symmetric matrix of class dsCMatrix.

### See Also

[Gryphon](#) and [pedigree](#) for a type of applications where declaring a precision matrix is useful.

### Examples

```
## Not run:
data("blackcap")
# a 'dist' object can be used to specify a corrMatrix:
MLdistMat <- MaternCorr(proxy::dist(blackcap[,c("latitude", "longitude")] ),
  nu=0.6285603, rho=0.0544659) # a 'dist' object!
blackcap$name <- as.factor(rownames(blackcap))
fitme(migStatus ~ means + corrMatrix(1|name), data=blackcap,
  corrMatrix=MLdistMat)

#### Same result by different input and algorithm:
fitme(migStatus ~ means + corrMatrix(1|name), data=blackcap,
  covStruct=list(precision=as_precision(MLdistMat)))

# Manual version of the same:
as_mat <- proxy::as.matrix(MLdistMat, diag=1)
prec_mat <- solve(as_mat) ## precision factor matrix
fitme(migStatus ~ means + corrMatrix(1|name), data=blackcap,
  covStruct=list(precision=prec_mat))

# Since no correlation parameter is estimated,
# HLcor(., method="ML") is here equivalent to fitme()

## End(Not run)
```

div\_info

*Information about numerical problems***Description**

This function displays information about parameter values for which some numerical problems have occurred. It is preliminary, has yet no good example of application, but some warnings might suggest its use.

**Usage**

```
div_info(object, ...)
```

**Arguments**

object	An object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
...	Currently not used

**Value**

Used mainly for the side effects (printed output) but returns invisibly either a single parameter vector (if a single numerical problem occurred) or a matrix of parameter ranges, or `NULL` if there is no problem to report.

**Examples**

```
if (spaMM.getOption("example_maxtime")>25) {
  set.seed(1L)
  d <- data.frame(y = rbinom(100, 1, 0.5), time = 1:100)
  (logLik(numpb <- fitme(y ~ 1 + AR1(1|time), data = d,
    family = binomial(link=cauchit), method = "PQL"))
  div_info(numpb) # High lambda is often part of the problem,
    # here only for negative AR parameter:
  fitme(y ~ 1 + AR1(1|time), data = d, family = binomial(link=cauchit),
    method = "PQL", lower=list(ARphi=0))
  # Less successful fix (or cover-up):
  fitme(y ~ 1 + AR1(1|time), data = d, family = binomial(link=cauchit),
    method = "PQL", upper=list(lambda=20))
}
```

dofuture

*Interface for parallel computations***Description**

interface to apply some function `fn` in parallel on columns of a matrix. It is not logically restricted to mixed-effect applications, hence it can be used more widely. Depending on the `nb_cores` argument, parallel or serial computation is performed, calling the `future.apply::future_apply` function. A socket cluster is used by default for parallel computations, but a fork cluster can be requested on linux and alike operating systems by using argument `cluster_args=list(type="FORK")`.

**Usage**

```
dofuture(newresp, fn, nb_cores=NULL, fit_env, control=list(),
         cluster_args=NULL, debug.=FALSE, iseed=NULL,
         showpbar="ignored", pretest_cores="ignored",
         ... )
```

**Arguments**

<code>newresp</code>	A matrix on whose columns <code>fn</code> will be applied (e.g., as used internally in <code>spaMM</code> , the return value of a <code>simulate.HLfit()</code> call).
<code>fn</code>	Function, whose first argument is named <code>y</code> , to be applied to each column of <code>newresp</code> .
<code>nb_cores</code>	Integer. Number of cores to use for parallel computations. If <code>&gt;1</code> , a cluster of <code>nb_cores</code> nodes is used. Otherwise, no parallel computation is performed.
<code>fit_env</code>	(for socket clusters only:) An environment, or a list, containing variables to be exported on the nodes of the cluster (by <code>parallel::clusterExport</code> ).
<code>control</code>	A list. The only effective control is <code>.combine="rbind"</code> (mimicking the <code>foreach</code> syntax used in the alternative interface <code>dopar</code> ).
<code>cluster_args</code>	A list of arguments passed to <code>parallel::makeCluster</code> or <code>parallel::makeForkCluster</code> . E.g., <code>outfile="log.txt"</code> may be useful to collect output from the nodes, and <code>type="FORK"</code> to force a fork cluster on linux(-alikes).
<code>debug.</code>	(for socket clusters only:) For debugging purposes. Effect, if any, is to be defined by the <code>fn</code> as provided by the user.
<code>iseed</code>	Integer, or <code>NULL</code> . If an integer, it is used to initialize "L'Ecuyer-CMRG" random-number generator ( <code>iseed</code> argument of <code>clusterSetRNGStream</code> ), with identical effect across different models of parallelisation. If <code>iseed</code> is <code>NULL</code> , the seed is not controlled.
<code>showpbar,pretest_cores</code>	Currently ignored; for consistency with <code>dopar</code> fromal arguments.
<code>...</code>	Further arguments to be passed (unevaluated) to <code>future.apply</code> (and then possibly to <code>fn</code> ).

**Value**

The result of calling `future.apply`. If the `progressr` package is loaded, a side-effect of `dofuture` is to show a progress bar with character 'S' or 'P' or 'F' depending on parallelisation status (serial/socket/fork).

**See Also**

[dopar](#) for an alternative implementation of (essentially) the same functionalities, and [wrap\\_parallel](#) for its differences from `dofuture`.

**Examples**

```
## Not run:
if (requireNamespace("future.apply", quietly = TRUE)) {

  # Useless function, but requiring some argument beyond the first
  foo <- function(y, somearg, ...) {
    if ( is.null(somearg) || TRUE ) length(y)
  }

  # Whether FORK can be used depends on OS and whether Rstudio is used:
  dofuture(matrix(1,ncol=4,nrow=3), foo, fit_env=list(), somearg=NULL,
            nb_cores=2, cluster_args=list(type="FORK"))
}

## End(Not run)
```

---

dopar

*Interface for parallel computations*


---

**Description**

An interface to apply some function `fn` in parallel on columns of a matrix. `dopar` is used internally in `spaMM`, but is not logically restricted to mixed-effect applications, hence it can be used more widely. Depending on the `nb_cores` argument, parallel or serial computation is performed. A socket cluster is used by default for parallel computations, but a fork cluster can be requested on linux and alike operating systems by using argument `cluster_args=list(type="FORK")`.

**Usage**

```
dopar(newresp, fn, nb_cores = NULL, fit_env, control = list(),
      cluster_args = NULL, debug. = FALSE, iseed = NULL,
      showpbar = eval(spaMMgetOption("barstyle")),
      pretest_cores =NULL, ...)
```

**Arguments**

<code>newresp</code>	A matrix on whose columns <code>fn</code> will be applied (e.g., as used internally in <code>spaMM</code> , the return value of a <code>simulate.HLfit()</code> call).
<code>fn</code>	Function, whose first argument is named <code>y</code> , to be applied to each column of <code>newresp</code> .
<code>nb_cores</code>	Integer. Number of cores to use for parallel computations. If $>1$ , a cluster of <code>nb_cores</code> nodes is used. Otherwise, no parallel computation is performed.
<code>fit_env</code>	(for socket clusters only:) An environment, or a list, containing variables to be exported on the nodes of the cluster (by <code>parallel::clusterExport</code> ).
<code>control</code>	A list. In particular if the <code>doSNOW</code> package is attached, <code>foreach</code> is called with default arguments including <code>i = 1:ncol(newresp)</code> , <code>.combine = "cbind"</code> , <code>.inorder = TRUE</code> , <code>.errorhandling = "remove"</code> , <code>.packages = "spaMM"</code> . <code>control</code> may be used to provide non-default values of these arguments. For example, <code>.errorhandling = "pass"</code> is useful to get error messages from the nodes. If <code>doSNOW</code> is not attached, the result is still in the format returned by <code>foreach</code> with default <code>.combine="cbind"</code> or possible non-default <code>.combine="rbind"</code> . Alternatively, if a for cluster is used, <code>control\$mc.silent</code> can be used to control the <code>mc.silent</code> argument of <code>mclapply</code> .
<code>cluster_args</code>	A list of arguments passed to <code>parallel::makeCluster</code> . E.g., <code>outfile="log.txt"</code> may be useful to collect output from the nodes, and <code>type="FORK"</code> to force a fork cluster on linux(-alikes).
<code>debug.</code>	(for socket clusters only:) For debugging purposes. Effect, if any, is to be defined by the <code>fn</code> as provided by the user.
<code>iseed</code>	(all parallel contexts:) Integer, or <code>NULL</code> . If an integer, it is used to initialize "L'Ecuyer-CMRG" random-number generator ( <code>iseed</code> argument of <code>clusterSetRNGStream</code> ), yet not ensuring identical control of random number generator accross different parallelisation options (see alternative function <code>dofuture</code> for such control). If <code>iseed</code> is <code>NULL</code> , the default generator is selected on each node, where its seed is not controlled.
<code>showpbar</code>	(for socket clusters only:) Controls display of progress bar. See <code>barstyle</code> option for details.
<code>pretest_cores</code>	(for socket clusters only:) A function to run on the cores before running <code>fn</code> . It may be used to check that all arguments of the <code>fn</code> can be evaluated in the cores' environments (the internal function <code>.pretest_fn_on_cores</code> provides an example).
<code>...</code>	Further arguments to be passed (unevaluated) to <code>fn</code> .

**Value**

The result of calling `foreach`, `pbapply` or `mclapply`, as dependent on the `control` argument. A side-effect of `dopar` is to show a progress bar that informs about the type of parallelisation performed: a default "=" character for fork clusters, and otherwise "P" for parallel computation via `foreach` and `doSNOW`, "p" for parallel computation via `pbapply`, and "s" for serial computation via `pbapply`.

## See Also

[dofuture](#) for an alternative implementation of (essentially) the same functionalities, and [wrap\\_parallel](#) for its differences from dopar.

## Examples

```
## See source code of spaMM_boot()

## Not run:
# Useless function, but requiring some argument beyond the first
foo <- function(y, somearg, ...) {
  if ( is.null(somearg) || TRUE ) length(y)
}

# Whether FORK can be used depends on OS and whether Rstudio is used:
dopar(matrix(1,ncol=4,nrow=3), foo, fit_env=list(), somearg=NULL,
       nb_cores=2, cluster_args=list(type="FORK"))

## End(Not run)
```

---

eval\_replicate

*Evaluating bootstrap replicates*

---

## Description

`eval_replicate` is the default `simuland` function applied to simulated bootstrap samples by likelihood-ratio testing functions (`fixedLRT`, `LRT`, `anova.HLfit`). This documentation presents the requirements and possible features of this function and of possible user-defined alternatives.

An alternative function `spaMM:::eval_replicate2` is also provided. It is slower, as it refits the models compared with different initial values for random-effect parameters, which is useful in some difficult cases where initial values matter. The `eval_replicate` function may also refit the “full” models with different initial values when the `logLik` of the refitted full model is substantially lower than that of the refitted null model. “Substantially” means that a tolerance of  $1e-04$  is applied to account for inaccuracies of numerical maximization.

## Usage

```
eval_replicate(y)
```

## Arguments

`y` a response vector on which a previously fitted model may be refitted.

## Details

likelihood-ratio testing functions have a `debug.` argument whose effect depends on the `simuland` function. The default behaviour is thus defined by `eval_replicate`, as: if `debug.=TRUE`, upon error in the fitting procedures, `dump.frames` will be called, in which case **a dump file will be written on disk**; and a **list** with debugging information will be returned (so that, say, `pbapply` will not return a matrix). This behaviour may change in later versions, so non-default `debug.` values should not be used in reproducible code. In serial computation, `debug.=2` may induce a stop; this should not happen in parallel computation because the calling functions check against `debug.==2`.

Essential information such as the originally fitted models is passed to the function not as arguments but through its environment, which is controlled by the calling functions (see the `eval_replicate` source code to know which are these arguments). Users should thus not assume that they can control their own `simuland` function's environment as this environment will be altered.

Advanced users can define their own `simuland` function. The `eval_replicate` source code provides a template showing how to use the function's environment. The Example below illustrates another approach augmenting `eval_replicate`. A further example is provided in the file `tests/testthat/test-LRT-boot.R`, using `...` to pass additional arguments beyond response values.

## Value

A vector of the form `c(full=logLik(<refitted full model>), null=logLik(<refitted null model>))`; or possibly in debugging contexts, a list with the same elements each with some additional information provided as attribute.

## See Also

Calling functions [fixedLRT](#), [LRT](#).

## Examples

```
## Not run:
# Simple wrapper enhancing the default 'simuland'
# with a call to some obscure option, and dealing with
# the need to pass the environment assigned to 'simuland'
eval_with_opt <- function(y) {
  spaMM.options(some_obscure_option="some_obscure_value")
  eval_rep <- spaMM:::eval_replicate
  environment(eval_rep) <- parent.env(environment()) # passing the environment
  eval_rep(y)
}

## End(Not run)
```

## Description

spaMM is conceived to minimize installation issues but it nevertheless suggests using some external libraries. These are all accessed through R packages so their installation should be easy when installing binary packages. The Details below give hints for installing packages from source. For all cases not considered below, help yourself. Windows users should have a look at the package manager in the Rtools40 bash shell.

## Details

The `ROI.plugin.glpk` package requires the `Rglpk` package, which itself requires the external `glpk` library. For the latter, Debian-ists and alikes should `sudo apt-get install libglpk-dev`. MacOSX users should `brew install glpk` if using `brew`; Windows users should try using `pacman -S mingw-w64-x86_64-glpk` in the Rtools40 bash shell, together with `Sys.setenv(GLPK_HOME = "$(MINGW_PREFIX)")` in the R session (but I have not fully tested this; previously I had to install `glpk` from <https://sourceforge.net/projects/winglpk/>).

The `nloptr` package requires the external `NLopt` library. Windows users should try using `pacman -S mingw-w64-x86_64-nlopt` in the Rtools40 bash shell (but again I have not fully tested this; see also the README of `nloptr`).

---

extractors

*Functions to extract various components of a fit*

---

## Description

`formula` extracts the model formula. `family` extracts the response family. `terms` extracts the formula, with attributes describing the **fixed-effect** terms. `nobs` returns the length of the response vector. `logLik` extracts the log-likelihood (exact or approximated). `dev_resids` returns a vector of squared (unscaled) deviance residuals (the summands in McCullagh and Nelder 1989, p. 34). `deviance` returns the sum of squares of these (unscaled) deviance residuals, that is (consistently with `stats::deviance`) the unscaled deviance. `fitted` extracts fitted values (see [fitted.values](#)). `response` extracts the response (as a vector). `fixef` extracts the fixed effects coefficients,  $\beta$ . `ranef` extracts the predicted random effects,  $\mathbf{L}\mathbf{v}$  (default since version 1.12.0), or  $\mathbf{u}$  (see Details in [HLfit](#) for definitions), `print.ranef` controls their printing. `getDistMat` returns a distance matrix for a geostatistical (Matérn etc.) random effect.

## Usage

```
## S3 method for class 'HLfit'
formula(x, which="hyper", ...)
## S3 method for class 'HLfit'
family(object, ...)
## S3 method for class 'HLfit'
terms(x, ...)
## S3 method for class 'HLfit'
nobs(object, ...)
## S3 method for class 'HLfit'
```

```

logLik(object, which, ...)
## S3 method for class 'HLfit'
fitted(object, ...)
## S3 method for class 'HLfit'
fixef(object, ...)
## S3 method for class 'HLfit'
ranef(object, type = "correlated", ...)
## S3 method for class 'ranef'
print(x, max.print = 40L, ...)
## S3 method for class 'HLfit'
deviance(object, ...)
##
getDistMat(object, scaled=FALSE, which = 1L)
response(object,...)
dev_resids(object,...)

```

### Arguments

object	An object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
type	For <code>ranef</code> , use <code>type="correlated"</code> (default) to display the correlated random effects ( $Lv$ ), whether in a spatial model, or a random-coefficient model. Use <code>type="uncorrelated"</code> to pretty-print the elements of the <code>&lt;object&gt;\$ranef</code> vector ( $u$ ).
which	For <code>logLik</code> , the name of the element of the APHLs list to return (see Details for any further possibility). The default depends on the fitting method. In particular, if it was REML or one of its variants, the function returns the log restricted likelihood (exact or approximated). For <code>getDistMat</code> , an integer, to select a random effect from several for which a distance matrix may be constructed. For formula, by default the model formula with non-expanded multIMRF random-effect terms is returned, while for <code>which=""</code> a formula with multIMRF terms expanded as IMRF terms is returned.
scaled	If <code>FALSE</code> , the function ignores the scale parameter <i>rho</i> and returns unscaled distance.
x	For <code>print.ranef</code> : the return value of <code>ranef.HLfit</code> .
max.print	Controls options("max.print") locally.
...	Other arguments that may be needed by some method.

### Details

With `which="LogL_Lap"`, `logLik()` returns a Laplace approximation of log-likelihood based on the observed Hessian, rather than the expected Hessian. This is implemented only for the case `family=Gamma(log)`, for demonstration purposes.

### Value

formula returns a formula, except a list of them from `fitmv()` output.

terms returns an object of class `c("terms", "formula")` which contains the *terms* representation of a symbolic model. See [terms.object](#) for its structure. `terms(<fitmv() result>)` returns a list of such terms.

Other return values are numeric (for `logLik`), vectors (most cases), matrices or dist objects (for `getDistMat`), or a family object (for `family`). `ranef` returns a list of vectors or matrices (the latter for random-coefficient terms).

## References

McCullagh, P. and Nelder J. A. (1989) Generalized linear models. Second ed. Chapman & Hall: London.

Lee, Y., Nelder, J. A. (2001) Hierarchical generalised linear models: A synthesis of generalised linear models, random-effect models and structured dispersions. *Biometrika* 88, 987-1006.

Lee, Y., Nelder, J. A. and Pawitan, Y. (2006) Generalized linear models with random effects: unified analysis via h-likelihood. Chapman & Hall: London.

## See Also

See [residuals.HLfit](#) to extract various residuals, [residVar](#) to extract residual variances or information about residual variance models, [hatvalues](#) to extract leverages, [get\\_matrix](#) to extract the model matrix and derived matrices, and [vcov.HLfit](#) to extract covariances matrices from a fit, [get\\_RLRsim\\_args](#) to extract arguments for (notably) tests of random effects in LMMs.

## Examples

```
data("wafers")
m1 <- HLfit(y ~ X1+X2+(1|batch), resid.model = ~ 1,
           data=wafers, method="ML")
fixef(m1)
ranef(m1)

data("blackcap")
fitobject <- fitme(migStatus ~ 1 + Matern(1|longitude+latitude), data=blackcap,
                 fixed=list(nu=4, rho=0.4, phi=0.05))
getDistMat(fitobject)
```

---

fitme

*Fitting function for fixed- and mixed-effect models with GLM response.*

---

## Description

This is a common interface for fitting most models that spaMM can fit, from linear models to mixed models with non-gaussian random effects, therefore substituting to `corrHLfit`, `HLCor` and `HLfit`. By default, it uses ML rather than REML (differing in this respect from the other fitting functions). It may use “outer optimization”, i.e., generic optimization methods for estimating all dispersion parameters, rather than the iterative methods implemented in `HLfit`. The results of REML fits

of non-gaussian mixed models by these different methods may (generally slightly) differ. Outer optimization should generally be faster than the alternative algorithms for large data sets when the residual variance model is a single constant term (no structured dispersion). For mixed models, `fitme` by default tries to select the fastest method when both can be applied, but precise decision criteria are subject to change in the future. `corrHLfit` (with non-default arguments to control the optimization method most suitable to a particular problem) may be used to ensure better consistency over successive versions of `spaMM`.

## Usage

```
fitme(formula, data, family = gaussian(), init = list(), fixed = list(),
      lower = list(), upper = list(), resid.model = ~1, init.HLfit = list(),
      control = list(), control.dist = list(), method = "ML",
      HLmethod = method, processed = NULL, nb_cores = NULL, objective = NULL,
      ...)
```

## Arguments

<code>formula</code>	Either a linear model <code>formula</code> (as handled by various fitting functions) or a predictor, i.e. a formula with attributes (see <a href="#">Predictor</a> and examples below). See Details in <a href="#">spaMM</a> for allowed terms in the formula.
<code>data</code>	A data frame containing the variables in the response and the model formula.
<code>family</code>	Either a response <code>family</code> or a <code>multi</code> value.
<code>init</code>	An optional list of initial values for correlation and/or dispersion parameters and/or response family parameters, e.g. <code>list(rho=1, nu=1, lambda=1, phi=1)</code> where <code>rho</code> and <code>nu</code> are parameters of the Matérn family (see <a href="#">Matern</a> ), and <code>lambda</code> and <code>phi</code> are dispersion parameters (see Details in <a href="#">spaMM</a> for the meaning of these parameters). All are optional, but giving values for a dispersion parameter changes the ways it is estimated (see Details and Examples). <code>rho</code> may be a vector (see <a href="#">make_scaled_dist</a> ) and, in that case, it is possible that some or all of its elements are NA, for which <code>fitme</code> substitutes automatically determined values.
<code>fixed</code>	A list similar to <code>init</code> , but specifying fixed values of the parameters not estimated. See <a href="#">fixed</a> for further information; and keep in mind that fixed fixed-effect coefficients can be passed as the <code>etaFix</code> argument as part of the <code>'...'</code> .
<code>lower</code>	An optional (sub)list of values of the parameters specified through <code>init</code> , in the same format as <code>init</code> , used as lower values in calls to <code>optim</code> . See Details for default values.
<code>upper</code>	Same as <code>lower</code> , but for upper values.
<code>resid.model</code>	See identically named <a href="#">HLfit</a> argument.
<code>init.HLfit</code>	See identically named <a href="#">HLfit</a> argument.
<code>control</code>	A list of control parameters, with two possible elements: <ul style="list-style-type: none"> <li><code>nloptr</code>, itself a list of control parameters to be copied in the <code>opts</code> argument of <a href="#">nloptr</a>. Default controls are given by <code>spaMM.getOption('nloptr')</code></li> </ul>

- `refit`, a boolean, or a list of booleans with possible elements `$phi`, `$lambda` and `$ranCoefs`. If either element is set to `TRUE`, then the corresponding parameters are refitted by the internal `HLfit` methods (see [Details](#)). If `$refit` is a single boolean, it affects of parameters. By default only `lambda` is refitted, but this default may change in the future.

<code>control.dist</code> method, <code>HLmethod</code>	See <code>control.dist</code> in <a href="#">HLCor</a>  Character: the fitting method to be used, such as "ML", "REML" or "PQL/L". "ML" is the default, in contrast to "REML" for <code>HLfit</code> , <code>HLCor</code> and <code>corrHLfit</code> . Other possible values of <code>HLfit</code> 's method argument are handled.
<code>nb_cores</code>	<b>Not yet operative</b> , only for development purposes. Number of cores to use for parallel computations.
<code>processed</code>	For programming purposes, not documented.
<code>objective</code>	For development purpose, not documented.
<code>...</code>	Optional arguments passed to (or operating as if passed to) <a href="#">HLCor</a> , <a href="#">HLfit</a> or <a href="#">mat_sqrt</a> , for example <code>rand.family</code> , <code>control.HLfit</code> , <code>verbose</code> or the <code>distMatrix</code> argument of <code>HLCor</code> (so that estimation of Matern or Cauchy parameters can be combined with use of an ad hoc distance matrix). In a <code>fitme</code> call, the <code>verbose</code> vector of booleans may include a <code>TRACE=TRUE</code> element, in which case information is displayed for each set of correlation and dispersion parameter values considered by the optimiser. Non-boolean values of <code>TRACE</code> are meaningful, but the source code of <code>spaMM:::do_TRACE</code> should be consulted for their meaning.

## Details

For approximations of likelihood, see [method](#). For the possible structures of random effects, see [random-effects](#),

For `phi`, `lambda`, and `ranCoefs`, `fitme` may or may not use the internal fitting methods of `HLfit`. The latter methods are well suited for structured dispersion models, but require computations which can be slow for large datasets. Therefore, `fitme` tends to outer-optimize by default for large datasets, unless there is a non-trivial `resid.model`. The precise criteria for selection of default method by `fitme` are liable to future changes.

Further, the internal fitting methods of `HLfit` also provide some more information such as the "cond. SE" (about which see warning in [Details](#) of [HLfit](#)). To force the evaluation of such information after an outer-optimization by a `fitme` call, use the `control$refit` argument (see [Example](#)). Alternatively (and possibly of limited use), one can force inner-optimization of `lambda` for a given random effect, or of `phi`, by setting it to `NaN` in `init` (see [Example](#) using 'blackcap' data). The same syntax may be tried for `phi`.

## Value

The return value of an `HLCor` or an `HLfit` call, with additional attributes. The `HLCor` call is evaluated at the estimated correlation parameter values. These values are included in the return object as its `$corrPars` member. The attributes added by `fitme` include the original call of the function (which can be retrived by `getCall(<fitted object>)`), and information about the optimization call within `fitme`.

## Examples

```
## Examples with Matern correlations
## A likelihood ratio test based on the ML fits of a full and of a null model.
data("blackcap")
(fullfit <- fitme(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap) )
(nullfit <- fitme(migStatus ~ 1 + Matern(1|longitude+latitude),data=blackcap))
## p-value:
1-pchisq(2*(logLik(fullfit)-logLik(nullfit)),df=1)

## See ?spaMM for examples of conditional autoregressive model and of non-spatial models.

## Contrasting different optimization methods:
# We simulate Gamma deviates with mean mu=3 and variance=2,
# ie. phi= var/mu^2= 2/9 in the (mu, phi) parametrization of a Gamma
# GLM; and shape=9/2, scale=2/3 in the parametrisation of rgamma().
# Note that phi is not equivalent to scale:
# shape = 1/phi and scale = mu*phi.
set.seed(123)
gr <- data.frame(y=rgamma(100,shape=9/2,scale=2/3))
# Here fitme uses HLfit methods which provide cond. SE for phi by default:
fitme(y~1,data=gr,family=Gamma(log))
# To force outer optimization of phi, use the init argument:
fitme(y~1,data=gr,family=Gamma(log),init=list(phi=1))
# To obtain cond. SE for phi after outer optimization, use the 'refit' control:
fitme(y~1,data=gr,family=Gamma(log),,init=list(phi=1),
      control=list(refit=list(phi=TRUE))) ## or ...refit=TRUE...

## Outer-optimization is not necessarily the best way to find a global maximum,
# particularly when there is little statistical information in the data:
if (spaMM.getOption("example_maxtime")>1.6) {
  data("blackcap")
  fitme(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap) # poor
  # Compare with the following two ways of avoiding outer-optimization of lambda:
  corrHLfit(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
            method="ML")
  fitme(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
        init=list(lambda=NaN))
}

## see help("COMPOisson"), help("negbin"), help("Loaloo"), etc., for further examples.
```

---

fitmv

*Fitting multivariate responses*


---

## Description

This function extends the `fitme` function to fit a joint model for different responses (following possibly different response families) sharing some random-effects, including a new type of random effect defined to exhibit correlations across different responses (see [mv](#)). The extension of `spaMM` to multivariate-response models is under advanced development but a few features available for analysis of univariate response may not yet work (see [Details](#)).

**Usage**

```
fitmv(submodels, data, fixed=NULL, init=list(), lower=list(), upper=list(),
      control=list(), control.dist = list(), method="ML", init.HLfit=list(), ...)
```

**Arguments**

submodels	A list of sublists each specifying a model for each univariate response. The names given to each submodel in the main list are currently ignored. The names and syntax of elements within each sublist are those of a <code>fitme</code> call. In most cases, each sublist should not contain arguments provided as formal arguments of <code>fitmv</code> itself (with the possible exception of <code>fixed</code> ).
data	A data frame containing the variables in the response and the model formulas.
fixed	A list of fixed values of the parameters controlling random effects. The syntax is that of the same argument in <code>fitme</code> (the optional <code>fixed</code> argument in each sublist of <code>submodels</code> may also be used but this feature may be confusing).
init, lower, upper	Lists of initial values or bounds. The syntax is that of the same arguments in <code>fitme</code> . In these lists, random effects should be indexed according to their order of appearance in the total model (see <a href="#">Details</a> ). Any <code>init</code> , <code>lower</code> , or <code>upper</code> in a sublist of <code>submodels</code> will be ignored.
control	A list of control parameters, with possible elements as described for <a href="#">fitme</a>
control.dist	See <code>control.dist</code> in <a href="#">HLCor</a>
method	Character: the fitting method to be used, such as "ML", "REML" or "PQL/L". "ML" is the default, as for <code>fitme</code> and in contrast to "REML" for the other fitting functions. Other possible values of <code>HLfit</code> 's <code>method</code> argument are handled.
init.HLfit	See identically named <a href="#">HLfit</a> argument.
...	Optional arguments passed to (or operating as if passed to) <a href="#">HLCor</a> , <a href="#">HLfit</a> or <a href="#">mat_sqrt</a> , for example <code>control.HLfit</code> or the <code>covStruct</code> , <code>distMatrix</code> , <code>corrMatrix</code> or <code>adjMatrix</code> arguments of <a href="#">HLCor</a> .

**Details****Matching random effects accross submodels, and referring to them;**

Random effects are recognized as identical accross submodels by matching the formula terms. As shown in the [Examples](#), if the two models formulas share the `(1|clinic)` term, this term is recognized as a single random effect shared between the two responses. But the `(1|clinic)` and `(1|clinic2)` terms are recognized as distinct random effects. In that case, the `init` argument `init=list(lambda=c('1'=1, '2'=0.5))` is shown to refer to these by names 1, 2... where the order is defined as the order of first appearance of the terms accross the model formulas in the order of the `submodels` list. Alternatively, the syntax `fixed=list(lambda=c('clinic2'=0.5, 'clinic'=1))` works: this syntax makes order of input irrelevant but assumes that the user guesses names correctly (these are typically the names that appear in the summary of lambda values from the fit object or, more programmatically, `names(<fit object>$lambda.object$print_namesTerms)`). Finally, fixed values of parameters can **also** be specified through each sub-model, with indices referring to the order of random effects with each model.

The matching of random-effect terms occurs after expansion of `multIMRF` terms, if any. This may have subtle consequences if two `multIMRF` terms differ only by their number of levels, as some of the expanded IMRF terms are then shared.

#### Capacities and limitations:

Practically all features of models that can be fitted by `fitme` should be available: this includes all combinations of GLM response families, residual dispersion models, and all types of random-effect terms, whether autocorrelated or not. Among the arguments handled through the `...`, `covStruct`, `distMatrix`, `corrMatrix` should be effective; `control.HLfit$LevenbergM` and `verbose=c(TRACE=TRUE)` will work but some other controls available in `fitme` may not.

The `codemulti` family-like syntax for multinomial models should not be used, but `fitmv` could provide other means to model multinomial responses.

Most post-fit functions work, at least with default arguments. This includes point prediction and prediction variances calculations *sensu lato*, including with `newdata`; but also `simulate`, `spaMM_boot`, `confint`, `anova`, `update_resp`, and `update`. Usage of the `re.form` argument of some of these functions has not been systematically checked.

Some plotting functions may fail. `update.formula` fails (see `update_formulas` for details). `terms` returns a list, which is not usable by other base R functions. `step` is a good example of resulting limitations, as it is currently unable to perform any sensible operation on `fitmv` output. `spaMM::MSFDR` which rests both on `terms` and on `step` likewise fails. `multcomp::glht` fails.

A perhaps not entirely satisfying feature is that `simulate` by default stacks the results of simulating each model in a single vector. Everything with `newdata` may return results in an inconvenient format.

```
update_resp(<fit>, newresp = simulate(<fit>, ...),
           evaluate = FALSE)$data
```

may then be particularly useful to reformat simulation results. `newdata` with insufficient information for prediction of all responses should generally cause troubles (as it may already in univariate-response models).

#### Which arguments belong to submodels?:

Overall, arguments specifying individuals submodels should go into `submodels`, while other arguments of `fitmv` should be those potentially affecting several submodels (notably, random-effect structures, `lower`, and `upper`) and fitting controls (such as `init` and `init.HLfit`). One rarely-used exception is `REMLformula` which controls the fitting method but should be specified through the `submodels`.

The function proceeds by first preprocessing all submodels independently, before merging the resulting information by matching random effects across submodels. The merging operation includes some checks of consistency accross submodels, implying that redundant arguments may be needed across submodels (e.g. specifying twice a non-default `rand.family` for a random effect shared by two submodels).

## Value

A (single) list of class `HLfit`, as returned by other fitting functions in `spaMM`. The main difference is that it contains a `families` element describing the response families, instead of the `family` elements of fitted objects for univariate response.

**See Also**

See further examples in [mv](#) (modelling correlated random effects over the different submodels), and [residVar](#).

**Examples**

```
# Data preparation
npos <- c(11,16,14,2,6,1,1,4,10,22,7,1,0,0,1,6)
ntot <- c(36,20,19,16,17,11,5,6,37,32,19,17,12,10,9,7)
treatment <- c(rep(1,8),rep(0,8))
clinic <- c(seq(8),seq(8))
clinics <- data.frame(npos=npos,nneg=ntot-npos,treatment=treatment,clinic=clinic)

climv <- data.frame(npos=npos, nneg=ntot-npos, treatment=treatment,
  clinic=clinic, clinic2=clinic)
(fitClinics <- HLfit(cbind(npos,nneg)~treatment+(1|clinic),
  family=binomial(),data=clinics))

set.seed(123)
climv$np2 <- simulate(fitClinics, type="residual")
#
### fits

# Shared random-effect
(mvfit <- fitmv(
  submodels=list(mod1=list(formula=cbind(npos,nneg)~treatment+(1|clinic),family=binomial()),
    mod2=list(formula=np2~treatment+(1|clinic),
      family=poisson(), fixed=list(lambda=c("1"=1))),
  data=climv))

# Two univariate-response independent fits because random effect terms are distinct
# (note how two lambda values are set; same syntax for 'init' values):
(mvfit <- fitmv(
  submodels=list(mod1=list(formula=cbind(npos,nneg)~treatment+(1|clinic),family=binomial()),
    mod2=list(formula=np2~treatment+(1|clinic2),family=poisson()))),
  data=climv, fixed=list(lambda=c('1'=1,'2'=0.5))) # '1': (1|clinic); '2': (1|clinic2)

# Specifying fixed (but not init) values in submodels is also possible (maybe not a good idea)
# (mvfit <- fitmv(
#   submodels=list(mod1=list(formula=cbind(npos,nneg)~treatment+(1|clinic),
#     family=binomial(),fixed=list(lambda=c('1'=1))), # '1': (1|clinic)
#     mod2=list(formula=np2~treatment+(1|clinic2),family=poisson(),
#       fixed=list(lambda=c('1'=0.5))), # '2': (1|clinic2)
#   data=climv))
```

## Description

The fitting functions allow some parameters to be fixed rather than estimated. Fixed-effect coefficients can be set by by way of the `etaFix` argument (linear predictor coefficients) for all fitting functions. Random-effect parameters can be set by an argument with a different name for the different fitting functions: `fixed` for `fitme`, `ranFix` for `HLfit` and `corrHLfit`, and `ranPars` for `HLCor`. This diversity of names may be confusing, but keep in mind that `ranFix` allows one to fix parameters that `HLfit` and `corrHLfit` would otherwise estimate, while `ranPars` can be used to set correlation parameters that `HLCor` does not estimate but nevertheless requires (e.g., Matérn parameters).

## Details

**etaFix** is a list with principal element `beta`, which should be a vector of (a subset of) the coefficients ( $\beta$ ) of the fixed effects, with names as shown in a fit without such given values. If REML is used to fit random effect parameters, then `etaFix` affects by default the REML correction for estimation of dispersion parameters, which depends only on which  $\beta$  coefficients are estimated rather than given. This default behaviour will be overridden whenever a non-null REML formula is provided to the fitting functions (see Example). REML formula is the preferred way to control non-standard REML fits. Alternatively, with a non-NULL `etaFix$beta`, REML can also be performed as if all  $\beta$  coefficients were estimated, by adding attribute `keepInREML=TRUE` to `etaFix$beta`. Using an REML formula will override such a specification.

