

# Package ‘lmmlasso’

February 20, 2015

**Type** Package

**Title** Linear mixed-effects models with Lasso

**Version** 0.1-2

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**Description** This package fits (gaussian) linear mixed-effects models for high-dimensional data ( $n \ll p$ ) using a Lasso-type approach for the fixed-effects parameter.

**Depends** methods, emulator, miscTools, penalized

**License** GPL

**LazyLoad** yes

**Repository** CRAN

**Repository/R-Forge/Project** lmmlasso

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## R topics documented:

lmmlasso-package . . . . .	2
classroomStudy . . . . .	2
lmmlasso . . . . .	3
lmmlassoControl . . . . .	7
plot.lmmlasso . . . . .	8
print.lmmlasso . . . . .	9
summary.lmmlasso . . . . .	9

<b>Index</b>	<b>11</b>
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lmlasso-package      *lmlasso*

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### Description

Fits (gaussian) linear mixed-effects models with lasso penalty for the fixed effects.

### Details

Package:    lmlasso  
Type:        Package  
Version:    0.1-2  
Date:        2010-08-19  
License:    GPL  
LazyLoad:  yes

This is an early test version.

### Author(s)

Juerg Schelldorfer

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### References

J. Schelldorfer, P. Buehlmann and S. van de Geer (2011), Estimation for High-Dimensional Linear Mixed-Effects Models Using  $\ell_1$ -penalization, arXiv preprint 1002.3784v2

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classroomStudy      *Dataset of students math achievements*

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### Description

This is a subset of the Classroom Study described in West et. al. (2007) with 156 observations and 6 variables.

### Usage

data(classroomStudy)

**Format**

A list with the following four components.

Response variable. The students math achievement gain.

**grp** Grouping variable comprising the class of the students.

**X** Fixed-effect design matrix. The first column is the intercept, then sex, minority, mathkind, ses, yearstea and mathprep.

**Z** Random-effects design matrix. Only one column in order to fit a random intercept model.

**Details**

A detailed description of the covariates can be found in West et. al. (2007) and was carried out by Hill et. al. (2005)

**Source**

<http://www-personal.umich.edu/~bwest/classroom.csv>

**References**

Brady T. West, Kathleen B. Welch and Andrzej T. Galecki (2007), *Linear Mixed Models, A Practical Guide Using Statistical Software*, Chapman and Hall.

H.C. Hill, B. Rowan and D.L. Ball (2005) "Effect of teachers" mathematical knowledge for teaching on student achievements, *American Educational Research Journal*, 42, 371-406.

**Examples**

```
data(classroomStudy)
```

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lmmlasso	<i>Function to fit high-dimensional (gaussian) linear mixed-effects models</i>
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**Description**

Fits the solution for a high-dimensional (gaussian) linear mixed-effects models

**Usage**

```
lmmlasso(x, ...)

## Default S3 method:
lmmlasso(x, y, z = x, grp, weights = NULL, coefInit=NULL, lambda,
startValue = 1, nonpen = 1:dim(z)[[2]], pdMat = c("pdIdent", "pdDiag", "pdSym"),
method = "ML", CovOpt = c("nlminb", "optimize"), stopSat = TRUE,
standardize = TRUE, control = lmmlassoControl(), ranInd=1:dim(z)[[2]],...)
```

**Arguments**

x	matrix of dimension $ntot \times p$ including the fixed-effects covariables. An intercept has to be included in the first column as (1,...,1).
y	response variable of length $ntot$ .
z	random effects matrix of dimension $ntot \times q$ . It has to be a matrix, even if $q=1$ .
grp	grouping variable of length $ntot$
weights	weights for the fixed-effects covariates: NA means no penalization, 0 means drop this covariate ; if given, the argument nonpen is ignored. By default each covariate has weight 1
coefInit	list with three components used as starting values for the fixed effects, the random effects variance components and the error standard deviation.
lambda	positive regularization parameter
startValue	Choice of the starting values for the fixed effects using linear regression. 1 means 10-fold cross-validation with L1-penalty, 2 means 10-fold cross-validation Ridge Regression and 0 means that all the covariates are set to zero and the intercept is the mean of the response variable
nonpen	index of fixed effects with no penalization, ignored if the argument weights is specified, default is 1, which means that only the intercept (the first column in X )is not penalized.
pdMat	Covariance structure for the random effects. pdIdent, pdDiag and pdSym are already implemented. Default to pdIdent. pdIdent: $b_i \sim \mathcal{N}(0, \theta^2 I)$ (1 parameter), pdDiag: $b_i \sim \mathcal{N}(0, diag(\theta_1, \dots, \theta_q))$ (q parameters), pdSym: $b_i \sim \mathcal{N}(0, \Psi)$ where $\Psi$ is symmetric positive definit ( $q(q + 1)/2$ parameters)
method	Only "ML" is allowed. "REML" is not yet implemented.
CovOpt	which optimization routine should be used for updating the variance components parameters. optimize or nlmnb. nlmnb uses the estimate of the last iteration as a starting value. nlmnb is faster if there are many Gauss-Seidel iterations.
stopSat	logical. Should the algorithm stop when $ntot > p$ ?
standardize	Should the x matrix be standardized such that each column has mean 0 and standard deviation 1? Be careful if the x matrix includes dummy variables.
control	control parameters for the algorithm and the Armijo Rule, see lmmlassoControl for the details
ranInd	Index of the random effects with respect to the x matrix
...	not used.

