Package 'adelie'

July 22, 2025

Title Group Lasso and Elastic Net Solver for Generalized Linear Models

Version 1.0.8

Date 2025-06-28

Description Extremely efficient procedures for fitting the entire group lasso and group elastic net regularization path for GLMs, multinomial, the Cox model and multi-task Gaussian models. Similar to the R package 'glmnet' in scope of models, and in computational speed. This package provides R bindings to the C++ code underlying the corresponding Python package 'adelie'. These bindings offer a general purpose group elastic net solver, a wide range of matrix classes that can exploit special structure to allow large-scale inputs, and an assortment of generalized linear model classes for fitting various types of data. The package is an implementation of Yang, J. and Hastie, T. (2024) <doi:10.48550/arXiv.2405.08631>.

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Encoding UTF-8

RoxygenNote 7.3.2

LinkingTo Rcpp, RcppEigen

SystemRequirements C++17

Imports Matrix, r2r, Rcpp, methods, stringr, utils

Suggests ggplot2, gridExtra, testthat (>= 3.0.0), knitr, rmarkdown

Config/testthat/edition 3

VignetteBuilder knitr

URL https://github.com/JamesYang007/adelie-r

BugReports https://github.com/JamesYang007/adelie-r/issues

NeedsCompilation yes

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Repository CRAN

Date/Publication 2025-07-01 17:50:06 UTC

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constraint.box *Create a box constraint for a group.*

Description

A box constraint sets upper and lower bounds for coefficients in a model. This is done per group, and this function is used separately to set the bounds for each group in the model. The constraints are returned as a list, with number of elements the number of groups. List entries can be NULL, which means no constraints for that group. Currently works with single-response models (so glm.multinomial and glm.multigaussian are excluded). Note that for each group for which non-null constraints are provide, a separate call to constraint.box() must be made (i.e. the constraint object cannot be replicated). See the second example below.

Usage

```
constraint.box(lower, upper, max_iters = 100, tol = 1e-09)
```

Arguments

lower	lower bound for each coefficient in the group. If the group has m variables, this should be a vector of length m. Values can be -Inf.
upper	upper bound for each coefficient in the group. If the group has m variables, this should be a vector of length m. Values can be Inf.
max_iters	maximum number of proximal Newton iterations; default is 100.
tol	convergence tolerance for proximal Newton; default is 1e-9.

Value

Box constraint object.

Author(s)

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Examples

```
# Group of length 10, with positivity constraint on all the coefficients.
lower <- rep(0,10)
upper <- rep(Inf,10)
cont <- constraint.box(lower = lower, upper = upper)

# 10 singleton groups, and non-negativity constraints on all parameters.
cont <- lapply(1:10, function(i)constraint.box(lower = 0, upper = Inf))

# Same as above, but non-negativity constraints only on first 5 parameters.
cont <- lapply(1:5, function(i)constraint.box(lower = 0, upper = Inf))
cont <- c(cont, rep(list(NULL), 5)) # rep rule does not apply to NULL
```

`cv.glintnet` *Cross-validation for glintnet*

Description

Does k-fold cross-validation for glintnet

Usage

```
cv.glintnet(
  X,
  glm,
  offsets = NULL,
  intr_keys = NULL,
  intr_values,
  levels = NULL,
  n_folds = 10,
  foldid = NULL,
  n_threads = 1,
  ...
)
```

Arguments

`X`	Feature matrix. Either a regular R matrix, or else an `adelie` custom matrix class, or a concatination of such.
`glm`	GLM family/response object. This is an expression that represents the family, the reponse and other arguments such as weights, if present. The choices are `glm.gaussian()`, `glm.binomial()`, `glm.poisson()`, `glm.multinomial()`, `glm.cox()`, `glm.multinomial()`, and `glm.multigaussian()`. This is a required argument, and there is no default. In the simple example below, we use `glm.gaussian(y)`.
`offsets`	Offsets, default is `NULL`. If present, this is a fixed vector or matrix corresponding to the shape of the natural parameter, and is added to the fit.
`intr_keys`	List of feature indices. This is a list of all features with which interactions can be formed. Default is `1:p` where `p` is the number of columns in `X`.
`intr_values`	List of integer vectors of feature indices. For each of the `m <= p` indices listed in `intr_keys`, there is a vector of indices indicating which columns are candidates for interaction with that feature. If a vector is `NULL`, that means all other features are candidates for interactions. The default is a list of length `m` where each element is `NULL`; that is `rep(list(NULL), m`.
`levels`	Number of levels for each of the columns of `mat`, with `1` representing a quantitative feature. A factor with `K` levels should be represented by the numbers `0,1,...,K-1`.
`n_folds`	(default 10). Although `n_folds` can be as large as the sample size (leave-one-out CV), it is not recommended for large datasets. Smallest value allowable is `n_folds=3`.

foldid	An optional vector of values between 1 and n_folds identifying what fold each observation is in. If supplied, n_folds can be missing.
n_threads	Number of threads, default 1.
...	Additional named arguments to grpnet.