Despite its different name for different fitting functions, the argument for fixing random-effect parameters has a common syntax for all functions. It is a list, with the following possible elements, whose nature is further detailed below: **phi** (variance of residual error, for gaussian and Gamma HGLMs), **lambda** (random-effect variances, except for random-coefficient terms), **ranCoefs** (random-coefficient parameters), and **corrPars** (correlation parameters, when handled by the fitting function). Individual correlation parameters such as **rho**, **nu**, **Nugget**, **ARphi**... are also possible. When there is no ambiguity as to which random effect these correlation parameters apply. This was the original syntax, conceived when `spaMM` handled a single spatial random effect, and it is still convenient when applicable, but it should not be mixed with `corrPars` usage.

**phi** may be a single value or a vector of the same length as the response vector (the number of rows in the data, once non-informative rows are removed).

**lambda** may be a single value (if there is a single random effect, or a vector allowing to specify unambiguously variance values for some random effect(s). It can thus take the form `lambda=c(NA, 1)` or `lambda=c("2"=1)` (note the name) to assign a value only to the variance of the second of two random effects.

**ranCoefs** is a list of numeric vectors, each numeric vector specifying the variance and correlation parameters for a random-coefficient term. As for `lambda`, it may be incomplete, using names to specify the random effect to which the parameters apply. For example, to assign variances values 3 and 7, and correlation value -0.05, to a second random effect, one can use `ranCoefs=list("2"=c(3, -0.05, 7))` (note the name). The elements of each vector are variances and correlations, matching those of the printed summary of a fit. The order of these elements must be the order of the `lower.tri` of a covariance matrix, as shown e.g. by

```
m2 <- matrix(NA, ncol=2, nrow=2); m2[lower.tri(m2, diag=TRUE)] <- seq(3); m2.
```

`fitme` accepts partially fixed parameters for a random coefficient term, e.g., `ranCoefs=list("2"=c(NA, -0.05, NA))`, although this may not mix well with some obscure options, such as `control=list(refit=list(ranCoefs=TRUE))` which will ignore the fixed values.

**corrPars** is a list, and it may also be incomplete, using names to specify the affected random effect as shown for `lambda` and `ranCoefs`. For example, `ranFix=list(corrPars=list("1"=list(nu=0.5)))` makes explicit that `nu=0.5` applies to the first ("1") random effect in the model formula. Its elements may be the correlation parameters of the given random effect. For the Matérn model, these are the correlation parameters `rho` (scale parameter(s)), `nu` (smoothness parameter), and (optionally) Nugget (see [Matern](#)). The `rho` parameter can itself be a vector with different values for different geographic coordinates. For the adjacency model, the only correlation parameter is a scalar `rho` (see [adjacency](#)). For the AR1 model, the only correlation parameter is a scalar `ARphi` (see [AR1](#)). Consult the documentation for other types of random effects, such as [Cauchy](#) or [IMRF](#), for any information missing here.

## Examples

```
## Not run:
data("wafers")
# Fixing random-coefficient parameters:
HLfit(y~X1+(X2|batch), data=wafers, ranFix=list(ranCoefs=list("1"=c(2760, -0.1, 1844))))
# fixing coefficients of the linear predictor, but with REML as if they were not fixed:
HLfit(y ~X1+X2+X1*X3+X2*X3+I(X2^2)+(1|batch), data=wafers, family=Gamma(log),
      etaFix=list(beta=c("Intercept")=5.61208, X1=0.08818, X2=-0.21163, X3=-0.13948,
                        "I(X2^2)"=-0.10378, "X1:X3"=-0.08987, "X2:X3"=-0.08779)),
      REMLformula=y ~X1+X2+X1*X3+X2*X3+I(X2^2)+(1|batch))

data("Loaloe")
# Fixing some Matern correlation parameters, in corrHLfit:
corrHLfit(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
          +Matern(1|longitude+latitude),
          data=Loaloe,family=binomial(),ranFix=list(nu=0.5,Nugget=2/7))
# Fixing all mandatory Matern correlation parameters, in HLCor:
HLCor(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
      +Matern(1|longitude+latitude),
      data=Loaloe,family=binomial(),ranPars=list(nu=0.5,rho=0.7))

## End(Not run)
```

---

fixedLRT

*Likelihood ratio test of fixed effects.*

---

## Description

`fixedLRT` performs a likelihood ratio (LR) test between two models, the “full” and the “null” models, currently differing only in their fixed effects. Parametric bootstrap p-values can be computed, either using the raw bootstrap distribution of the likelihood ratio, or a bootstrap estimate of the Bartlett correction of the LR statistic. This function differs from `LRT` in its arguments (model fits for `LRT`, versus all arguments required to fit the models for `fixedLRT`), and in the format of its return value.

**Usage**

```
fixedLRT(null.formula, formula, data, method, HLmethod = method,
         REMLformula = NULL, boot.repl=0, control="DEPRECATED",
         control.boot="DEPRECATED", fittingFunction, seed=NULL,
         resp_testfn = NULL, ...)
```

**Arguments**

<code>null.formula</code>	Either a formula (as in <code>glm</code> ) or a predictor (see <code>Predictor</code> ) for the null model.
<code>formula</code>	Either a formula or a predictor for the full model.
<code>data</code>	A data frame containing the variables in the model.
<code>method</code>	A method to fit the full and null models. See <a href="#">method</a> information about such methods. The two most meaningful values of <code>method</code> in <code>fixedLRT</code> calls are: 'ML' for an LRT based on ML fits (generally recommended); and 'PQL/L' for an LRT based on PQL/L fits (recommended for spatial binary data). Also feasible, but more tricky, and not really recommended (see Rousset and Ferdy, 2014), is 'REML'. This will perform an LRT based on two REML fits of the data, *both* of which use the same conditional (or “restricted”) likelihood of residuals for estimating dispersion parameters $\lambda$ and $\phi$ (see <code>REMLformula</code> argument). Further, REML will not be effective on a given dispersion parameter if a non-trivial <code>init.corrHLfit</code> value is provided for this parameter.
<code>HLmethod</code>	Kept for back-compatibility. Same as <code>method</code> , but may work only for <code>fittingFunction=corrHLfit</code> .
<code>REMLformula</code>	a formula specifying the fixed effects which design matrix is used in the REML correction for the estimation of dispersion parameters, if these are estimated by REML. This formula is by default that for the *full* model.
<code>boot.repl</code>	the number of bootstrap replicates.
<code>control</code>	Deprecated.
<code>control.boot</code>	Deprecated.
<code>fittingFunction</code>	Character string giving the function used to fit each model: either "corrHLfit" or "fitme". Default is "corrHLfit" for small data sets (fewer than 300 observations), and "fitme" otherwise, but this may change in future versions.
<code>seed</code>	Passed to <a href="#">simulate.HLfit</a>
<code>resp_testfn</code>	See argument <code>resp_testfn</code> of <a href="#">spaMM_boot</a>
<code>...</code>	Further arguments passed to or from other methods; presently, additional arguments passed to fitting functions.

**Details**

Comparison of REML fits is a priori not suitable for performing likelihood ratio tests. Nevertheless, it is possible to contrive them for testing purposes (Wehler & Thompson 1997). This function generalizes some of Wehler & Thompson’s methods to GLMMs.

See [Details in LRT](#) for details of the bootstrap procedures.

**Value**

An object of class `fixedLRT`, actually a list with as-yet unstable format, but here with typical elements (depending on the options)

<code>fullfit</code>	the <code>HLfit</code> object for the full model;
<code>nullfit</code>	the <code>HLfit</code> object for the null model;
<code>LRTori</code>	A likelihood ratio chi-square statistic
<code>LRTprof</code>	Another likelihood ratio chi-square statistic, after a profiling step, if any.
<code>df</code>	the number of degrees of freedom of the test.
<code>trace.info</code>	Information on various steps of the computation.

and, if a bootstrap was performed, the additional elements described in [LRT](#).

**References**

Rousset F., Ferdy, J.-B. (2014) Testing environmental and genetic effects in the presence of spatial autocorrelation. *Ecography*, 37: 781-790. doi: [10.1111/ecog.00566](https://doi.org/10.1111/ecog.00566)

Welham, S. J., and Thompson, R. (1997) Likelihood ratio tests for fixed model terms using residual maximum likelihood, *J. R. Stat. Soc. B* 59, 701-714.

**See Also**

See also [corrHLfit](#) and [LRT](#).

**Examples**

```
if (spaMM.getOption("example_maxtime")>1.9) {
  data("blackcap")
  ## result comparable to the corrHLfit examples based on blackcap
  fixedLRT(null.formula=migStatus ~ 1 + Matern(1|longitude+latitude),
           formula=migStatus ~ means + Matern(1|longitude+latitude),
           method='ML',data=blackcap)
}
if (spaMM.getOption("example_maxtime")>156) {
  ## longer version with bootstrap
  fixedLRT(null.formula=migStatus ~ 1 + Matern(1|longitude+latitude),
           formula=migStatus ~ means + Matern(1|longitude+latitude),
           method='ML',data=blackcap, boot.repl=100, seed=123)
}
```

fix\_predVar

*Prediction from models with nearly-singular covariance matrices***Description**

This explains how to handle a warning occurring in computation of prediction variance, where the user is directed here.

For **Matern or Cauchy** correlation models with vanishing scale factor for distances, a warning may be produced when `predict.HLfit` (or `get_predVar`, etc.) is called with non-NULL `newdata`, because a nearly-singular correlation matrix of the random effect is met. **To decide what to do** in that case, users should compare the values of `get_predVar(.)` and `get_predVar(., newdata=myfit$data)` (see Example below). In the absence of numerical inaccuracies, the two values should be identical, and in the presence of such inaccuracies, the more reliable value is the first one. In really poor cases, the second syntax may yield negative prediction variances. If users deem the inaccuracies too large, they should use `control=list(fix_predVar=TRUE)` in the next call to `predict.HLfit` (or `get_predVar`, etc.) as shown in the Example. The drawback of this control is that the computation may be slower, and might even exceed memory capacity for large problems (some matrix operations being performed with exact rational arithmetic, which is memory-consuming for large matrices). It is also still experimental, in the sense that I fear that bugs (stop) may occur. If the user instead chooses `control=list(fix_predVar=FALSE)`, the default standard floating-point arithmetic is used, but no warning is issued.

For `fix_predVar` left NULL (the default), standard floating-point arithmetic is also used. But in addition (with exceptions: see Details), the warning keeps being issued, and the (possibly costly) computation of the inverse of the correlation matrix is not stored in the fitted model object, hence is repeated for each new prediction variance computation. This is useful to remind users that something needs to be done, but for programming purposes where repeated warnings may be a nuisance, one can use `control=list(fix_predVar=NA)` which will issue a warning then perform as `control=list(fix_predVar=FALSE)`, i.e. store an approximate inverse so the warning is not issued again. Finally, `control=list(fix_predVar=NaN)` will remove the inverse of the correlation matrix from the fitted model object, and start afresh as if the control was NULL.

**Details**

Nearly-singular correlation matrices of random effects occur in several contexts. For random-slope models, it commonly occurs that the fitted correlation between the random effects for Intercept and slope is 1 or -1, in which case the correlation matrix between these random effects is singular. This led to quite inaccurate computations of prediction variances in `spaMM` prior to version 3.1.0, but this problem has been fixed.

`control=list(fix_predVar=NaN)` may be more appropriate than `control=list(fix_predVar=NULL)` when `predict.HLfit` is called through code that one cannot control. For this reason, `spaMM` provides another mode of control of the default. It will convert `control=list(fix_predVar=NULL)` to other values when the call stack has call names matching the patterns given by `spaMM.getOption("fix_predVar")` (as understood by `grep`). Thus if `spaMM.getOption("fix_predVar")$"NA"=="MSL|bboptim"`, the default behaviour is that defined by `control=list(fix_predVar=NA)` when `predict.HLfit` is called through `Infusion::MSL` or `blackbox::bboptim`. `FALSE` or `TRUE` are handled in a similar way.

**Examples**

```

data("blackcap")
fitobject <- corrHLfit(migStatus ~ 1 + Matern(1|longitude+latitude),data=blackcap,
                      ranFix=list(nu=10,rho=0.001)) ## numerically singular C
get_predVar(fitobject,newdata=blackcap[6,])
## => warning => let us apply the recommended procedure:
get_predVar(fitobject)
get_predVar(fitobject,newdata=fitobject$data)
# Negative values again in the second case => easy decision:
get_predVar(fitobject,newdata=blackcap[1:6,],
            control=list(fix_predVar=TRUE)) # now it's accurate
            # and the accuracy control is stored in the object:
get_predVar(fitobject,newdata=blackcap[1:6,])
# Clean and start afresh:
get_predVar(fitobject,newdata=blackcap[1:6,],
            control=list(fix_predVar=NaN))

```

---

freight

*Freight dataset*


---

**Description**

A set of data on airfreight breakage. Data are given on 10 air shipments, each carrying 1000 ampules of some substance. For each shipment, the number of ampules found broken upon arrival, and the number of times the shipments were transferred from one aircraft to another, are recorded.

**Usage**

```
data("freight")
```

**Format**

The data frame includes 10 observations on the following variables:

**broken** number of ampules found broken upon arrival.

**transfers** number of times the shipments were transferred from one aircraft to another.

**id** Shipment identifier.

**Source**

The data set is reported by Kutner et al. (2003) and used by Sellers & Shmueli (2010) to illustrate COMPOisson analyses.

**References**

Kutner MH, Nachtsheim CJ, Neter J, Li W (2005, p. 35). Applied Linear Regression Models, Fourth Edition. McGraw-Hill.

Sellers KF, Shmueli G (2010) A Flexible Regression Model for Count Data. Ann. Appl. Stat. 4: 943–961

**Examples**

```
## see ?COMpoisson for examples
```

---

```
get_cPredVar
```

*Estimation of prediction variance with bootstrap correction*

---

**Description**

This function is similar to [get\\_predVar](#) except that it uses a bootstrap procedure to correct for bias in the evaluation of the prediction variance.

**Usage**

```
get_cPredVar(pred_object, newdata, nsim, seed, type = "residual",
             variances=NULL, nb_cores = NULL, fit_env = NULL,
             sim_object=pred_object)
```

**Arguments**

pred_object	an object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
newdata	passed to <a href="#">predict.HLfit</a> (it thus represents a prediction design, not to be confused with the bootstrap samples)
nsim	passed to <a href="#">simulate.HLfit</a>
seed	passed to <a href="#">simulate.HLfit</a>
type	passed to <a href="#">simulate.HLfit</a>
variances	NULL or list; <code>variances["cov"]</code> will be passed to <a href="#">predict.HLfit</a> to control whether a covariance matrix is computed or not. Other elements are currently ignored.
nb_cores	integer: number of cores to use for parallel computation of bootstrap. The default is <code>spaMM.getOption("nb_cores")</code> , and 1 if the latter is NULL. <code>nb_cores=1</code> prevents the use of parallelisation procedures.
fit_env	For parallel computations: an environment containing objects to be passed to the cores. They should have the same name in <code>fit_env</code> as in the environment they are passed from.
sim_object	an object of class <code>HLfit</code> , passed to <a href="#">simulate.HLfit</a> as its object argument. Simulating from this object must produce response values that can be used as replacement to those of the original fitted <code>pred_object</code> . In standard usage, <code>sim_object=pred_object</code> (the default).

## Details

The result provided by `get_cPredVar` is similar to the CMSEP (Conditional Mean Standard Error of Prediction) introduced by Booth and Hobert (1998; “B&H”). This paper is known for pointing the importance of using conditional variances when they differ from unconditional ones. This is hard to miss in spatial models, where the relevant prediction variance typically depends on the variance of random effects conditional on the data. Thus, the alternative function `get_predVar` already accounts for this and returns a prediction variance that depends on a joint covariance of fixed-effect estimates and of random effects given the data.

B&H also used a conditional bootstrap procedure to correct for some bias. `get_cPredVar` implements a similar procedure, in contrast to `get_predVar`. Their conditional bootstrap procedure is not applicable for autocorrelated random effects, and parametric bootstrapping of the residuals of the fitted model (as implied by the default value of argument `type`) is used instead here. Apart from this difference, the returned value includes exactly the same terms as those discussed by B&H: their “naive estimate”  $\nu_i$  and its bootstrap correction  $b_i$ , their correction  $\beta$  for uncertainty in fixed-effect coefficients, and their correction  $\sigma^2$  for uncertainty in dispersion parameters.

This use of the bootstrap does not account for uncertainty in correlation parameters “outer-optimized” by `fitme` or `corrHLfit`, because the correlation parameters are fixed when the model is refitted on the bootstrap replicates. Even if it the orrelation parameters where refitted, the full computation would not be sufficient to account for uncertainty in them. To account for uncertainty in correlation parameters, one should rather perform a parametric bootstrap of the full model (typically using `spaMM_boot(. , type="residual")`), which may take much more time.

The “naive estimate”  $\nu_i$  is not generally an estimate of anything uniquely defined by the model parameters: for correlated random effects, it depends on the “root” of the correlation matrix of the random effects, which is not unique. Thus  $\nu_i$  is not unique, and may differ for example for equivalent fits by sparse-precision methods vs. other methods. Nevertheless, `attr(cpredvar, "info")$naive` does recover published values in the Examples below, as they involve no correlation matrix.

## Value

A vector of prediction variances, with an attribute `info` which is an **environment** containing variables:

<code>SEs</code>	the standard errors of the estimates (which are those of the bootstrap replicates)
<code>bias</code>	the bias term
<code>maive</code>	B&H’s “naive” $\nu_i$

## References

Booth, J.G., Hobert, J.P. (1998) Standard errors of prediction in generalized linear mixed models. *J. Am. Stat. Assoc.* 93: 262-272.

## Examples

```
## Not run:
if(requireNamespace("rsae", quietly = TRUE)) {
  # LMM example from Booth & Hobert 1998 JASA
  data("landsat", package = "rsae")
  fitCorn <- fitme(HACorn ~ PixelsCorn + PixelsSoybeans + (1|CountyName), data=landsat[-33,])
}
```

```

newXandZ <- unique(data.frame(PixelsCorn=landsat$MeanPixelsCorn,
                             PixelsSoybeans=landsat$MeanPixelsSoybeans,
                             CountyName=landsat$CountyName))
(cpredvar <- get_cPredVar(fitCorn, newdata=newXandZ, nsim=200L, seed=123)) # serial computation
(cpredvar <- get_cPredVar(fitCorn, newdata=newXandZ, nsim=200L, seed=123,
                          nb_cores=parallel::detectCores()-1L, fit_env=list2env(list(newXandZ=newXandZ))))
}

# GLMM example from Booth & Hobert 1998 JASA
npos <- c(11,16,14,2,6,1,1,4,10,22,7,1,0,0,1,6)
ntot <- c(36,20,19,16,17,11,5,6,37,32,19,17,12,10,9,7)
treatment <- c(rep(1,8),rep(0,8))
clinic <-c(seq(8),seq(8))
clinics <- data.frame(npos=npos,nneg=ntot-npos,treatment=treatment,clinic=clinic)
#
fitClinics <- HLfit(cbind(npos,nneg)~treatment+(1|clinic),family=binomial(),data=clinics)
#
(get_cPredVar(fitClinics, newdata=clinics[1:8,], nsim=200L, seed=123)) # serial computation
(get_cPredVar(fitClinics, newdata=clinics[1:8,], nsim=200L, seed=123,
              nb_cores=parallel::detectCores()-1, fit_env=list2env(list(clinics=clinics))))

## End(Not run)

```

---

```
get_inits_from_fit      Initiate a fit from another fit
```

---

## Description

`get_inits_from_fit` is an extractor of some fitted values from a fit in a convenient format to initiate a next fit.

## Usage

```
get_inits_from_fit(from, template = NULL, to_fn = NULL, inner_lambdas=FALSE)
```

## Arguments

<code>from</code>	Fit object (inheriting from class "HLfit") from which fitted values are taken.
<code>template</code>	Another fit object. Usage with a template fit object is suitable for refitting this object using fitted values from the <code>from</code> object as starting values.
<code>to_fn</code>	NULL or character: the name of the function to be used the next fit. If NULL, taken from <code>template</code> (if available), else from <code>from</code> . It is meaningful to provide a <code>to_fn</code> distinct from the function used to fit a template.
<code>inner_lambdas</code>	Boolean; Whether the output should include estimates of the dispersion parameters estimated by the iterative methods implemented in HLfit.

**Value**

A list with elements

`init`, `init.corrHLfit`  
 (depending on the fitting function) giving initial values for outer-optimization;

`init.HLfit` giving initial values for the iterative algorithms in `HLfit`. It is itself a list with possible elements:

`fixef` for the coefficients of the linear predictor, adjusted to the format of the coefficients of the linear predictor of the template object, if available;

`ranCoefs` random-coefficients parameters (if **not** outer-optimized).

**See Also**

[get\\_ranPars](#) and [VarCorr](#).

**Examples**

```
## Not run:
data("blackcap")
(corrhlfit <- corrHLfit(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
  method="ML"))
inits <- get_inits_from_fit(corrhlfit, to_fn = "fitme")
(fitfit <- fitme(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
  init=inits$init))
inits <- get_inits_from_fit(corrhlfit, template = fitfit)
fitme(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
  init=inits$init)
# In these examples, inits$init.HLfit is useless
# as it is ignored when LMMs are fitted by fitme().

## End(Not run)
```

---

get\_matrix

*Extract matrices from a fit*

---

**Description**

`get_matrix` is a first attempt at a unified extractor of various matrices from a fit. All augmented matrices follow (Henderson's) block order (upper blocks: X,Z; lower blocks: 0,I). `get_ZALMatrix` returns the design matrix for the random effects  $v$ .

**Usage**

```
get_matrix(object, which="model.matrix", augmented=TRUE, ...)
get_ZALMatrix(object, force_bind=TRUE)
```

**Arguments**

object	An object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
augmented	Boolean; whether to return an augmented matrix for all model coefficients (fixed-effects coefficients and random-effect predictions) or only for fixed effects. Not operative for all which values (currently only for <code>which="left_ginv"</code> ).
which	Which element to extract. For <code>"model.matrix"</code> , the design matrix for fixed effects (similarly to <code>stats::model.matrix</code> ); for <code>"ZAL"</code> , the design matrix for random effects (same as <code>get_ZALMatrix()</code> ); for <code>"AugX"</code> , the (unweighted) augmented design matrix of the least-square problem; for <code>"hat.matrix"</code> , the projection matrix that gives model predictions from the (augmented) response vector; for <code>"left_ginv"</code> , the pseudo-inverse that gives the model coefficients from the (augmented) response vector. See Details for definitions and further options.
force_bind	Boolean; with the non-default value <code>FALSE</code> , the function may return an object of class <code>ZAXlist</code> , which is poorly documented and for development purposes only.
...	Other arguments that may be needed in some future versions of <code>spaMM</code> .

**Details**

(Given the pain that it is to write maths in R documentation files, readers are gently asked to be tolerant about any imperfections of the following).

Model coefficients estimates of a (weighted) linear model can be written as  $(\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{y}$  where  $\mathbf{X}$  is the design matrix for fixed effects,  $\mathbf{W}$  a diagonal weight matrix, and  $\mathbf{y}$  the response vector. In a linear mixed model, the same expression holds in terms of Henderson's augmented design matrix, of an augmented (still diagonal) weight matrix, and of an augmented response vector. For GLMMs and hierarchical GLMs generally, the solution of each step of the iteratively reweighted least squares algorithm again has the same expression in terms of appropriately defined augmented matrices and vectors.

`get_matrix` returns, for given values of the `which` argument, the following matrices from the model fit: `"AugX"`:  $\mathbf{X}$ ; `"wei_AugX"`:  $\mathbf{W}\mathbf{X}$ ; `"wAugX"`:  $\sqrt{(\mathbf{W})}\mathbf{X}$ ; `"left_ginv"`:  $\mathbf{X}^{-}=(\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}$  (viewed as a pseudo-inverse since  $\mathbf{X}^{-}\mathbf{X}$  is an identity matrix); `"hat.matrix"`:  $\mathbf{X}\mathbf{X}^{-}=\mathbf{X}(\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}$ .

**Value**

A matrix, possibly in sparse-matrix format.

---

get\_ranPars

*Operations on lists of parameters*

---

**Description**

`get_ranPars` returns various subsets of random-effect parameters (correlation or variance parameters), as controlled by its `which` argument. A distinct documentation exists for `get_inits_from_fit` which extracts a broader set of estimated parameters from a fit, in a form suitable to initialize another fit. `VarCorr` is yet another extractor for dispersion parameters.

`remove_from_parlist` removes elements from a list of parameters, and from its type attribute.

**Usage**

```
get_ranPars(object, which=NULL, ...)
remove_from_parlist(parlist, removand=NULL, rm_names=names(unlist(removand)))
```

**Arguments**

<code>object</code>	An object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
<code>which</code>	NULL or character string. Use <code>which="corrPars"</code> to get the correlation parameters. Use <code>which="lambda"</code> to get variances. see <code>Details</code> for the meaning of this for heteroscedastic models, and <code>Value</code> for other possible <code>which</code> values.
<code>...</code>	Other arguments that may be needed by some method.
<code>parlist</code>	A list of parameters. see <code>Details</code> .
<code>removand</code>	Optional. A list of parameters to be removed from <code>parlist</code> .
<code>rm_names</code>	Names of parameters to be removed from <code>parlist</code> . Mandatory if <code>removand</code> is not given.

**Details**

For heteroscedastic models, such as conditional autoregressive models, the variance parameter “lambda” refers to a common scaling coefficient. For other random-effect models, “lambda” typically refers to the single variance parameter.

`remove_from_parlist` is designed to manipulate structured lists of parameters, such as a list with elements `phi`, `lambda`, and `corrPars`, the latter being itself a list structured as the return value of `get_ranPars(. , which="corrPars")`. `parlist` may have an attribute `type`, also with elements `phi`, `lambda`, and `corrPars...` If given, `removand` must have the same structure (but typically not all the elements of `parlist`); otherwise, `rm_names` must have elements which match names of `unlist(names(parlist))`.

**Value**

`get_ranPars(. , which="corrPars")` returns a (possibly nested) list of correlation parameters (or NULL if there is no such parameter). Top-level elements correspond to the different random effects. The list has a “`type`” attribute having the same nested-list structure and describing whether and how the parameters were fitted: “`fix`” means they were fixed, not fitted; “`var`” means they were fitted by `HLfit`’s specific algorithms; “`outer`” means they were fitted by a generic optimization method.

`get_ranPars(. , which="lambda")` returns a vector of variance values, one per random effect, including both “outer”- and “inner”-optimized ones.

`get_ranPars(. , which="outer_lambda")` returns only “outer”-optimized variance parameters, ignoring those fitted by `HLfit`’s specific algorithms.

`get_ranPars(. which="ranef_var")` (experimental) returns a list with elements

`Var` same as `get_ranPars(. , which="lambda")`

`lambda_est` A vector of variance values, one for each level of each random effect

`outer` A vector or outer-optimized variance values, as returned by `get_ranPars(. , which="outer_lambda")`

`...` Other elements, subject to change in later versions.

remove\_from\_parlist returns a list of model parameters with given elements removed, and likewise for its (optional) type attribute. See Details for context of application.

### See Also

See [residVar](#) to extract residual variances or information about residual variance models. [get\\_inits\\_from\\_fit](#) and [VarCorr](#) can extract random effect parameters in different formats.

### Examples

```
data("wafers")
m1 <- HLfit(y ~X1+X2+(1|batch), resid.model = ~ 1, data=wafers, method="ML")
get_ranPars(m1,which="corrPars") # NULL since no correlated random effect

parlist1 <- list(lambda=1,phi=2,corrPars=list("1"=list(rho=3,nu=4),"2"=list(rho=5)))
parlist2 <- list(lambda=NA,corrPars=list("1"=list(rho=NA))) # values of elements do not matter
remove_from_parlist(parlist1,parlist2) ## same result as:
remove_from_parlist(parlist1,rm_names = names(unlist(parlist2)))
```

---

get\_RLRsim\_args

*Extractors of arguments for functions from package RLRsim*

---

### Description

get\_RLRsim\_args extracts a list of arguments suitable for a call to `RLRsim::RLRTSim()` or `RLRsim::LRTSim()`. These functions use an efficient simulation procedure to compute restricted or marginal likelihood ratio tests, respectively, comparing a fixed-effect model and a mixed-effect model with one random effect. They are notably used to test for the presence of one random effect, although the models compared by marginal likelihood (`LRTSim()`) may differ both in their random and in their fixed effects (as shown in the Example). The tests are exact for small samples (up to simulation error) for LMMs with no free parameters in the random effect (beyond the variance being tested), so not for time-series or spatial models with estimated correlation parameters. Heteroscedasticity of the residuals or of the random effect variance are also not taken into account by the simulation procedure (see Value field below for an hint why this is so).

get\_RLRTSim\_args is the older extractor, originally for `RLRsim::RLRTSim()` only, now handling also ML fits with a warning (though the possible absence of the `nullfit` argument will result in an error).

### Usage

```
get_RLRsim_args(fullfit, nullfit, verbose=TRUE, REML=NA, ...)
get_RLRTSim_args(object, verbose=TRUE, ...)
```

### Arguments

object, fullfit

An object of class `HLfit`, as returned by the fitting functions in `spaMM`, for the more complete model to be compared.

nullfit	Same for the less complete model; required only for (marginal) LR test, as opposed to restricted LR test.
verbose	NA or boolean; Whether to display some message or not.
REML	For programming purposes, not documented.
...	Additional arguments (currently not used).

### Details

If the models compared do not differ in their fixed effects, under the null hypothesis there is a probability mass  $P$  for a zero likelihood ratio, and the distribution of p-values can be uniform only on the range  $(0,1-P)$ . If the fixed effects differ (as handled by `RLRsim::LRTsim()`), this does not occur.

### Value

A list of arguments for a call to `RLRsim::RLRTsim()` or `RLRsim::LRTsim()`. The main arguments are the design matrix for the fixed effects, and the **ZA** matrix and **L** detailed in [random-effects](#) (here represented by the **Z** and `sqrt.Sigma` elements). The models handled by the testing procedure are the ones that are sufficiently characterized by these two matrices. `LRTsim` additionally requires `q`, the difference in number of parameters of fixed effects between the models.

### Note

The inconsistent capitalisation of 's' in the function names is consistent with the inconsistencies in the `RLRsim` package.

### References

Crainiceanu, C. and Ruppert, D. (2004) Likelihood ratio tests in linear mixed models with one variance component, *Journal of the Royal Statistical Society: Series B*, **66**, 165–185.

### See Also

The bootstrap procedure in [LRT](#) is more general but slower. It appears to provide results quite similar to those of `RLRsim` when both are applicable.

### Examples

```
## Not run:
## Derived from example in RLRsim::LRTsim
set.seed(123)
dat <- data.frame(g = rep(1:10, e = 10), x = (x<-rnorm(100)),
                  y = 0.1 * x + rnorm(100))
m <- fitme(y ~ x + (1|g), data=dat)
m0 <- fitme(y ~ 1, data=dat)
(obs.LRT <- 2*(logLik(m)-logLik(m0)))
args <- get_RLRsim_args(m,m0)
sim.LRT <- do.call(RLRsim::LRTsim, args )
(RLRpval <- (sum(sim.LRT >= obs.LRT) + 1) / (length(sim.LRT) + 1))
## comparable test using LRT():
```

```
# (bootpval <- LRT(m,m0, boot.repl = 199L)$rawBootLRT$p_value)

## End(Not run)
```

---

good-practice

*Clear and trustworthy formulas*

---

## Description

Base fitting functions in R will seek variables in the environment where the formula was defined (i.e., typically in the global environment), if they are not in the data. This increases the memory size of fit objects (as the formula and attached environment are part of such objects). This also easily leads to errors (see example in the discussion of [update.HLfit](#)). Indeed Chambers (2008, p.221), after describing how the environment is defined, comments that “Where clear and trustworthy software is a priority, I would personally avoid such tricks. Ideally, all the variables in the model frame should come from an explicit, verifiable data source...”. Fitting functions in spaMM try to adhere to such a principle, as they assume by default that all variables from the formula should be in the data argument (and then, **one never needs to specify “data\$” in the formula.** The variables defining the prior.weights should also be in the data.

However, variables used in other arguments such as `ranFix` are looked up neither in the data nor in the formula environment, but in the calling environment as usual.

spaMM implements this by default by stripping the formula environment from any variable. It is also possible to assign a given environment to the formula, through the control `control.HLfit$formula_env`: see Examples. However, the search mechanism of R is such that variables present in the formula but not in the data nor in the formula environment will still be sought in the global environment, so bugs are not entirely preventable.

## References

Chambers J.M. (2008) Software for data analysis: Programming with R. Springer-Verlag New York

## Examples

```
set.seed(123)
d2 <- data.frame(y = seq(10)/2+rnorm(5)[gl(5,2)], x1 = sample(10), grp=gl(5,2), seq10=seq(10))
# Using only variables in the data: basic usage
# HLfit(y ~ x1 + seq10+(1|grp), data = d2)
# is practically equivalent to
HLfit(y ~ x1 + seq10+(1|grp), data = d2,
      control.HLfit = list(formula_env=list2env(list(data=d2))))
#
# The 'formula_env' avoids the need for the 'seq10' variable:
HLfit(y ~ x1 + I(seq_len(nrow(data)))+(1|grp), data = d2,
      control.HLfit = list(formula_env=list2env(list(data=d2))))
#
# Internal implementation exploits partial matching of argument names
# so that this can also be in 'control' if 'control.HLfit' is absent:
fitme(y ~ x1 + I(seq_len(nrow(data)))+(1|grp), data = d2,
      control = list(formula_env=list2env(list(data=d2))))
```

Gryphon

*Gryphon data***Description**

Loading these data loads three objects describing a mythical 'Gryphon' population used by Wilson et al. to illustrate mixed-effect modelling in quantitative genetics. These objects are a data frame `Gryphon_df` containing the model variables, a genetic relatedness matrix `Gryphon_A`, and another data frame `Gryphon_pedigree` containing pedigree information (which can be used by some packages to reconstruct the relatedness matrix).

**Usage**

```
data("Gryphon")
```

**Format**

`Gryphon_df` is

```
'data.frame': 1084 obs. of 6 variables:
 $ ID   : int  1029 1299 ...: individual identifier
 $ sex  : Factor w/ 2 levels "1","2": sex, indeed
 $ year : Factor w/ 34 levels "968","970", ...: birth year
 $ mother: Factor w/ 429 levels "1","2",...: individual's mother identifier
 $ BWT  : num  10.77 9.3 ...: birth weight
 $ TARSUS: num  24.8 22.5 12 ...: tarsus length
```

`Gryphon_A` is a genetic relatedness matrix, in sparse matrix format, for 1309 individuals.