**Details**

All the details of the algorithm can be found in Schelldorfer et. al. (2010).

**Value**

A lmmlasso object is returned, for which coef, resid, fitted, print, summary, plot methods exist.

coefficients	estimated fixed-effects coefficients $\hat{\beta}$
pars	free parameters in the covariance matrix $\Psi$ of the random effects
sigma	standard deviation $\hat{\sigma}$ of the errors
random	vector with random effects, sorted by groups
u	vector with the standardized random effects, sorted by effect
ranef	vector with random effects, sorted by effect
fixef	estimated fixed-effects coefficients $\hat{\beta}$
fitted.values	The fitted values $\hat{y} = \hat{X}\beta + Z\hat{b}_i$
residuals	raw residuals $y - \hat{y}$
Psi	Covariance matrix $\Psi$ of the random effects
corPsi	Correlation matrix of the random effects
logLik	value of the log-likelihood function
deviance	deviance = $-2 * \logLik$
npar	Number of parameters. Corresponds to the cardinality of the active set of coefficients plus the number of free parameters in Psi
aic	AIC
bic	BIC
data	data set, as a list with four components: x, y, z, grp (see above)
weights	weights for the fixed-effects covariates
nonpen	nonpenalized covariates. Differ from the input if weights is explicitly given
coefInit	list with three components used as starting values
lambda	positive regularization parameter
converged	Does the algorithm converge? 0: correct convergence ; an odd number means that maxIter was reached ; an even number means that the Armijo step was not succesful. For each unsuccessfull Armijo step, 2 is added to converged. If converged is large compared to the number of iterations counter, you may increase maxArmijo.
counter	The number of iterations used.
stopped	logical. Does the algorithm stopped due to ntot > p?
pdMat	Covariance structure for the random effects
method	"ML"
CovOpt	optimization routine
control	see lmmlassoControl
call	call
stopped	logical. Does the algorithm stopped due to a too large active set?
ranInd	Index of the random effects with respect to the x matrix
objective	Value of the objective function at the final estimates

**Author(s)**

Juerg Schelldorfer, <schell@stat.math.ethz.ch>

**References**

J. Schelldorfer, P. Bühlmann and S. van de Geer (2011), Estimation for High-Dimensional Linear Mixed-Effects Models Using  $\ell_1$ -penalization, arXiv preprint 1002.3784v2

**Examples**

```
# (1) Use the lmmlasso on the classroomStudy data set
data(classroomStudy)
fit1 <-
lmmlasso(x=classroomStudy$X,y=classroomStudy$y,z=classroomStudy$Z,
grp=classroomStudy$grp,lambda=15,pdMat="pdIdent")
summary(fit1)
plot(fit1)

# (2) Use the lmmlasso on a small simulated data set
set.seed(54)

N <- 20          # number of groups
p <- 6           # number of covariates (including intercept)
q <- 2           # number of random effect covariates
ni <- rep(6,N)   # observations per group
ntot <- sum(ni)  # total number of observations

grp <- factor(rep(1:N,each=ni)) # grouping variable

beta <- c(1,2,4,3,0,0,0) # fixed-effects coefficients
x <- cbind(1,matrix(rnorm(ntot*p),nrow=ntot)) # design matrix

bi1 <- rep(rnorm(N,0,3),each=ni) # Psi=diag(3,2)
bi2 <- rep(rnorm(N,0,2),each=ni)
bi <- rbind(bi1,bi2)

z <- x[,1:2,drop=FALSE]

y <- numeric(ntot)
for (k in 1:ntot) y[k] <- x[k,]%*%beta + t(z[k,])%*%bi[,grp[k]] + rnorm(1)

# correct random effects structure
fit2 <- lmmlasso(x=x,y=y,z=z,grp=grp,lambda=10,pdMat="pdDiag")
summary(fit2)
plot(fit2)

# wrong random effects structure
fit3 <- lmmlasso(x=x,y=y,z=x[,1:3],grp=grp,lambda=10,pdMat="pdDiag")
summary(fit3)
plot(fit3)
```

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lmmlassoControl      *Options for the lmmlasso Algorithm*


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**Description**

Definition of various kinds of options in the algorithm.