Details

The function runs glintnet n_folds+1 times; the first to get the lambda sequence, and then the remainder to compute the fit with each of the folds omitted. The out-of-fold deviance is accumulated, and the average deviance and standard deviation over the folds is computed. Note that cv.glintnet does NOT search for values for alpha. A specific value should be supplied, else alpha=1 is assumed by default. If users would like to cross-validate alpha as well, they should call cv.glintnet with a pre-computed vector foldid, and then use this same foldid vector in separate calls to cv.glintnet with different values of alpha. Note also that the results of cv.glintnet are random, since the folds are selected at random. Users can reduce this randomness by running cv.glintnet many times, and averaging the error curves.

Value

A list of class "glintnet", which inherits from class "grpnet". This has a a few additional components such as pairs, groups and levels. Users typically use methods like predict(), print(), plot() etc to examine the object.

Author(s)

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References

Lim, Michael and Hastie, Trevor (2015) *Learning interactions via hierarchical group-lasso regularization*, JCGS doi:10.1080/10618600.2014.938812
Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.
Friedman, J., Hastie, T. and Tibshirani, R. (2008) *Regularization Paths for Generalized Linear Models via Coordinate Descent (2010), Journal of Statistical Software, Vol. 33(1), 1-22*, doi:10.18637/jss.v033.i01.
Simon, N., Friedman, J., Hastie, T. and Tibshirani, R. (2011) *Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent, Journal of Statistical Software, Vol. 39(5), 1-13*, doi:10.18637/jss.v039.i05.
Tibshirani,Robert, Bien, J., Friedman, J., Hastie, T.,Simon, N.,Taylor, J. and Tibshirani, Ryan. (2012) *Strong Rules for Discarding Predictors in Lasso-type Problems, JRSSB, Vol. 74(2), 245-266*, https://arxiv.org/abs/1011.2234.

See Also

cv.glintnet, predict.glintnet, plot.glintnet, print.glintnet.

Examples

```
set.seed(0)
n=500
d_cont = 5     # number of continuous features
d_disc = 5     # number of categorical features
Z_cont = matrix(rnorm(n*d_cont), n, d_cont)
levels = sample(2:5,d_disc, replace = TRUE)
Z_disc = matrix(0,n,d_disc)
for(i in seq(d_disc))Z_disc[,i] = sample(0:(levels[i]-1),n,replace=TRUE)
Z = cbind(Z_cont,Z_disc)
levels = c(rep(1,d_cont),levels)

xmat = model.matrix(~Z_cont[,1]*factor(Z_disc[,2]))
nc=ncol(xmat)
beta = rnorm(nc)
y = xmat%*%beta+rnorm(n)*1.5

cvfit <- cv.glintnet(Z, glm.gaussian(y), levels=levels, intr_keys = 1)
plot(cvfit)
predict(cvfit, newx=Z[1:5,])
```

---

cv.grpnet *Cross-validation for grpnet*

Description

Does k-fold cross-validation for grpnet

Usage

```
cv.grpnet(
  X,
  glm,
  n_folds = 10,
  foldid = NULL,
  min_ratio = 0.01,
  lmda_path_size = 100,
  offsets = NULL,
  progress_bar = FALSE,
  n_threads = 1,
  ...
)
```

Arguments

X	Feature matrix. Either a regualr R matrix, or else an adelie custom matrix class, or a concatination of such.

glm	GLM family/response object. This is an expression that represents the family, the reponse and other arguments such as weights, if present. The choices are `glm.gaussian()`, `glm.binomial()`, `glm.poisson()`, `glm.multinomial()`, `glm.cox()`, `glm.multinomial()`, and `glm.multigaussian()`. This is a required argument, and there is no default. In the simple example below, we use `glm.gaussian(y)`.
n_folds	(default 10). Although `n_folds` can be as large as the sample size (leave-one-out CV), it is not recommended for large datasets. Smallest value allowable is `n_folds=3`.
foldid	An optional vector of values between 1 and `n_folds` identifying what fold each observation is in. If supplied, `n_folds` can be missing.
min_ratio	Ratio between smallest and largest value of lambda. Default is 1e-2.
lmda_path_size	Number of values for `lambda`, if generated automatically. Default is 100.
offsets	Offsets, default is `NULL`. If present, this is a fixed vector or matrix corresponding to the shape of the natural parameter, and is added to the fit.
progress_bar	Progress bar. Default is `FALSE`.
n_threads	Number of threads, default `1`.
...	Other arguments that can be passed to `grpnet`

Details

The function runs `grpnet` `n_folds+1` times; the first to get the `lambda` sequence, and then the remainder to compute the fit with each of the folds omitted. The out-of-fold deviance is accumulated, and the average deviance and standard deviation over the folds is computed. Note that `cv.grpnet` does NOT search for values for `alpha`. A specific value should be supplied, else `alpha = 1` is assumed by default. If users would like to cross-validate `alpha` as well, they should call `cv.grpnet` with a pre-computed vector `foldid`, and then use this same `foldid` vector in separate calls to `cv.grpnet` with different values of `alpha`. Note also that the results of `cv.grpnet` are random, since the folds are selected at random (unless supplied via `foldid`). Users can reduce this randomness by running `cv.grpnet` many times, and averaging the error curves.