`Gryphon_pedigree` is

```
'data.frame': 1309 obs. of 3 variables:
 $ ID : int  1306 1304 ...: individual identifier
 $ Dam : int  NA NA ...: individual's mother
 $ Sire: int  NA NA ...: individual's father
```

**References**

Wilson AJ, et al. (2010) An ecologist's guide to the animal model. *Journal of Animal Ecology* 79(1): 13-26. doi: [10.1111/j.13652656.2009.01639.x](https://doi.org/10.1111/j.13652656.2009.01639.x)

**Examples**

```
#### Bivariate-response model used as example in Wilson et al. (2010):
# joint modelling of birth weight (BWT) and tarsus length (TARSUS).

# The relatedness matrix is specified as a 'corrMatrix'. The random
# effect 'corrMatrix(0+mv(1,2)|ID)' then represents genetic effects
```

```

# correlated over traits and individuals (see help("composite-ranef")).
# The ...(0+...) syntax avoids contrasts being used in the design
# matrix of the random effects, as it would not does make much sense
# to represent TARSUS as a contrast to BWT.

# The relatedness matrix will be specified through its inverse,
# using as_precision(), so that spaMM does not have to find out and
# inform the user that using the inverse is better (as is typically
# the case for relatedness matrices). But using as_precision() is
# not required. See help("algebra") for Details.

# The second random effect '(0+mv(1,2)|ID)' represents correlated
# environmental effects. Since measurements are not repeated within
# individuals, this effect also absorbs all residual variation. The
# residual variances 'phi' must then be fixed to some negligible values
# in order to avoid non-identifiability.

if (spaMM.getOption("example_maxtime")>7) {
  data("Gryphon")
  gry_prec <- as_precision(Gryphon_A)
  gry_GE <- fitmv(
    submodels=list(BWT ~ 1 + corrMatrix(0+mv(1,2)|ID)+(0+mv(1,2)|ID),
                  TARSUS ~ 1 + corrMatrix(0+mv(1,2)|ID)+(0+mv(1,2)|ID)),
    fixed=list(phi=c(1e-6,1e-6)),
    corrMatrix = gry_prec,
    data = Gryphon_df, method = "REML")

  # Estimates are practically identical to those reported for package
  # 'asreml' (https://www.vsni.co.uk/software/asreml-r)
  # according to Supplementary File 3 of Wilson et al., p.7:

  lambda_table <- summary(gry_GE, digits=5,verbose=FALSE)$lambda_table
  by_spaMM <- na.omit(unlist(lambda_table[,c("Var.", "Corr.")]))[1:6]
  by_asreml <- c(3.368449,12.346304,3.849875,17.646017,0.381463,0.401968)
  by_spaMM/by_asreml-1 # relative differences ~ 0(1e-4)

}

```

---

hatvalues.HLfit

*Leverage extractor for HLfit objects*


---

## Description

This gets “leverages” or “hat values” from an object. However, there is hidden complexity in what this may mean, so care must be used in selecting proper arguments for a given use (see Details). To get the full hat matrix, see `get_matrix(., which="hat_matrix")`.

**Usage**

```
## S3 method for class 'HLfit'
hatvalues(model, type = "projection", which = "resid", force=FALSE, ...)
```

**Arguments**

model	An object of class HLfit, as returned by the fitting functions in spaMM.
type	Character: "projection", "std", or more cryptic values not documented here.
which	Character: "resid" for the traditional leverages of the observations, "ranef" for random-effect leverages, or "both" for both.
force	Boolean: to force recomputation of the leverages even if they are available in the object, for checking purposes.
...	For consistency with the generic.

**Details**

Leverages may have distinct meaning depending on context. The textbook version for linear models is that leverages ( $q_i$ ) are the diagonal elements of a projection matrix (“hat matrix”), and that they may be used to standardize (“studentize”) residuals as follows. If the residual variance  $\phi$  is known, then the variance of each fitted residual  $\hat{e}_i$  is  $\phi(1 - q_i)$ . Standardized residuals, all with variance 1, are then  $\hat{e}_i/\sqrt{\phi(1 - q_i)}$ . This standardization of variance no longer holds exactly with estimated  $\phi$ , but if one uses here an unbiased (REML) estimator of  $\phi$ , the studentized residuals may still practically have a unit expected variance.

The need for distinguishing “standardizing” from “projection” leverages arises from generalizations of this standardization to other contexts. Indeed, when a simple linear model is fitted by ML, the variance of the fitted residuals is less than  $\phi$ , but  $\hat{\phi}$  is downward biased so that residuals standardized only by  $\sqrt{\phi}$ , without any leverage correction, more closely have expected unit variance than if corrected by the previous leverages. This hints for another definition of leverages such that they are here zero, contrary to the ones derived from the projection matrix.

Leverages also appear in expressions for derivatives, with respect to the dispersion parameters, of the logdet(Hessian) term of Laplace approximations for marginal or restricted likelihood (Lee et al. 2006). This provides a basis to generalize the concept of standardizing leverages for ML and REML in mixed-effect models. In particular, in an ML fit, one considers leverages ( $q^*_i$ ) that are no longer the diagonal elements of the projection matrix for the mixed model (these ( $q^*_i$ ) are zero in the simple linear model). The generalized standardizing leverages may include corrections for non-Gaussian response, for non-Gaussian random effects, and for taking into account the variation of the GLM weights in the logdet(Hessian) derivatives. Which corrections are included depend on the precise method used to fit the model (e.g., EQL vs PQL vs REML). Standardizing leverages are also defined for the random effects.

These distinctions suggest breaking the usual synonymy between “leverages” or “hat values”: the term “hat values” better stands for the diagonal elements of a projection matrix, while “leverages” better stands for the standardizing values. `hatvalues(., type="std")` returns the standardizing leverages. By contrast, `hatvalues(., type="projection")` will always return hat values from the fitted projection matrix. Note that these values typically differ between ML and REML fit because the fitted projection matrix differs between them.

**Value**

A list with separate components `resid` (leverages of the observations) and `ranef` if `which="both"`, and a vector otherwise.

**References**

Lee, Y., Nelder, J. A. and Pawitan, Y. (2006) Generalized linear models with random effects: unified analysis via h-likelihood. Chapman & Hall: London.

**Examples**

```
if (spaMM.getOption("example_maxtime")>0.8) {
  data("Orthodont", package = "nlme")
  rngc <- (107:108)

  # all different:
  #
  hatvalues(rlfit <- fitme(distance ~ age+(age|Subject),
                        data = Orthodont, method="REML"))[rngc]
  hatvalues(mlfit <- fitme(distance ~ age+(age|Subject),
                        data = Orthodont))[rngc]
  hatvalues(mlfit, type="std")[rngc]
}
```

---

HLCor

*Fits a (spatially) correlated mixed model, for given correlation parameters*

---

**Description**

A fitting function acting as a convenient interface for `HLfit`, constructing the correlation matrix of random effects from the arguments, then estimating fixed effects and dispersion parameters using `HLfit`. Various arguments are available to constrain the correlation structure, `covStruct` and `distMatrix` being the more general ones (for any number of random effects), and `adjMatrix` and `corrMatrix` being alternatives to `covStruct` for a single correlated random effect. `uniqueGeo` is deprecated.

**Usage**

```
HLCor(formula, data, family = gaussian(), ranPars = NULL, distMatrix,
      adjMatrix, corrMatrix, covStruct=NULL,
      method = "REML", verbose = c(trace=FALSE),
      control.dist = list(), ...)
```

**Arguments**

formula	A predictor, i.e. a formula with attributes (see <a href="#">Predictor</a> ), or possibly simply a simple formula if an offset is not required.
ranPars	A list of values for correlation parameters (some of which are mandatory), and possibly also dispersion parameters (optional, but passed to <code>HLfit</code> if present). See <a href="#">ranPars</a> for further information.
data	The data frame to be analyzed.
family	A family object describing the distribution of the response variable. See <a href="#">HLfit</a> for further information.
distMatrix	<b>Either</b> a distance matrix between geographic locations, forwarded to <code>MaternCorr</code> or <code>CauchyCorr</code> . It overrides the (by default, Euclidean) distance matrix that would otherwise be deduced from the variables in a <code>Matern(.)</code> or <code>Cauchy(.)</code> term; <b>or</b> a list of such matrices. The list format is useful when there are several <code>Matern/Cauchy</code> terms, to avoid that all of them are affected by the same <code>distMatrix</code> . NULL list elements may be necessary, e.g. <code>distMatrix=list("1"=NULL,"2"=&lt;.&gt;)</code> when a matrix is specified only for the second random effect.
adjMatrix	An single adjacency matrix, used if a random effect of the form <code>y ~ adjacency(1 &lt;location index&gt;)</code> is present. See <a href="#">adjacency</a> for further details. If adjacency matrices are needed for several random effects, use <code>covStruct</code> .
corrMatrix	A matrix <b>C</b> used if a random effect term of the form <code>corrMatrix(1 &lt;stuff&gt;)</code> is present. This allows to analyze non-spatial model by giving for example a matrix of genetic correlations. Each row corresponds to levels of a variable <code>&lt;stuff&gt;</code> . The covariance matrix of the random effects for each level is then $\lambda C$ , where as usual $\lambda$ denotes a variance factor for the random effects (if <b>C</b> is a correlation matrix, then $\lambda$ is the variance, but other cases are possible). See <a href="#">corrMatrix</a> for further details. If matrices are needed for several random effects, use <code>covStruct</code> .
covStruct	An interface for specifying correlation structures for different types of random effect ( <code>corrMatrix</code> or <code>adjacency</code> ). See <a href="#">covStruct</a> for details.
method	Character: the fitting method to be used, such as "ML", "REML" or "PQL/L". "REML" is the default. Other possible values of <code>HLfit</code> 's <code>method</code> argument are handled.
verbose	A vector of booleans. <code>trace</code> controls various diagnostic (possibly messy) messages about the iterations.
control.dist	A list of arguments that control the computation of the distance argument of the correlation functions. Possible elements are <b>rho.mapping</b> a set of indices controlling which elements of the rho scale vector scales which dimension(s) of the space in which (spatial) correlation matrices of random effects are computed. See same argument in <a href="#">make_scaled_dist</a> for details and examples. <b>dist.method</b> method argument of <code>proxy::dist</code> function (by default, "Euclidean", but see <a href="#">make_scaled_dist</a> for other distances such as spherical ones.)
...	Further parameters passed to <code>HLfit</code> or to <a href="#">mat_sqrt</a> .

## Details

For approximations of likelihood, see [method](#). For the possible structures of random effects, see [random-effects](#), but note that HLCor cannot adjust parameters of correlation models (with the exception of conditional autoregressive ones). Any such parameter must be specified by the `ranPars` argument. More generally, the correlation matrix for random effects can be specified by various combinations of formula terms and other arguments (see Examples):

**Basic Matérn model** `Matern(1|<...>)`, using the spatial coordinates in `<...>`. This will construct a correlation matrix according to the Matérn correlation function (see [MaternCorr](#));

**Basic Cauchy model** `Cauchy(1|<...>)`, as for Matern (see [CauchyCorr](#));

**Same models with given distance matrix** as provided by `distMatrix` (see Examples);

**Given correlation matrix** `corrMatrix(1|<...>)` with `corrMatrix` argument. See [corrMatrix](#) for further details.

**CAR model with given adjacency matrix** `adjacency(1|<...>)` with `adjMatrix`. See [adjacency](#) for further details;

**AR1 model** `AR1(1|<...>)` See [AR1](#) for further details.

## Value

The return value of an `HLfit` call, with the following additional attributes:

`HLCorcall` the HLCor call  
`info.uniqueGeo` Unique geographic locations.

## See Also

[autoregressive](#) for additional examples, [MaternCorr](#), [HLfit](#), and [corrHLfit](#)

## Examples

```
# Example with an adjacency matrix (autoregressive model):
# see 'adjacency' documentation page

#### Matern correlation using only the Matern() syntax
data("blackcap")
(fitM <- HLCor(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
  method="ML", ranPars=list(nu=0.6285603,rho=0.0544659)))

#### Using the 'distMatrix' argument
data("blackcap")
#
# Build distance matrix (here equivalent to the default one for a Matern() term)
MLdistMat <- as.matrix(proxy::dist(blackcap[,c("latitude","longitude")]))
#
(fitD <- HLCor(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
  distMatrix=MLdistMat, method="ML", ranPars=list(nu=0.6285603,rho=0.0544659)))
# : result here must be equivalent to the one without the distMatrix.
diff(c(logLik(fitM),logLik(fitD)))
```

## Description

This function fits GLMMs as well as some hierarchical generalized linear models (HGLM; Lee and Nelder 2001). HLfit fits both fixed effects parameters, and dispersion parameters i.e. the variance of the random effects (full covariance for random-coefficient models), and the variance of the residual error. The linear predictor is of the standard form  $\text{offset} + X\beta + Zb$ , where  $X$  is the design matrix of fixed effects and  $Z$  is a design matrix of random effects (typically an incidence matrix with 0s and 1s, but not necessarily). Models are fitted by an iterative algorithm alternating estimation of fixed effects and of dispersion parameters. The residual dispersion may follow a “structured-dispersion model” modeling heteroscedasticity. Estimation of the latter parameters is performed by a form of fit of debiased residuals, which allows fitting a structured-dispersion model (Smyth et al. 2001). However, evaluation of the debiased residuals can be slow in particular for large datasets. For models without structured dispersion, it is then worth using the `fitme` function (or the `corrHLfit` function with non-default arguments). These functions can optimize the likelihood of HLfit fits for different given values of the dispersion parameters (“outer optimization”), thereby avoiding the need to estimate debiased residuals.

## Usage

```
HLfit(formula, data, family = gaussian(), rand.family = gaussian(),
      resid.model = ~1, REMLformula = NULL, verbose = c(trace = FALSE),
      HLmethod = "HL(1,1)", method="REML", control.HLfit = list(),
      control.glm = list(), init.HLfit = list(), ranFix = list(),
      etaFix = list(), prior.weights = NULL, processed = NULL)
## see 'rand.family' argument for inverse.Gamma
```

## Arguments

formula	A <a href="#">formula</a> ; or a predictor, i.e. a formula with attributes created by <a href="#">Predictor</a> , if design matrices for random effects have to be provided. See Details in <a href="#">spaMM</a> for allowed terms in the formula (except spatial ones).
data	A data frame containing the variables named in the model formula.
family	A family object describing the distribution of the response variable. See Details in <a href="#">spaMM</a> for handled families.
rand.family	A family object describing the distribution of the random effect, or a list of family objects for different random effects (see Examples). Possible options are <code>gaussian()</code> , <code>Gamma(log)</code> , <code>Gamma(identity)</code> (see Details), <code>Beta(logit)</code> , <code>inverse.Gamma(-1/mu)</code> , and <code>inverse.Gamma(log)</code> . For discussion of these alternatives see Lee and Nelder 2001 or Lee et al. 2006, p. 178-. Here the family gives the distribution of a random effect $u$ and the link gives $v$ as function of $u$ (see Details). If there are several random effects and only one family is given, this family holds for all random effects.

resid.model	<p><b>Either</b> a formula (without left-hand side) for the dispersion parameter <math>\phi</math> of the residual error. A log link is assumed by default;</p> <p><b>or</b> a list, with at most three possible elements if its formula involves only fixed effects:</p> <p><b>formula</b> model formula as in formula-only case, without left-hand side</p> <p><b>family</b> Always Gamma, with by default a log link. <code>Gamma(identity)</code> can be tried but may fail because only the log link ensures that the fitted <math>\phi</math> is positive.</p> <p><b>fixed</b> can be used to specify the residual dispersion parameter of the residual dispersion model itself. The default value is 1; this argument can be used to set another value, and <code>fixed=list(phi=NA)</code> will force estimation of this parameter.</p> <p>and additional possible elements (all named as <code>fitme</code> arguments) if its formula involves random effects: see <a href="#">phiHGLM</a>.</p>
REMLformula	<p>A model formula that controls the estimation of dispersion parameters and the computation of restricted likelihood (<code>p_bv</code>), where the conditioning inherent in REML is defined by a model different from the predictor formula. A simple example (useless in practice) of its effect is to replicate an ML fit by specifying <code>method="REML"</code> and an <code>REMLformula</code> with no fixed effect. The latter implies that no conditioning is performed and that <code>p_bv</code> equals the marginal likelihood (or its approximation), <code>p_v</code>. One of the examples in <a href="#">update.HLfit</a> shows how <code>REMLformula</code> can be useful, but otherwise this argument may never be needed for standard REML or ML fits. For non-standard likelihood ratio tests using <code>REMLformula</code>, see <a href="#">fixedLRT</a>.</p>
verbose	<p>A vector of booleans. The trace element controls various diagnostic messages (possibly messy) about the iterations. This should be distinguished from the <code>TRACE</code> element, meaningful in <code>fitme</code> or <code>corrHLfit</code> calls. <code>phifit</code> (which defaults to <code>TRUE</code>) controls messages about the progress of residual dispersion fits in DHGLMs.</p>
method	<p>Character: the fitting method. allowed values are "REML", "ML", "EQL-" and "EQL+" for all models; "PQL" (= "REPQL") and "PQL/L" for GLMMs only; and further values for those curious to experiment (see <a href="#">method</a>). <b>The default is REML</b> (standard REML for LMMs, an extended definition for other models). REML can be viewed as a form of conditional inference, and non-standard conditionings can be called by using a non-standard <code>REMLformula</code>.</p>
HLmethod	<p>Same as <code>method</code>. It is useless to specify <code>HLmethod</code> when <code>method</code> is specified. The default value "HL(1,1)" means the same as <code>method="REML"</code>, but more accurately relates to definitions of approximations of likelihood in the <math>h</math>-likelihood literature.</p>
control.HLfit	<p>A list of parameters controlling the fitting algorithms, which should be ignored in routine use. Such a parameter, <code>resid.family</code>, was previously documented here (before version 2.6.40), and will still operate as previously documented, but should not be used in new code.</p> <p>Possible parameters are:</p> <p><code>conv.threshold</code> and <code>spaMM_tol</code>: <code>spaMM_tol</code> is a list of tolerance values, with elements <code>Xtol_rel</code> and <code>Xtol_abs</code> that define thresholds for relative and absolute changes in parameter values in iterative algorithms (used in tests of the</p>

form “ $d(\text{param}) < \text{Xtol\_rel} * \text{param} + \text{Xtol\_abs}$ ”, so that `Xtol_abs` is operative only for small parameter values). `conv.threshold` is the older way to control `Xtol_rel`. Default values are given by `spaMM.getOption("spaMM_tol")`;

`break_conv_logL`, a boolean specifying whether the iterative algorithm should terminate when log-likelihood appears to have converged (roughly, when its relative variation over on iteration is lower than  $1e-8$ ). Default is `FALSE` (convergence is then assessed on the parameter estimates rather than on log-likelihood).

`iter.mean.dispFix`, the number of iterations of the iterative algorithm for coefficients of the linear predictor, if no dispersion parameters are estimated by the iterative algorithm. Defaults to 200 except for Gamma(log)-family models;

`iter.mean.dispVar`, the number of iterations of the iterative algorithm for coefficients of the linear predictor, if some dispersion parameter(s) is estimated by the iterative algorithm. Defaults to 50 except for Gamma(log)-family models;

`max.iter`, the number of iterations of the iterative algorithm for joint estimation of dispersion parameters and of coefficients of the linear predictor. Defaults to 200. This is typically much more than necessary, unless there is little information to separately estimate  $\lambda$  and  $\phi$  parameters. `algebra`, `sparse_precision` See [algebra](#).

<code>control.glm</code>	List of parameters controlling GLM fits, passed to <code>glm.control</code> ; e.g. <code>control.glm=list(maxit=100)</code> . See <a href="#">glm.control</a> for further details.
<code>init.HLfit</code>	A list of initial values for the iterative algorithm, with possible elements of the list are <code>fixef</code> for fixed effect estimates (beta), <code>v_h</code> for random effects vector $\mathbf{v}$ in the linear predictor, <code>lambda</code> for the parameter determining the variance of random effects $u$ as drawn from the <code>rand.family</code> distribution <code>phi</code> for the residual variance. However, this argument can be ignored in routine use.
<code>ranFix</code>	A list of fixed values of random effect parameters. See <a href="#">ranFix</a> for further information.
<code>etaFix</code>	A list of given values of the coefficients of the linear predictor. See <a href="#">etaFix</a> for further information.
<code>prior.weights</code>	An optional vector of prior weights as in <a href="#">glm</a> . This fits the data to a probability model with residual variance <code>phi/prior.weights</code> , and all further outputs are defined to be consistent with this (see section IV in Details).
<code>processed</code>	A list of preprocessed arguments, for programming purposes only (as in <code>corrHLfit</code> ).

## Details

**I. Approximations of likelihood:** see [method](#).

**II. Possible structure of Random effects:** see [random-effects](#), but note that `HLfit` does not fit models with autocorrelated random effects).

**III. The standard errors** reported may sometimes be misleading. For each set of parameters among  $\beta$ ,  $\lambda$ , and  $\phi$  parameters these are computed assuming that the other parameters are known without error. This is why they are labelled `Cond. SE` (conditional standard error). This is most uninformative in the unusual case where  $\lambda$  and  $\phi$  are not separately estimable parameters. Further, the SEs for  $\lambda$  and  $\phi$  are rough approximations as discussed in particular by Smyth et al. (2001;  $V_1$  method).

**IV. prior weights.** This controls the likelihood analysis of heteroscedastic models. In particular, changing the weights by a constant factor  $f$  should, and will, yield a fit with unchanged likelihood and (Intercept) estimates of  $\phi$  also increased by  $f$  (except if a non-trivial `resid.formula` with log link is used). This is consistent with what `glm` does, but other packages may not follow this logic (whatever their documentation may say: check by yourself by changing the weights by a constant factor).

## Value

An object of class `HLfit`, which is a list with many elements, not all of which are documented.

A few extractor functions are available (see [extractors](#)), and should be used as far as possible as they should be backward-compatible from version 1.4 onwards, while the structure of the return object may still evolve. The following information will be useful for extracting further elements of the object.

Elements include **descriptors of the fit**:

<code>eta</code>	Fitted values on the linear scale (including the predicted random effects);
<code>fv</code>	Fitted values ( $\mu = \text{inverse-link}(\eta)$ ) of the response variable (returned by the fitted function);
<code>fixef</code>	The fixed effects coefficients, $\beta$ (returned by the <code>fixef</code> function);
<code>v_h</code>	The random effects on the linear scale, $v$ , with attribute the random effects $u$ (returned by <code>ranef(*, type="uncorrelated")</code> );
<code>phi</code>	The residual variance $\phi$ ;
<code>phi.object</code>	A possibly more complex object describing $\phi$ ;
<code>lambda</code>	The random-effect ( $u$ ) variance(s) $\lambda$ in compact form;
<code>lambda.object</code>	A possibly more complex object describing $\lambda$ ;
<code>corrPars</code>	Agglomerates information on correlation parameters, either fixed, or estimated by <code>HLfit</code> , <code>corrHLfit</code> or <code>fitme</code> ;
<code>APHLs</code>	A list which elements are various likelihood components, include conditional likelihood, h-likelihood, and the two adjusted profile h-likelihoods: the (approximate) marginal <b>likelihood</b> <code>p_v</code> and the (approximate) <b>restricted likelihood</b> <code>p_bv</code> (the latter two available through the <code>logLik</code> function). See the extractor function <a href="#">get_any_IC</a> for information criteria (“AIC”) and effective degrees of freedom;  The covariance matrix of $\beta$ estimates is not included as such, but can be extracted by <code>vcov</code> ;

**Information about the input** is contained in output elements named as `HLfit` or `corrHLfit` arguments (`data`, `family`, `resid.family`, `ranFix`, `prior.weights`), with the following notable exceptions or modifications:

<code>predictor</code>	The formula, possibly reformatted;
<code>resid.predictor</code>	Analogous to <code>predictor</code> , for the residual variance;
<code>rand.families</code>	corresponding to the <code>rand.family</code> input;

**Further miscellaneous diagnostics and descriptors of model structure:**

X.pv	The design matrix for fixed effects;
ZAList, struList	Two lists of matrices, respectively the design matrices “ <b>Z</b> ”, and the “ <b>L</b> ” matrices, for the different random-effect terms. The extractor <code>get_ZALMatrix</code> can be used to reconstruct a single “ <b>ZL</b> ” matrix for all terms.
BinomialDen	(binomial data only) the binomial denominators;
y	the response vector; for binomial data, the frequency response.
models	Additional information on model structure for $\eta$ , $\lambda$ and $\phi$ ;
HL	A set of indices that characterize the approximations used for likelihood;
leve_phi, lev_lambda	Leverages;
dfs	degrees of freedom for different components of the model;
warnings	A list of warnings for events that may have occurred during the fit.

Finally, the object includes programming tools: `call`, `spaMM.version`, `fit_time` and `envir`.

**References**

- Lee, Y., Nelder, J. A. (2001) Hierarchical generalised linear models: A synthesis of generalised linear models, random-effect models and structured dispersions. *Biometrika* 88, 987-1006.
- Lee, Y., Nelder, J. A. and Pawitan, Y. (2006). Generalized linear models with random effects: unified analysis via h-likelihood. Chapman & Hall: London.
- Smyth GK, Huele AF, Verbyla AP (2001). Exact and approximate REML for heteroscedastic regression. *Statistical Modelling* 1, 161-175.

**See Also**

`HLCor` for estimation with given spatial correlation parameters; `corrHLfit` for joint estimation with spatial correlation parameters; `fitme` as an alternative to all these functions.

**Examples**

```
data("wafers")
## Gamma GLMM with log link

HLfit(y ~ X1+X2+X1*X3+X2*X3+I(X2^2)+(1|batch), family=Gamma(log),
      resid.model = ~ X3+I(X3^2) , data=wafers)

## Gamma - inverseGamma HGLM with log link
HLfit(y ~ X1+X2+X1*X3+X2*X3+I(X2^2)+(1|batch), family=Gamma(log),
      rand.family=inverse.Gamma(log),
      resid.model = ~ X3+I(X3^2) , data=wafers)
```

---

how	<i>Extract information about how an object was obtained</i>
-----	---

---

### Description

how is defined as a generic with currently only one non-default method, for objects of class `HLfit`. This method provide information about how such a fit was obtained.

### Usage

```
how(object, ...)
## S3 method for class 'HLfit'
how(object, devel=FALSE, verbose=TRUE, format=print, ...)
## S3 method for class 'HLfitlist'
how(object, devel=FALSE, verbose=TRUE, format=print, ...)
```

### Arguments

object	Any R object.
devel	Boolean; Whether to provide additional cryptic information. For development purposes, not further documented.
verbose	Boolean; Whether to print information about the input object.
format	wrapper for printing format. E.g., <code>cat(crayon::yellow(s), "\n")</code> could be used instead of the default.
...	Other arguments that may be needed by some method.

### Value

A list, returned invisibly, whose elements are not further described here, some being slightly cryptic or subject to future changes However, `how(.)$fit_time` is a clean way of getting the fit time. If `verbose` is `TRUE`, the function prints a message presenting some of these elements.

### Examples

```
foo <- HLfit(y~x, data=data.frame(x=runif(3), y=runif(3)), method="ML", ranFix=list(phi=1))
how(foo)
```

**Description**

Several parameters (notably the dispersion parameters: the variance of random effects and the residual variance parameter, if any) can be estimated either by iterative algorithms, or by generic optimization methods. The development of the `fitme` function aims to provide full control of the selection of algorithms. For example, if two random effects are fitted, then `init=list(lambda=c(NA,NaN))` enforces generic optimization for the first variance and iterative algorithms for the second. `init=list(lambda=c(0.1,NaN))` has the same effect and additionally provides control of the initial value for optimization (whereas `init.HLfit=list(lambda=c(NA,0.1))` will provide control of the initial value for iterations).

How to know which algorithm has been selected for each parameter? `fitme(., verbose=c(TRACE=TRUE))` shows successive values of the variables estimated by optimization (See Examples; if no value appears, then all are estimated by iterative methods). The first lines of the summary of a fit object should tell which variances are estimated by the “outer” method.

`corrHLfit`, which uses inner optimization by default, can be forced to perform outer optimization. Its control is more limited, as NAs and NaNs are not allowed. Instead, only numeric values as in `init=list(lambda=0.1)` are allowed.

**Examples**

```
## Not run:
air <- data.frame(passengers = as.numeric(AirPassengers),
                 year_z = scale(rep(1949:1960, each = 12)),
                 month = factor(rep(1:12, 12)))
air$time <- 1:nrow(air)
# Use verbose to find that lambda is estimated by optimization
fitme(passengers ~ month * year_z + AR1(1|time), data = air,
      verbose=c(TRACE=TRUE))
# Use init to enforce iterative algorithm for lambda estimation:
fitme(passengers ~ month * year_z + AR1(1|time), data = air,
      verbose=c(TRACE=TRUE), init=list(lambda=NaN))
# (but then it may be better to enforce it also for phi: init=list(lambda=NaN, phi=NaN))
#
# Use init to enforce generic optimization for lambda estimation,
# and control initial value:
fitme(passengers ~ month * year_z + AR1(1|time), data = air,
      verbose=c(TRACE=TRUE), init=list(lambda=0.1))

# See help("multinomial") for more examples of control by initial values.

## End(Not run)
```

---

inverse.Gamma	<i>Distribution families for Gamma and inverse Gamma-distributed random effects</i>
---------------	---

---

### Description

For dispersion parameter  $\lambda$ , Gamma means that random effects are distributed as  $u \text{ Gamma}(\text{shape}=1/\lambda, \text{scale}=\lambda)$ , so  $u$  has mean 1 and variance  $\lambda$ . Both the log ( $v = \log(u)$ ) and identity ( $v = u$ ) links are possible, though in the latter case the variance of  $u$  is constrained below 1 (otherwise Laplace approximations fail).

The two-parameter inverse Gamma distribution is the distribution of the reciprocal of a variable distributed according to the Gamma distribution Gamma with the same shape and scale parameters. `inverse.Gamma` implements the one-parameter inverse Gamma family with `shape=1+1/λ` and `rate=1/λ` (`rate=1/scale`). It is used to model the distribution of random effects. Its mean=1; and its variance  $=\lambda/(1-\lambda)$  if  $\lambda < 1$ , otherwise infinite. The default link is `"-1/mu"`, in which case  $v=-1/u$  is `"-Gamma"`-distributed with the same shape and rate, hence with mean  $-(\lambda+1)$  and variance  $\lambda(\lambda+1)$ , which is a different one-parameter Gamma family than the above-described Gamma. The other possible link is `v=log(u)` in which case  $v = \log(X \text{ Gamma}(1 + 1/\lambda, 1/\lambda))$ , with mean  $-(\log(1/\lambda) + \text{digamma}(1 + 1/\lambda))$  and variance  $\text{trigamma}(1 + 1/\lambda)$ .

### Usage

```
inverse.Gamma(link = "-1/mu")
# Gamma(link = "inverse") using stats::Gamma
```

### Arguments

link	For Gamma, allowed links are <code>log</code> and <code>identity</code> (the default link from <a href="#">Gamma</a> , <code>"inverse"</code> , cannot be used for the random effect specification). For <code>inverse.Gamma</code> , allowed links are <code>"-1/mu"</code> (default) and <code>log</code> .
------	---

### Examples

```
# see help("HLfit") for fits using the inverse.Gamma distribution.
```

---

is_separated	<i>Checking for (quasi-)separation in binomial-response model.</i>
--------------	--

---

**Description**

Separation occurs in binomial response models when a combination of the predictor variables perfectly predict a level of the response. In such a case the estimates of the coefficients for these variables diverge to (+/-)infinity, and the numerical algorithms typically fail. To anticipate such a problem, the fitting functions in spaMM try to check for separation by default. The check may take much time, and is skipped if the “problem size” exceeds a threshold defined by `spaMM.options(separation_max=<.>)`, in which case a message will tell users by how much they should increase `separation_max` to force the check (its exact meaning and default value are subject to changes without notice but the default value aims to correspond to a separation check time of the order of 1s on the author’s computer).

`is_separated` is a convenient interface to procedures from the ROI package, which can be called explicitly by the user to check bootstrap samples (see Example in [anova](#)). `is_separated.formula` is a variant (not yet a formal S3 method) that performs the same check, but using arguments similar to those of `fitme(., family=binomial())`.

**Usage**

```
is_separated(x, y, verbose = TRUE, solver=spaMM.getOption("sep_solver"))
is_separated.formula(formula, ..., separation_max=spaMM.getOption("separation_max"),
                     solver=spaMM.getOption("sep_solver"))
```

**Arguments**

<code>x</code>	Design matrix for fixed effects.
<code>y</code>	Numeric response vector
<code>formula</code>	A model formula
<code>...</code>	data and possibly other arguments of a <code>fitme</code> call. <code>family</code> is ignored if present.
<code>separation_max</code>	numeric: non-default value allow for easier local control of this spaMM option.
<code>solver</code>	character: name of linear programming solver used to assess separation; passed to <code>ROI_solve</code> ’s <code>solver</code> argument. One can select other solvers if the corresponding ROI plugin is installed.
<code>verbose</code>	Whether to print some messages or not.

**Value**

Returns a boolean; TRUE means there is (quasi-)separation.

**References**

The method accessible by `solver="glpk"` implements algorithms described by Konis, K. 2007. Linear Programming Algorithms for Detecting Separated Data in Binary Logistic Regression Models. DPhil Thesis, Univ. Oxford. <https://ora.ox.ac.uk/objects/uuid:8f9ee0d0-d78e-4101-9ab4-f9cbceed2a2a>.

**See Also**

See also the ‘safeBinaryRegression’ and ‘detectseparation’ package.

**Examples**

```
set.seed(123)
d <- data.frame(success = rbinom(10, size = 1, prob = 0.9), x = 1:10)
is_separated.formula(formula= success~x, data=d) # FALSE
is_separated.formula(formula= success~I(success^2), data=d) # TRUE
```

Loaloa

*Loa loa prevalence in North Cameroon, 1991-2001***Description**

This data set describes prevalence of infection by the nematode *Loa loa* in North Cameroon, 1991-2001. This is a superset of the data discussed by Diggle and Ribeiro (2007) and Diggle et al. (2007). The study investigated the relationship between altitude, vegetation indices, and prevalence of the parasite.

**Usage**

```
data("Loaloa")
```

**Format**

The data frame includes 197 observations on the following variables:

**latitude** latitude, in degrees.

**longitude** longitude, in degrees.

**ntot** sample size per location

**npos** number of infected individuals per location

**maxNDVI** maximum normalised-difference vegetation index (NDVI) from repeated satellite scans

**seNDVI** standard error of NDVI

**elev1** altitude, in m.

**elev2,elev3,elev4** Additional altitude variables derived from the previous one, provided for convenience: respectively, positive values of altitude-650, positive values of altitude-1000, and positive values of altitude-1300

**maxNDVI1** a copy of maxNDVI modified as `maxNDVI1[maxNDVI1>0.8] <-0.8`

**Source**

The data were last retrieved on March 1, 2013 from P.J. Ribeiro's web resources at [www.leg.ufpr.br/doku.php/pessoais:paulojus:mbgbook:datasets:loaloa.txt](http://www.leg.ufpr.br/doku.php/pessoais:paulojus:mbgbook:datasets:loaloa.txt). The current (2019-06-10) link seems to be <http://www.leg.ufpr.br/lib/exe/fetch.php/pessoais:paulojus:mbgbook:datasets:loaloa.txt>.

## References

Diggle, P., and Ribeiro, P. 2007. Model-based geostatistics, Springer series in statistics, Springer, New York.

Diggle, P. J., Thomson, M. C., Christensen, O. F., Rowlingson, B., Obsomer, V., Gardon, J., Wanji, S., Takougang, I., Enyong, P., Kamgno, J., Remme, J. H., Boussinesq, M., and Molyneux, D. H. 2007. Spatial modelling and the prediction of Loa loa risk: decision making under uncertainty, *Ann. Trop. Med. Parasitol.* 101, 499-509.

## Examples

```
data("Loaloo")
if (spaMM.getOption("example_maxtime")>5) {
  fitme(cbind(npos,ntot-npos)~1 +Matern(1|longitude+latitude),
        data=Loaloo, family=binomial())
}

### Variations on the model fit by Diggle et al.
###   on a subset of the Loaloo data
### In each case this shows the slight differences in syntax,
###   and the difference in 'typical' computation times,
###   when fit using corrHLfit() or fitme().

if (spaMM.getOption("example_maxtime")>4) {
  corrHLfit(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
            +Matern(1|longitude+latitude),method="HL(0,1)",
            data=Loaloo, family=binomial(),ranFix=list(nu=0.5))
}
if (spaMM.getOption("example_maxtime")>1.6) {
  fitme(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
        +Matern(1|longitude+latitude),method="HL(0,1)",
        data=Loaloo, family=binomial(),fixed=list(nu=0.5))
}

if (spaMM.getOption("example_maxtime")>5.8) {
  corrHLfit(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
            +Matern(1|longitude+latitude),
            data=Loaloo, family=binomial(),ranFix=list(nu=0.5))
}
if (spaMM.getOption("example_maxtime")>2.5) {
  fitme(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
        +Matern(1|longitude+latitude),
        data=Loaloo, family=binomial(),fixed=list(nu=0.5),method="REML")
}

## Diggle and Ribeiro (2007) assumed (in this package notation) Nugget=2/7:
if (spaMM.getOption("example_maxtime")>7) {
  corrHLfit(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
            +Matern(1|longitude+latitude),
            data=Loaloo, family=binomial(),ranFix=list(nu=0.5,Nugget=2/7))
}
```

```

if (spaMM.getOption("example_maxtime")>1.3) {
  fitme(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
        +Matern(1|longitude+latitude),method="REML",
        data=Loaloe, family=binomial(),fixed=list(nu=0.5,Nugget=2/7))
}

## with nugget estimation:
if (spaMM.getOption("example_maxtime")>17) {
  corrHLfit(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
            +Matern(1|longitude+latitude),
            data=Loaloe, family=binomial(),
            init.corrHLfit=list(Nugget=0.1),ranFix=list(nu=0.5))
}
if (spaMM.getOption("example_maxtime")>5.5) {
  fitme(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
        +Matern(1|longitude+latitude),
        data=Loaloe, family=binomial(),method="REML",
        init=list(Nugget=0.1),fixed=list(nu=0.5))
}

```

---

LRT

*Likelihood ratio test of fixed effects.*


---

## Description

LRT performs a likelihood ratio (LR) test between two model fits, the “full” and the “null” model fits. The `anova` method for fit objects from `spaMM` is an alias for LRT.