**Usage**

```
lmmlassoControl(tol = 10-4), trace = 1, maxIter = 1000,
maxArmijo = 20, number = 5, a_init = 1, delta = 0.1, rho = 0.001,
gamma = 0, lower = 10-6, upper = 108, seed = 532,
VarInt = c(0, 10), CovInt = c(-5, 5), thres = 10-4)
```

**Arguments**

tol	convergence tolerance
trace	integer. 1 prints no output, 2 prints warnings, 3 prints the current function values and warnings (not recommended)
maxIter	maximum number of (outer) iterations
maxArmijo	maximum number of steps to be chosen in the Armijo Rule. If the maximum is reached, the algorithm continues with optimizing the next coordinate.
number	integer. Determines the active set algorithm. The zero fixed-effects coefficients are only updated each number iteration. It may be that a smaller number increases the speed of the algorithm. Use $0 \leq number \leq 5$ .
a_init	$\alpha_{init}$ in the Armijo step. See Schelldorfer et. al. (2010).
delta	$\delta$ in the Armijo step. See Schelldorfer et. al. (2010)
rho	$\rho$ in the Armijo step. See Schelldorfer et. al. (2010)
gamma	$\gamma$ in the Armijo step. See Schelldorfer et. al. (2010)
lower	lower bound for the Hessian
upper	upper bound for the Hessian
seed	set.seed for calculating the starting value, which performs a 10-fold cross-validation.
VarInt	Only for opt="optimize". The interval for the variance parameters used in "optimize". See help("optimize")
CovInt	Only for opt="optimize". The interval for the covariance parameters used in "optimize". See help("optimize")
thres	If a variance or covariance parameter has smaller absolute value than thres, the parameter is set to exactly zero.

**Details**

For the Armijo step parameters, see Bertsekas (2003)

## References

Dimitri P. Bertsekas (2003) *Nonlinear Programming*, Athena Scientific.

J. Schelldorfer, P. Bühlmann and S. van de Geer (2011), Estimation for High-Dimensional Linear Mixed-Effects Models Using  $\ell_1$ -penalization, arXiv preprint 1002.3784v2

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plot.lmlasso                      *Diagnostic Plots for a lmlasso object*

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## Description

Plots six diagnostic plots for checking the model assumptions and supporting model selection for a lmlasso object

## Usage

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

## Arguments

x	a lmlasso object
...	not used.

## Details

plot.lmlasso shows six diagnostic plots which support checking the model assumption, model fit and may give hints for another model. 1) The first plot depicts the Tukey-Anscombe plot in order to check the assumptions about the errors. Points with the same color belong to the same group. 2) QQ-Plot of the residuals with equal coloring for each group. 3) QQ-Plot of the predicted random effects. Be careful with the interpretation since the random effects have not been standardized. The color shows which points belong to the same random-effects covariate. 4) Boxplot of the predicted random effects for each random-effects variable. 5) Plot of the fitted y-values against the observed y-values. 6) A histogram of the fixed-effects coefficients.

## Examples

```
data(classroomStudy)
fit <- lmlasso(x=classroomStudy$X, y=classroomStudy$y, z=classroomStudy$Z, grp=classroomStudy$grp, lambda=15, pdMat)
plot(fit)
```



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print.lmlasso	<i>Print a short summary of a lmlasso object.</i>
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**Description**

Prints a short summary of an lmlasso object comprising information about the variance components parameters and the number of nonzero fixed-effects coefficients.

**Usage**

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

**Arguments**

x	a lmlasso object
...	not used

**See Also**

summary.lmlasso

**Examples**

```
data(classroomStudy)  
fit <-  
lmlasso(x=classroomStudy$X,y=classroomStudy$y,z=classroomStudy$Z,  
grp=classroomStudy$grp,lambda=15,pdMat="pdIdent")  
print(fit)
```

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summary.lmlasso	<i>Summarize an lmlasso object</i>
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**Description**

Providing an elaborate summary of a lmlasso object.

**Usage**

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

**Arguments**

object	a lmlasso object
...	not used.

**Details**

This function shows a detailed summary of a `lmmlasso` object. In the fixed-effects part, (n) right from a fixed-effects coefficient means that this coefficient was not subject to penalization.

**Examples**

```
data(classroomStudy)
fit <-
lmmlasso(x=classroomStudy$X, y=classroomStudy$y, z=classroomStudy$Z,
grp=classroomStudy$grp, lambda=15, pdMat="pdIdent")
summary(fit)
```

# Index

- \*Topic **datasets**
  - classroomStudy, 2
- \*Topic **hplot**
  - plot.lmlasso, 8
- \*Topic **methods**
  - summary.lmlasso, 9
- \*Topic **misc**
  - lmlassoControl, 7
- \*Topic **models**
  - lmlasso, 3
- \*Topic **package**
  - lmlasso-package, 2
- \*Topic **regression**
  - lmlasso, 3

classroomStudy, 2

lmlasso, 3

lmlasso-package, 2

lmlassoControl, 7

plot.lmlasso, 8

print.lmlasso, 9

summary.lmlasso, 9