Value

an object of class `"cv.grpnet"` is returned, which is a list with the ingredients of the cross-validation fit.

lambda	the values of `lambda` used in the fits.
cvm	The mean cross-validated deviance - a vector of length `length(lambda)`.
cvsd	estimate of standard error of `cvm`.
cvup	upper curve = `cvm+cvsd`.
cvlo	lower curve = `cvm-cvsd`.
nzero	number of non-zero coefficients at each `lambda`.
name	a text string indicating type of measure (for plotting purposes). Currently this is `"deviance"`
grpnet.fit	a fitted grpnet object for the full data.

`lambda.min`	value of `lambda` that gives minimum `cvm`.
`lambda.1se`	largest value of `lambda` such that mean deviance is within 1 standard error of the minimum.
`index`	a one column matrix with the indices of `lambda.min` and `lambda.1se` in the sequence of coefficients, fits etc.

Author(s)

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References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.
Friedman, J., Hastie, T. and Tibshirani, R. (2008) *Regularization Paths for Generalized Linear Models via Coordinate Descent (2010), Journal of Statistical Software, Vol. 33(1), 1-22*, doi:10.18637/jss.v033.i01.
Simon, N., Friedman, J., Hastie, T. and Tibshirani, R. (2011) *Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent, Journal of Statistical Software, Vol. 39(5), 1-13*, doi:10.18637/jss.v039.i05.
Tibshirani,Robert, Bien, J., Friedman, J., Hastie, T.,Simon, N.,Taylor, J. and Tibshirani, Ryan. (2012) *Strong Rules for Discarding Predictors in Lasso-type Problems, JRSSB, Vol. 74(2), 245-266*, https://arxiv.org/abs/1011.2234.

See Also

`print.cv.grpnet`, `predict.cv.grpnet`, `coef.cv.grpnet`, `plot.cv.grpnet`.

Examples

```
set.seed(0)
n <- 100
p <- 200
X <- matrix(rnorm(n * p), n, p)
y <- X[,1:25] %*% rnorm(25)/4 + rnorm(n)
groups <- c(1, sample(2:199, 60, replace = FALSE))
groups <- sort(groups)
cvfit <- cv.grpnet(X, glm.gaussian(y), groups = groups)
print(cvfit)
plot(cvfit)
predict(cvfit, newx = X[1:5,])
predict(cvfit, type = "nonzero")
```

gaussian_cov *Solves group elastic net via covariance method.*

Description

Solves group elastic net via covariance method.

Usage

```
gaussian_cov(
  A,
  v,
  constraints = NULL,
  groups = NULL,
  alpha = 1,
  penalty = NULL,
  lmda_path = NULL,
  max_iters = as.integer(1e+05),
  tol = 1e-07,
  rdev_tol = 0.001,
  newton_tol = 1e-12,
  newton_max_iters = 1000,
  n_threads = 1,
  early_exit = TRUE,
  screen_rule = "pivot",
  min_ratio = 0.01,
  lmda_path_size = 100,
  max_screen_size = NULL,
  max_active_size = NULL,
  pivot_subset_ratio = 0.1,
  pivot_subset_min = 1,
  pivot_slack_ratio = 1.25,
  check_state = FALSE,
  progress_bar = FALSE,
  warm_start = NULL
)
```

Arguments

A	Positive semi-definite matrix.
v	Linear term.
constraints	Constraints.
groups	Groups.
alpha	Elastic net parameter.
penalty	Penalty factor.

lmda_path	The regularization path.
max_iters	Maximum number of coordinate descents.
tol	Coordinate descent convergence tolerance.
rdev_tol	Relative percent deviance explained tolerance.
newton_tol	Convergence tolerance for the BCD update.
newton_max_iters	Maximum number of iterations for the BCD update.
n_threads	Number of threads.
early_exit	TRUE if the function should exit early.
screen_rule	Screen rule (currently the only value is the default "pivot".
min_ratio	Ratio between largest and smallest regularization parameter, default is 0.01.
lmda_path_size	Number of regularization steps in the path, default is 100.
max_screen_size	Maximum number of screen groups, default is NULL for no maximum.
max_active_size	Maximum number of active groups, default is NULL for no maximum.
pivot_subset_ratio	Subset ratio of pivot rule, default is 0.1.
pivot_subset_min	Minimum subset of pivot rule, default is 1.
pivot_slack_ratio	Slack ratio of pivot rule, default is 1.25.
check_state	Check state, default is FALSE.
progress_bar	Progress bar, default is FALSE.
warm_start	Warm start, default is NULL (no warm start).

Value

State of the solver.

Examples

```
set.seed(0)
n <- 100
p <- 200
X <- matrix(rnorm(n * p), n, p)
y <- X[,1] * rnorm(1) + rnorm(n)
A <- t(X) %*% X / n
v <- t(X) %*% y / n
state <- gaussian_cov(A, v)
```

glintnet *fit a GLM interaction model with group lasso or group elastic-net regularization*

Description

This function is an implementation of the `glinternet` model of Lim and Hastie, for fitting interactions between pairs of variables in a model. The method creates *interaction matrices* and enforces hierarchy using the *overlap group lasso*. Once the augmented model matrix is set up, `glintnet` uses `grpnet` to fit the overlap group lasso path. It hence inherits all the capabilities of `grpnet`, and in particular can fit interaction models for all the GLM families.