If the models differ only in their fixed effects, a standard test based on the asymptotic chi-square distribution is performed, with number of degrees of freedom determined by the function. In addition, parametric bootstrap p-values can be computed, either using the raw bootstrap distribution of the likelihood ratio, or a bootstrap estimate of the Bartlett correction of the LR statistic. This function differs from `fixedLRT` in its arguments (model fits for LRT, but all arguments required to fit the models for `fixedLRT`), and in the format of its return value. By conceptual drift, `anova` works as an alias for LRT.

If the two models differ in their random effects, a bootstrap test may be performed. Either the full and null model can be told apart by a simple comparison of the model formulas, or the model with the lower likelihood is assumed to be the null one (the latter is subject to numerical uncertainties when both fit are equivalent). No number of degrees of freedom is deduced, so no asymptotic test is performed.

If the two models differ in both their fixed and random components, the same bootstrap test can be performed (see Examples), but the procedure further checks that the same model is nested in the other for both components. This requires that a simple comparison of the model formulas is sufficient to assess this for random effects, and may therefore fail).

**Usage**

```
## S3 method for class 'HLfit'
anova(object, object2, ..., method="")
LRT(object, object2, boot.repl = 0, resp_testfn = NULL,
     simuland = eval_replicate,
     # many further arguments can be passed to spaMM_boot via the '...'
     # These include arguments for parallel computations, such as
     # nb_cores, fit_env,
     # as well as other named arguments and spaMM_boot's own '...'
     ...)
```

**Arguments**

`object, object2` Two models fits being compared (their order does not matter).

`boot.repl` the number of bootstrap replicates.

`resp_testfn` See argument `resp_testfn` of [spaMM\\_boot](#)

`method` For development purposes, not documented.

`simuland` a function, passed to [spaMM\\_boot](#). See argument [eval\\_replicate](#) for default value and requirements.

`...` Further arguments, passed to [spaMM\\_boot](#) (e.g., for parallelization).

**Details**

A raw bootstrap p-value can be computed from the simulated distribution as  $(1 + \sum(t \geq t_0)) / (N+1)$  where  $t_0$  is the original likelihood ratio,  $t$  the vector of bootstrap replicates and  $N$  its length. See Davison & Hinkley (1997, p. 141) for discussion of the adjustments in this formula. However, a computationally more economical use of the bootstrap is to provide a Bartlett correction for the likelihood ratio test in small samples. According to this correction, the mean value  $m$  of the likelihood ratio statistic under the null hypothesis is computed (here estimated by a parametric bootstrap) and the original LR statistic is multiplied by  $n/m$  where  $n$  is the number of degrees of freedom of the test.

If random effects are tested, only the raw p-value is computed. Its null distribution may include a probability mass in 1 (the discussion in Details of [get\\_RLRsim\\_args](#) applies).

**Value**

An object of class `fixedLRT`, actually a list with as-yet unstable format, but here with typical elements (depending on the options)

`fullfit` the `HLfit` object for the full model;

`nullfit` the `HLfit` object for the null model;

`basicLRT` A data frame including values of the likelihood ratio chi2 statistic, its degrees of freedom, and the p-value;

and, if a bootstrap was performed:

`rawBootLRT` A data frame including values of the likelihood ratio chi2 statistic, its degrees of freedom, and the raw bootstrap p-value;

**BartBootLRT** A data frame including values of the Bartlett-corrected likelihood ratio chi2 statistic, its degrees of freedom, and its p-value;

**bootInfo** a list with the following elements:  
**bootreps** A table of fitted likelihoods for bootstrap replicates;  
**meanbootLRT** The mean likelihood ratio chi-square statistic for bootstrap replicates;

## References

Bartlett, M. S. (1937) Properties of sufficiency and statistical tests. Proceedings of the Royal Society (London) A 160: 268-282.

Davison A.C., Hinkley D.V. (1997) Bootstrap methods and their applications. Cambridge Univ. Press, Cambridge, UK.

## See Also

See also [fixedLRT](#) and [get\\_RLRsim\\_args](#).

## Examples

```
data("wafers")
## Gamma GLMM with log link
m1 <- HLfit(y ~X1+X2+X1*X3+X2*X3+I(X2^2)+(1|batch),family=Gamma(log),
            resid.model = ~ X3+I(X3^2) ,data=wafers,method="ML")
m2 <- update(m1,formula.= ~ . -I(X2^2))
anova(m1,m2)

# Using resp_testfn argument:
## Not run:
set.seed(1L)
d <- data.frame(success = rbinom(10, size = 1, prob = 0.9), x = 1:10)
xx <- cbind(1,d$x)
table(d$success)
m_x <- fitme(success ~ x, data = d, family = binomial())
m_0 <- fitme(success ~ 1, data = d, family = binomial())
anova(m_x, m_0, boot.repl = 100,
      resp_testfn=function(y) {! is_separated(xx,as.numeric(y),verbose=FALSE)})

## End(Not run)

## Models differing both in fixed and random effects:
if (spaMM.getOption("example_maxtime")>11) {
  set.seed(123)
  dat <- data.frame(g = rep(1:10, e = 10), x = (x<-rnorm(100)),
                    y = 0.1 * x + rnorm(100))
  m <- fitme(y ~ x + (1|g), data=dat)
  m0 <- fitme(y ~ 1, data=dat)
  (bootpval <- LRT(m,m0, boot.repl = 199L)$rawBootLRT$p_value)
  ## See help("get_RLRsim_args") for a fast and accurate test procedure
}
```

---

make_scaled_dist	<i>Scaled distances between unique locations</i>
------------------	--

---

### Description

This function computes scaled distances from whichever relevant argument it can use (see Details). The result can directly be used as input for computation of the Matérn correlation matrix. It is usually called internally by HLCor, so that users may ignore it, except if they wish to control the distance used through `control.dist$method`, or the parametrization of the scaling through `control.dist$rho.mapping`. `control.dist$method` provide access to the distances implemented in the proxy package, as well as to "EarthChord" and "Earth" methods defined in spaMM (see Details).

### Usage

```
make_scaled_dist(uniqueGeo, uniqueGeo2=NULL, distMatrix, rho,
                 rho.mapping=seq_len(length(rho)),
                 dist.method="Euclidean",
                 return_matrix=FALSE)
```

### Arguments

uniqueGeo	A matrix of geographical coordinates (e.g. 2 columns for latitude and longitude), without replicates of the same location.
uniqueGeo2	NULL, or a second matrix of geographical coordinates, without replicates of the same location. If NULL, scaled distances among uniqueGeo locations are computed. Otherwise, scaled distances between locations in the two input matrices are computed.
distMatrix	A distance matrix.
rho	A scalar or vector of positive values. Scaled distance is computed as $\langle \text{distances in each coordinate} \rangle * \text{rho}$ , unless a non-trivial <code>rho.mapping</code> is used.
rho.mapping	A set of indices controlling which elements of the rho scale vector scales which dimension(s) of the space in which (spatial) correlation matrices of random effects are computed. Scaled distance is generally computed as $\langle \text{distances in each coordinate} \rangle * \text{rho}[\text{rho.mapping}]$ . As shown in the Example, if one wishes to combine isotropic geographical distance and some environmental distance, the coordinates being latitude, longitude and one environmental variable, the scaled distance may be computed as (say) $(\text{lat}, \text{long}, \text{env}) * \text{rho}[c(1, 1, 2)]$ so that the same scaling <code>rho[1]</code> applies for both geographical coordinates. In this case, rho should have length 2 and <code>rho.mapping</code> should be <code>c(1, 1, 2)</code> .
dist.method	method argument of <code>proxy::dist</code> function (by default, "Euclidean", but other distances are possible (see Details)).
return_matrix	Whether to return a matrix rather than a <code>proxy::dist</code> or <code>proxy::crossdist</code> object.

## Details

The function uses the `distMatrix` argument if provided, in which case `rho` must be a scalar. Vectorial `rho` (i.e., different scaling of different dimensions) is feasible only by providing `uniqueGeo`.

The `dist.method` argument gives access to distances implemented in the `proxy` package, or to user-defined ones that are made accessible to `proxy` through its database. Of special interest for spatial analyses are distances computed from longitude and latitude (`proxy` implements "Geodesic" and "Chord" distances but they do not use such coordinates: instead, they use Euclidean distance for 2D computations, i.e. Euclidean distance between points on a circle rather than on a sphere). `spaMM` implements two such distances: "Earth" and "EarthChord", using longitude and latitude inputs **in that order** (see Examples). The "EarthChord" distance is the 3D Euclidean distance "through Earth". The "Earth" distance is also known as the orthodromic or great-circle distance, on the Earth surface. Both distances return values in km and are based on approximating the Earth by a sphere of radius 6371.009 km.

## Value

A matrix or `dist` object. If there are two input matrices, rows of the return value correspond to rows of the first matrix.

## Examples

```
data("blackcap")
## a biologically not very meaningful, but syntactically correct example of rho.mapping
fitme(migStatus ~ 1 + Matern(1|longitude+latitude+means),
      data=blackcap, fixed=list(nu=0.5,phi=1e-6),
      init=list(rho=c(1,1)), control.dist=list(rho.mapping=c(1,1,2)))

## Using orthodromic distances:
# order of variables in Matern(.|longitude+latitude) matters;
# Matern(1|latitude+longitude) should cause a warning
fitme(migStatus ~ 1 + Matern(1|longitude+latitude),data=blackcap,
      method="ML", fixed=list(nu=0.5,phi=1e-6),
      control.dist=list(dist.method="Earth"))
```

---

mapMM

*Colorful plots of predictions in two-dimensional space.*

---

## Description

These functions provide either a map of predicted response in analyzed locations, or a predicted surface. `mapMM` is a straightforward representation of the analysis of the data, while `filled.mapMM` uses interpolation to cope with the fact that all predictor variables may not be known in all locations on a fine spatial grid. `map_ranef` maps a single spatial random effect. These three functions takes an `HLfit` object as input. `mapMM` calls `spaMMplot2D`, which is similar but takes a more conventional `(x,y,z)` input.

Using `filled.mapMM` may involve questionable choices. Plotting a filled contour generally requires prediction in non-observed locations, where predictor variables used in the original data analysis

may be missing. In that case, the original model formula cannot be used and an alternative model (controlled by the `map.formula` argument) must be used to interpolate (not smooth) the predicted values in observed locations (these predictions still resulting from the original analysis based on predictor variables). `filled.mapMM` always performs such interpolation (it does not allow one to provide values for the predictor variables). As a result (1) `filled.mapMM` will be slower than a mere plotting function, since it involves the analysis of spatial data; (2) the results may have little useful meaning if the effect of the original predictor variables is not correctly represented by this interpolation step. For example, prediction by interpolation may be biased in a way analogous to prediction of temperature in non-observed locations while ignoring effect of variation in altitude in such locations. Likewise, the `variance` argument of `filled.mapMM` allows one only to plot the prediction variance of its own interpolator, rather than that of the input object.

`map_ranef` is free of the limitations of `filled.mapMM`.

## Usage

```
spaMMplot2D(x, y, z, xrange=range(x, finite = TRUE),
            yrange=range(y, finite = TRUE),
            margin=1/20, add.map= FALSE, nlevels = 20,
            color.palette = spaMM.colors, map.asp=NULL,
            col = color.palette(length(levels) - 1),
            plot.title=NULL, plot.axes=NULL, decorations=NULL,
            key.title=NULL, key.axes=NULL, xaxs = "i",
            yaxs = "i", las = 1, axes = TRUE, frame.plot = axes, ...)

mapMM(fitobject, Ztransf=NULL, coordinates,
      add.points, decorations=NULL, plot.title=NULL, plot.axes=NULL, envir=-3, ...)

filled.mapMM(fitobject, Ztransf = NULL, coordinates, xrange = NULL,
            yrange = NULL, margin = 1/20, map.formula, phi =
            1e-05, gridSteps = 41, decorations =
            quote(points(pred[, coordinates], cex = 1, lwd = 2)),
            add.map = FALSE, axes = TRUE, plot.title = NULL,
            plot.axes = NULL, map.asp = NULL, variance = NULL,
            var.contour.args = list(), smoothObject = NULL, ...)

map_ranef(fitobject, re.form, Ztransf=NULL, xrange = NULL, yrange = NULL,
          margin = 1/20, gridSteps = 41,
          decorations = quote(points(fitobject$data[, coordinates], cex = 1, lwd = 2)),
          add.map = FALSE, axes = TRUE, plot.title=NULL,
          plot.axes=NULL, map.asp = NULL, ...)
```

## Arguments

<code>fitobject</code>	The return object of a <code>corrHLfit</code> or <code>fitme</code> call.
<code>x,y,z</code>	Three vectors of coordinates, with <code>z</code> being expectedly the response.
<code>re.form</code>	A model formula giving the single random effect term to plot, needed only if there are several spatial random effects in the fitted model. In that case, it must be formatted as <code>. ~ &lt;term&gt;</code> , as for the <code>re.form</code> argument of <code>predict.HLfit</code> .

Ztransf	A transformation of the predicted response, given as a function whose only required argument can be a one-column matrix. The name of this argument must be Z (not x), as is appropriate for use in <code>do.call(Ztransf, list(Z=Zvalues))</code> .
coordinates	The geographical coordinates. By default they are deduced from the model formula. For example if this formula is <code>resp ~ 1 + Matern(1   x + y)</code> the default coordinates are <code>c("x", "y")</code> . If this formula is <code>resp ~ 1 + Matern(1   x + y + z)</code> , the user must choose two of the three coordinates.
xrange	The x range of the plot (a vector of length 2); by default defined to cover all analyzed points.
yrange	The y range of the plot (a vector of length 2); by default defined to cover all analyzed points.
margin	This controls how far (in relative terms) the plot extends beyond the x and y ranges of the analyzed points, and is overridden by explicit <code>xrange</code> and <code>yrange</code> arguments.
map.formula	NULL, or a formula whose left-hand side is ignored. Provides the formula used for interpolation. If NULL, a default formula with the same spatial effect(s) as in the input <code>fitobject</code> is used.
phi	This controls the phi value assumed in the interpolation step. Ideally phi would be zero, but problems with numerically singular matrices may arise when phi is too small.
gridSteps	The number of levels of the grid of x and y values
variance	Either NULL, or the name of a component of variance of prediction <i>by the interpolator</i> to be plotted. Must name one of the components that can be returned by <code>predict.HLfit</code> . <code>variance="predVar"</code> is suitable for uncertainty in point prediction.
var.contour.args	A list of control parameters for rendering of prediction variances. See <a href="#">contour</a> for possible arguments (except x, y, z and add).
add.map	Either a boolean or an explicit expression, enclosed in quote (see Examples). If TRUE, the map function from the maps package (which much therefore the loaded) is used to add a map from its default world database. <code>xrange</code> and <code>yrange</code> are used to select the area, so it is most convenient if the coordinates are longitude and latitude (in this order and in standard units). An explicit expression can also be used for further control.
levels	a set of levels which are used to partition the range of z. Must be strictly increasing (and finite). Areas with z values between consecutive levels are painted with the same color.
nlevels	if <code>levels</code> is not specified, the range of z, values is divided into *approximately* this many levels (a call to <a href="#">pretty</a> determines the actual number of levels).
color.palette	a color palette function to be used to assign colors in the plot.
map.asp	the y/x aspect ratio of the 2D plot area (not of the full figure including the scale). By default, the scales for x and y are identical unless the x and y ranges are too different. Namely, the scales are identical if $(\text{plotted y range})/(\text{plotted x range})$ is $1/4 < . < 4$ , and <code>map.asp</code> is 1 otherwise.

<code>col</code>	an explicit set of colors to be used in the plot. This argument overrides any palette function specification. There should be one less color than levels
<code>plot.title</code>	statements which add titles to the main plot. See Details for differences between functions.
<code>plot.axes</code>	statements which draw axes (and a box) on the main plot. See Details for differences between functions.
<code>decorations</code>	Either NULL or Additional graphic statements (points, polygon, etc.), enclosed in quote (the default value illustrates the latter syntax). .
<code>add.points</code>	Obsolete, use <code>decorations</code> instead.
<code>envir</code>	Controls the environment in which <code>plot.title</code> , <code>plot.axes</code> , and <code>decorations</code> are evaluated. <code>mapMM</code> calls <code>spaMM2Dplot</code> from where these graphic arguments are evaluated, and the default value <code>-3</code> means that they are evaluated within the environment from where <code>mapMM</code> was called.
<code>key.title</code>	statements which add titles for the plot key.
<code>key.axes</code>	statements which draw axes on the plot key.
<code>xaxs</code>	the x axis style. The default is to use internal labeling.
<code>yaxs</code>	the y axis style. The default is to use internal labeling.
<code>las</code>	the style of labeling to be used. The default is to use horizontal labeling.
<code>axes, frame.plot</code>	logicals indicating if axes and a box should be drawn, as in <code>plot.default</code> .
<code>smoothObject</code>	Either NULL, or an object inheriting from class <code>HLfit</code> (hence, an object on which <code>predict.HLfit</code> can be called), predicting the response surface in any coordinates. See Details for typical usages.
<code>...</code>	further arguments passed to or from other methods. For <code>mapMM</code> , all such arguments are passed to <code>spaMMplot2D</code> ; for <code>spaMMplot2D</code> , currently only additional graphical parameters passed to <code>title()</code> (see Details). For <code>filled.mapMM</code> and <code>map_ranef</code> , these parameters are those that can be passed to <a href="#">spaMM.filled.contour</a> .

## Details

The `smoothObject` argument may be used to redraw a figure faster by recycling the predictor of the response surface returned invisibly by a previous call to `filled.mapMM`.

For `smoothObject=NULL` (the default), `filled.mapMM` interpolates the predicted response, with sometimes unpleasant effects. For example, if one interpolates probabilities, the result may not be within  $[0,1]$ , and then (say) a logarithmic `Ztransf` may generate NaN values that would otherwise not occur. The `smoothObject` argument may be used to overcome the default behaviour, by providing an alternative predictor.

If you have values for all predictor variables in all locations of a fine spatial grid, `filled.mapMM` may not be a good choice, since it will ignore that information (see `map.formula` argument). Rather, one should use `predict(<fitobject>, newdata= <all predictor variables >)` to generate all predictions, and then either `spaMM.filled.contour` or some other raster functions.

The different functions are (currently) inconsistent among themselves in the way they handle the `plot.title` and `plot.axes` argument:



MaternCorr

*Matern correlation function and Matern formula term.***Description**

The Matérn correlation function describes realizations of Gaussian spatial processes with different smoothnesses (i.e. either smooth or rugged surfaces, controlled by the  $\nu$  parameter). It also includes a  $\rho$  scaling parameter and an optional 'nugget' parameter. A random effect specified in a model formula as `Matern(1|<...>)` has pairwise correlations given by the Matérn function at the scaled Euclidean distance between coordinates specified in `<...>`, using "+" as separator (e.g., `Matern(1|longitude+latitude)`). The Matern family can be used in Euclidean spaces of any dimension; and also for correlations on a sphere (with maximum smoothness `nu=0.5`).

A syntax of the form `Matern(1|longitude+latitude %in% grp)` can be used to specify a Matern random effect with independent realizations (but identical correlation parameters) for each level of the grouping variable `grp`. Alternatively, the `Matern(<T/F factor>|longitude+latitude)` may be used to specify Matern effects specific to individuals identified by the `<T/F factor>` (see [Example with females and males](#)). In that case distinct correlation parameters are fitted for each such Matern term.

When group-specific autocorrelated random effects are fitted, it may be wise to allow for different means for each group in the Intercept (a message will point this out if the fit results for Matern or Cauchy terms suggest so).

By default, `fitme` and `corrHLfit` performs optimization over the  $\rho$  and  $\nu$  parameters. It is possible to estimate different scaling parameters for the different Euclidean dimensions: see examples in [make\\_scaled\\_dist](#).

The `MaternCorr` function may be used to visualize these correlations, using distances as input.

**Usage**

```
## Default S3 method:
MaternCorr(d, rho = 1, smoothness, nu = smoothness, Nugget = NULL)
# Matern(1|...)
```

**Arguments**

<code>d</code>	A distance or a distance matrix.
<code>rho</code>	A scaling factor for distance. The 'range' considered in some formulations is the reciprocal of this scaling factor
<code>smoothness</code>	The smoothness parameter, $>0$ . $\nu = 0.5$ corresponds to the exponential correlation function, and the limit function when $\mu$ goes to $\infty$ is the squared exponential function (as in a Gaussian).
<code>nu</code>	Same as <code>smoothness</code>
<code>Nugget</code>	(Following the jargon of Kriging) a parameter describing a discontinuous decrease in correlation at zero distance. Correlation will always be 1 at $d = 0$ , and from which it immediately drops to $(1-\text{Nugget})$
<code>...</code>	Names of coordinates, using "+" as separator (e.g., <code>Matern(1 longitude+latitude)</code> )

**Details**

The correlation at distance  $d > 0$  is

$$(1 - \text{Nugget}) \frac{(\rho d)^\nu K_\nu(\rho d)}{2^{(\nu-1)} \Gamma(\nu)}$$

where  $K_\nu$  is the [besseIK](#) function of order  $\nu$ .

By default the Nugget is set to 0. See one of the examples on data set [Loaloa](#) for a fit including the estimation of the Nugget.

**Value**

Scalar/vector/matrix depending on input.

**References**

Stein, M.L. (1999) *Statistical Interpolation of Spatial Data: Some Theory for Kriging*. Springer, New York.

**See Also**

See [corMatern](#) for an implementation of this correlation function as a `corSpatial` object for use with `lme` or `glmmPQL`.

**Examples**

```
## See examples in help("HLCor"), help("Loaloa"), help("make_scaled_dist"), etc.
## Matern correlations in 4-dimensional space:
set.seed(123)
randpts <- matrix(rnorm(20),nrow=5)
distMatrix <- as.matrix(proxy::dist(randpts))
MaternCorr(distMatrix,nu=2)

## Group-specific random effects
if (spaMM.getOption("example_maxtime")>1.6) {
  data("blackcap")
  # grouped effect using the '%in%' syntax:
  fm <- cbind(blackcap,sex=c(rep(TRUE,7),rep(FALSE,7)))
  fitme(migStatus ~ 1 + Matern(1|longitude+latitude %in% sex),data=fm)

  # Superficially similar aim for distinct random effects for each sex,
  # but here with distinct covariance parameters for each of them:
  fm$female <- fm$sex; fm$male <- ! fm$female
  fitme(migStatus ~ 1 + Matern(female|longitude+latitude)+
        Matern(male|longitude+latitude),data=fm)

  # Although the results of these fits do not explicitly call for it,
  # adding a group-specific intercept may make more sense, as in e.g.
  fitme(migStatus ~ sex + Matern(1|longitude+latitude %in% sex), data=fm)
}
```

mat\_sqrt

*Computation of “square root” of symmetric positive definite matrix***Description**

mat\_sqrt is not usually directly called by users, but arguments may be passed to it through higher-level calls (see Examples). For given matrix **C**, it computes a factor **L** such that  $C = L * t(L)$ , handling issues with nearly-singular matrices. The default behavior is to try Cholesky factorization, and use `eigen` if it fails. Matrix roots are not unique (for example, they are lower triangular for `t(chol(.))`, and symmetric for `svd(.)`). As matrix roots are used to simulate samples under the fitted model (in particular in the parametric bootstrap implemented in `fixedLRT`), this implies that for given seed of random numbers, these samples will differ with these different methods (although their distribution should be identical).

**Usage**

```
mat_sqrt(m = NULL, symSVD = NULL, try.chol = TRUE, condnum=1e12)
```

**Arguments**

m	The matrix which 'root' is to be computed. This argument is ignored if symSVD is provided.
symSVD	A list representing the symmetric singular value decomposition of the matrix which 'root' is to be computed. Must have elements \$u, a matrix of eigenvectors, and \$d, a vector of eigenvalues.
try.chol	If try.chol=TRUE, the Cholesky factorization will be tried.
condnum	(large) numeric value. In the case chol() was tried and failed, the matrix is regularized so that its (matrix 2-norm) condition number is reduced to condnum.

**Value**

For non-NULL m, its matrix root, with rows and columns labelled according to the columns of the original matrix. If eigen was used, the symmetric singular value decomposition (a list with members u (matrix of eigenvectors) and d (vector of eigenvalues)) is given as attribute.

**Examples**

```
## Not run:
## try.chol argument passed to mat_sqrt
## through the '...' argument of higher-level functions
## such as HLCor, corrHLfit, fixedLRT:
data("scotlip")
HLCor(cases~I(prop.ag/10) +adjacency(1|gridcode)+offset(log(expec)),
      ranPars=list(rho=0.174),adjMatrix=Nmatrix,family=poisson(),
      data=scotlip,try.chol=FALSE)

## End(Not run)
```

method

*Fitting methods (objective functions maximized)***Description**

Many approximations for likelihood have been defined to fit mixed models (e.g. Noh and Lee (2007) for some overview), and fitting functions in `spaMM` implement several of them, and some additional ones. In particular, PQL as originally defined by Breslow and Clayton (1993) uses REML to estimate dispersion parameters, but `spaMM` allows one to use an ML variant of PQL. Moreover, it allows some non-standard specification of the model formula that determines the conditional distribution used in REML.

EQL stands for the EQL method of Lee and Nelder (2001). The '+' version includes the  $d v / d \tau$  correction described p. 997 of that paper, and the '-' version ignores it. PQL can be seen as the version of EQL- for GLMMs. It estimates fixed effects by maximizing h-likelihood and dispersion parameters by an approximation of REML, i.e. by maximization of an approximation of restricted likelihood. PQL/L is PQL without the leverage corrections that define REML estimation of random-effect parameters. Thus, it estimates dispersion parameters by an approximation of marginal likelihood.

The method (or `HLmethod`) argument of fitting functions also accepts value of the form "`HL(<. . .>)`", "`ML(<. . .>)`" and "`RE(<. . .>)`", e.g. `method="RE(1, 1)`", which allow a more direct specification of the approximations used. HL and RE are equivalent (both imply an REML correction). The first '1' means that a first order Laplace approximation to the likelihood is used to estimate fixed effects (a '0' would instead mean that the h likelihood is used as the objective function). The second '1' means that a first order Laplace approximation to the likelihood or restricted likelihood is used to estimate dispersion parameters, this approximation including the  $dv/d\tau$  term specifically discussed by Lee & Nelder 2001, p. 997 (a '0' would instead mean that these terms are ignored).

It is possible to enforce the EQL approximation for estimation of dispersion parameter (i.e., Lee and Nelder's (2001) method) by adding a third index with value 0. "EQL+" is thus "`HL(0, 1, 0)`", while "EQL-" is "`HL(0, 0, 0)`". "PQL" is EQL- for GLMMs. "REML" is "`HL(1, 1)`". "ML" is "`ML(1, 1)`".

Some of these distinctions make sense for **GLMs**, and `glm` methods use approximations, which make a difference for Gamma GLMs. This means in particular that, (as stated in `stats::logLik`) the `logLik` of a Gamma GLM fit by `glm` differs from the exact likelihood. Further, the dispersion estimate returned by `summary.glm` differs from the one implied by `logLik`, because `summary.glm` uses Pearson residuals instead of deviance residuals. This may be confusing, and no method in `spaMM` tries to reproduce simultaneously these distinct features (however, `spaMM.glm` may do so). An "`ML(0, 0, 0)`" approximation of true ML provides the same log likelihood as `stats::logLik`, and the dispersion estimate returned by an "`HL(. , . , 0)`" fit matches what can be computed from residual deviance and residual degrees of freedom of a `glm` fit, but this is not the estimate displayed by `summary.glm`. With a log link, the fixed effect estimates are unaffected by these distinctions.

**References**

- Breslow, NE, Clayton, DG. (1993). Approximate Inference in Generalized Linear Mixed Models. *Journal of the American Statistical Association* 88, 9-25.
- Lee, Y., Nelder, J. A. (2001) Hierarchical generalised linear models: A synthesis of generalised linear models, random-effect models and structured dispersions. *Biometrika* 88, 987-1006.

Noh, M., and Lee, Y. (2007). REML estimation for binary data in GLMMs, *J. Multivariate Anal.* 98, 896-915.

---

MSFDR

*Multiple-Stage False Discovery Rate procedure*


---

### Description

This implements the procedure described by Benjamini and Gavrilov (2009) for model-selection of **fixed-effect terms** based on False Discovery Rate (FDR) concepts. It uses forward selection based on penalized likelihoods. The penalization for the number of parameters is distinct from that in Akaike's Information Criterion, and variable across iterations of the algorithm (but functions from the stats package for AIC-based model-selection are still called, so that some screen messages refer to AIC).

### Usage

```
MSFDR(nullfit, fullfit, q = 0.05, verbose = TRUE)
```

### Arguments

nullfit	An ML fit to the minimal model to start the forward selection from; an object of class <code>HLfit</code> .
fullfit	An ML fit to the maximal model; an object of class <code>HLfit</code> .
q	Nominal error rate of the underlying FDR procedure (expected proportion of incorrectly rejected null out of the rejected). Benjamini and Gavrilov (2009) recommend $q=0.05$ on the basis of minimizing mean-squared prediction error in various simulation conditions considering only linear models.
verbose	Whether to print information about the progress of the procedure.

### Value

The fit of the final selected model; an object of class `HLfit`.

### References

A simple forward selection procedure based on false discovery rate control. *Ann. Appl. Stat.* 3, 179-198 (2009).

### Examples

```
if (spaMM.getOption("example_maxtime")>1.4) {
  data("wafers")
  nullfit <- fitme(y~1+(1|batch), data=wafers, family=Gamma(log))
  fullfit <- fitme(y ~X1+X2+X1*X3+X2*X3+I(X2^2)+(1|batch), data=wafers, family=Gamma(log))
  MSFDR(nullfit=nullfit,fullfit=fullfit)
}
```

**Description**

IMRF is a syntax to specify random-effect terms of the forms considered by Lindgren et al. (2011) or Nychka et al. (2015, 2019). For example, using IMRF with its `model` argument provides good approximations of random effects with Matern correlation structure with fixed smoothness $<2$ .

The random effects considered here all involve a multivariate Gaussian random effect over a lattice, from which the random-effect value in any spatial position is determined by interpolation of values on the lattice. **IMRF** stands for **I**nterpolated **M**arkov **R**andom **F**ield because the specific process considered on the lattice is currently known as a Gaussian Markov Random Field (see the Details for further information). Lindgren et al. considered irregular lattices that can be specified by the `model` argument, while Nychka et al. considered regular grids that can be specified by the other arguments.

The `multIMRF` syntax implements the multiresolution model of Nychka et al. Any `multIMRF` term in a formula is immediately converted to IMRF terms. This has distinct implications for controlling the parameters of these or other random effects in the model by `init` or `fixed` values: see Details if you need such control.

**Usage**

```
# IMRF( 1 | <coordinates>, model, nd, m, no, ce, ...)
# multIMRF( 1 | <coordinates>, levels, margin, coarse=10L,
#           norm=TRUE, centered=TRUE )
```

**Arguments**

<code>model</code>	An <code>inla.spde2</code> object as produced by <code>INLA::inla.spde2.matern</code> or <code>INLA::inla.spde2.pcmatern</code> (see Examples below, and <a href="https://www.r-inla.org">https://www.r-inla.org</a> for further information).
<code>levels</code>	integer; Number of levels in the hierarchy, i.e. number of component IMRFs.
<code>margin, m</code>	integer; width of the margin, as a number of additional grid points on each side (applies to all levels of the hierarchy).
<code>coarse</code>	integer; number of grid points (excluding the margins) per dimension for the coarsest IMRF. The number of grids steps nearly doubles with each level of the hierarchy (see Details).
<code>nd</code>	integer; number of grid steps (excluding the margins) per dimension for the given IMRF.
<code>norm, no</code>	Boolean; whether to apply normalization (see Details), or not.
<code>centered, ce</code>	Boolean; whether to center the grid in all dimensions, or not.
<code>...</code>	Not documented, for programming purposes

## Details

Gaussian Markov Random Field (MRF) and conditional autoregressive models are essentially the same thing, apart from details of specification. `adjacency` and `AR1` random effects can be seen as specific MRFs. The common idea is the Markov-like property that the distribution of each element  $b_i$  of the random-effect  $\mathbf{b}$ , given values of a few specific elements (the “neighbours” of  $i$ ), is independent of other elements (i.e., of non-neighbours). The non-zero non-diagonal elements of a precision matrix characterize the neighbours.

Given the inferred vector  $\mathbf{b}$  of values of the MRF on the lattice, the interpolation of the MRF in any focal point is of the form  $\mathbf{A}\mathbf{b}$  where each row of  $\mathbf{A}$  weights the values of  $\mathbf{b}$  according to the position of the focal point relative to the vertices of the lattice. Following the original publications, for regular grids (NULL model), the weights are computed as `<Wendland function>` (`<scaled Euclidean distances between focal point and vertices>`); and for grids given by `model=inla.spde2 object`, the non-zero weights are the barycentric coordinates of the focal point in the enclosing triangle from the mesh triangulation (points from outside the mesh would have zero weights, so the predicted effect  $\mathbf{A}\mathbf{b}=\mathbf{0}$ ).

The IMRF model defines both a lattice in space, the precision matrix for a Gaussian MRF over this lattice, and the  $\mathbf{A}$  weights. The full specification of the MRF on **irregular lattices** is complex. The  $\kappa$  parameter considered by `spaMM` is the  $\kappa$  considered by Lindgren et al. The  $\alpha$  argument of the `INLA::inla.spde2.matern` controls the smoothness of the approximated Matern model, as  $\alpha = \nu + d/2$  where  $d$  is the dimension of the space. Correlation models created by `INLA::inla.spde2.pcmatern` are handled so as to give the same results as when `INLA::inla.spde2.matern` is used with the same mesh and alpha argument (thus, the extra functionalities of “pc”`matern` are ignored).

Not all options of the INLA functions may be compatible or meaningful when used with `spaMM` (only the effect of alpha and cutoff has been checked). The correlation models thus defined are fitted by the same methods as other models in `spaMM`. `spaMM` does not call INLA code except optionally `INLA::inla.spde.make.A` (if available to the R session) to construct the  $\mathbf{A}$  matrix.

For the MRFs on default **regular grids** (missing `model` argument), the precision matrix is defined (up to a variance parameter) as  $\mathbf{M}'\mathbf{M}$  where the diagonal elements  $m_{ii}$  of  $\mathbf{M}$  are  $4+\kappa^2$  and the  $m_{ij}$  for the four nearest neighbours are -1 (note that  $\mathbf{M}'\mathbf{M}$  involves more than these four neighbours).

The precision matrix defined in this way is the inverse of an heteroscedastic covariance matrix  $\mathbf{C}$ , but by default a normalization is applied so that the random effect is homoscedastic. As for other random effects, the variance is further controlled by a multiplicative factor  $\lambda$ . The **normalization** is as follows: the design matrix of the random effect term is viewed as  $\mathbf{W}\mathbf{A}\mathbf{L}$  where  $\mathbf{W}$  is a diagonal normalization matrix,  $\mathbf{A}$  is the above-described weight matrix, and  $\mathbf{L}$  is a “square root” of  $\mathbf{C}$ . If no normalization is applied, the covariance matrix of the random effect is of the form  $\lambda\mathbf{A}\mathbf{L}\mathbf{L}'\mathbf{A}'$ , which is heteroscedastic;  $\lambda$  may then be quite different from the marginal variance of the random effect, and is difficult to describe in a simple way. Hence, by default,  $\mathbf{W}$  is defined such that  $\mathbf{W}\mathbf{A}\mathbf{L}\mathbf{L}'\mathbf{A}'\mathbf{W}'$  has unit diagonal; then,  $\lambda$  is the marginal variance of the random effect.

By default (meaning in particular that `model` is not used to specify a lattice defined by the INLA procedures), the IMRF lattice is rectangular (currently the only option) and is made of a core lattice, to which margins of `margin` steps are added on each side. The core lattice is defined as follows: in each of the two spatial dimensions, the range of axial coordinates is determined. The largest range is divided in `nd-1` steps, determining `nd` values and step length  $L$ . The other range is divided in steps of the same length  $L$ . If it extends over (say)  $2.5L$ , a grid of 2 steps and 3 values is defined, and by default centered on the range (the extreme points therefore typically extend slightly beyond

the grid, within the first of the additional steps defined by the margin; if not centered, the grid start from the lower coordinate of the range).

multIMRF implements multilevel IMRFs. It defines a sequence of IMRFs, with progressively finer lattices, a common  $\kappa$  value `hy_kap` for these IMRFs, and a single variance parameter `hy_lam` that determines  $\lambda$  values decreasing by a factor of 4 for successive IMRF terms. By default, each component IMRF is normalized independently as described above (as in Nychka et al. 2019), and `hy_lam` is the sum of the variances of these terms (e.g., if there are three levels and `hy_lam=1`, the successive variances are  $(1, 1/4, 1/16)/(21/16)$ ). The `nd` of the first IMRF is set to the coarse value, and its lattice is defined accordingly. If `coarse=4` and `margin=5`, a grid of 14 coordinates is therefore defined over the largest range. In the second IMRF, the grid spacing is halved, so that new steps are defined halfway between the previous ones (yielding a grid of 27 steps in the widest range). The third IMRF proceeds from the second in the same way, and so on.

To control initial or fixed values of multIMRF  $\kappa$  and variance parameters, which are hyper-parameter controlling several IMRF terms, the hyper syntax shown in the Examples should be used. `hyper` is a nested list whose possible elements are named "1", "2", ... referring to successive multIMRF terms in the input formula, not to successive random effect in the expanded formula with distinct IMRF terms (see Examples). But the different IMRF terms should be counted as distinct random effects when controlling other parameters (e.g., for fixing the variances of other random effects).

## References

- D. Nychka, S. Bandyopadhyay, D. Hammerling, F. Lindgren, S. Sain (2015) A multiresolution gaussian process model for the analysis of large spatial datasets. *Journal of Computational and Graphical Statistics* 24 (2), 579-599. doi: [10.1080/10618600.2014.914946](https://doi.org/10.1080/10618600.2014.914946)
- D. Nychka, D. Hammerling, Mitchel. Krock, A. Wiens (2018) Modeling and emulation of nonstationary Gaussian fields. *Spat. Stat.* 28: 21-38. doi: [10.1016/j.spasta.2018.08.006](https://doi.org/10.1016/j.spasta.2018.08.006)
- Lindgren F., Rue H., Lindström J. (2011) An explicit link between Gaussian fields and Gaussian Markov random fields: the stochastic partial differential equation approach *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 73: 423-498. doi: [10.1111/j.1467-9868.2011.00777.x](https://doi.org/10.1111/j.1467-9868.2011.00777.x)

## Examples

```
if (spaMM.getOption("example_maxtime")>6) {

data("blackcap") ## toy examples; but IMRF may be useful only for much larger datasets
## and when using the 'cutoff' parameter of INLA::inla.mesh.2d()

##### Irregular lattice specified by 'model':
#
data("small_spde") ## load object of class 'inla.spde2', created and saved by :
# spd <- sp::SpatialPointsDataFrame(coords = blackcap[, c("longitude", "latitude")],
# data = blackcap)
# small_mesh <- INLA::inla.mesh.2d(loc = INLA::inla.mesh.map(sp::coordinates(spd)),
# max.n=100, # only for demonstration purposes
# max.edge = c(3, 20))
# small_spde <- INLA::inla.spde2.matern(small_mesh)
# save(small_spde, file="small_spde.RData", version=2)
```

```

#
fit_SPDE <- fitme(migStatus ~ means + IMRF(1|longitude+latitude, model=small_spde),
                 data=blackcap)

##### Regular lattices:
#
#Using 'hyper' to control fixed hyper-parameters
#
(mrf <- fitme(migStatus ~ 1 + (1|pos) +
              multIMRF(1|longitude+latitude,margin=5,levels=2),
              data=blackcap, fixed=list(phi=1,lambda=c("1"=0.5),
              hyper=list("1"=list(hy_kap=0.1,hy_lam=1)))) )

# Using 'hyper' to control initial hyper-parameters
#
(mrf <- fitme(migStatus ~ 1 + multIMRF(1|longitude+latitude,margin=5,levels=2),
              data=blackcap, method="ML", fixed =list(phi=1),
              init=list(hyper=list("1"=list(hy_kap=0.1,hy_lam=1)))) )

# *Independent* IMRF terms with default rectangular lattice (often giving dubious results)
#
(mrf <- fitme(migStatus ~ 1 + IMRF(1|longitude+latitude,margin=5, nd=4L)
              + IMRF(1|longitude+latitude,margin=5, nd=7L),
              data=blackcap,
              fixed=list(phi=1,lambda=c(1/4,1/16),
              corrPars=list("1"=list(kappa=0.1),"2"=list(kappa=0.1)))) )

}

```

---

multinomial

*Analyzing multinomial data*


---

## Description

These functions facilitate the conversion and analysis of multinomial data as a series of nested binomial data. The main interface is the `multi` “family”, to be used in the `family` argument of the fitting functions. Fits using it call `binomialize`, which can be called directly to check how the data are converted to nested binomial data, and to use these data directly. The `fitted.HLfitlist` method of the fitted generic function returns a matrix of fitted multinomial probabilities. The `logLik.HLfitlist` method of the `logLik` generic function returns a log-likelihood for the joint fits.

## Usage

```

multi(binResponse=c("npos", "nneg"), binfamily=binomial(), input="types", ...)
binomialize(data, responses, sortedTypes=NULL, binResponse=c("npos", "nneg"),
            depth=Inf, input="types")
## S3 method for class 'HLfitlist'
fitted(object, version=2L, ...)

```

```
## S3 method for class 'HLfitlist'
logLik(object,which,...)
```

### Arguments

<code>data</code>	The data frame to be analyzed.
<code>object</code>	A list of binomial fits returned by a multinomial analysis
<code>responses</code>	column names of the data, such that <code>&lt;data&gt;[, &lt;responses&gt;]</code> contain the multinomial response data, as levels of factor variables.
<code>sortedTypes</code>	Names of multinomial types, i.e. levels of the multinomial response factors. Their order determines which types are taken first to define the nested binomial samples. By default, the most common types are considered first.
<code>binResponse</code>	The names to be given to the number of “success” and “failures” in the binomial response.
<code>depth</code>	The maximum number of nested binomial responses to be generated from the multinomial data.
<code>binfamily</code>	The family applied to each binomial response.
<code>input</code>	If <code>input="types"</code> , then the responses columns must contain factor levels of the binomial response. If <code>input="counts"</code> , then the responses columns must contain counts of different factor levels, and the column names are the types.
<code>which</code>	Which element of the APHLs list to return. The default depends on the fitting method. In particular, if it was REML or one of its variants, the function returns the log restricted likelihood (exact or approximated).
<code>version</code>	Integer, for <code>fitted.HLfitlist</code> (i.e. for multinomial fits using <code>multi</code> ); 1 will provide the result of past versions up to 3.5.0 (See Value).
<code>...</code>	Other arguments passed from or to other functions.

### Details

A multinomial response, say counts 17, 13, 25, 8, 3, 1 for types `type1` to `type6`, can be represented as a series of nested binomials e.g. `type1` against others (17 vs 50) then among these 50 others, `type2` versus others (13 vs 37), etc. The `binomialize` function generates such a representation. By default the representation considers types in decreasing order of the number of positives, i.e. first `type3` against others (25 vs 42), then `type1` against others within these 42, etc. It stops if it has reached `depth` nested binomial responses. This can be modified by the `sortedTypes` argument, e.g. `sortedTypes=c("type6","type4","type2")`. `binomialize` returns a list of data frames which can be directly provided as a `data` argument for the fitting functions, with binomial response.

Alternatively, one can provide the multinomial response data frame, which will be internally converted to nested binomial data if the `family` argument is a call to `multinomial` (see Examples).

For mixed models, the multinomial data can be fitted to a model with the same correlation parameters, and either the same or different variances of random effects, for all binomial responses. Which analysis is performed depends on whether the variances are fitted by “outer optimization” or by `HLfit`’s “inner iterative” algorithm, as controlled by the `init` or `init.corrHLfit` arguments (see Examples). These initial values therefore affect the definition of the model being fitted. `corrHLfit` will fit different variances by default. Adding an `init.corrHLfit` will force estimation of a single

variance across models. `fitme`'s default optimization strategy is more complex, and has changed and still change over versions. This creates a **back-compatibility issue** where the model to be fitted may change over versions of `spaMM`. To avoid that, it is strongly advised to use an explicit initial value when fitting a multi model by `fitme`.

## Value

`binomialize` returns a list of data frames appropriate for analysis as binomial response. Each data frame contains the original one plus two columns named according to `binResponse`.

The main fitting functions, when called on a model with `family=multi(.)`, return an object of class `HLfitlist`, which is a list with attributes. The list elements are fits of the nested binomial models (objects of class `HLfit`). The attributes provide additional information about the overall multinomial model, such as global log-likelihood values and other information properly extracted by the `how()` function.

`multi` is a function that returns a list, but users may never need to manipulate this output.

`fitted.HLfitlist` returns a matrix. The current default `version=2L` provides meaningful fitted values (predicted multinomial frequencies for each response type) even for data rows where the nested binomial fit for a type had no response information remaining. By contrast, the first version provided a matrix with 0s for these row\*fit combinations, except for the last column; in many cases this may be confusing.

## Examples

```
## Adding colour to the famous 'iris' dataset:
iriscol <- iris
set.seed(123) # Simulate colours, then fit colour frequencies:
iriscol$col <- sample(c("yellow", "purple", "blue"),replace = TRUE,
                    size = nrow(iriscol), prob=c(0.5,0.3,0.2))
colfit <- fitme(cbind(npos,nneg) ~ 1+(1|Species), family=multi(responses="col"),
              data=iriscol, init=list(lambda=NA)) # note warning if no 'init'...
head(fitted(colfit))

# To only generate the binomial datasets:
binomialize(iriscol,responses="col")

## An example considering pseudo-data at one diploid locus for 50 individuals
set.seed(123)
genecopy1 <- sample(4,size=50,prob=c(1/2,1/4,1/8,1/8),replace=TRUE)
genecopy2 <- sample(4,size=50,prob=c(1/2,1/4,1/8,1/8),replace=TRUE)
alleles <- c("122","124","126","128")
genotypes <- data.frame(type1=alleles[genecopy1],type2=alleles[genecopy2])
## Columns "type1","type2" each contains an allele type => input is "types" (the default)
datalist <- binomialize(genotypes,responses=c("type1","type2"))

## two equivalent fits:
f1 <- HLfit(cbind(npos,nneg)~1,data=datalist, family=binomial())
f2 <- HLfit(cbind(npos,nneg)~1,data=genotypes, family=multi(responses=c("type1","type2")))
fitted(f2)

if (spaMM.getOption("example_maxtime")>1.7) {
```

```
##### Control of lambda estimation over different binomial submodels

genoInSpace <- data.frame(type1=alleles[genecopy1],type2=alleles[genecopy2],
                          x=runif(50),y=runif(50))
method <- "PQL" # for faster example

## Fitting distinct variances for all binomial responses:

multifit <- corrHLfit(cbind(npos,nneg)~1+Matern(1|x+y),data=genoInSpace,
                    family=multi(responses=c("type1","type2")),
                    ranFix=list(rho=1,nu=0.5), method=method)
length(unique(unlist(lapply(multifit, get_ranPars, which="lambda")))) # 3

multifit <- fitme(cbind(npos,nneg)~1+Matern(1|x+y),data=genoInSpace,
                family=multi(responses=c("type1","type2")),
                init=list(lambda=NaN), # forcing 'inner' estimation for fitme
                fixed=list(rho=1,nu=0.5), method=method)
length(unique(unlist(lapply(multifit, get_ranPars, which="lambda")))) # 3

## Fitting the same variance for all binomial responses:

multifit <- fitme(cbind(npos,nneg)~1+Matern(1|x+y),data=genoInSpace,
                family=multi(responses=c("type1","type2")),
                init=list(lambda=NA), # forcing 'outer' estimation for fitme
                fixed=list(rho=1,nu=0.5), method=method)
length(unique(unlist(lapply(multifit, get_ranPars, which="lambda")))) # 1

multifit <-
  corrHLfit(cbind(npos,nneg)~1+Matern(1|x+y),data=genoInSpace,
            family=multi(responses=c("type1","type2")),
            init.corrHLfit=list(lambda=1), # forcing 'outer' estimation for corrHLfit
            ranFix=list(rho=1,nu=0.5), method=method)
length(unique(unlist(lapply(multifit, get_ranPars, which="lambda")))) # 1
}
```

---

mv

*Virtual factor for multivariate responses*


---

## Description

In a multivariate-response model fitted by `fitmv`, one may wish to fit a random-coefficient term appearing in  $s$  submodels, that is a random effect with realized values for each of these submodels and each group, with values possibly correlated among submodels within groups. Hence one might wish to specify it as a term of the form (`<submodel>|group`), where `<submodel>` would represent a factor for the  $s$  submodels. But the data are not expected to contain a factor for these submodels, so such a syntax would not work without substantial data reshaping. Instead, this effect can be stated as `mv(...)` where the `...` are the indices of the submodels here the random effect appears. For example if submodels 2 and 3 include this random-coefficient term, the term can be specified as `mv(2,3)|group`.

The `mv(...)` expression is treated as a factor for all purposes, meaning for example that  $(\theta + mv(2, 3) | group)$  can also be used, leading (as for any factor) to an alternative parametrization of the same random-coefficient model (see Examples). The random-effect term is treated as a random-coefficient term for all purposes, meaning for example that fixed values can be specified for it using the `ranCoefs` syntax (see Examples).

## Usage

```
# mv(...)
```

## Arguments

```
...           Indices of all the submodels where the random effect involving this virtual factor
              appears.
```

## Value

Not a function, hence no return value. In the summary of the fit, levels for the different submodels  $s$  within each group are labelled `.mvs`.

## Examples

```
if (spaMM.getOption("example_maxtime")>1.1) {
  ## data preparation
  data("wafers")
  me <- fitme(y ~ 1+(1|batch), family=Gamma(log), data=wafers, fixed=list(lambda=0.2))

  set.seed(123)
  wafers$y1 <- simulate(me, type="marginal")
  wafers$y2 <- simulate(me, type="marginal")

  ## fits
  (fitmv1 <- fitmv(
    submodels=list(mod1=list(formula=y1~X1+(mv(1,2)|batch), family=Gamma(log)),
                    mod2=list(formula=y2~X1+(mv(1,2)|batch), family=Gamma(log))),
    data=wafers))
  # alternative '0+' parametrization of the same model:
  (fitmv2 <- fitmv(
    submodels=list(mod1=list(formula=y1~X1+(0+mv(1,2)|batch), family=Gamma(log)),
                    mod2=list(formula=y2~X1+(0+mv(1,2)|batch), family=Gamma(log))),
    data=wafers))
  # relationship between the *correlated* effects of the two fits
  ranef(fitmv2)[[1]][,2]-rowSums(ranef(fitmv1)[[1]]) # ~ 0

  # fit with given correlation parameter:
  update(fitmv2, fixed=list(ranCoefs=list("1"=c(NA,-0.5,NA))))
}
```

---

negbin	<i>Family function for GLMs and mixed models with negative binomial and zero-truncated negative binomial response.</i>
--------	--

---

### Description

`family` object that specifies the information required to fit a negative binomial generalized linear model, with known or unknown underlying Gamma shape parameter. The zero-truncated variant can be specified either as `Tnegbin(.)` or as `negbin(., trunc = 0L)`.

### Usage

```
negbin(shape = stop("negbin's 'shape' must be specified"), link = "log", trunc = -1L)
Tnegbin(shape = stop("negbin's 'shape' must be specified"), link = "log")
# (the shape parameter is actually not requested unless this is used in a glm() call)
```

### Arguments

shape	Shape parameter of the underlying Gamma distribution, given that the negbin family can be represented as a Poisson-Gamma mixture, where the conditional Poisson mean is $\mu$ times a Gamma random variable with mean 1 and shape shape (as produced by <code>rgamma(., shape=shape, scale=1/shape)</code> ).
link	log, sqrt or identity link, specified by any of the available ways for GLM links (name, character string, one-element character vector, or object of class <code>link-glm</code> as returned by <code>make.link</code> ).
trunc	Either <code>0L</code> for zero-truncated distribution, or <code>-1L</code> for default untruncated distribution.

### Details

shape is the  $k$  parameter of McCullagh and Nelder (1989, p.373) and the theta parameter of Venables and Ripley (2002, section 7.4). The latent Gamma variable has mean 1 and variance  $1/\text{shape}$ , and the negbin with mean  $\mu$  has variance  $\mu + \mu^2/\text{shape}$ . The negbin family is sometimes called the NegBin1 model (as the first, historically) in the literature on negative binomial models, and sometimes the NegBin2 model (because its variance is a quadratic function of its mean).

spaMM does not handle models with the “other” negative-binomial response family where the variance is a linear function of the mean, because this is not an exponential-family model. However, it can approximate it, through a Laplace approximation and a bit of additional programming, as a Poisson-Gamma mixture model with an heteroscedastic Gamma random-effect, specified e.g. as `(weights-1|.)` where the weights need to be updated iteratively as function of predicted response. File `test-negbin1.R` in the `/test` directory provides one example. Other mean-variance relationship can be handled in the same way.

The name `NB_shape` should be used to set values of shape in control arguments of the fitting functions (e.g., `fitme(., init=list(NB_shape=1))`).

**Value**

A family object.

**References**

McCullagh, P. and Nelder, J.A. (1989) *Generalized Linear Models*, 2nd edition. London: Chapman & Hall.

Venables, W. N. and Ripley, B. D. (2002) *Modern Applied Statistics with S-PLUS*. Fourth Edition. Springer.

**Examples**

```
## Fitting negative binomial model with estimated scale parameter:
data("scotlip")
fitme(cases~I(prop.ag/10)+offset(log(expec)),family=negbin(), data=scotlip)
negfit <- fitme(I(1+cases)~I(prop.ag/10)+offset(log(expec)),family=lnegbin(), data=scotlip)
simulate(negfit,nsim=3)
```

---

options	<i>spaMM options settings</i>
---------	-------------------------------

---

**Description**

Allow the user to set and examine a variety of *options* which affect operations of the spaMM package.

**Usage**

```
spaMM.options(..., warn = TRUE)
```

```
spaMM.getOption(x)
```

**Arguments**

x	a character string holding an option name.
warn	Boolean: whether to warn if a previously undefined options is being defined (a protection against typos).
...	A named value or a list of named values. The following values, with their defaults, are used in spaMM: <ul style="list-style-type: none"> <li>LevenbergM=NULL: NULL or boolean. Whether to use a Levenberg-Marquardt-like algorithm (see Details) by default in most computations. But it is advised to use instead <code>control.HLfit=list(LevenbergM=...)</code> to control this on a case-by-case basis. The joint default behaviour is that Levenberg-Marquardt is used by default for binomial response data that takes only extreme values (in particular, for binary 0/1 response), and that for other</li> </ul>

models the fitting algorithm switches to it if divergence is suspected. FALSE inhibits its use; TRUE forces its use for all iterative least-square fits, except when 'confint()' is called.

**example\_maxtime=0.7:** Used in the documentation and tests to control whether the longer examples should be run. The approximate running time of given examples on one author's laptop is compared to this value.

**optimizer1D="optimize":** Optimizer for one-dimensional optimization. If you want to control the initial value, you should select another optimizer.

**optimizer=".safe\_opt":** Optimizer for optimization in several dimensions. Use **optimizer="nloptr"** to call **nloptr** with method "NLOPT\_LN\_BOBYQA"; use **optimizer="bobyqa"** to call **bobyqa**; and use **optimizer="L-BFGS-B"** to call **optim** with method "L-BFGS-B". The default ".safe\_opt" uses **nloptr** except in some cases where it expects or detects problems with it (the source code should be consulted for details). The optimizer can also be specified on a fit-by-fit basis as the value of `control$optimizer` in a `fitme` call, or as the value of `control.corrHLfit$optimizer`.

**nloptr:** Default control values of **nloptr** calls.

**bobyqa:** Default control values of **bobyqa** calls.

**maxLambda=1e10:** The maximum value of lambda: higher fitted lambda values in **HLfit** are reduced to this. Since version 3.1.0, a much smaller lambda bound is deduced from **maxLambda** for **COMPoisson** and log-link response families.

**regul\_lev\_lambda** Numeric (default: 1e-8); lambda leverages numerically 1 are replaced by 1- `regul_lev_lambda`

**COMP\_maxn:** Number of terms for truncation of infinite sums that are evaluated in the fitting of **COMPoisson** models.

**COMP\_asympto\_cond:** Condition for applying an approximation or the **COMPoisson** response family, as detailed in **COMPoisson**.

**Gamma\_min\_y=1e-10:** A minimum response value in Gamma-response models; used to check data, and in `simulate()` to correct the simulation results.

**QRmethod:** A character string, to control whether dense matrix or sparse matrix methods are used in intensive matrix computations, overcoming the defaults choices made by **spaMM** in this respect. Possible values are "dense" and "sparse".

**matrix\_method:** A character string, to control the factorization of dense model matrices. Default value is "def\_sXaug\_EigenDense\_QRP\_scaled". The source code should be consulted for further information.

**Matrix\_method:** A character string, to control the factorization of sparse model matrices. Default value is "def\_sXaug\_Matrix\_QRP\_scaled". The source code should be consulted for further information.

**stylefns:** Default colors of some screen output (notably that of some fitting functions when called with argument `verbose=c(TRACE=TRUE)`)

**barstyle:** Integer, or Boolean interpreted as Integer, or quoted expression evaluating to such types; controlling the display of some progress bars. If zero, no progress bar should be displayed; otherwise, a bar should be displayed. Further, when **txtProgressBar** is called, `barstyle` is passed as its `style`

argument. Default is `quote(if(interactive()) {3L} else {0L})` (in a parallel setting, child processes may display the bar if the parent process is interactive).

and many other undocumented values for programming or development purposes. Additional options without default values can also be used (e.g., see [algebra](#)).

## Details

`spaMM.options()` provides an interface for changing maximal values of parameters of the Matérn correlation function. However, it is not recommended to change these values unless a `spaMM` message specifically suggests so.

By default `spaMM` use Iteratively Reweighted Least Squares (IRLS) methods to estimate fixed-effect parameters (jointly with predictions of random effects). However, a Levenberg-Marquardt algorithm, as described by Nocedal & Wright (1999, p. 266), is also implemented. The Levenberg-Marquardt algorithm is designed to optimize a single objective function with respect to all its parameters. It is thus well suited to compute a PQL fit, which is based on maximization of a single function, the h-likelihood. By contrast, in a fit of a mixed model by (RE)ML, one computes jointly fixed-effect estimates that maximizes marginal likelihood, and random-effect values that maximize h-likelihood given the fixed-effect estimates. The gradient of marginal likelihood with respect to fixed-effect coefficients does not generally vanishes at the solution (although it remains close to zero except in “difficult” cases with typically little information in the data). The Levenberg-Marquardt algorithm is not directly applicable in this case, as it may produce random-effect values that increases marginal likelihood rather than h-likelihood. The (RE)ML variant of the algorithm implemented in `spaMM` may therefore use additional nested h-likelihood-maximizing steps for correcting random-effect values. In version 3.1.0 this variant was revised for improved performance in difficult cases.

## Value

For `spaMM.getOption`, the current value set for option `x`, or `NULL` if the option is unset.

For `spaMM.options()`, a list of all set options. For `spaMM.options(<name>)`, a list of length one containing the set value, or `NULL` if it is unset. For uses setting one or more options, a list with the previous values of the options changed (returned invisibly).

## References

Jorge Nocedal and Stephen J. Wright (1999) Numerical Optimization. Springer-Verlag, New York.

## Examples

```
spaMM.options()
spaMM.getOption("example_maxtime")
## Not run:
spaMM.options(maxLambda=1e06)

## End(Not run)
```

**Description**

This example illustrates how to use spaMM for quantitative genetic analyses. spaMM appears competitive in terms of speed for GLMMs with large data sets, particularly when using the PQL method, which may be a quite good approximation in such cases. For large pedigrees it may be useful to compute the inverse of the relationship matrix using some efficient ad hoc algorithm, then to provide it as argument of the fit using the `covStruct(list(precision=...))` syntax. If the precision matrix is not specified, spaMM will generally evaluate it to assess whether it should use sparse-precision methods. see [sparse\\_precision](#) for further control of this computation, on another example from quantitative genetics.

**See Also**

[sparse\\_precision](#)

**Examples**

```
## Not run:
if(requireNamespace("pedigreemm", quietly=TRUE)) {
## derived from help("pedigreemm")
  p1 <- new("pedigree",
            sire = as.integer(c(NA,NA,1, 1,4,5)),
            dam  = as.integer(c(NA,NA,2,NA,3,2)),
            label = as.character(1:6))
  A <- pedigreemm::getA(p1) ## relationship matrix
  ## data simulation
  cholA <- chol(A)
  varU <- 0.4; varE <- 0.6; rep <- 20
  n <- rep*6
  set.seed(108)
  bStar <- rnorm(6, sd=sqrt(varU))
  b <- crossprod(as.matrix(cholA),bStar)
  ID <- rep(1:6, each=rep)
  e0 <- rnorm(n, sd=sqrt(varE))
  y <- b[ID]+e0
  obs <- data.frame(y=y,IDgen=ID,IDenv=ID) ## two copies of ID for readability of GLMM results
  ## fits
  fitme(y ~ 1+ corrMatrix(1|IDgen) , corrMatrix=A,data=obs,method="REML")
  obs$y01 <- ifelse(y<1.3,0,1)
  fitme(y01 ~ 1+ corrMatrix(1|IDgen)+(1|IDenv), corrMatrix=A,data=obs,
        family=binomial(), method="REML")
  prec_mat <- solve(A)
  colnames(prec_mat) <- rownames(prec_mat) <- rownames(A) # important
  fitme(y01 ~ 1+ corrMatrix(1|IDgen)+(1|IDenv) , covStruct=list(precision=prec_mat),
        data=obs, family=binomial(), method="REML")
}
```

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

---

```
phiHGLM
```

```
Fitting random effects in the residual dispersion model
```

---

## Description

$\phi$  parameters are estimated by fitting a Gamma HGLM to response values computed by the parent fitting function (e.g., by `HLfit` in the Examples). The `fitme` function is used to perform this fit. The `resid.model` of the parent call is used to control the arguments of this `fitme` call.

## Usage

```
# 'resid.model' argument of main fitting functions
```

## Arguments

`resid.model` is **either** a formula (without left-hand side) for the dispersion parameter  $\phi$  of the residual error (a log link is assumed); **or** a list of arguments similar to those of a standard fit. The following arguments may be useful:

`model` formula as in formula-only case, without left-hand side. Random effects can be included and this appears to work well in simple cases (block effects, or geostatistical models) but has not been tested, or hardly so, for other cases.

`family` The family is always Gamma. The default link is log. The identity link can be tried but may fail because only the log link ensures that the fitted  $\phi$  is positive.

`fixed` fixed values of parameters. Same usage as documented in `fitme`

`control.dist` A list of arguments that control the computation of the distance argument of the correlation functions. Same usage as documented in `HLCor`

`rand.family` A family object or a list of family objects describing the distribution of the random effect(s). Same usage as documented for `HLfit`

`init, lower, upper, control` with same usage as documented in `fitme`, may be at least partly heeded. Other arguments should be ignored (see Details).

## Details

The following elements in `resid.model` should be ignored:

**method** which is constrained to be identical to the method from the parent call;

**control.HLfit, control.glm** constrained to be identical to the same-named controls from the parent call;

**resid.model** constrained: no `resid.model` for a `resid.model`;

**REMLformula** constrained to NULL;

**data** The data of the parent call are used, so they must include all the variables required for the resid.model;

**prior.weights** constrained: no prior weights;

**verbose** constrained: will display a progress line summarizing the results of the resid.model fit at each iteration of main loop of the parent call.

**init.HLfit** Ignored. Users would have hard time guessing good initial values, which would be have to be ignored in most contexts anyway.

## References

Lee, Y., Nelder, J. A. and Pawitan, Y. (2006) Generalized linear models with random effects: unified analysis via h-likelihood. Chapman & Hall: London.

## Examples

```
data("crack") # crack data, Lee et al. 2006 chapter 11 etc
hlfit <- HLfit(y~crack0+(1|specimen), family=Gamma(log),
              data=crack, rand.family=inverse.Gamma(log),
              resid.model=list(formula=~cycle+(1|specimen)) )
```

---

plot.HLfit

*Model checking plots for mixed models*

---

## Description

This function provides diagnostic plots for residual errors from the mean model and for random effects. Plots for the mean models are similar to those for GLMs. They use *standardized* deviance residuals as described by Lee et al. (2006, p.52). This means that plots for residual errors use the residuals provided by `residuals(<fit object>, type="std_dev_res")`; and that plots for random effects likewise consider standardized values.

## Usage

```
## S3 method for class 'HLfit'
plot(x, which = c("mean", "ranef"),
     titles = list(
       meanmodel=list(outer="Mean model",devres="Deviance residuals",
                       absdevres="|Deviance residuals|", resq="Residual quantiles",
                       devreshist="Deviance residuals"),
       ranef=list(outer="Random effects and leverages",qq="Random effects Q-Q plot",
                  levphi=expression(paste("Leverages for ",phi)),
                  levlambda=expression(paste("Leverages for ",lambda)))
     ),
     control= list(), ask=TRUE, ...)
```

**Arguments**

x	An object of class HLfit, as returned by the fitting functions in spaMM.
which	A vector of keywords for different types of plots. By default, two types of plots are presented on different devices: diagnostic plots for mean values, and diagnostic plots for random effects. Either one can be selected using this argument. Use keyword "predict" for a plot of predicted response against actual response.
titles	A list of the main (inner and outer) titles of the plots. See the default value for the format.
control	A list of default options for the plots. Defaults are pch="+" and pcol="blue" for points, and lcol="red" for curves.
ask	Logical; passed to devAskNewPage which is run when a new device is opened by code.HLfit.
...	Options passed from plot.HLfit to par.

**Details**

In principle the standardized deviance residuals for the mean model should have a nearly Gaussian distribution hence form a nearly straight line on a Q-Q plot. However this is (trivially) not so for well-specified (nearly-)binary response data nor even for well-specified Poisson response data with moderate expectations. Hence this plot is not so useful. The DHARMA package proposes better-behaved diagnostic plots (but the p-value that appears on one of these plots may not stand for a valid goodness-of-fit test). The current version of DHARMA should handle spaMM fit objects; otherwise, see <https://github.com/florianhartig/DHARMA/issues/95> for how to run DHARMA procedures on spaMM output.

**Value**

Returns the input object invisibly.

**References**

Lee, Y., Nelder, J. A. and Pawitan, Y. (2006). Generalized linear models with random effects: unified analysis via h-likelihood. Chapman & Hall: London.

**Examples**

```
data("blackcap")
fit <- fitme(migStatus ~ 1+ Matern(1|longitude+latitude), data=blackcap,
            fixed=list(lambda=1, nu=1, rho=1))
plot(fit)
```

## Description

The following functions evaluate or plot *partial-dependence* effects.

`pdep_effects` evaluates the effect of a given fixed-effect variable, as (by default, the average of) predicted values on the response scale, over the empirical distribution of all other fixed-effect variables in the data, and of inferred random effects. This can be seen as the result of an experiment where specific treatments (given values of the focal variable) are applied over all conditions defined by the other fixed effects and by the inferred random effects. Thus, apparent dependencies induced by associations between predictor variables are avoided (see Friedman, 2001, from which the name “partial dependence plot” is taken; or Hastie et al., 2009, Section 10.13.2). This also avoids biases of possible alternative ways of plotting effects. In particular, such biases occur if the response link is not identity, and if averaging is performed on the linear-predictor scale or when other variables are set to some conventional value other than its average.

`pdep_effects` also compute intervals of the type defined by its `intervals` argument (by default, prediction intervals). By default, it returns a data frame of average values of point predictions and interval bounds for each value of the focal variable, but it can also return lists of all predictions.

`plot_effects` calls `pdep_effects` and produces a simple plot (using only base graphic functions) of its results, including prediction bands representing the two average one-sided widths of intervals. If added to the plot, the raw data may appear to depart from the partial-dependence predictions, since the data are a priori affected by the associations between variables which the predictions free themselves from. An adapted plot of fit residuals may be then be more useful, and the Example shows how it can be performed.

## Usage

```
pdep_effects(object, focal_var, newdata = object$data, length.out = 20,
             levels = NULL, intervals = "predVar", indiv = FALSE, ...)
plot_effects(object, focal_var, newdata = object$data, effects = NULL,
            xlab = focal_var, ylab = NULL, rgb.args = col2rgb("blue"),
            add = FALSE, ylim=NULL, ...)
```

## Arguments

<code>object</code>	An object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
<code>focal_var</code>	Character string: the name of the predictor variable whose effect is to be represented
<code>newdata</code>	If non-NULL, a data frame passed to <code>predict.HLfit</code> , whose documentation should be consulted for further details.
<code>effects</code>	If non-NULL, a data frame to substitute to the one produced by default by <code>pdep_effects</code> .
<code>xlab</code>	If non-NULL, a character string: X-axis label for the plot.

ylab	If non-NULL, a character string: Y-axis label for the plot.
ylim	The plot's ylim argument. Default is based on the (0.025,0.975) quantiles of the response.
rgb.args	Color control arguments, in the format produced by <code>col2rgb</code> .
add	Boolean: whether to add graphic elements of a previous plot produced by <code>plot_effects</code>
length.out	Numeric: for a numeric predictor variable, the number of values at which predictions are evaluated. If zero, predictions are made for the actual value of the focal predictor in the data (see a possible use in Example).
levels	If non-NULL, a character vector: for a factor predictor variable, the levels for which which predictions are evaluated.
intervals	Passed to <code>predict.HLfit</code> , whose documentation should be consulted for further details.
indiv	Boolean: whether to return all predictions given the values of other predictors in the <code>newdata</code> , or only their means.
...	Further arguments passed by <code>plot_effects</code> to <code>pdep_effects</code> , or by <code>pdep_effects</code> to <code>predict.HLfit</code> .

### Value

For `pdep_effects`, a nested list, or a data frame storing values of the `focal_var`, average point predictions `pointp` and bounds `low` and `up` of intervals, depending on the `indiv` argument. When `indiv` is `TRUE`, each sublist contains vectors for `pointp`, `low` and `up`.

For `plot_effects`, the same value, returned invisibly.

### References

J.H. Friedman (2001). Greedy Function Approximation: A Gradient Boosting Machine. *Annals of Statistics* 29(5):1189-1232.