Usage

```
glintnet(
  X,
  glm,
  offsets = NULL,
  intr_keys = NULL,
  intr_values,
  levels = NULL,
  n_threads = 1,
  save.X = FALSE,
  ...
)
```

Arguments

`X`	A dense matrix, which can include factors with levels coded as non-negative integers starting at 0.
`glm`	GLM family/response object. This is an expression that represents the family, the reponse and other arguments such as weights, if present. The choices are `glm.gaussian()`, `glm.binomial()`, `glm.poisson()`, `glm.multinomial()`, `glm.cox()`, `glm.multinomial()`, and `glm.multigaussian()`. This is a required argument, and there is no default. In the simple example below, we use `glm.gaussian(y)`.
`offsets`	Offsets, default is `NULL`. If present, this is a fixed vector or matrix corresponding to the shape of the natural parameter, and is added to the fit.
`intr_keys`	List of feature indices. This is a list of all features with which interactions can be formed. Default is `1:p` where `p` is the number of columns in `X`.
`intr_values`	List of integer vectors of feature indices. For each of the `m <= p` indices listed in `intr_keys`, there is a vector of indices indicating which columns are candidates for interaction with that feature. If a vector is `NULL`, that means all other features are candidates for interactions. The default is a list of length `m` where each element is `NULL`; that is `rep(list(NULL), m`.

levels	Number of levels for each of the columns of mat, with 1 representing a quantitative feature. A factor with K levels should be represented by the numbers 0,1,...,K-1.
n_threads	Number of threads, default 1.
save.X	Logical flag, default FALSE. If TRUE, the internally constructed X matrix is returned.
...	Additional named arguments to grpnet.

Details

The input matrix can be composed of quantitative variables or columns representing factors. The argument levels indicates which are quantitative, and which are factors. The later are represented by numbers starting at 0, up to one less than the number of levels (sorry!) Each of the factors are converted to "one-hot" matrices, and hence a group of columns are created for each of these. This is done using the matrix utility function matrix.one_hot(). In addition interaction matrices are created. For each pair of variables for which an interaction is considered, a matrix is created consisting of the cross-product of each of the constituent matrices, as described in the "glinternet" reference. Once this much bigger matrix is established, the model is handed to grpnet to produce the fit.

Value

A list of class "glintnet", which inherits from class "grpnet". This has a a few additional components such as pairs, groups and levels. Users typically use methods like predict(), print(), plot() etc to examine the object.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie <hastie@stanford.edu>

References

Lim, Michael and Hastie, Trevor (2015) *Learning interactions via hierarchical group-lasso regularization*, JCGS doi:10.1080/10618600.2014.938812
Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.
Friedman, J., Hastie, T. and Tibshirani, R. (2008) *Regularization Paths for Generalized Linear Models via Coordinate Descent (2010), Journal of Statistical Software, Vol. 33(1), 1-22*, doi:10.18637/jss.v033.i01.
Simon, N., Friedman, J., Hastie, T. and Tibshirani, R. (2011) *Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent, Journal of Statistical Software, Vol. 39(5), 1-13*, doi:10.18637/jss.v039.i05.
Tibshirani,Robert, Bien, J., Friedman, J., Hastie, T.,Simon, N.,Taylor, J. and Tibshirani, Ryan. (2012) *Strong Rules for Discarding Predictors in Lasso-type Problems, JRSSB, Vol. 74(2), 245-266*, https://arxiv.org/abs/1011.2234.

See Also

cv.glintnet, predict.glintnet, plot.glintnet, print.glintnet.

Examples

```
set.seed(0)
n=500
d_cont = 5     # number of continuous features
d_disc = 5     # number of categorical features
Z_cont = matrix(rnorm(n*d_cont), n, d_cont)
levels = sample(2:5,d_disc, replace = TRUE)
Z_disc = matrix(0,n,d_disc)
for(i in seq(d_disc))Z_disc[,i] = sample(0:(levels[i]-1),n,replace=TRUE)
Z = cbind(Z_cont,Z_disc)
levels = c(rep(1,d_cont),levels)

xmat = model.matrix(~Z_cont[,1]*factor(Z_disc[,2]))
nc=ncol(xmat)
beta = rnorm(nc)
y = xmat%*%beta+rnorm(n)*1.5

fit <- glintnet(Z, glm.gaussian(y), levels=levels, intr_keys = 1)
print(fit)
```

---

glm.binomial *Creates a Binomial GLM family object.*

Description

A GLM family object specifies the type of model fit, provides the appropriate response object and makes sure it is represented in the right form for the model family, and allows for optional parameters such as a weight vector.

Usage

```
glm.binomial(y, weights = NULL, link = "logit")
```

Arguments

y	Binary response vector, with values 0 or 1, or a logical vector. Alternatively, if data are represented by a two-column matrix of proportions (with row-sums = 1), then one can provide one of the columns as the response. This is useful for grouped binomial data, where each observation represents the result of m[i] successes out of n[i] trials. Then the response is provided as y[i] = m[i]/n[i] and the corresponding element of the weight vector as w[i]=n[i]. Alternatively can use glm.multinomial() instead.

`weights`	Observation weight vector, with default `NULL`, which results in weight `1/n` for each observation.
`link`	The link function type, with choice `"logit"` (default) or `"probit"`).

Value

Binomial GLM object.

Author(s)

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See Also

`glm.gaussian`, `glm.binomial`, `glm.poisson`, `glm.multinomial`, `glm.multigaussian`, `glm.cox`.

Examples

```
n <- 100
y <- rbinom(n, 1, 0.5)
obj <- glm.binomial(y)
```

`glm.cox` *Creates a Cox GLM family object.*

Description

A GLM family object specifies the type of model fit, provides the appropriate response object and makes sure it is represented in the right form for the model family, and allows for optional parameters such as a weight vector.

Usage

```
glm.cox(
  stop,
  status,
  start = -Inf,
  strata = NULL,
  weights = NULL,
  tie_method = c("efron", "breslow")
)
```

Arguments

stop	Stop time vector.
status	Binary status vector of same length as stop, with 1 a "death", and 0 censored.
start	Start time vector. Default is a vector of -Inf of same length as stop.
strata	Observations can belong in strata, labeled 1,2, ... If strata = NULL then all observations are in a single stratum.
weights	Observation weights, with default NULL.
tie_method	The tie-breaking method - one of "efron" (default) or "breslow".

Value

Cox GLM object.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
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See Also

glm.gaussian, glm.binomial, glm.poisson, glm.multinomial, glm.multigaussian, glm.cox.

Examples

```
n <- 100
start <- sample.int(20, size = n, replace = TRUE)
stop <- start + 1 + sample.int(5, size = n, replace = TRUE)
status <- rbinom(n, 1, 0.5)
strata <- sample(c(1,2), n, replace = TRUE)
obj1 <- glm.cox(stop, status)
obj2 <- glm.cox(stop, status, start = start)
obj3 <- glm.cox(stop, status, start = start, strata = strata)
```

---

glm.gaussian *Creates a Gaussian GLM family object.*

Description

A GLM family object specifies the type of model fit, provides the appropriate response object and makes sure it is represented in the right form for the model family, and allows for optional parameters such as a weight vector.

Usage

```
glm.gaussian(y, weights = NULL, opt = TRUE)
```

Arguments

y	Response vector.
weights	Observation weight vector, with default NULL.
opt	If TRUE (default), an optimized routine is run.

Value

Gaussian GLM

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
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See Also

glm.gaussian, glm.binomial, glm.poisson, glm.multinomial, glm.multigaussian, glm.cox.

Examples

```
n <- 100
y <- rnorm(n)
obj <- glm.gaussian(y)
```

---

glm.multigaussian *Creates a MultiGaussian GLM family object.*

Description

A GLM family object specifies the type of model fit, provides the appropriate response object and makes sure it is represented in the right form for the model family, and allows for optional parameters such as a weight vector.

Usage

```
glm.multigaussian(y, weights = NULL, opt = TRUE)
```

Arguments

y	Response matrix, with two or more columns.
weights	Observation weight vector, with default NULL.
opt	If TRUE (default), an optimized routine is run.

Value

MultiGaussian GLM object.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

See Also

`glm.gaussian`, `glm.binomial`, `glm.poisson`, `glm.multinomial`, `glm.multigaussian`, `glm.cox`.

Examples

```
n <- 100
K <- 5
y <- matrix(rnorm(n*K), n, K)
obj <- glm.multigaussian(y)
```

---

glm.multinomial *Creates a Multinomial GLM family object.*

Description

A GLM family object specifies the type of model fit, provides the appropriate response object and makes sure it is represented in the right form for the model family, and allows for optional parameters such as a weight vector.

Usage

```
glm.multinomial(y, weights = NULL)
```

Arguments

`y`	Response matrix with `K>1` columns, and row sums equal to 1. This can either be a "one-hot" encoded version of a K-category factor variable, or else a matrix of proportions. This is useful for grouped multinomial data, where column `y[i, k]` represents the proportion of outcomes in category k in `n[i]` trials. Then the corresponding element of the weight vector is `w[i]=n[i]`.
`weights`	Observation weights.

Value

Multinomial GLM object.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

See Also

glm.gaussian, glm.binomial, glm.poisson, glm.multinomial, glm.multigaussian, glm.cox.

Examples

```
n <- 100
K <- 5
y <- t(rmultinom(n, 1, rep(1/K, K)))
obj <- glm.multinomial(y)
```

---

glm.poisson *Creates a Poisson GLM family object.*

Description

A GLM family object specifies the type of model fit, provides the appropriate response object and makes sure it is represented in the right form for the model family, and allows for optional parameters such as a weight vector.

Usage

```
glm.poisson(y, weights = NULL)
```

Arguments

y	Response vector of non-negative counts.
weights	Observation weight vector, with default NULL.

Value

Poisson GLM object.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

See Also

glm.gaussian, glm.binomial, glm.poisson, glm.multinomial, glm.multigaussian, glm.cox.