J. Friedman, T. Hastie and R. Tibshirani (2009) *The Elements of Statistical Learning*, 2nd ed. Springer.

### Examples

```
data("scotlip")
hlcor <- HLCor(cases~I(prop.ag/10) +adjacency(1|gridcode)+offset(log(expec)),
              adjMatrix=Nmatrix,family=poisson(),data=scotlip)
plot_effects(hlcor,focal_var="prop.ag",ylim=c(0,max(scotlip$cases)))
points(cases~prop.ag, data=scotlip, col="blue",pch=20)

### Adding 'partial residuals' on the plot:

# One first needs predictions for actual values of the predictor variable,
# provided by pdep_effects(.,length.out=0L):
#
pdep_points <- pdep_effects(hlcor,focal_var="prop.ag",length.out=0L)

# Rename for easy prediction for each observation, and add the residuals
```

```
# of the actual fit, using the default residuals() i.e. deviance ones:
#
rownames(pdep_points) <- pdep_points$focal_var
pdep_res <- pdep_points[paste(hlcor$data$prop.ag), "pointp"] +
  residuals(hlcor)

points(x = hlcor$data$prop.ag, y = pdep_res, col = "red", pch = 20)
```

Poisson

*Family function for GLMs and mixed models with Poisson and zero-truncated Poisson response.*

### Description

Poisson (with a capital P) is a **family** that specifies the information required to fit a Poisson generalized linear model. Differs from the base version `stats::poisson` only in that it handles the zero-truncated variant, which can be specified either as `Tpoisson(<link>)` or as `Poisson(<link>, trunc = 0L)`. The truncated poisson with mean  $\mu_T$  is defined from the un-truncated poisson with mean  $\mu_U$ , by restricting its response strictly positive value.  $\mu_T = \mu_U / (1 - p_0)$ , where  $p_0 := \exp(-\mu_U)$  is the probability that the response is 0.

### Usage

```
Poisson(link = "log", trunc = -1L)
Tpoisson(link="log")
# <Poisson object>$linkfun(mu, mu_truncated = FALSE)
# <Poisson object>$linkinv(eta, mu_truncated = FALSE)
```

### Arguments

link	log, sqrt or identity link, specified by any of the available ways for GLM links (name, character string, one-element character vector, or object of class <code>link-glm</code> as returned by <code>make.link</code> ).
trunc	Either <code>0L</code> for zero-truncated distribution, or <code>-1L</code> for default untruncated distribution.
eta, mu	Numeric (scalar or array). The linear predictor; and the expectation of response, truncated or not depending on <code>mu_truncated</code> argument.
mu_truncated	Boolean. For <code>linkinv</code> , whether to return the expectation of truncated ( $\mu_T$ ) or un-truncated ( $\mu_U$ ) response. For <code>linkfun</code> , whether the <code>mu</code> argument is $\mu_T$ , or is $\mu_U$ but has $\mu_T$ as attribute ( $\mu_U$ without the attribute is not sufficient).

### Details

The `mu.eta` member function is that of the base `poisson` family, hence ignores truncation.

`predict`, when applied on an object with a truncated-response family, by default returns  $\mu_T$ . The simplest way to predict  $\mu_U$  is to get the linear predictor value by `predict(., type="link")`, and deduce  $\mu_U$  using `linkinv(.)` (with default argument `mu_truncated=FALSE`), since getting  $\mu_U$  from  $\mu_T$  is comparatively less straightforward.

**Value**

A family object.

**References**

McCullagh, P. and Nelder, J.A. (1989) Generalized Linear Models, 2nd edition. London: Chapman & Hall.

**Examples**

```
data("scotlip")
logLik(glm(I(1+cases)~1,family=Tpoisson(),data=scotlip))
logLik(fitme(I(1+cases)~1+(1|id),family=Tpoisson(),fixed=list(lambda=1e-8),data=scotlip))
```

---

post-fit

*Applying post-fit procedures on spaMM results*

---

**Description**

Packages implementing post-fit procedures define helper functions that may handle a limited range of classes of fit results. This documentation topic gives further directions to apply some post-fit procedures that handle objects of class `HLfit`. For other procedures, `spaMM` results may or may not be handled correctly by default. In such cases, diagnosing a failure in a debugging session may suggest a simple solution (such as providing the `coef.` argument to `multcomp::glht`).

**Details**

For multiple comparison procedures by `multcomp::glht`, one has to explicitly give the argument `coef.=fixef.HLfit` (see Examples; `fixef.HLfit` is the `spaMM` method for the generic function `fixef`);

For DHARMA plots, see [plot.HLfit](#);

For using `RLRsim::RLRTSim()`, see [get\\_RLRTSim\\_args](#).

**Examples**

```
if (requireNamespace("multcomp", quietly = TRUE)) {
  library(multcomp)
  set.seed(123)
  iris <- cbind(iris,id=sample(4,replace=TRUE,size=nrow(iris)))
  irisfit <- fitme(Petal.Length~ Species +(1|id), data=iris, family=Gamma(log))
  summary(glht(irisfit,mcp("Species" = "Tukey"), coef.=fixef.HLfit))
}
```

---

 predict

*Prediction from a model fit*


---

### Description

The following functions can be used to compute point predictions and/or various measures of uncertainty associated to such predictions. `predict` can be used for prediction of the response variable by its expected value obtained as (the inverse link transformation of) the linear predictor ( $\eta$ ) and more generally for terms of the form  $\mathbf{X}_n\beta + \mathbf{Z}_n\mathbf{L}\mathbf{v}$ , for new design matrices  $\mathbf{X}_n$  and  $\mathbf{Z}_n$ . Various components of prediction variances and predictions intervals can also be computed using `predict`. The `get_...` functions are convenient extractors for such components. `get_predCov_var_fix` extracts a block of a prediction covariance matrix. It was conceived for the specific purpose of computing the spatial prediction covariances between two “new” sets of geographic locations, without computing the full covariance matrix for both the new locations and the original (fitted) locations. When one of the two sets of new locations is fixed while the other varies, some expensive computations can be performed once for all sets of new locations, and be provided as the `fix_X_ZAC.object` argument. The `preprocess_fix_corr` extractor is designed to compute this argument.

### Usage

```
## S3 method for class 'HLfit'
predict(object, newdata = newX, newX = NULL, re.form = NULL,
        variances=list(), binding = FALSE, intervals = NULL,
        level = 0.95, blockSize = 2000L, type = "response",
        verbose=c(showpbar=eval(spaMM.getOption("barstyle"))),
        control=list(), ...)
get_predCov_var_fix(object, newdata = NULL, fix_X_ZAC.object, fixdata, re.form = NULL,
                    variances=list(disp=TRUE, residVar=FALSE, cov=FALSE),
                    control=list(), ...)
preprocess_fix_corr(object, fixdata, re.form = NULL,
                   variances=list(residVar=FALSE, cov=FALSE), control=list())
get_fixefVar(...)
get_predVar(..., variances=list(), which="predVar")
get_residVar(...)
get_respVar(...)
get_intervals(..., intervals="predVar")
```

### Arguments

<code>object</code>	The return object of fitting functions <code>HLfit</code> , <code>corrHLfit</code> , <code>HLCor...</code> returning an object inheriting from <code>HLfit</code> class.
<code>newdata</code>	<b>Either</b> <code>NULL</code> , a matrix or data frame, or a numeric vector. If <code>NULL</code> , the original data are reused. Otherwise, all variables required to evaluate model formulas must be included. Which variables are required may depend on other arguments: see “prediction with given phi’s” example, also illustrating the syntax when formulas include an offset.

If `newdata` is a numeric vector, its names (if any) are ignored. This makes it easier to use `predict` as an objective function for an optimization procedure such as `optim`, which calls the objective function on unnamed vectors. However, one must make sure that the order of elements in the vector is the order of first occurrence of the variables in the model formula. This order can be checked in the error message returned when calling `predict` on a `newX` vector of clearly wrong size, e.g. `predict(<object>, newdata=numeric(0))`.

<code>newX</code>	equivalent to <code>newdata</code> , available for back-compatibility
<code>re.form</code>	formula for random effects to include. By default, it is <code>NULL</code> , in which case all random effects are included. If it is <code>NA</code> , no random effect is included. If it is a formula, only the random effects it contains are retained. The other variance components are removed from both point prediction and variances calculations. If you want to retain only the spatial effects in the point prediction, but all variances, either use <code>re.form</code> and add missing variances (on linear predictor scale) manually, or ignore this argument and see <a href="#">Details and Examples</a> for different ways of controlling variances.
<code>variances</code>	A list whose elements control the computation of different estimated variances. <code>predict</code> can return four components of prediction variance: <code>fixefVar</code> , <code>predVar</code> , <code>residVar</code> and <code>respVar</code> . They are all returned as attributes of the point predictions.  In particular, <code>variances=list(predVar=TRUE)</code> is suitable for uncertainty in point prediction, distinguished from the response variance given by <code>list(respVar=TRUE)</code> . See the <a href="#">predVar</a> help page for further explanations and other options.
<code>intervals</code>	<code>NULL</code> or character string or vector of strings. Provides prediction intervals with nominal level <code>level</code> , deduced from the given prediction variance term, e.g. <code>intervals="predVar"</code> . Currently only intervals from <code>fixefVar</code> and <code>predVar</code> (and for LMMs <code>respVar</code> including the residual variance) may have a probabilistic meaning. Intervals returned in other cases are (currently) meaningless.
<code>which</code>	any of <code>"predVar"</code> , <code>"respVar"</code> , <code>"residVar"</code> , <code>"fixefVar"</code> , <code>"intervals"</code> , or <code>"naive"</code>
<code>level</code>	Coverage of the intervals.
<code>binding</code>	If <code>binding</code> is a character string, the predicted values are bound with the <code>newdata</code> and the result is returned as a data frame. The predicted values column name is the given <code>binding</code> , or a name based on it if the <code>newdata</code> already include a variable with this name. If <code>binding</code> is <code>FALSE</code> , The predicted values are returned as a one-column matrix and the data frame used for prediction is returned as an attribute (unless it was <code>NULL</code> ). If <code>binding</code> is <code>NA</code> , a vector is returned, without the previous attributes.
<code>fixdata</code>	A data frame describing reference data whose covariances with variable <code>newdata</code> may be requested.
<code>fix_X_ZAC.object</code>	The return value of calling <code>preprocess_fix_corr</code> (see <a href="#">trivial Example</a> ). This is a more efficient way of providing information about the <code>fixdata</code> for repeated calls to <code>get_predCov_var_fix</code> with variable <code>newdata</code> .
<code>blockSize</code>	Mainly for development purposes. For original or new data with many rows, it may be more efficient to split these data in small blocks, and this gives the

	maximum number or rows of the blocks. However, this will be ignored if a prediction covariance matrix is requested.
type	character string; The returned point prediction is on the response scale if type="response" (the default; for binomial response, a frequency $0 < . < 1$ ). It is on the linear predictor scale if type="link".
control	A list; a warning will direct you to relevant usage when needed.
verbose	A vector of booleans; its single currently used element is "showpbar", which controls whether to show a progress bar in certain prediction variance computations.
...	further arguments passed to or from other methods. For the get_... functions, they are passed to predict.

### Details

See the [predVar](#) help page for information about the different concepts of prediction variances handled by spaMM (uncertainty of point prediction vs. of response) and about options controlling their computation.

If newdata is NULL, predict returns the fitted responses, including random effects, from the object. Otherwise it computes new predictions including random effects as far as possible. For spatial random effects it constructs a correlation matrix  $\mathbf{C}$  between new locations and locations in the original fit. Then it infers the random effects in the new locations as  $\mathbf{C} (\mathbf{L}')^{-1} \mathbf{v}$  (see [spaMM](#) for notation). For non-spatial random effects, it checks whether any group (i.e., level of a random effect) in the new data was represented in the original data, and it adds the inferred random effect for this group to the prediction for individuals in this group.

In the **point prediction** of the linear predictor, the unconditional expected value of  $u$  is assigned to the realizations of  $u$  for unobserved levels of non-spatial random effects (it is zero in GLMMs but not for non-gaussian random effects), and the inferred value of  $u$  is assigned in all other cases. Corresponding values of  $v$  are then deduced. This computation yields the classical "BLUP" or empirical Bayes predictor in LMMs, but otherwise it may yield less well characterized predictors, where "unconditional"  $v$  may not be its expected value when the rand.family link is not identity.

**Intervals** computations use the relevant variance estimates plugged in a Gaussian approximation, except for the simple linear model where it uses Student's  $t$  distribution.

### Value

See Details in [Tpoisson](#) for questions specific to truncated distributions.

For predict, a matrix or data frame (according to the binding argument), with optional attributes frame, intervals, predVar, fixefVar, residVar, and/or respVar, the last four holding one or more variance vector or covariance matrices. The further attribute fittedName contains the binding name, if any.

The get\_... extractor functions call predict and extract from its result the attribute implied by the name of the extractor. By default, get\_intervals will return prediction intervals using predVar. get\_predVar with non-default which argument has the same effect as the get\_... function whose name is implied by which.

**See Also**

[predVar](#) for information specific to prediction variances *sensu lato*; [get\\_cPredVar](#) for a bootstrap-corrected version of [get\\_predVar](#); [residVar](#) for an alternative extractor for residual variances, more general than [get\\_residVar](#).

**Examples**

```

data("blackcap")
fitobject <- fitme(migStatus ~ 1 + Matern(1|longitude+latitude),data=blackcap,
                 fixed=list(nu=4,rho=0.4,phi=0.05))
predict(fitobject)

#### multiple controls of prediction variances
## (1) fit with an additional random effect
grouped <- cbind(blackcap,grp=c(rep(1,7),rep(2,7)))
fitobject <- fitme(migStatus ~ 1 + (1|grp) +Matern(1|longitude+latitude),
                 data=grouped, fixed=list(nu=4,rho=0.4,phi=0.05))

## (2) re.form usage to remove a random effect from point prediction and variances:
predict(fitobject,re.form= ~ 1 + Matern(1|longitude+latitude))

## (3) comparison of covariance matrices for two types of new data
moregroups <- grouped[1:5,]
rownames(moregroups) <- paste0("newloc",1:5)
moregroups$grp <- rep(3,5) ## all new data belong to an unobserved third group
cov1 <- get_predVar(fitobject,newdata=moregroups,
                  variances=list(linPred=TRUE,cov=TRUE))
moregroups$grp <- 3:7 ## all new data belong to distinct unobserved groups
cov2 <- get_predVar(fitobject,newdata=moregroups,
                  variances=list(linPred=TRUE,cov=TRUE))
cov1-cov2 ## the expected off-diagonal covariance due to the common group in the first fit.

## Not run:
#### Other extractors:
fix_X_ZAC.object <- preprocess_fix_corr(fitobject,fixdata=blackcap)
# ... for use in multiple calls to get_predCov_var_fix():
get_predCov_var_fix(fitobject,newdata=blackcap[14,],fix_X_ZAC.object=fix_X_ZAC.object)

#### Prediction with distinct given phi's in different locations,
# as specified by a resid.model:
varphi <- cbind(blackcap,logphi=runif(14))
vphifit <- fitme(migStatus ~ 1 + Matern(1|longitude+latitude),
                resid.model = list(formula=~0+offset(logphi)),
                data=varphi, fixed=list(nu=4,rho=0.4))

# For respVar computation (i.e., response variance, often called prediction variance),
# one then also needs to provide the variables used in 'resid.model', here 'logphi':
get_respVar(vphifit,newdata=data.frame(latitude=1,longitude=1,logphi=1))

# For default 'predVar' computation (i.e., uncertainty in point prediction),
# this is not needed:
get_predVar(vphifit,newdata=data.frame(latitude=1,longitude=1))

```

```
#### point predictions and variances with new X and Z
if(requireNamespace("rsae", quietly = TRUE)) {
  data("landsat", package = "rsae")
  fitobject <- fitme(HACorn ~ PixelsCorn + PixelsSoybeans + (1|CountyName),
                    data=landsat[-33,])
  newXandZ <- unique(data.frame(PixelsCorn=landsat$MeanPixelsCorn,
                                PixelsSoybeans=landsat$MeanPixelsSoybeans,
                                CountyName=landsat$CountyName))
  predict(fitobject,newdata=newXandZ,variances = list(predVar=TRUE))
  get_predVar(fitobject,newdata=newXandZ,variances = list(predVar=TRUE))
}

## End(Not run)
```

---

predVar

*Prediction and response variances*

---

## Description

spaMM allows computation of four variance components of prediction, returned by predict as “...Var” attributes: predVar, fixefVar, residVar, or respVar. The phrase “prediction variance” is used inconsistently in the literature. Often it is used to denote the uncertainty in the response (therefore, including the residual variance), but spaMM departs from this usage. Here, this uncertainty is called the response variance (respVar), while prediction variance (predVar) is used to denote the uncertainty in the linear predictor (as in Booth & Hobert, 1998). The respVar is the predVar plus the residual variance residVar.

Which components are returned is controlled in particular by the type and variances arguments of the relevant functions. variances is a list of booleans whose possible elements either match the possible returned components: predVar, fixefVar, residVar, or respVar; or may additionally include linPred, disp, cov, as\_tcrossfac\_list and possibly other cryptic ones.

The predict default value for all elements is NULL, which jointly translate to no component being computed, equivalently to setting all elements to FALSE. However, setting one component to TRUE may reverse the default effect for other components. In particular, by default, component predVar implies linPred=TRUE, disp=TRUE and component respVar additionally implies residVar=TRUE; in both cases, the linPred=TRUE default by default implies fixefVar=TRUE. Calling for one variance may imply that some of its components are not only computed but also returned as a distinct attribute.

By default the returned components are vectors of variances (with exceptions for some type value). To obtain covariance matrices (when applicable), set cov=TRUE. as\_tcrossfac\_list=TRUE can be used to return a list of matrices  $X_i$  such that the predVar\ covariance matrix equals  $\sum_i X_i X_i'$ . It thus provides a representation of the predVar that may be useful in particular when the predVar has large dimension, as the component  $X_i$ s may require less memory (being possibly non-square or sparse).

residVar=TRUE evaluates residVar the residual variances for Gaussian or Gamma responses.

fixefVar=TRUE evaluates fixefVar, the variance due to uncertainty in fixed effects ( $\mathbf{X}\beta$ ).

Computations implying linPred=TRUE will take into account the variances of the linear predictor  $\eta$ , i.e. the uncertainty in fixed effects ( $\mathbf{X}\beta$ ) and random effects ( $\mathbf{ZL}\mathbf{v}$ ), **for given dispersion parameters** (see Details). For fixed-effect models, the fixefVar calculations reduces to the linPred one.

Computations implying disp=TRUE additionally include the effect of uncertainty in estimates of dispersion parameters ( $\lambda$  and  $\phi$ ), with some limitations: this effect can be computed for a scalar residual variance ( $\phi$ ) and for several random effects with scalar variances ( $\lambda$ ). Thus, the argument variances=list(predVar=TRUE) implies that uncertainty if linear predictor, including uncertainty in dispersion parameters, is taken into account, and the argument variances=list(respVar=TRUE) additionally includes residual variance.

## Details

fixefVar is the (co)variance of  $\mathbf{X}\beta$ , deduced from the asymptotic covariance matrix of  $\beta$  estimates. linPred is the prediction (co)variance of  $\eta=\mathbf{X}\beta+\mathbf{Z}\mathbf{v}$  (see [HLfit](#) Details for notation, and keep in mind that new matrices may replace the ones from the fit object when newdata are used), by default computed for given dispersion parameters. It takes into account the joint uncertainty in estimation of  $\beta$  and prediction of  $\mathbf{v}$ . In particular, for new levels of the random effects, predVar computation takes into account uncertainty in prediction of  $\mathbf{v}$  for these new levels. For **prediction covariance** with a new  $\mathbf{Z}$ , it matters whether a single or multiple new levels are used: see Examples.

For computations implying disp=TRUE, prediction variance may also include a term accounting for uncertainty in  $\phi$  and  $\lambda$ , computed following Booth and Hobert (1998, eq. 19). This computation ignores uncertainties in spatial correlation parameters.

respVar is the sum of predVar (pre- and post-multiplied by  $\partial\mu/\partial\eta$  for models with non-identity link) and of residVar.

These variance calculations are approximate except for LMMs, and cannot be guaranteed to give accurate results.

## References

Booth, J.G., Hobert, J.P. (1998) Standard errors of prediction in generalized linear mixed models. J. Am. Stat. Assoc. 93: 262-272.

## Examples

```
## Not run:
# (but run in help("get_predVar"))
data("blackcap")
fitobject <- fitme(migStatus ~ 1 + Matern(1|longitude+latitude), data=blackcap,
                 fixed=list(nu=4, rho=0.4, phi=0.05))

#### multiple controls of prediction variances
# (1) fit with an additional random effect
grouped <- cbind(blackcap, grp=c(rep(1,7), rep(2,7)))
fitobject <- fitme(migStatus ~ 1 + (1|grp) + Matern(1|longitude+latitude),
                 data=grouped, fixed=list(nu=4, rho=0.4, phi=0.05))
```

```

# (2) re.form usage to remove a random effect from point prediction and variances:
predict(fitobject,re.form= ~ 1 + Matern(1|longitude+latitude))

# (3) comparison of covariance matrices for two types of new data
moregroups <- grouped[1:5,]
rownames(moregroups) <- paste0("newloc",1:5)
moregroups$grp <- rep(3,5) ## all new data belong to an unobserved third group
cov1 <- get_predVar(fitobject,newdata=moregroups,
                   variances=list(linPred=TRUE,cov=TRUE))
moregroups$grp <- 3:7 ## all new data belong to distinct unobserved groups
cov2 <- get_predVar(fitobject,newdata=moregroups,
                   variances=list(linPred=TRUE,cov=TRUE))
cov1-cov2 ## the expected off-diagonal covariance due to the common group in the first fit.

## End(Not run)
## see help("get_predVar") for further examples

```

---

random-effects

*Structure of random effects*


---

## Description

The structure of random-effect models adjustable by spaMM can generally be described by the following steps.

First, independent and identically distributed (iid) random effects  $\mathbf{u}$  are drawn from one of the following distributions: **Gaussian** with zero mean, unit variance, and identity link; **Beta**-distributed, where  $u \sim B(1/(2\lambda), 1/(2\lambda))$  with mean=1/2, and var=  $\lambda/[4(1+\lambda)]$ ; and with logit link  $v=\text{logit}(u)$ ; **Gamma**-distributed random effects, where  $u \sim \text{Gamma}(\text{shape}=1+1/\lambda, \text{scale}=1/\lambda)$ : see [Gamma](#) for allowed links and further details; and **Inverse-Gamma**-distributed random effects, where  $u \sim \text{inverse-Gamma}(\text{shape}=1+1/\lambda, \text{rate}=1/\lambda)$ : see [inverse.Gamma](#) for allowed links and further details.

Second, a transformation  $\mathbf{v} = f(\mathbf{u})$  is applied (this defines  $\mathbf{v}$  whose elements are still iid).

Third, correlated random effects are obtained as  $\mathbf{M}\mathbf{v}$ , where the matrix  $\mathbf{M}$  can describe spatial correlation between observed locations, block effects (or repeated observations in given locations), and correlations involving unobserved locations. In most cases  $\mathbf{M}$  is determined from the model formula, but it can also be controlled by `covStruct` argument.  $\mathbf{M}$  takes the form  $\mathbf{Z}\mathbf{L}$  or  $\mathbf{Z}\mathbf{A}\mathbf{L}$ , where  $\mathbf{Z}$  is determined from the model formula, the optional  $\mathbf{A}$  factor is given by the optional "AMatrices" attribute of argument `covStruct` of `HLCor` (also handled by `fitme` and `corrHLfit`), and  $\mathbf{L}$  can be determined from the model formula or from `covStruct`. In particular:

$\mathbf{Z}$  is typically an incidence matrix: its elements  $z_{ij}$  are 1 if the  $i$ th observation is affected by the  $j$ th element of `ALb`, and zero otherwise.

For spatial random effects,  $\mathbf{L}$  is typically the Cholesky "square root" of a correlation matrix determined by the random effect specification (e.g., `Matern(...)`), or given by the `covStruct` argument. This may be meaningful only for Gaussian random effects. Coefficients for each level of a random-coefficient model can also be represented as  $\mathbf{L}\mathbf{v}$  where  $\mathbf{L}$  is the "square root" of a correlation matrix.

If there is one response value per location,  $\mathbf{L}$  for a spatial random effect is thus a square matrix whose dimension is the number of observations. Alternatively, several observations may be taken in the same location, and a matrix  $\mathbf{Z}$  (automatically constructed) tells which element of  $\mathbf{L}\mathbf{v}$  affects each observation. The linear predictor then contains a term of the form  $\mathbf{Z}\mathbf{L}\mathbf{v}$ , where  $\dim(\mathbf{Z})$  is (number of observations, number of locations).

in [IMRF](#) random effects (IMRF for Interpolated Markov Random Fields), the realized random effects in response locations are defined as linear combinations  $\mathbf{A}\mathbf{L}\mathbf{v}$  of random effects  $\mathbf{L}\mathbf{v}$  in distinct locations. In that case the dimension of  $\mathbf{L}$  is the number of such distinct locations, an automatically constructed  $\mathbf{A}$  matrix maps them to the observed locations, and  $\mathbf{Z}$  again maps them to possibly repeated observations in observed locations.

---

rankinfo

*Checking the rank of the fixed-effects design matrix*


---

## Description

By default, fitting functions in spaMM check the rank of the design matrix for fixed effects, as `stats::lm` or `stats::glm` do (but not, say, `nlme::lme`). This computation can be quite long. To save time when fitting different models with the same fixed-effect terms to the same data, the result of the check can be extracted from a return object by `get_rankinfo()`, and can be provided as argument `control.HLfit$rankinfo` to another fit. Alternatively, the check will not be performed if `control.HLfit$rankinfo` is set to NA.

## Usage

```
get_rankinfo(object)
```

## Arguments

`object`            An object of class `HLfit`, as returned by the fitting functions in spaMM.

## Details

The check is performed by a call to `qr()` methods for either dense or sparse matrices. If the design matrix is singular, a set of columns from the design matrix that define a non-singular matrix is identified. Note that different sets may be identified by sparse- and dense-matrix `qr` methods.

## Value

A list with elements `rank`, `whichcols` (a set of columns that define a non-singular matrix), and `method` (identifying the algorithm used).

**Examples**

```
## Data preparation
# Singular matrix from ?Matrix::qr :
singX <- cbind(int = 1,
               b1=rep(1:0, each=3), b2=rep(0:1, each=3),
               c1=rep(c(1,0,0), 2), c2=rep(c(0,1,0), 2), c3=rep(c(0,0,1),2))
rownames(singX) <- paste0("r", seq_len(nrow(singX)))
donn <- as.data.frame(singX)
set.seed(123)
donn$y <- runif(6)

fitlm <- fitme(y~int+ b1+b2+c1+c2+c3,data=donn)
get_rankinfo(fitlm)
```

---

residuals.HLfit	<i>Extract model residuals</i>
-----------------	--------------------------------

---

**Description**

Extracts several types of residuals from an object of class HLfit.

**Usage**

```
## S3 method for class 'HLfit'
residuals(object,
           type = c("deviance", "pearson", "response", "std_dev_res"), force=FALSE, ...)
```

**Arguments**

object	An object of class HLfit, as returned by the fitting functions in spaMM.
type	The type of residuals which should be returned. The alternatives are: "deviance" (default), "pearson", "response" and "std_dev_res". See <a href="#">residuals.glm</a> for more information about the first three, and the Details for the last one.
force	Boolean: to force recomputation of the "std_dev_res" residuals even if they are available in the object, for checking purposes.
...	For consistency with the generic.

**Details**

Following Lee et al. (2006, p.52), the standardized deviance residuals returned for type="std\_dev\_res" are defined as the deviance residuals divided by  $\phi\sqrt{(1-q)}$ , where the deviance residuals are defined as for a GLM,  $\phi$  is the dispersion parameter of the response family (a vector of values, for heteroscedastic cases), and  $q$  is a vector of leverages given by `hatvalues(., type="std")` (see [hatvalues](#) for details about these specific standardizing leverages).

**Value**

A vector of residuals

**References**

Lee, Y., Nelder, J. A. and Pawitan, Y. (2006). Generalized linear models with random effects: unified analysis via h-likelihood. Chapman & Hall: London.

**Examples**

```
data("wafers")
fit <- fitme(y ~X1+(1|batch) ,data=wafers, init=list(phi=NaN)) # : this 'init'
#               implies that standardized deviance residuals are saved in the
#               fit result, allowing the following comparison:

r1 <- residuals(fit, type="std_dev_res") # gets stored value
r2 <- residuals(fit, type="std_dev_res", force=TRUE) # forced recomputation
if (diff(range(r1-r2))>1e-14) stop()
```

residVar

*Residual variance extractor***Description**

Extracts from a fit object the residual variance. If a non-default which values is used, it can also return a vector of values of the dispersion parameter phi, which is not the residual variance itself for gamma-response models, or further information about the residual variance model.

**Usage**

```
residVar(object, which = "var", submodel = NULL, newdata = NULL)
```

**Arguments**

object	An object of class <code>HLfit</code> , as returned by the fitting functions in <code>spaMM</code> .
which	Character: "var" for the fitted residual variances, "phi" for the fitted phi values, "fam_parm" for the dispersion parameter of <code>COMPOisson</code> and <code>negbin</code> families, "fit" for the fitted residual model (a GLM or a mixed model for residual variances, if not a simpler object), and "family" or "formula" for such properties of the residual model.
submodel	integer: the index of a submodel, if object is a multivariate-response model fitted by <code>fitmv</code> . This argument is mandatory for all which values except "var" and "phi".
newdata	<b>Either</b> <code>NULL</code> , a matrix or data frame, or a numeric vector. See <a href="#">predict.HLfit</a> for details.

**Value**

Default `which="var"` (or `"phi"`) always return a vector of residual variances (or, alternatively, `phi` values) of length the number of responses of the fit (or only the number of responses for a submodel, if relevant). `which="fit"` returns an object of class `HLfit`, `glm`, or a single scalar depending on the residual dispersion model. Other `which` values return an object of class `family` or formula as expected.

**See Also**

`get_residVar` is an alternative extractor of residual variances with different features inherited from `get_predVar`. In particular, it is more suited for computing the residual variances of new realizations of a fitted model, not accounting for prior weights used in fitting the model (basic examples of using the `Isorix` package provide a context where this is the appropriate design decision). By contrast, `residVar` aims to account for prior weights.

**Examples**

```
# data preparation: simulated trivial life-history data
set.seed(123)
nind <- 20L
u <- rnorm(nind)
lfh <- data.frame(
  id=seq_len(nind), id2=seq_len(nind),
  feco= rpois(nind, lambda = exp(1+u)),
  growth=rgamma(nind,shape=1/0.2, scale=0.2*exp(1+u)) # mean=exp(1+u), var= 0.2*mean^2
)
# multivariate-response fit
fitlfh <- fitmv(submodels=list(list(feco ~ 1+(1|id), family=poisson()),
                              list(growth ~ 1+(1|id), family=Gamma(log))),
              data=lfh)
#
residVar(fitlfh)
residVar(fitlfh, which="phi") # shows fixed phi=1 for Poisson responses
residVar(fitlfh, submodel=2)
residVar(fitlfh, which="family", submodel=2)
residVar(fitlfh, which="formula", submodel=2)
residVar(fitlfh, which="fit", submodel=2) # Fit here characterized by a single scalar
```

---

salamander

*Salamander mating data*


---

**Description**

Data from a salamander mating experiment discussed by McCullagh and Nelder (1989, Ch. 14). Twenty males and twenty females from two populations (Rough Butt and Whiteside) were each paired with 6 individuals from their own or from the other population. The experiments were later published by Arnold et al. (1996).

**Usage**

```
data("salamander")
```

**Format**

The data frame includes 360 observations on the following variables:

**Female** Index of the female;

**Male** Index of the male;

**Mate** Whether the pair successfully mated or not;

**TypeF** Population of origin of female;

**TypeM** Population of origin of male;

**Cross** Interaction term between TypeF and TypeM;

**Season** A factor with levels Summer and Fall;

**Experiment** Index of experiment

**Source**

The data frame was borrowed from the HGLMMM package (Molas and Lesaffre, 2011), version 0.1.2.

**References**

Arnold, S.J., Verrell, P.A., and Tilley S.G. (1996) The evolution of asymmetry in sexual isolation: a model and a test case. *Evolution* 50, 1024-1033.

McCullagh, P. and Nelder, J.A. (1989). *Generalized Linear Models*, 2nd edition. London: Chapman & Hall.

Molas, M., Lesaffre, E. (2011) Hierarchical Generalized Linear Models: The R Package HGLMMM. *Journal of Statistical Software* 39, 1-20.

**Examples**

```
data("salamander")

## Not run:

HLfit(cbind(Mate, 1-Mate)~TypeF+TypeM+TypeF*TypeM+(1|Female)+(1|Male),
      family=binomial(), data=salamander, method="ML")
# equivalent fo using fitme(), but here a bit faster

## End(Not run)
```

---

 scotlip

*Lip cancer in Scotland 1975 - 1980*


---

### Description

This data set provides counts of lip cancer diagnoses made in Scottish districts from 1975 to 1980, and additional information relative to these data from Clayton and Kaldor (1987) and Breslow and Clayton (1993). The data set contains (for each district) counts of disease events and estimates of the fraction of the population involved in outdoor industry (agriculture, fishing, and forestry) which exposes it to sunlight.

`data("scotlip")` actually loads a data frame, `scotlip`, and an adjacency matrix, `Nmatrix`, between 56 Scottish districts, as given by Clayton and Kaldor (1987, Table 1).

### Usage

```
data("scotlip")
```

### Format

The data frame includes 56 observations on the following 7 variables:

**gridcode** alternative district identifier.

**id** numeric district identifier (1 to 56).

**district** district name.

**cases** number of lip cancer cases diagnosed 1975 - 1980.

**population** total person years at risk 1975 - 1980.

**prop.ag** percent of the population engaged in outdoor industry.

**expec** offsets considered by Breslow and Clayton (1993, Table 6, 'Exp' variable)

The rows are ordered according to `gridcode`, so that they match the rows of `Nmatrix`.

### References

Clayton D, Kaldor J (1987). Empirical Bayes estimates of age-standardized relative risks for use in disease mapping. *Biometrics*, 43: 671 - 681.

Breslow, NE, Clayton, DG. (1993). Approximate Inference in Generalized Linear Mixed Models. *Journal of the American Statistical Association*: 88 9-25.

### Examples

```
data("scotlip")
fitme(cases~I(log(expec)), data=scotlip, adjMatrix=Nmatrix, family=poisson)
```

```
## see 'help(autoregressive)' for additional examples involving 'scotlip'.
```

---

`seaMask`*Masks of seas or lands*

---

## Description

These convenient masks can be added to maps of (parts of) the world to mask map information for these areas.

## Usage

```
data("seaMask")
data("landMask")
# data("worldcountries") # deprecated and removed
# data("oceanmask") # deprecated and removed
```

## Format

`seaMask` and `landMask` are data frames with two variables, `x` and `y` for longitude and latitude. Its contents are suitable for use with `polypath`: they define different polygones, each separated by a row of NAs.

`worldcountries` and `oceanmask` were `sp::SpatialPolygonsDataFrame` objects previously included in `spaMM` (see Details for replacement). Such objects were useful for creating land masks for different geographical projections.

## Details

The removed objects `worldcountries` and `oceanmask` were suitable for plots involving geographical projections not available through `map`, and more generally for raster plots. A land mask could be produced out of `worldcountries` by filling the countries, as by `fill="black"` in the code for `country.layer` in the Examples in [https://kimura.univ-montp2.fr/~rousset/spaMM/example\\_raster.html](https://kimura.univ-montp2.fr/~rousset/spaMM/example_raster.html). These objects may now be available through the same web page, but a better place to look for the same functionality is the `IsoriX` package (objects `CountryBorders` and `OceanMask`).

`seaMask` and `landMask` were created from the world map in the `maps` package. `polypath` requires polygons, while `map(interior=FALSE,plot=FALSE)` returns small segments. `landMask` is the result of reconnecting the segments into full coastlines of all land blocks.

## See Also

[https://kimura.univ-montp2.fr/~rousset/spaMM/example\\_raster.html](https://kimura.univ-montp2.fr/~rousset/spaMM/example_raster.html) for access to, and use of `worldcountries` and `oceanmask`; <https://cran.r-project.org/package=IsoriX> for replacement `CountryBorders` and `OceanMask` for these objects.