Examples

```
n <- 100
y <- rpois(n, 1)
obj <- glm.poisson(y)
```

grpnet *fit a GLM with group lasso or group elastic-net regularization*

Description

Computes a group elastic-net regularization path for a variety of GLM and other families, including the Cox model. This function extends the abilities of the `glmnet` package to allow for grouped regularization. The code is very efficient (core routines are written in C++), and allows for specialized matrix classes.

Usage

```
grpnet(
  X,
  glm,
  constraints = NULL,
  groups = NULL,
  alpha = 1,
  penalty = NULL,
  offsets = NULL,
  lambda = NULL,
  standardize = TRUE,
  irls_max_iters = as.integer(10000),
  irls_tol = 1e-07,
  max_iters = as.integer(1e+05),
  tol = 1e-07,
  adev_tol = 0.9,
  ddev_tol = 0,
  newton_tol = 1e-12,
  newton_max_iters = 1000,
  n_threads = 1,
  early_exit = TRUE,
  intercept = TRUE,
  screen_rule = c("pivot", "strong"),
  min_ratio = 0.01,
  lmda_path_size = 100,
  max_screen_size = NULL,
  max_active_size = NULL,
  pivot_subset_ratio = 0.1,
  pivot_subset_min = 1,
  pivot_slack_ratio = 1.25,
  check_state = FALSE,
  progress_bar = FALSE,
  warm_start = NULL
)
```

Arguments

X	Feature matrix. Either a regular R matrix, or else an adelie custom matrix class, or a concatination of such.
glm	GLM family/response object. This is an expression that represents the family, the reponse and other arguments such as weights, if present. The choices are glm.gaussian(), glm.binomial(), glm.poisson(), glm.multinomial(), glm.cox(), glm.multinomial(), and glm.multigaussian(). This is a required argument, and there is no default. In the simple example below, we use glm.gaussian(y).
constraints	Group-wise constraints on the parameters, supplied as a list with an element for each group. Default is NULL, which means no constraints. List elements can be NULL as well. Currently only 'box constraints' are supported, which means upper and lower limits. The function constraint.box() must be used to set the constraints for each group that has constraints. Details are given in the documentation for constraint.box.
groups	This is an ordered vector of integers that represents the groupings, with each entry indicating where a group begins. The entries refer to column numbers in the feature matrix, and hence the memebers of a group have to be contiguous. If there are p features, the default is 1:p (no groups; i.e. p groups each of of size 1). So the length of groups is the number of groups. (Note that in the state output of grpnet this vector might be shifted to start from 0, since internally adelie uses zero-based indexing.)
alpha	The elasticnet mixing parameter, with $0 \leq \alpha \leq 1$. The penalty is defined as $$(1-\alpha)/2 \sum_j ||\beta_j||_2^2 + \alpha \sum_j ||\beta_j||_2,$$ where thte sum is over groups. alpha=1 is pure group lasso penalty, and alpha=0 the pure ridge penalty.
penalty	Separate penalty factors can be applied to each group of coefficients. This is a number that multiplies lambda to allow differential shrinkage for groups. Can be 0 for some groups, which implies no shrinkage, and that group is always included in the model. Default is square-root of group sizes for each group.
offsets	Offsets, default is NULL. If present, this is a fixed vector or matrix corresponding to the shape of the natural parameter, and is added to the fit.
lambda	A user supplied lambda sequence. Typical usage is to have the program compute its own lambda sequence based on lmda_path_size and min_ratio. This is returned with the fit.
standardize	If TRUE (the default), the columns of X are standardized before the fit is computed. This is good practice if the features are on different scales, because it has an impact on the penalty. The regularization path is computed using the standardized features, and the standardization information is saved on the object for making future predictions. The different matrix classes have their own methods for standardization. For example, for a sparse matrix the standardization information will be computed, but not actually applied (eg centering would destroy the sparsity). Rather, the methods for matrix multiply will be aware, and incorporate the standardization information.

irls_max_iters	Maximum number of IRLS iterations, default is 1e4.
irls_tol	IRLS convergence tolerance, default is 1e-7.
max_iters	Maximum total number of coordinate descent iterations, default is 1e5.
tol	Coordinate descent convergence tolerance, default 1e-7.
adev_tol	Fraction deviance explained tolerance, default 0.9. This can be seen as a limit on overfitting the training data.
ddev_tol	Difference in fraction deviance explained tolerance, default 0. If a step in the path changes the deviance by this amount or less, the algorithm truncates the path.
newton_tol	Convergence tolerance for the BCD update, default 1e-12. This parameter controls the iterations in each block-coordinate step to establish the block solution.
newton_max_iters	Maximum number of iterations for the BCD update, default 1000.
n_threads	Number of threads, default 1.
early_exit	TRUE if the function should be allowed to exit early.
intercept	Default TRUE to include an unpenalized intercept.
screen_rule	Screen rule, with default "pivot". Other option is "strong". (an empirical improvement over "strong", the other option.)
min_ratio	Ratio between smallest and largest value of lambda. Default is 1e-2.
lmda_path_size	Number of values for lambda, if generated automatically. Default is 100.
max_screen_size	Maximum number of screen groups. Default is NULL.
max_active_size	Maximum number of active groups. Default is NULL.
pivot_subset_ratio	Subset ratio of pivot rule. Default is 0.1. Users not expected to fiddle with this.
pivot_subset_min	Minimum subset of pivot rule. Defaults is 1. Users not expected to fiddle with this.
pivot_slack_ratio	Slack ratio of pivot rule, default is 1.25. Users not expected to fiddle with this. See reference for details.
check_state	Check state. Internal parameter, with default FALSE.
progress_bar	Progress bar. Default is FALSE.
warm_start	Warm start (default is NULL). Internal parameter.

Value

A list of class "grpnet". This has a main component called state which represents the fitted path, and a few extra useful components such as the call, the family name, groups and group_sizes. Users are encouraged to use methods like predict(), coef(), print(), plot() etc to examine the object.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie <hastie@stanford.edu>

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.
Friedman, J., Hastie, T. and Tibshirani, R. (2008) *Regularization Paths for Generalized Linear Models via Coordinate Descent (2010), Journal of Statistical Software, Vol. 33(1), 1-22*, doi:10.18637/jss.v033.i01.
Simon, N., Friedman, J., Hastie, T. and Tibshirani, R. (2011) *Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent, Journal of Statistical Software, Vol. 39(5), 1-13*, doi:10.18637/jss.v039.i05.
Tibshirani,Robert, Bien, J., Friedman, J., Hastie, T.,Simon, N., Taylor, J. and Tibshirani, Ryan. (2012) *Strong Rules for Discarding Predictors in Lasso-type Problems, JRSSB, Vol. 74(2), 245-266*, https://arxiv.org/abs/1011.2234.

See Also

`cv.grpnet`, `predict.grpnet`, `coef.grpnet`, `plot.grpnet`, `print.grpnet`.

Examples

```
set.seed(0)
n <- 100
p <- 200
X <- matrix(rnorm(n * p), n, p)
y <- X[,1] * rnorm(1) + rnorm(n)
## Here we create 60 groups randomly. Groups need to be contiguous, and the `groups` variable
## indicates the beginning position of each group.
groups <- c(1, sample(2:199, 60, replace = FALSE))
groups <- sort(groups)
print(groups)
fit <- grpnet(X, glm.gaussian(y), groups = groups)
print(fit)
plot(fit)
coef(fit)
cvfit  <- cv.grpnet(X, glm.gaussian(y), groups = groups)
print(cvfit)
plot(cvfit)
predict(cvfit,newx=X[1:5,], lambda="lambda.min")
```

`io.snp_phased_ancestry` *IO handler for SNP phased, ancestry matrix.*

Description

IO handler for SNP phased, ancestry matrix.

Usage

```
io.snp_phased_ancestry(filename, read_mode = "file")
```

Arguments

filename	File name.
read_mode	Reading mode.

Value

IO handler for SNP phased, ancestry data.

Examples

```
n <- 123
s <- 423
A <- 8
filename <- paste(tempdir(), "snp_phased_ancestry_dummy.snpdat", sep="/")
handle <- io.snp_phased_ancestry(filename)
calldata <- matrix(
    as.integer(sample.int(
        2, n * s * 2,
        replace=TRUE,
        prob=c(0.7, 0.3)
    ) - 1),
    n, s * 2
)
ancestries <- matrix(
    as.integer(sample.int(
        A, n * s * 2,
        replace=TRUE,
        prob=rep_len(1/A, A)
    ) - 1),
    n, s * 2
)
handle$write(calldata, ancestries, A, 1)
handle$read()
file.remove(filename)
```

---

io.snp_unphased *IO handler for SNP unphased matrix.*

Description

IO handler for SNP unphased matrix.

Usage

```
io.snp_unphased(filename, read_mode = "file")
```

Arguments

filename	File name.
read_mode	Reading mode.

Value

IO handler for SNP unphased data.

Examples

```
n <- 123
s <- 423
filename <- paste(tempdir(), "snp_unphased_dummy.snpdat", sep="/")
handle <- io.snp_unphased(filename)
mat <- matrix(
    as.integer(sample.int(
        3, n * s,
        replace=TRUE,
        prob=c(0.7, 0.2, 0.1)
    ) - 1),
    n, s
)
impute <- double(s)
handle$write(mat, "mean", impute, 1)
handle$read()
file.remove(filename)
```

---

matrix.block_diag *Creates a block-diagonal matrix.*

Description

Creates a block-diagonal matrix.

Usage

```
matrix.block_diag(mats, method = c("naive", "cov"), n_threads = 1)
```

Arguments

mats	List of matrices.
method	Method type, with default method="naive".
n_threads	Number of threads.

Value

Block-diagonal matrix.