## Examples

```
## Predicting behaviour for a land bird: simplified fit for illustration
data("blackcap")
bfit <- fitme(migStatus ~ means+ Matern(1|longitude+latitude),data=blackcap,
             fixed=list(lambda=0.5537,phi=1.376e-05,rho=0.0544740,nu=0.6286311))

## the plot itself, with a sea mask,
## and an ad hoc 'pointmask' to see better the predictions on small islands
#
def_pointmask <- function(xy,r=1,npts=12) {
  theta <- 2*pi/npts *seq(npts)
  hexas <- lapply(seq(nrow(xy)), function(li){
    p <- as.numeric(xy[li,])
    hexa <- cbind(x=p[1]+r*cos(theta),y=p[2]+r*sin(theta))
    rbind(rep(NA,2),hexa) ## initial NA before each polygon
  })
  do.call(rbind,hexas)
}
ll <- blackcap[,c("longitude","latitude")]
pointmask <- def_pointmask(ll[c(2,4,5,6,7),],r=0.8) ## small islands only
#
if (spaMM.getOption("example_maxtime")>1) {
  data("seaMask")

  filled.mapMM(bfit,add.map=TRUE,
              plot.title=title(main="Inferred migration propensity of blackcaps",
                              xlab="longitude",ylab="latitude"),
              decorations=quote(points(pred[,coordinates],cex=1,pch="+")),
              plot.axes=quote({axis(1);axis(2);
                              polypath(rbind(seaMask,pointmask),border=FALSE,
                                             col="grey", rule="evenodd")
                              })))
}
```

---

 seeds

*Seed germination data*


---

## Description

A classic toy data set, “from research conducted by microbiologist Dr P. Whitney of Surrey University. A batch of tiny seeds is brushed onto a plate covered with a certain extract at a given dilution. The numbers of germinated and ungerminated seeds are subsequently counted” (Crowder, 1978). Two seed types and two extracts are here considered in a 2x2 factorial design.

## Usage

```
data("seeds")
```

**Format**

The data frame includes 21 observations on the following variables:

**plate** Factor for replication;

**seed** Seed type, a factor with two levels O73 and O75;

**extract** Root extract, a factor with two levels Bean and Cucumber;

**r** Number of seeds that germinated;

**n** Total number of seeds tested

**Source**

Crowder (1978), Table 3.

**References**

Crowder, M.J., 1978. Beta-binomial anova for proportions. *Appl. Statist.*, 27, 34-37.

Y. Lee and J. A. Nelder. 1996. Hierarchical generalized linear models (with discussion). *J. R. Statist. Soc. B*, 58: 619-678.

**Examples**

```
# An extended quasi-likelihood (EQL) fit as considered by Lee & Nelder (1996):
data("seeds")
fitme(cbind(r,n-r)~seed*extract+(1|plate),family=binomial(),
      rand.family=Beta(),
      method="EQL-", # see help("method") for difference with "EQL+" method
      data=seeds)
```

---

simulate.HLfit

*Simulate realizations of a fitted model.*

---

**Description**

From an HLfit object, simulate.HLfit function generates new samples given the estimated fixed effects and dispersion parameters. Simulation may be unconditional (the default, useful in many applications of parametric bootstrap), or conditional on the predicted values of random effects, or may draw from the conditional distribution of random effects given the observed response. Simulations may be run for the original values of fixed-effect predictor variables and of random effect levels (spatial locations for spatial random effects), or for new values of these.

**Usage**

```
## S3 method for class 'HLfit'
simulate(object, nsim = 1, seed = NULL, newdata = NULL,
         type = "marginal", re.form, conditional = NULL,
         verbose = c(type=TRUE,
                     showpbar=eval(spaMM.getOption("barstyle"))),
         sizes = NULL, resp_testfn = NULL, phi_type = "predict",
         prior.weights = object$prior.weights, variances=list(), ...)
## S3 method for class 'HLfitlist'
simulate(object, nsim = 1, seed = NULL,
         newdata = object[[1]]$data, sizes = NULL, ...)
```

**Arguments**

object	The return object of HLfit or similar function.
nsim	number of response vectors to simulate. Defaults to '1'.
seed	A seed for <a href="#">set.seed</a> . If such a value is provided, the initial state of the random number generator at a global level is restored on exit from simulate.
newdata	A data frame closely matching the original data, except that response values are not needed. May provide new values of fixed predictor variables, new spatial locations, or new individuals within a block.
re.form	formula for random effects to condition on. Default behaviour depends on the type argument. The joint default is the latter's default, i.e., unconditional simulation. re.form is currently ignored when type="Vlinpred" (with a warning). Otherwise, re.form=NULL conditions on all random effects (as type="residual" does), and re.form=NA conditions on none of the random effects (as type="marginal" or re.form=~0 do).
type	character string specifying which uncertainties are taken into account in the linear predictor and notably in the random effect terms. Whatever the type, the residual variance is always accounted in the simulation output. "marginal" accounts for the marginal variance of the random effect (and, by default, also for the uncertainty in fixed effects); "predVar" accounts for the conditional distribution of the random effects given the data (see Details); and "residual" should perhaps be "none" as no uncertainty is accounted in the linear predictor: the simulation variance is only the residual variance of the fitted model.
conditional	Obsolete and will be deprecated. Boolean; TRUE and FALSE are equivalent to type="residual" and type="marginal", respectively.
verbose	Either a single boolean (which determines verbose[["type"]]), or a vector of booleans with possible elements "type" (to display basic information about the type of simulation) and "showpbar" (see <code>codepredict(.,verbose)</code> ).
sizes	A vector of sample sizes to simulate in the case of a binomial fit. Defaults to the sizes in the original data.
resp_testfn	NULL, or a function that tests a condition which simulated samples should satisfy. This function takes a response vector as argument and return a boolean (TRUE indicating that the sampel satisfies the condition).

phi_type	Character string, either "predict" or one of the values possible for type. This controls the residual variance parameter $\phi$ . The default is to use predicted $\phi$ values from the fit, which are the fitted $\phi$ values except when a structured-dispersion model is involved together with non-NULL newdata. However, when a structured-dispersion model is involved, it is also possible to simulate new $\phi$ values, and for a mixed-effects structured-dispersion model, the same types of simulation controlled by type for the main response can be performed as controlled by phi_type. For a fixed-effects structured-dispersion model, these types cannot be distinguished, and any phi_type distinct from "predict" will imply simulation under the fixed-effect model (see Examples).
prior.weights	Prior weights that may be substituted to those of the original fit, with the same effect on the residual variance.
variances	Used when type="predVar": see Details.
...	further arguments passed to or from other methods; currently only passed to predict in a speculative bit of code (see Details).

## Details

type="predVar" accounts for the uncertainty of the linear predictor, by drawing new values of the predictor in a multivariate gaussian distribution with mean and covariance matrix of prediction. In this case, the user has to provide a variances argument, passed to predict, which controls what goes into this covariance matrix. For example, with variances=list(linPred=TRUE, disp=TRUE), the covariance matrix takes into account the joint uncertainty in the fixed-effect coefficients and of any random effects given the response and the point estimates of dispersion and correlation parameters ("linPred" variance component), and in addition accounts for uncertainty in the dispersion parameters (effect of "disp" variance component as further described in [predict.HLfit](#)). The total simulation variance is then the response variance. Uncertainty in correlation parameters (such a parameters of the Matern family) is not taken into account. The "linPred" uncertainty is known exactly in LMMs, and otherwise approximated as a Gaussian distribution with mean vector and covariance matrix given as per the Laplace approximation.

type="(ranef|response)" can be viewed as a special version of type="predVar" where variances=list(linPred=TRUE) and only the uncertainty in the random effects is taken into account.

A full discussion of the merits of the different types is beyond the scope of this documentation, but these different types may not all be useful. type="marginal" is typically used for computation of confidence intervals by parametric bootstrap methods. type="residual" is used by [get\\_cPredVar](#) for its evaluation of a bias term. The other types may be used to simulate the uncertainty in the random effects, conditionally on the data, and may therefore be more akin to the computation of prediction intervals conditionally on an (unknown but inferred) realization of the random effects. But these should presumably not be used in a bootstrap computation of such intervals, as this would represent a double accounting of the uncertainty that the bootstrap aims to quantify.

## Value

For the HLfitlist method (i.e., the result of a multinomial fit), a list of simulated responses. Otherwise, a vector (if nsim=1) or a matrix with nsim columns, each containing a simulated response.

## Examples

```

data("Loaloe")
HLC <- HLCor(cbind(npos,ntot-npos)~Matern(1|longitude+latitude),
             data=Loaloe,family=binomial(),
             ranPars=list(lambda=1,nu=0.5,rho=1/0.7))
simulate(HLC,nsim=2)

## Structured dispersion model
data("wafers")
hl <- HLfit(y ~X1+X2+X1*X3+X2*X3+I(X2^2)+(1|batch),family=Gamma(log),
            resid.model = ~ X3+I(X3^2) ,data=wafers)
simulate(hl,type="marginal",phi_type="simulate",nsim=2)

```

## Description

Fits a range of mixed-effect models, including those with spatially correlated random effects. The random effects are either Gaussian (which defines GLMMs), or other distributions (which defines the wider class of hierarchical GLMs), or simply absent (which makes a LM or GLM). Multivariate-response models can be fitted by the `fitmv` function. Other models can be fitted by `fitme` (the most general function). Also available are previously conceived fitting functions `HLfit` (sometimes faster, for non-spatial models), `HLCor` (sometimes faster, for conditional-autoregressive models and fixed-correlation models), and `corrHLfit` (now of lesser interest). Additional functions are available such as `fixedLRT` for likelihood-ratio testing, `simulate` and `predict`.

Both maximum likelihood (ML) and restricted likelihood (REML) can be used for linear mixed models, and extensions of these methods using Laplace approximations are used for non-Gaussian random response. Several variants of these methods discussed in the literature are included (see Details in `HLfit`), the most notable of which may be “PQL/L” for binary-response GLMMs (see Example for `arabidopsis` data). PQL methods implemented in spaMM are closer to (RE)ML methods than those implemented in `MASS::glmPQL`.

## Details

The standard response families `gaussian`, `binomial`, `poisson`, and `Gamma` are handled, as well as negative binomial (see `negbin`), zero-truncated poisson and negative binomial, and Conway-Maxwell-Poisson response (see `Tpoisson`, `Tnegbin` and `COMPoisson`). A multi family look-alike is also available for `multinomial` response, with some constraints.

The variance parameter of residual error is denoted  $\phi$  (phi): this is the residual variance for gaussian response, but for Gamma-distributed response, the residual variance is  $\phi\mu^2$  where  $\mu$  is expected response. A fixed-effects linear predictor for  $\phi$ , modeling heteroscedasticity, can be considered (see Examples).

The package fits models including several nested or crossed random effects, including autocorrelated ones with the following correlation models: `Matern`, `Cauchy`, interpolated Markov Random Fields (`IMRF`), first-order autoregressive (`AR1`), conditional autoregressive as specified by an

`adjacency` matrix, or any fixed correlation matrix (`corrMatrix`). GLMMs and HGLMs are fit via Laplace approximations for (1) the marginal likelihood with respect to random effects and (2) the restricted likelihood (as in REML), i.e. the likelihood of random effect parameters given the fixed effect estimates.

All handled models can be formulated in terms of a linear predictor of the traditional form  $\text{offset} + \mathbf{X}\beta + \mathbf{Z}\mathbf{b}$ , where  $\mathbf{X}$  is the design matrix of fixed effects,  $\beta$  (beta) is a vector of fixed-effect coefficients,  $\mathbf{Z}$  is a “design matrix” for the random effects (which is instead denoted  $\mathbf{M}=\mathbf{ZAL}$  elsewhere in the package documentation), and  $\mathbf{b}$  a vector of random effect values. The general structure of  $\mathbf{Mb}$  is described in [random-effects](#).

Gaussian and non-gaussian random effects can be fitted. Different **gaussian** random-effect terms are handled, with the following effects:

- \* (1|<RHS>), for non-autocorrelated random effects as in lme4;
- \* (<LHS>|<RHS>), for random-coefficient terms as in lme4, \*and additional terms depending on the <LHS> type\* (iurther detailed below);
- \* (<LHS> || <RHS>), interpreted as in lme4 (see `help('expandDoubleVerts')` in lme4, including the comment that it will fail to break up factors into separate terms). Any such term is immediately converted to  $(1|<RHS>) + (0+<LHS>|<RHS>)$ , and should be counted as two random effects for all purposes (e.g., for fixing the variances of the random effects);
- \* <prefix>(1|<RHS>), to specify autocorrelated random effects, e.g. `Matern(1|long+lat)`.
- \* <prefix>(<LHS>|<RHS>), where the <LHS> can be used to alter the autocorrelated random effect as detailed below.

Different LHS types of **gaussian** (<LHS>|<RHS>) random-effect terms are handled, with the following effects:

- \* <logical> (TRUE/FALSE): affects only responses for which <LHS> is TRUE;
- \* <factor built from a logical>: same a <logical> case;
- \* <factor not built from a logical>: random-coefficient term as in lme4;
- \* 0 + <factor not built from a logical>: same but contrasts are not used;
- \* factors specified by the `mv(...)` expression, generate random-coefficient terms specific to multivariate-response models fitted by `fitmv()` (see `help("mv")`). `0 + mv(...)` has the expected effect of not using contrasts;
- \* <numeric> (but not '0+<numeric>'): random-coefficient term as in lme4, with 2\*2 covariance matrix of effects on Intercept and slope;
- \* 0 + <numeric>: no Intercept so no covariance matrix (random-slope-only term).

The '0 + <numeric>' effect is achieved by direct control of the elements of the incidence matrix  $\mathbf{Z}$  through the <LHS> term: for numeric  $z$ , such elements are multiplied by  $z$  values, and thus provide a variance of order  $O(z \text{ squared})$ .

If one wishes to fit uncorrelated group-specific random-effects (say random effects with distinct variances for males and females or for different response variables), two syntaxes are thus possible, illustrated in “Elementary multivariate-response” example below: one can fit a `(0 + <factor>|.)` random-coefficient term with correlation fixed to 0; Alternatively, one can define **numeric**

(0|1) variables such as `numF <-as.numeric(<boolean for females>)` and a term of the form `(0 + numF | <block>)` (and similarly for males).

The following **gaussian** `<prefix>(<LHS>|<RHS>)` random-effect terms are handled:

\* Since version 3.9.0 it is possible to fit `corrMatrix(<LHS>|<RHS>)` terms that combines features of any of the above LHS types and of a random effect with given `corrMatrix`. See [composite-ranef](#) for details.

\* It is possible to fit some random-effect terms involving other (`<prefix>`) correlation models and a non-‘1’ LHS. Only the LHS types that do not imply estimating a random-coefficient covariance matrix are currently handled. For example, independent Matérn effects can be fitted for males and females by using the syntax `Matern(male|. ) + Matern(female|. )`, where `male` and `female` are TRUE/FALSE factors; and `Matern(0+<numeric>|. )` represents an autocorrelated random-slope (only) term (or, equivalently, a direct specification of heteroscedasticity of the Matérn random effect). By contrast, `Matern(z|. )` (with effect similar to that described in [composite-ranef](#)) is not yet implemented. \* In these autocorrelated random effects the `<RHS>` is generally restricted to the simplest form, except for AR1 and geostatistical models where the `<.>%in%<.>` form of nested random effect is allowed (see example in [MaternCorr](#)).

The syntax `(z-1|. )`, for **numeric** `z` only, can also be used to fit **some heteroscedastic non-Gaussian** random effects. For example, a Gamma random-effect term `(wei-1|block)` specifies an heteroscedastic Gamma random effect  $u$  with constant mean 1 and variance  $wei^2 \lambda$ , where  $\lambda$  is still the estimated variance parameter. See Details of [negbin](#) for a possible application. Here, this effect is not implemented through direct control of  $\mathbf{Z}$  (multiplying the elements of an incidence matrix  $\mathbf{Z}$  by `wei`), as this would have a different effect on the distribution of the random effect term. `(z|. )` is not defined for *non-Gaussian* random effects. It could mean that a correlation structure between random intercepts and random slopes for (say) Gamma-distributed random effects is considered, but such correlation structures are not well-specified by their correlation matrix.

### Author(s)

spaMM was initially published by François Rousset and Jean-Baptiste Ferdy, and is continually developed by F. Rousset and tested by Alexandre Courtiol.

### References

Lee, Y., Nelder, J. A. and Pawitan, Y. (2006). Generalized linear models with random effects: unified analysis via h-likelihood. Chapman & Hall: London.

Rousset F., Ferdy, J.-B. (2014) Testing environmental and genetic effects in the presence of spatial autocorrelation. *Ecography*, 37: 781-790. doi: [10.1111/ecog.00566](https://doi.org/10.1111/ecog.00566)

### See Also

The `test` directory of the package provides many additional examples of spaMM usage beyond those from the formal documentation.

### Examples

```
data("wafers")
data("scotlip") ## loads 'scotlip' data frame, but also 'Nmatrix'

##      Linear model
```

```

fitme(y ~ X1, data=wafers)

##      GLM
fitme(y ~ X1, family=Gamma(log), data=wafers)
fitme(cases ~ I(log(population)), data=scotlip, family=poisson)

##      Non-spatial GLMMs
fitme(y ~ 1+(1|batch), family=Gamma(log), data=wafers)
fitme(cases ~ 1+(1|gridcode), data=scotlip, family=poisson)
#
# Random-slope model (mind the output!)
fitme(y~X1+(X2|batch),data=wafers, method="REML")

## Spatial, conditional-autoregressive GLMM
if (spaMM.getOption("example_maxtime")>2) {
  fitme(cases ~ I(log(population))+adjacency(1|gridcode), data=scotlip, family=poisson,
        adjMatrix=Nmatrix) # with adjacency matrix provided by data("scotlip")
}
# see ?adjacency for more details on these models

## Spatial, geostatistical GLMM:
# see e.g. examples in ?fitme, ?corrHLfit, ?Loaloo, or ?arabidopsis;
# see examples in ?Matern for group-specific spatial effects.

##      Hierarchical GLMs with non-gaussian random effects
data("salamander")
if (spaMM.getOption("example_maxtime")>1) {
  # both gaussian and non-gaussian random effects
  fitme(cbind(Mate,1-Mate)~1+(1|Female)+(1|Male),family=binomial(),
        rand.family=list(gaussian(),Beta(logit)),data=salamander)

  # Random effect of Male nested in that of Female:
  fitme(cbind(Mate,1-Mate)~1+(1|Female/Male),
        family=binomial(),rand.family=Beta(logit),data=salamander)
  # [ also allowed is cbind(Mate,1-Mate)~1+(1|Female)+(1|Male %in% Female) ]
}

##      Modelling residual variance (= structured-dispersion models)
# GLM response, fixed effects for residual variance
fitme( y ~ 1,family=Gamma(log),
      resid.model = ~ X3+I(X3^2) ,data=wafers)
#
# GLMM response, and mixed effects for residual variance
if (spaMM.getOption("example_maxtime")>1.5) {
  fitme(y ~ 1+(1|batch),family=Gamma(log),
        resid.model = ~ 1+(1|batch) ,data=wafers)
}

## Elementary multivariate-response model (see fitmv() for a more general procedure)
# Data preparation
fam <- rep(c(1,2),rep(6,2)) # define two biological 'families'
ID <- gl(6,2) # define 6 'individuals'
resp <- as.factor(rep(c("x","y"),6)) # distinguishes two responses per individual

```

```

set.seed(123)
toymv <- data.frame(
  fam = factor(fam), ID = ID, resp = resp,
  y = 1 + (resp=="x") + rnorm(4)[2*(resp=="x")+fam] + rnorm(12)[6*(resp=="x")+as.integer(ID)],
  respX = as.numeric(resp=="x"),
  respY = as.numeric(resp=="y")
)
#
# fit response-specific variances of random effect and residuals:
(fitme(y ~ resp+ (0+respX|fam)+ (0+respY|fam), resid.model = ~ 0+resp ,data=toymv))
#
# Same result by different syntax:
#
(fitme(y ~ resp+ (0+resp|fam), resid.model = ~ 0+resp ,data=toymv,
      fixed=list(ranCoefs=list("1"=c(NA,0,NA))))))

```

---

spaMM-conventions

*spaMM conventions and differences from related fitting procedures*


---

## Description

**input arguments** are generally similar to those of `glm` and `(g)lmer`, in particular for the `spaMM::fitme` function, with the exception of the `prior.weights` argument, which is simply `weights` in the other packages. The name `prior.weights` seems more consistent, since e.g. `glm` returns its input `weights` as output `prior.weights`, while its output `weights` are instead the weights in the final iteration of an iteratively weighted least-square fit.

The `bolddefault` likelihood target for dispersion parameters is restricted likelihood (REML estimation) for `corrHLfit` and (marginal) likelihood (ML estimation) for `fitme`. Model fits may provide restricted likelihood values (ReL) even if restricted likelihood is not used as an objective function at any step in the analysis.

See [good-practice](#) for advice about the proper syntax of formula.

**Computation times** depend on control parameters given by `spaMM.getOption("spaMM_tol")` parameters (for iterative algorithms), and `spaMM.getOption("nloptr")` parameters for the default optimizer. Do not use `spaMM.options()` to control them globally, unless you know what you are doing. Rather control them locally by the `control.HLfit` argument to control `spaMM_tol`, and by the control arguments of `corrHLfit` and `fitme` to control `nloptr`. If `nloptr$Xtol_rel` is set above `5e-06`, `fitme` will by default refit the fixed effects and dispersion parameters (but not other correlation parameters estimated by `nloptr`) by the iterative algorithm after `nloptr` convergence. Increasing `nloptr$Xtol_rel` value may therefore switch the bulk of computation time from the optimizer to the iterative algorithm, and may increase or decrease computation time depending on which algorithm is faster for a given input. Use `control$refit` if you wish to inhibit this, but note that by default it provides a rescue to a poor `nloptr` result due to a too large `Xtol_rel`.

## References

Chambers J.M. (2008) Software for data analysis: Programming with R. Springer-Verlag New York

---

spaMM.colors	<i>A flashy color palette.</i>
--------------	--------------------------------

---

### Description

spaMM.colors is the default color palette for some color plots in spaMM.

### Usage

```
spaMM.colors(n = 64, redshift = 1, adjustcolor_args=NULL)
```

### Arguments

n	Number of color levels returned by the function. A calling graphic function with argument nlevels will typically take the first (i.e., bluest) nlevels color levels. If n<nlevels, the color levels are recycled
redshift	The higher it is, the more the palette blushes....
adjustcolor_args	Either NULL or a list of arguments for <a href="#">adjustcolor</a> , in which case adjustcolor is called to modify spaMM.colors's default vector of colors. See the documentation of the latter function for further information. All arguments except col are possible.

### Details

If you don't like this color palette, have a look at the various ones provided by the `fields` package.

### Value

A vector giving the colors in a hexadecimal format.

### Examples

```
## see mapMM examples
```

---

spaMM.filled.contour	<i>Level (Contour) Plots with better aspect ratio control (for geographical maps, at least)</i>
----------------------	---

---

### Description

This function is derived from `filled.contour` in the `graphics` package, and this documentation is likewise heavily based on that of `filled.contour`.

This function likewise produces a contour plot with the areas between the contours filled in solid color, and a key showing how the colors map to z values is likewise shown to the right of the plot. The only difference is the way the aspect ratio is determined and can be controlled (using the `map.asp` parameter instead of `asp`), They thus easily provide nice-looking maps with meaningful latitude/longitude ratio (see Examples). However, this does not work well with `rstudio`.

**Usage**

```
spaMM.filled.contour(x = seq(0, 1, length.out = nrow(z)),
                    y = seq(0, 1, length.out = ncol(z)),
                    z,
                    xrange = range(x, finite = TRUE),
                    yrange = range(y, finite = TRUE),
                    zrange = range(z, finite = TRUE),
                    margin=1/20,
                    levels = pretty(zrange, nlevels), nlevels = 20,
                    color.palette = spaMM.colors,
                    col = color.palette(length(levels) - 1),
                    plot.title, plot.axes, key.title=NULL, key.axes=NULL,
                    map.asp = NULL, xaxs = "i", yaxs = "i", las = 1,
                    axes = TRUE, frame.plot = axes, ...)
```

**Arguments**

x, y	locations of grid lines at which the values in z are measured. These must be in ascending order. (The rest of this description does not apply to <code>.filled.contour</code> .) By default, equally spaced values from 0 to 1 are used. If x is a list, its components <code>x\$x</code> and <code>x\$y</code> are used for x and y, respectively. If the list has component z this is used for z.
z	a numeric matrix containing the values to be plotted.. Note that x can be used instead of z for convenience.
xrange	x range of the plot.
yrange	y range of the plot.
zrange	z range of the plot.
margin	This controls how far (in relative terms) the plot extends beyond the x and y ranges of the analyzed points, and is overridden by explicit xrange and yrange arguments.
levels	a set of levels which are used to partition the range of z. Must be <b>strictly</b> increasing (and finite). Areas with z values between consecutive levels are painted with the same color.
nlevels	if levels is not specified, the range of z, values is divided into approximately this many levels.
color.palette	a color palette function to be used to assign colors in the plot.
col	an explicit set of colors to be used in the plot. This argument overrides any palette function specification. There should be one less color than levels
plot.title	statements which add titles to the main plot.
plot.axes	statements which draw axes (and a <b>box</b> ) on the main plot. This overrides the default axes.
key.title	statements which add titles for the plot key.
key.axes	statements which draw axes on the plot key. This overrides the default axis.

map.asp	the y/x aspect ratio of the 2D plot area (not of the full figure including the scale). Default is (plotted y range)/(plotted x range) (i.e., scales for x are identical).
xaxs	the x axis style. The default is to use internal labeling.
yaxs	the y axis style. The default is to use internal labeling.
las	the style of labeling to be used. The default is to use horizontal labeling.
axes, frame.plot	logicals indicating if axes and a box should be drawn, as in <a href="#">plot.default</a> .
...	additional <a href="#">graphical parameters</a> , currently only passed to <a href="#">title()</a> .

### Details

The values to be plotted can contain NAs. Rectangles with two or more corner values are NA are omitted entirely: where there is a single NA value the triangle opposite the NA is omitted.

Values to be plotted can be infinite: the effect is similar to that described for NA values.

### Note

Builds heavily on `filled.contour` by Ross Ihaka and R-core. `spaMM.filled.contour` uses the [layout](#) function and so is restricted to a full page display.

The output produced by `spaMM.filled.contour` is actually a combination of two plots; one is the filled contour and one is the legend. Two separate coordinate systems are set up for these two plots, but they are only used internally – once the function has returned these coordinate systems are lost. If you want to annotate the main contour plot, for example to add points, you can specify graphics commands in the `plot.axes` argument. See the Examples.

### References

Cleveland, W. S. (1993) *Visualizing Data*. Summit, New Jersey: Hobart.

### See Also

[contour](#), [image](#), [palette](#); [contourplot](#) and [levelplot](#) from package `lattice`.

### Examples

```
spaMM.filled.contour(volcano, color = spaMM.colors) # simple

## Comparing the layout with that of filled.contour:
# (except that it does not always achieve the intended effect
# in RStudio Plots pane).

x <- 10*1:nrow(volcano)
y <- 10*1:ncol(volcano)
spaMM.filled.contour(x, y, volcano, color = terrain.colors,
  plot.title = title(main = "The Topography of Maunga Whau",
    xlab = "Meters North", ylab = "Meters West"),
  plot.axes = { axis(1, seq(100, 800, by = 100))
    axis(2, seq(100, 600, by = 100)) },
  key.title = title(main = "Height\n(meters)"),
```

```

    key.axes = axis(4, seq(90, 190, by = 10)) # maybe also asp = 1
mtext(paste("spaMM.filled.contour(.) from", R.version.string),
      side = 1, line = 4, adj = 1, cex = .66)

## compare with

filled.contour(x, y, volcano, color = terrain.colors,
  plot.title = title(main = "The Topography of Maunga Whau",
    xlab = "Meters North", ylab = "Meters West"),
  plot.axes = { axis(1, seq(100, 800, by = 100))
    axis(2, seq(100, 600, by = 100)) },
  key.title = title(main = "Height\n(meters)"),
  key.axes = axis(4, seq(90, 190, by = 10)) # maybe also asp = 1
mtext(paste("filled.contour(.) from", R.version.string),
      side = 1, line = 4, adj = 1, cex = .66)

```

---

spaMM\_boot

*Parametric bootstrap*


---

## Description

This simulates samples from a fit object inheriting from class "HLfit", as produced by spaMM's fitting functions, and applies a given function to each simulated sample. Parallelization is supported (see Details). A typical usage of the parametric bootstrap is to fit by one model some samples simulated under another model (see Example).

## Usage

```

spaMM_boot(object, simuland, nsim, nb_cores=NULL, seed=NULL,
  resp_testfn=NULL, control.foreach=list(),
  debug. = FALSE, type, fit_env=NULL, cluster_args=NULL,
  showpbar= eval(spaMM.getOption("barstyle")),
  ...)

```

## Arguments

object	The fit object to simulate from.
simuland	The function to apply to each simulated sample. See Details for requirements of this function.
nsim	Number of samples to simulate and analyze.
nb_cores	Number of cores to use for parallel computation. The default is spaMM.getOption("nb_cores"), and 1 if the latter is NULL. nb_cores=1 prevents the use of parallelisation procedures.
seed	Passed to <code>simulate.HLfit</code>

<code>resp_testfn</code>	Passed to <code>simulate.HLfit</code> ; NULL, or a function that tests a condition which simulated samples should satisfy. This function takes a response vector as argument and return a boolean (TRUE indicating that the sample satisfies the condition).
<code>control.foreach</code>	list of control arguments for <code>foreach</code> . These include in particular <code>.combine</code> (with default value "rbind"), and <code>.errorhandling</code> (with default value "remove", but "pass" is quite useful for debugging).
<code>debug.</code>	Boolean (or integer, interpreted as boolean). For debugging purposes, particularly from parallel computations. The effect of <code>debug.=TRUE</code> depends on what <code>simuland</code> does of it. The default <code>simuland</code> for likelihood ratio testing functions, <code>eval_replicate</code> , shows how <code>debug.</code> can be used.
<code>type</code>	Character: passed to <code>simulate.HLfit</code> . Defaults, with a warning, to <code>code_type="marginal"</code> in order to replicate the behaviour of previous versions. But this is not necessarily the appropriate type for all possible uses. See Details of <code>simulate.HLfit</code> for other implemented options.
<code>fit_env</code>	An environment or list containing variables necessary to evaluate <code>simuland</code> on each sample, and not included in the fit object. E.g., use <code>fit_env=list(phi_fix=phi_fix)</code> if the fit assumed <code>fixed=list(phi=phi_fix)</code>
<code>cluster_args</code>	NULL or a list of arguments, passed to <code>makeCluster</code> .
<code>showpbar</code>	Controls display of progress bar. See <code>barstyle</code> option for details.
<code>...</code>	Further arguments passed to the <code>simuland</code> function.

### Details

`spaMM_boot` handles parallel backends with different features. `pbapply::pbapply` has a very simple interface (essentially equivalent to `apply`) and provides progress bars, but (in version 1.4.0, at least) does not have efficient load-balancing. `doSNOW` also provides a progress bar and allows more efficient load-balancing, but its requires `foreach`. `foreach` handles errors differently from `pbapply` (which will simply stop if fitting a model to a bootstrap replicate fails): see the `foreach` documentation.

`spaMM_boot` calls `simulate.HLfit` on the fit object and applies `simuland` on each column of the matrix returned by this call. `simulate.HLfit` uses the `type` argument, which must be explicitly provided.

The `simuland` function must take as first argument a vector of response values, and may have other arguments including `'...'`. When required, these additional arguments must be passed through the `'...'` arguments of `spaMM_boot`. Variables needed to evaluate them must be available from within the `simuland` function or otherwise provided as elements of `fit_env`.

### Value

A list, with two elements (unless `debug.` is TRUE):

**bootreps** `nsim` return values in the format returned either by `apply` or `parallel::parApply` or by `foreach::`%dopar%`` as controlled by `control.foreach$.combine` (which is here "rbind" by default).

**RNGstate** the state of `.Random.seed` at the beginning of the sample simulation.

**Examples**

```

if (spaMM.getOption("example_maxtime")>7) {
  data("blackcap")

  # Generate fits of null and full models:
  lrt <- fixedLRT(null.formula=migStatus ~ 1 + Matern(1|longitude+latitude),
                 formula=migStatus ~ means + Matern(1|longitude+latitude),
                 method='ML',data=blackcap)

  # The 'simuland' argument:
  myfun <- function(y, what=NULL, lrt, ...) {
    data <- lrt$fullfit$data
    data$migStatus <- y ## replaces original response (! more complicated for binomial fits)
    full_call <- getCall(lrt$fullfit) ## call for full fit
    full_call$data <- data
    res <- eval(full_call) ## fits the full model on the simulated response
    if (!is.null(what)) res <- eval(what)(res=res) ## post-process the fit
    return(res) ## the fit, or anything produced by evaluating 'what'
  }
  # where the 'what' argument (not required) of myfun() allows one to control
  # what the function returns without redefining the function.

  # Call myfun() with no 'what' argument: returns a list of fits
  spaMM_boot(lrt$nullfit, simuland = myfun, nsim=1, lrt=lrt, type="marginal")["bootreps"]

  # Return only a model coefficient for each fit:
  spaMM_boot(lrt$nullfit, simuland = myfun, nsim=7,
             what=quote(function(res) fixef(res)[2L]), lrt=lrt, type="marginal")["bootreps"]
}

```

spaMM\_glm.fit

*Fitting generalized linear models without initial-value or divergence headaches*

**Description**

spaMM\_glm.fit is a stand-in replacement for glm.fit, which can be called through glm by using glm(<>,method="spaMM\_glm.fit"). Input and output structure are exactly as for glm.fit. It uses a Levenberg-Marquardt algorithm to prevent divergence of estimates. If the rcdd package is installed, the function can automatically find valid starting values or else indicate that no parameter value is feasible. spaMM\_glm is a convenient wrapper, calling glm with default method glm.fit, then calling method spaMM\_glm.fit, with possibly different initial values, if glm.fit failed.

**Usage**

```

spaMM_glm.fit(x, y, weights = rep(1, nobs), start = NULL, etastart = NULL,
             mustart = NULL, offset = rep(0, nobs), family = gaussian(),
             control = list(maxit=200), intercept = TRUE, singular.ok = TRUE)
spaMM_glm(formula, family = gaussian, data, weights, subset,

```

```
na.action, start = NULL, etastart, mustart, offset,
control = list(...), model = TRUE, method = c("glm.fit", "spaMM_glm.fit"),
x = FALSE, y = TRUE, singular.ok = TRUE, contrasts = NULL, strict=FALSE, ...)
```

## Arguments

All arguments except `strict` are common to these functions and their stats package equivalents, `glm` and `glm.fit`. Most arguments operate as for the latter functions, whose documentation is repeated below. The `control` argument may operate differently.

an object of class `"formula"` (or one that can be coerced to that class): a symbolic description of the model to be fitted. The details of model specification are given in the ‘Details’ section of `glm`.

<code>family</code>	a description of the error distribution and link function to be used in the model. For <code>spaMM_glm</code> this can be a character string naming a family function, a family function or the result of a call to a family function. For <code>spaMM_glm.fit</code> only the third option is supported. (See <code>family</code> for details of family functions.)
<code>data</code>	an optional data frame, list or environment (or object coercible by <code>as.data.frame</code> to a data frame) containing the variables in the model. If not found in <code>data</code> , the variables are taken from <code>environment(formula)</code> , typically the environment from which <code>glm</code> is called.
<code>weights</code>	an optional vector of ‘prior weights’ to be used in the fitting process. Should be <code>NULL</code> or a numeric vector.
<code>subset</code>	an optional vector specifying a subset of observations to be used in the fitting process.
<code>na.action</code>	a function which indicates what should happen when the data contain NAs. The default is set by the <code>na.action</code> setting of <code>options</code> , and is <code>na.fail</code> if that is unset. The ‘factory-fresh’ default is <code>na.omit</code> . Another possible value is <code>NULL</code> , no action. Value <code>na.exclude</code> can be useful.
<code>start</code>	starting values for the parameters in the linear predictor.
<code>etastart</code>	starting values for the linear predictor.
<code>mustart</code>	starting values for the vector of means.
<code>offset</code>	this can be used to specify an <i>a priori</i> known component to be included in the linear predictor during fitting. This should be <code>NULL</code> or a numeric vector of length equal to the number of cases. One or more <code>offset</code> terms can be included in the formula instead or as well, and if more than one is specified their sum is used. See <code>model.offset</code> .
<code>control</code>	a list of parameters for controlling the fitting process. This is passed to <code>glm.control</code> , as for <code>glm.fit</code> . Because one can assume that <code>spaMM_glm.fit</code> will converge in many cases where <code>glm.fit</code> does not, <code>spaMM_glm.fit</code> allows more iterations (200) by default. However, if <code>spaMM_glm.fit</code> is called through <code>glm(..., method="spaMM_glm.fit")</code> , then the number of iterations is controlled by the <code>glm.control</code> call within <code>glm</code> , so that it is 25 by default, overriding the <code>spaMM_glm.fit</code> default.
<code>model</code>	a logical value indicating whether <i>model frame</i> should be included as a component of the returned value.

method	A 2-elements vector specifying first the method to be used by <code>spaMM_glm</code> in the first attempt to fit the model, second the method to be used in a second attempt if the first failed. Possible methods include those shown in the default, "model.frame", which returns the model frame and does no fitting, or user-supplied fitting functions. These functions can be supplied either as a function or a character string naming a function, with a function which takes the same arguments as <code>glm.fit</code> .
x, y	For <code>spaMM_glm</code> : x is a design matrix of dimension $n * p$ , and y is a vector of observations of length n. For <code>spaMM_glm.fit</code> : x is a design matrix of dimension $n * p$ , and y is a vector of observations of length n.
singular.ok	logical; if FALSE a singular fit is an error.
contrasts	an optional list. See the <code>contrasts.arg</code> of <code>model.matrix.default</code> .
intercept	logical. Should an intercept be included in the <i>null</i> model?
strict	logical. Whether to perform a fit by <code>spaMM_glm.fit</code> if <code>glm.fit</code> returned the warning "glm.fit: algorithm did not converge".
...	arguments to be used to form the default control argument if it is not supplied directly.

### Value

An object inheriting from class `glm`. See [glm](#) for details.

### Note

The source and documentation is derived in large part from those of `glm.fit`.

### Examples

```
x <- c(8.752,20.27,24.71,32.88,27.27,19.09)
y <- c(5254,35.92,84.14,641.8,1.21,47.2)

# glm(.) fails:
(check_error <- try(glm(y~ x,data=data.frame(x,y),family=Gamma(log)), silent=TRUE))
if ( ! inherits(check_error,"try-error")) stop("glm(.) call unexpectedly succeeded")

spaMM_glm(y~ x,data=data.frame(x,y),family=Gamma(log))

## Gamma(inverse) examples
x <- c(43.6,46.5,21.7,18.6,17.3,16.7)
y <- c(2420,708,39.6,16.7,46.7,10.8)

# glm(.) fails (can't find starting value)
(check_error <- suppressWarnings(try(glm(y~ x,data=data.frame(x,y),family=Gamma()), silent=TRUE)))
if ( ! inherits(check_error,"try-error")) stop("glm(.) call unexpectedly succeeded.")

if (requireNamespace("rcdd",quietly=TRUE)) {
  spaMM_glm(y~ x,data=data.frame(x,y),family=Gamma())
}
```

---

stripHLfit	<i>Reduce the size of fitted objects</i>
------------	--

---

**Description**

Large matrices and other memory-expensive objects may be stored in a fit object. This function removes them in order to reduce the size of the object, particularly when stored on disk. In principle, the removed objects can be regenerated automatically when needed (e.g., for a predict()).

**Usage**

```
stripHLfit(object, ...)
```

**Arguments**

object	The result of a fit (an object of class HLfit).
...	Further arguments, not currently used.

**Value**

The input fit objects with some elements removed.

**Note**

The effect may change without notice between versions as the efficiency of the operation is highly sensitive to implementation details.

**Examples**

```
## Not run:
## rather unconvincing example : quantitative effect is small.

# measure size of saved object:
saveSize <- function (object,...) {
  tf <- tempfile(fileext = ".RData")
  on.exit(unlink(tf))
  save(object, file = tf,...)
  file.size(tf)
}
data("Loaloo")
lfit <- fitme(cbind(npos,ntot-npos)~elev1+elev2+elev3+elev4+maxNDVI1+seNDVI
             +Matern(1|longitude+latitude), method="HL(0,1)",
             data=Loaloo, family=binomial(), fixed=list(nu=0.5,rho=1,lambda=0.5))
saveSize(lfit)
pfit <- predict(lfit,newdata=Loaloo,variances=list(cov=TRUE)) # increases size!
saveSize(lfit)
lfit <- stripHLfit(lfit)
saveSize(lfit)

## End(Not run)
```

summary.HLfit

*Summary and print methods for fit and test results.***Description**

Summary and print methods for results from HLfit or related functions. summary may also be used as an extractor (see e.g. [beta\\_table](#)).

**Usage**

```
## S3 method for class 'HLfit'
summary(object, details=FALSE, max.print=100L, verbose=TRUE, ...)
## S3 method for class 'HLfitlist'
summary(object, ...)
## S3 method for class 'fixedLRT'
summary(object, verbose=TRUE, ...)
## S3 method for class 'HLfit'
print(x,...)
## S3 method for class 'HLfitlist'
print(x,...)
## S3 method for class 'fixedLRT'
print(x,...)
```

**Arguments**

object	An object of class HLfit, as returned by the fitting functions in spaMM.
x	The return object of HLfit or related functions.
verbose	For summary.HLfit, whether to print the screen output that is the primary purpose of summary. verbose=FALSE may be convenient when summary is used as an extractor. For summary.fixedLRT, whether to print the model fits or not.
max.print	Controls options("max.print") locally.
details	A vector with elements controlling whether to print some obscure details. Element ranCoefs=TRUE will print details about random-coefficients terms (see Details); and element p_value="Wald" will print a p-value for the t-value of each fixed-effect coefficient, assuming a gaussian distribution of the test statistic (but, beyond the generally questionable nature of p-value tables, see e.g. LRT and fixedLRT for alternative testing approaches).
...	further arguments passed to or from other methods.

**Details**

The random effect terms of the linear predictor are of the form  $\mathbf{ZL}\mathbf{v}$ . In particular, for **random-coefficients models** (i.e., including random-effect terms such as (z|group) specifying a random-slope component), correlated random effects are represented as  $\mathbf{b} = \mathbf{L}\mathbf{v}$  for some matrix  $\mathbf{L}$ , and where the elements of  $\mathbf{v}$  are uncorrelated. In the output of the fit, the Var. column gives the variances of the correlated effects,  $\mathbf{b}=\mathbf{L}\mathbf{v}$ . The Corr. column(s) give their correlation(s). If details is

TRUE, estimates and SEs of the (log) variances of the elements of  $\mathbf{v}$  are reported as for other random effects in the Estimate and cond. SE. columns of the table of lambda coefficients. However, this non-default output is potentially misleading as the elements of  $\mathbf{v}$  cannot generally be assigned to specific terms (such as intercept and slope) of the random-effect formula, and the representation of  $\mathbf{b}$  as  $\mathbf{L}\mathbf{v}$  is not unique.

## Value

These methods return the object invisibly. They print details of the fits in a convenient form.

## Examples

```
## see examples of fitme() or corrHLfit() usage
```

---

update.HLfit	<i>Updates a fit</i>
--------------	----------------------

---

## Description

update and update\_resp will update and (by default) re-fit a model. They do this mostly by extracting the call stored in the object, updating the call and evaluating that call. Using update(<fit>) is a risky programming style (see Details). update\_formulas(<mv fit>, ...) can update formulas from a fitmv fit as well as the single formula of a fit by the other fitting functions.

update\_resp handles a new response vector as produced by simulate.

## Usage

```
## S3 method for class 'HLfit'
update(object, formula., ..., evaluate = TRUE)
update_resp(object, newresp, ..., evaluate = TRUE)

update_formulas(object, formula., ...)
```

## Arguments

object	A return object from an HLfit call.
formula.	A standard formula; or a formula with a peculiar syntax only describing changes to the original model formula (see <a href="#">update.formula</a> for details); or (for multivariate-response models) a list of formula of such types.
newresp	New response vector.
...	Additional arguments to the call, or arguments with changed values. Use <i>name</i> = NULL to remove the argument with given <i>name</i> .
evaluate	If TRUE, evaluate the new call else return the call.

## Details

Early versions of spaMM's update method relied on `stats::update.formula` whose results endorse `stats`'s (sometimes annoying) convention that a formula without an explicit intercept term actually includes an intercept. `spaMM::update.HLfit` was then defined to avoid this problem. **Formula updates should still be carefully checked**, as getting them perfect has not been on the priority list.

Various post-fit functions from base R may use `update.formula` directly, rather than using automatic method selection for `update`. `update.formula` is not itself a generic, which leads to the following problem. To make `update.formula()` work on multivariate-response fits, one would like to be able to redefine it as a generic, with an `HLfit` method that would perform what `update_formulas` does, but redefinition appears to be forbidden in a package distributed on CRAN. Instead it is suggested to define a new generic `spaMM::update`, which could have a `spaMM::update.formula` as a method (possibly itself a generic). This would be of limited interest as the new `spaMM::update.formula` would be visible to `spaMM::update` but not to `stats::update`, and thus the post-fit functions from base R would still not use this method.

`update(<fit>, ...)`, as a general rule, is tricky. update methods are easily affected in a non-transparent way by changes in variables used in the original call. For example `foo <- rep(1, 10)`  
`m <- lm(rnorm(10)~1, weights=foo) rm(foo) update(m, .~.)` # Error To avoid such problems, spaMM tries to avoid references to variables in the global environment, by enforcing that the data are explicitly provided to the fitting functions by the `data` argument, and that any variable used in the `prior.weights` argument is in the data.

Bugs can also result when calling `update` on a fit produced within some function, say function `somefn` calling `fitme(data=mydata, ...)`, as e.g. `update(<fit>)` will then seek a global variable `mydata` that may differ from the fitted `mydata` which was local to `somefn`.

## Value

`update.formula(object)` returns an object of the same nature as `formula(object)`. The other functions and methods return an `HLfit` fit of the same type as the input object, or a call object, depending on the evaluate value.

## See Also

See also [HLCor](#), [HLfit](#).

## Examples

```
data("wafers")
## First the fit to be updated:
wFit <- HLfit(y ~X1*X3+X2*X3+I(X2^2)+(1|batch), family=Gamma(log),
             resid.model = ~ X3+I(X3^2) ,data=wafers)

newresp <- simulate(wFit)
update_resp(wFit, newresp=newresp)

# For estimates given by Lee et al., Appl. Stochastic Models Bus. Ind. (2011) 27: 315-328:
# Refit with given beta or/and phi values:

betavals <- c(5.55, 0.08, -0.14, -0.21, -0.08, -0.09, -0.09)
```

```

# reconstruct fitted phi value from predictor for log(phi)
Xphi <- with(wafers,cbind(1,X3,X3^2)) ## design matrix
phifit <- exp(Xphi %*% c(-2.90,0.1,0.95))
upd_wafers <- wafers
designX <- get_matrix(wFit)
upd_wafers$off_b <- designX %*% betavals
update(wFit,formula.= . ~ offset(off_b)+(1|batch), data=upd_wafers,
       ranFix=list(lambda=exp(-3.67),phi=phifit))

## There are subtlety in performing REML fits of constrained models,
## illustrated by the fact that the following fit does not recover
## the original likelihood values, because dispersion parameters are
## estimated but the REML correction changes with the formula:
upd_wafers$off_f <- designX %*% fixef(wFit) ## = predict(wFit,re.form=NA,type="link")
update(wFit,formula.= . ~ offset(off_f)+(1|batch), data=upd_wafers)
#
## To maintain the original REML correction, Consider instead
update(wFit,formula.= . ~ offset(off_f)+(1|batch), data=upd_wafers,
       REMLformula=formula(wFit)) ## recover original p_v and p_bv
## Alternatively, show original wFit as differences from betavals:
update(wFit,formula.= . ~ . +offset(off_f), data=upd_wafers)

```

vcov

*Extract covariance or correlation components from a fitted model object*

## Description

`summary(<fit object>)$beta_table` returns the table of fixed-effect coefficients as it is printed by `summary`, including standard errors and t-values. `vcov` returns the variance-covariance matrix of the fixed-effects coefficients. `Corr` returns a correlation matrix of random effects.

`VarCorr` returns (co)variance parameters of random effects, and optionally the residual variance(s), from a fit object, in a data frame format roughly consistent with the method of objects of class "lme", in particular including columns with consistent names for easier extraction. One may have to consult the summary of the object to check the meaning of the contents of this data frame (e.g., of 'variance' coefficients for non-gaussian random effects). Other extractors to consider are [get\\_ranPars](#) and [get\\_inits\\_from\\_fit](#), the latter providing parameters in a form suitable for initializing a fit.

The covariance matrix of residuals of a fit can be obtained as a block of the hat matrix (`get_matrix(. , which="hat_matrix"`). This is (as other covariances matrices above) a matrix of expected values, generally assuming that the fitted model is correct and that its parameters are "well" estimated, and should not to be confused with the computation of diagnostic correlations among inferred residuals of a fit.

## Usage

```

## S3 method for class 'HLfit'
vcov(object, ...)
## S3 method for class 'HLfit'

```

```
VarCorr(x, sigma = 1, add_residVars=TRUE, ...)
Corr(object, ...)
```

### Arguments

object, x	A fitted model object, inheriting from class "HLfit", as returned by the fitting functions in spaMM.
add_residVars	Boolean; whether to include residual variance information in the returned table.
sigma	ignored argument, included for consistency with the generic function.
...	Other arguments that may be needed by some method.

### Value

vcov returns a matrix. Corr returns a list, for the different random effect terms. For each random-effect term, the returned element is a non-trivial unconditional correlation matrix of the vector "v" of random effects (v as defined in see Details of HLfit) for this term, if there is any such matrix. Otherwise the returned element is a information message.

VarCorr returns either NULL (if no variance to report, as for a poisson GLM) or a data frame with columns for the grouping factor, term, variance of random effect, standard deviation (the root of the variance), and optionally for correlation of random effect in random-coefficient terms. Information about the residual variance is optionally included as the last row(s) of the data frame, when relevant (gaussian- or Gamma-response models with single scalar parameter; beware the meaning of the residual variance parameter for Gamma-response models).

### See Also

[get\\_inits\\_from\\_fit](#) and [get\\_ranPars](#).

### Examples

```
data("wafers")
m1 <- HLfit(y ~ X1+X2+(1|batch), resid.model = ~ 1 ,data=wafers, method="ML")
vcov(m1)

# Example from VarCorr() documentation in 'nlme' package
data("Orthodont",package = "nlme")
sp1 <- fitme(distance ~ age+(age|Subject), data = Orthodont, method="REML")
VarCorr(sp1)
```

**Description**

This data set was reported and analyzed by Robinson et al. (2006) and reanalyzed by Lee et al. (2011). The data “deal with wafers in a single etching process in semiconductor manufacturing. Wafers vary through time since there are some variables that are not perfectly controllable in the etching process. For this reason, wafers produced on any given day (batch) may be different from those produced on another day (batch). To measure variation over batch, wafers are tested by choosing several days at random. In this data, resistivity is the response of interest. There are three variables, gas flow rate (x1), temperature (x2), and pressure (x3) and one random effect (batch or day).” (Lee et al 2011).

**Usage**

```
data("wafers")
```

**Format**

The data frame includes 198 observations on the following variables:

**y** resistivity.

**batch** batch, indeed.

**X1** gas flow rate.

**X2** temperature.

**X3** pressure.

**Source**

This data set was manually pasted from Table 3 of Lee et al. (2011). Transcription errors may have occurred.

**References**

Robinson TJ, Wulff SS, Montgomery DC, Khuri AI. 2006. Robust parameter design using generalized linear mixed models. *Journal of Quality Technology* 38: 38–65.

Lee, Y., Nelder, J.A., and Park, H. 2011. HGLMs for quality improvement. *Applied Stochastic Models in Business and Industry* 27, 315-328.

**Examples**

```
## see examples in the main Documentation page for the package.
```

welding

*Welding data set***Description**

The data give the results of an unreplicated experiment for factors affecting welding quality conducted by the National Railway Corporation of Japan (Taguchi and Wu, 1980, cited in Smyth et al., 2001). It is a toy example for heterocedastic models and is also suitable for illustrating fit of overparameterized models.

**Usage**

```
data("welding")
```

**Format**

The data frame includes 16 observations on 10 variables:

**Strength** response variable;  
 ... nine two-level factors.

**Source**

The data were downloaded from <http://www.statsci.org/data/general/welding.txt> on 2014/08/19 and are consistent with those shown in table 5 of Bergman and Hynén (1997).

**References**

- Bergman B, Hynén A (1997) Dispersion effects from unreplicated designs in the  $2^{k-p}$  series. *Technometrics*, 39, 191–98.
- Smyth GK, Huele AF, Verbyla AP (2001). Exact and approximate REML for heteroscedastic regression. *Statistical Modelling* 1, 161-175.
- Taguchi G, Wu Y (1980) Introduction to off-line quality control. Nagoya, Japan: Central Japan Quality Control Association.

**Examples**

```
data("welding")
## toy example from Smyth et al.
fitme(Strength ~ Drying + Material, resid.model = ~ Material+Preheating ,data=welding, method="REML")
## toy example of overparameterized model
fitme(Strength ~ Rods+Thickness*Angle+(1|Rods), resid.model = ~ Rods+Thickness*Angle ,data=welding)
```

---

wrap_parallel	<i>Selecting interfaces for parallelisation</i>
---------------	---

---

### Description

spaMM implements two interfaces for parallelisation, `dopar` and `dofuture`, called in particular by its bootstrap procedures. Which one is used is determined by `spaMM.options(wrap_parallel="dopar")` (default) or `spaMM.options(wrap_parallel="dofuture")`. Depending on arguments, either serial computation (default), a socket cluster (parallelisation default), or a fork cluster (available in linux and alike operating systems) can be used.

`dopar` is based on a patchwork of backends: for socket clusters, depending whether the `doSNOW` package is attached, `foreach` or `pbapply` is called (`doSNOW` allows more efficient load balancing than `pbapply`); for fork clusters, `parallel::mclapply` is used. By contrast, `dofuture` is based only on the `future` and `future.apply` packages, ensuring identical control of random number generator accross these different cases, hence repeatable results accross them. This does **not** make a difference for bootstrap computations in spaMM as the bootstrap samples are never simulated in parallel: only refitting the models is performed in parallel, and fit results do not depend on random numbers. Further, the future-based code for socket clusters appears significantly slower than the one used by `dopar`. For these reasons, the latter function is used by default by spaMM.

---

ZAXlist	<i>S4 classes for structured matrices</i>
---------	---

---

### Description

A `ZAXlist` object is a representation of the “ZAL” matrix as an S4 class holding a list of descriptors of each ZAL block for each random effect.

A `Kronfacto` object is a representation of a Kronecker product as an S4 class holding its factors. Methods defined for this class may avoid the computation of the Kronecker product as an actual matrix of large dimensions.

This documentation is for development purposes and may be incomplete. The objects and methods are not part of the programming interface and are subject to modification without notice.

### Usage

```
# new("ZAXlist", LIST=.)
# new("Kronfacto", BLOB=.)
```

### Slots

**LIST:** A list whose each block is either a `(M|m)atrix`, or a list with two elements (and additional class `ZA_QCHM`): `ZA`, and the `Cholesky` factor `Q_CHMfactor` of the precision matrix (`L=solve(Q_CHMfactor, system="L`

**BLOB:** An environment holding `lhs` and `rhs`, the factors of the Kronecker product, and other objects initialized as promises. See the source code of the non-exported `.def_Kranfacto` constructor for further information.

# Index

- \* **datagen**
  - simulate.HLfit, [127](#)
- \* **datasets**
  - adjlg, [4](#)
  - arabidopsis, [10](#)
  - blackcap, [13](#)
  - freight, [51](#)
  - Gryphon, [61](#)
  - Loaloe, [76](#)
  - salamander, [122](#)
  - scotlip, [124](#)
  - seaMask, [125](#)
  - seeds, [126](#)
  - wafers, [148](#)
  - welding, [150](#)
- \* **family**
  - multinomial, [95](#)
- \* **hplot**
  - mapMM, [82](#)
  - plot.HLfit, [106](#)
- \* **htest**
  - fixedLRT, [47](#)
  - get\_RLRsim\_args, [58](#)
  - LRT, [78](#)
  - spaMM\_boot, [138](#)
- \* **log-linear**
  - spaMM\_glm.fit, [140](#)
- \* **logistic**
  - spaMM\_glm.fit, [140](#)
- \* **loglinear**
  - spaMM\_glm.fit, [140](#)
- \* **manip**
  - multinomial, [95](#)
- \* **models**
  - AIC, [5](#)
  - autoregressive, [11](#)
  - CauchyCorr, [14](#)
  - COMPoisson, [15](#)
  - corr\_family, [28](#)
  - MaternCorr, [87](#)
  - MSFDR, [91](#)
  - negbin, [100](#)
  - Poisson, [110](#)
  - spaMM\_glm.fit, [140](#)
- \* **model**
  - corrHLfit, [25](#)
  - fitme, [39](#)
  - fitmv, [42](#)
  - HLCor, [64](#)
  - HLfit, [67](#)
  - make\_scaled\_dist, [81](#)
  - multIMRF, [92](#)
  - multinomial, [95](#)
- \* **package**
  - spaMM, [130](#)
- \* **print**
  - summary.HLfit, [144](#)
- \* **regression**
  - COMPoisson, [15](#)
  - get\_RLRsim\_args, [58](#)
  - is\_separated, [74](#)
  - negbin, [100](#)
  - Poisson, [110](#)
  - spaMM\_glm.fit, [140](#)
- \* **spatial**
  - autoregressive, [11](#)
  - CauchyCorr, [14](#)
  - corr\_family, [28](#)
  - MaternCorr, [87](#)
  - multIMRF, [92](#)
  - spaMM, [130](#)
- \* **ts**
  - autoregressive, [11](#)
  - .eval\_replicate2(eval\_replicate), [35](#)
  - %%%, Kronfacto, numeric-method (ZAXlist), [151](#)
  - %%%, ZAXlist, Matrix-method (ZAXlist), [151](#)
  - %%%, ZAXlist, matrix-method (ZAXlist), [151](#)

- %%, ZAXlist, numeric-method (ZAXlist), 151
- %%, numeric, ZAXlist-method (ZAXlist), 151
- %%-methods (ZAXlist), 151
- adjacency, 47, 65, 66, 93, 131
- adjacency (autoregressive), 11
- adjlg, 4
- adjlgMat (adjlg), 4
- adjustcolor, 135
- AIC, 5
- algebra, 8, 22, 69, 103
- anova, 75
- anova (LRT), 78
- AR1, 47, 66, 93, 130
- AR1 (autoregressive), 11
- arabidopsis, 10, 130
- as.data.frame, 141
- as\_precision (covStruct), 29
- autoregressive, 11, 66
- barstyle, 34, 139
- barstyle (options), 101
- besselK, 88
- Beta (HLfit), 67
- Beta-distribution-random-effects (HLfit), 67
- beta\_table, 144
- beta\_table (vcov), 147
- binomialize (multinomial), 95
- blackcap, 13
- bobyqa, 102
- boot.ci, 21
- box, 136
- CAR (autoregressive), 11
- Cauchy, 47, 130
- Cauchy (CauchyCorr), 14
- CauchyCorr, 14, 66
- Cholesky, 151
- class:Kronfacto (ZAXlist), 151
- class:missingOrNULL (ZAXlist), 151
- class:ZAXlist (ZAXlist), 151
- clusterSetRNGStream, 32, 34
- coef.corMatern (corMatern), 23
- coef<- .corMatern (corMatern), 23
- col2rgb, 109
- COMPOisson, 15, 102, 130
- composite-ranef, 18
- confint, 21
- confint (confint.HLfit), 20
- confint.HLfit, 20
- contour, 84, 137
- contourplot, 137
- convergence, 22
- corFactor.corMatern (corMatern), 23
- corMatern, 23, 88
- corMatrix.corMatern (corMatern), 23
- Corr (vcov), 147
- corr\_family, 28
- corrHLfit, 25, 49, 66, 67, 71, 130
- corrMatrix, 9, 27, 65, 66, 131
- corrPars (fixed), 45
- covStruct, 9, 29, 65, 104, 118
- crossprod, Kronfacto, Matrix-method (ZAXlist), 151
- crossprod, Kronfacto, matrix-method (ZAXlist), 151
- crossprod, Kronfacto, numeric-method (ZAXlist), 151
- crossprod, ZAXlist, Matrix-method (ZAXlist), 151
- crossprod, ZAXlist, matrix-method (ZAXlist), 151
- crossprod, ZAXlist, numeric-method (ZAXlist), 151
- crossprod-methods (ZAXlist), 151
- dev\_resids (extractors), 37
- deviance (extractors), 37
- DHARMA (post-fit), 111
- dim.Kronfacto (ZAXlist), 151
- dist, 82
- div\_info, 31
- dofuture, 32, 34, 35, 151
- dopar, 6, 32, 33, 33, 151
- Earth (make\_scaled\_dist), 81
- EarthChord (make\_scaled\_dist), 81
- eigen, 89
- etaFix, 69
- etaFix (fixed), 45
- eval\_replicate, 35, 79, 139
- external-libraries, 36
- extractAIC (AIC), 5
- extractors, 37, 70

- family, [15](#), [26](#), [40](#), [100](#), [110](#), [141](#)
- family (extractors), [37](#)
- filled.mapMM (mapMM), [82](#)
- fitme, [25](#), [39](#), [43](#), [67](#), [71](#), [105](#), [130](#)
- fitmv, [42](#), [130](#)
- fitted (extractors), [37](#)
- fitted.HLfitlist (multinomial), [95](#)
- fitted.values, [37](#)
- fix\_predVar, [50](#)
- fixed, [40](#), [45](#)
- fixedLRT, [26](#), [27](#), [36](#), [47](#), [68](#), [80](#), [130](#)
- fixef (extractors), [37](#)
- formula, [25](#), [40](#), [67](#), [141](#)
- formula (extractors), [37](#)
- formula\_env (good-practice), [60](#)
- freight, [51](#)
  
- Gamma, [74](#), [118](#)
- Gamma (inverse.Gamma), [74](#)
- geometric (COMPoisson), [15](#)
- get\_any\_IC, [70](#)
- get\_any\_IC (AIC), [5](#)
- get\_cPredVar, [52](#), [115](#), [129](#)
- get\_fixefVar (predict), [112](#)
- get\_inits\_from\_fit, [54](#), [56](#), [58](#), [147](#), [148](#)
- get\_intervals (predict), [112](#)
- get\_matrix, [39](#), [55](#), [62](#), [147](#)
- get\_predCov\_var\_fix (predict), [112](#)
- get\_predVar, [52](#)
- get\_predVar (predict), [112](#)
- get\_rankinfo (rankinfo), [119](#)
- get\_ranPars, [55](#), [56](#), [147](#), [148](#)
- get\_residVar, [122](#)
- get\_residVar (predict), [112](#)
- get\_respVar (predict), [112](#)
- get\_RLRsim\_args, [39](#), [58](#), [79](#), [80](#)
- get\_RLRTSim\_args, [111](#)
- get\_RLRTSim\_args (get\_RLRsim\_args), [58](#)
- get\_ZALMatrix, [71](#)
- get\_ZALMatrix (get\_matrix), [55](#)
- getCovariate.corMatern (corMatern), [23](#)
- getDistMat (extractors), [37](#)
- glht (post-fit), [111](#)
- glm, [15](#), [69](#), [90](#), [141](#), [142](#)
- glm.control, [69](#), [141](#)
- glmmPQL, [24](#)
- good-practice, [60](#)
- graphical parameters, [137](#)
- grep, [50](#)
  
- Gryphon, [9](#), [30](#), [61](#)
- Gryphon\_A (Gryphon), [61](#)
- Gryphon\_df (Gryphon), [61](#)
- Gryphon\_pedigree (Gryphon), [61](#)
  
- hatvalues, [39](#), [120](#)
- hatvalues (hatvalues.HLfit), [62](#)
- hatvalues.HLfit, [62](#)
- HLCor, [26](#), [41](#), [43](#), [64](#), [71](#), [105](#), [130](#), [146](#)
- HLfit, [25](#), [26](#), [37](#), [40](#), [41](#), [43](#), [64–66](#), [67](#), [105](#), [117](#), [130](#), [146](#), [148](#)
- how, [72](#)
  
- image, [137](#)
- IMRF, [9](#), [47](#), [119](#), [130](#)
- IMRF (multIMRF), [92](#)
- Initialize.corMatern (corMatern), [23](#)
- inits, [22](#), [73](#)
- inla.spde2.matern (multIMRF), [92](#)
- inla.spde2.pcmatern (multIMRF), [92](#)
- intervals (predict), [112](#)
- inverse.Gamma, [74](#), [118](#)
- is\_separated, [74](#)
  
- kronecker, [18](#)
- Kronfacto (ZAXlist), [151](#)
- Kronfacto-class (ZAXlist), [151](#)
  
- landMask (seaMask), [125](#)
- layout, [137](#)
- levelplot, [137](#)
- LevenbergM (options), [101](#)
- lme, [24](#)
- Loaloa, [27](#), [76](#), [88](#)
- logDet.corMatern (corMatern), [23](#)
- logLik, [90](#)
- logLik (extractors), [37](#)
- logLik.HLfitlist (multinomial), [95](#)
- lower.tri, [46](#)
- LRT, [36](#), [48](#), [49](#), [59](#), [78](#)
  
- make.link, [100](#), [110](#)
- make\_scaled\_dist, [25](#), [40](#), [65](#), [81](#), [87](#)
- makeCluster, [139](#)
- map\_ranef (mapMM), [82](#)
- mapMM, [82](#)
- mat\_sqrt, [26](#), [41](#), [43](#), [65](#), [89](#)
- Matern, [23](#), [25](#), [40](#), [47](#), [130](#)
- Matern (MaternCorr), [87](#)

- MaternCorr, [23](#), [24](#), [66](#), [87](#), [132](#)
- mclapply, [34](#)
- method, [26](#), [41](#), [48](#), [66](#), [68](#), [69](#), [90](#)
- missingOrNULL (ZAXlist), [151](#)
- missingOrNULL-class (ZAXlist), [151](#)
- model.frame.HLfit (extractors), [37](#)
- model.matrix.HLfit (extractors), [37](#)
- model.offset, [141](#)
- MSFDR, [91](#)
- multcomp (post-fit), [111](#)
- multi, [26](#), [40](#), [44](#), [96](#)
- multi (multinomial), [95](#)
- multIMRF, [44](#), [92](#)
- multinomial, [95](#), [130](#)
- mv, [42](#), [45](#), [98](#)
  
- na.exclude, [141](#)
- na.fail, [141](#)
- na.omit, [141](#)
- negbin, [100](#), [130](#), [132](#)
- nloptr, [40](#), [102](#)
- Nmatrix (scotlip), [124](#)
- nobs (extractors), [37](#)
  
- oceanmask (seaMask), [125](#)
- offset, [141](#)
- optim, [102](#)
- options, [101](#), [141](#)
  
- palette, [137](#)
- pdep\_effects (plot\_effects), [108](#)
- pedigree, [9](#), [30](#), [104](#)
- phiHGLM, [68](#), [105](#)
- plot (plot.HLfit), [106](#)
- plot.default, [137](#)
- plot.HLfit, [106](#), [111](#)
- plot\_effects, [108](#)
- Poisson, [110](#)
- polypath, [125](#)
- post-fit, [111](#)
- predict, [112](#), [130](#)
- predict.HLfit, [52](#), [121](#), [129](#)
- Predictor, [25](#), [40](#), [65](#), [67](#)
- Predictor (covStruct), [29](#)
- predVar, [113–115](#), [116](#)
- preprocess\_fix\_corr (predict), [112](#)
- pretty, [84](#)
- print (summary.HLfit), [144](#)
- print.corr\_family (corr\_family), [28](#)
- print.raneff (extractors), [37](#)
  
- ranCoefs (fixed), [45](#)
- random-effects, [118](#)
- ranef (extractors), [37](#)
- ranFix, [25](#), [69](#)
- ranFix (fixed), [45](#)
- rankinfo, [119](#)
- ranPars, [65](#)
- ranPars (fixed), [45](#)
- recalc.corrMatern (corrMatern), [23](#)
- refit (update.HLfit), [145](#)
- REML formula, [44](#)
- REML formula (HLfit), [67](#)
- remove\_from\_parlist (get\_ranPars), [56](#)
- resid.model (phiHGLM), [105](#)
- residuals (residuals.HLfit), [120](#)
- residuals.glm, [120](#)
- residuals.HLfit, [39](#), [120](#)
- residVar, [39](#), [45](#), [58](#), [115](#), [121](#)
- response (extractors), [37](#)
- rho.mapping (make\_scaled\_dist), [81](#)
- RLRsim (post-fit), [111](#)
- ROI\_solve, [75](#)
  
- salamander, [122](#)
- SAR\_WWt (corr\_family), [28](#)
- scotlip, [124](#)
- seaMask, [86](#), [125](#)
- seeds, [126](#)
- separation (is\_separated), [74](#)
- set.seed, [128](#)
- simulate, [130](#)
- simulate (simulate.HLfit), [127](#)
- simulate.HLfit, [48](#), [52](#), [127](#), [138](#), [139](#)
- small\_spde (multIMRF), [92](#)
- spaMM, [18](#), [25](#), [40](#), [67](#), [114](#), [130](#)
- spaMM-conventions, [134](#)
- spaMM-package (spaMM), [130](#)
- spaMM.colors, [135](#)
- spaMM.filled.contour, [85](#), [135](#)
- spaMM.getOption (options), [101](#)
- spaMM.options, [26](#)
- spaMM.options (options), [101](#)
- spaMM\_boot, [21](#), [48](#), [79](#), [138](#)
- spaMM\_glm, [90](#)
- spaMM\_glm (spaMM\_glm.fit), [140](#)
- spaMM\_glm.fit, [140](#)
- spaMMplot2D (mapMM), [82](#)

sparse\_precision, [104](#)  
sparse\_precision (algebra), [8](#)  
str.inla.spde2 (multIMRF), [92](#)  
stripHLfit, [143](#)  
summary (summary.HLfit), [144](#)  
summary.HLfit, [18](#), [144](#)

t.ZAXlist (ZAXlist), [151](#)  
tcrossprod, ZAXlist, missingOrNULL-method  
(ZAXlist), [151](#)  
tcrossprod-methods (ZAXlist), [151](#)  
terms (extractors), [37](#)  
terms.object, [39](#)  
title, [137](#)  
Tnegbin, [130](#)  
Tnegbin (negbin), [100](#)  
Tpoisson, [114](#), [130](#)  
Tpoisson (Poisson), [110](#)  
txtProgressBar, [102](#)

update.formula, [145](#)  
update.formula (update.HLfit), [145](#)  
update.HLfit, [60](#), [68](#), [145](#)  
update\_formulas, [44](#)  
update\_formulas (update.HLfit), [145](#)  
update\_resp (update.HLfit), [145](#)

VarCorr, [55](#), [56](#), [58](#)  
VarCorr (vcov), [147](#)  
Variogram.corMatern (corMatern), [23](#)  
vcov, [70](#), [147](#)  
vcov.HLfit, [39](#)

wafers, [148](#)  
welding, [150](#)  
worldcountries (seaMask), [125](#)  
wrap\_parallel, [33](#), [35](#), [151](#)

ZAXlist, [56](#), [151](#)  
ZAXlist-class (ZAXlist), [151](#)