Author(s)

Trevor Hastie and James Yang
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
ps <- c(10, 20, 30)
mats <- lapply(ps, function(p) {
    X <- matrix(rnorm(n * p), n, p)
    matrix.dense(t(X) %*% X, method="cov")
})
out <- matrix.block_diag(mats, method="cov")
mats <- lapply(ps, function(p) {
    X <- matrix(rnorm(n * p), n, p)
    matrix.dense(X, method="naive")
})
out <- matrix.block_diag(mats, method="naive")
```

`matrix.concatenate` *Creates a concatenation of the matrices.*

Description

Creates a concatenation of the matrices.

Usage

```
matrix.concatenate(mats, axis = 2, n_threads = 1)
```

Arguments

`mats`	List of matrices.
`axis`	The axis along which the matrices will be joined. With axis = 2 (default) this function is equivalent to `cbind()` and axis = 1 is equivalent to `rbind()`.
`n_threads`	Number of threads.

Value

Concatenation of matrices. The object is an S4 class with methods for efficient computation in C++ by adelie. Note that for the object itself axis is represented with base 0 (so 1 less than the argument here).

Author(s)

Trevor Hastie and James Yang
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
ps <- c(10, 20, 30)
n <- 100
mats <- lapply(ps, function(p) {
    matrix.dense(matrix(rnorm(n * p), n, p))
})
out <- matrix.concatenate(mats, axis=2)
```

---

matrix.convex_relu *Creates a feature matrix for the convex relu problem.*

Description

Creates a feature matrix for the convex relu problem.

Usage

```
matrix.convex_relu(mat, mask, gated = FALSE, n_threads = 1)
```

Arguments

mat	Base feature matrix. It is either a dense or sparse matrix.
mask	Boolean mask matrix.
gated	Flag to indicate whether to use the convex gated relu feature matrix.
n_threads	Number of threads.

Value

Convex relu feature matrix. The object is an S4 class with methods for efficient computation in C++ by adelie.

Author(s)

Trevor Hastie and James Yang
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
p <- 20
m <- 10
Z_dense <- matrix(rnorm(n * p), n, p)
mask <- matrix(rbinom(n * m, 1, 0.5), n, m)
out <- matrix.convex_relu(Z_dense, mask)
Z_sparse <- as(Z_dense, "dgCMatrix")
out <- matrix.convex_relu(Z_sparse, mask)
```

---

matrix.dense *Creates a dense matrix object.*

Description

Creates a dense matrix object.

Usage

```
matrix.dense(mat, method = c("naive", "cov", "constraint"), n_threads = 1)
```

Arguments

mat	The dense matrix.
method	Method type, with default method="naive". If method="cov", the matrix is used with the solver gaussian_cov(). Used for glm.gaussian() and glm.multigaussian() families. Generally "naive" is used for wide matrices, and "cov" for tall matrices. If method="constraint", the matrix is used as input to the constraint objects.
n_threads	Number of threads.

Value

Dense matrix. The object is an S4 class with methods for efficient computation by adelie.

Author(s)

Trevor Hastie and James Yang
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
p <- 20
X_dense <- matrix(rnorm(n * p), n, p)
out <- matrix.dense(X_dense, method="naive")
A_dense <- t(X_dense) %*% X_dense
out <- matrix.dense(A_dense, method="cov")
out <- matrix.dense(X_dense, method="constraint")
```

matrix.eager_cov *Creates an eager covariance matrix.*

Description

Creates an eager covariance matrix.

Usage

```
matrix.eager_cov(mat, n_threads = 1)
```

Arguments

mat	A dense matrix to be used with the gaussian_cov() solver.
n_threads	Number of threads.

Value

The dense covariance matrix. This matrix is exactly t(mat)%*%mat, computed with some efficiency.

Examples

```
n <- 100
p <- 20
mat <- matrix(rnorm(n * p), n, p)
out <- matrix.eager_cov(mat)
```

matrix.interaction *Creates a matrix with pairwise interactions.*

Description

Creates a matrix with pairwise interactions.

Usage

```
matrix.interaction(
  mat,
  intr_keys = NULL,
  intr_values,
  levels = NULL,
  n_threads = 1
)
```

Arguments

`mat`	The dense matrix, which can include factors with levels coded as non-negative integers.
`intr_keys`	List of feature indices. This is a list of all features with which interactions can be formed. Default is `1:p` where `p` is the number of columns in `mat`.
`intr_values`	List of integer vectors of feature indices. For each of the `m <= p` indices listed in `intr_keys`, there is a vector of indices indicating which columns are candidates for interaction with that feature. If a list is `list(NULL)`, that means all other features are candidates for interactions. The default is a list of length `m` where each element is `list(NULL)`; that is `rep(list(NULL), m`.
`levels`	Number of levels for each of the columns of `mat`, with `1` representing a quantitative feature. A factor with `K` levels should be represented by the numbers `0,1,...,K-1`.
`n_threads`	Number of threads.

Value

Pairwise interaction matrix. Logic is used to avoid repetitions. For each factor variable, the column is one-hot-encoded to form a basis for that feature. The object is an S4 class with methods for efficient computation by adelie. Note that some of the arguments are transformed to C++ base 0 for internal use, and if the object is examined, it will reflect that.

Author(s)

Trevor Hastie and James Yang
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 10
p <- 20
X_dense <- matrix(rnorm(n * p), n, p)
X_dense[,1] <- rbinom(n, 4, 0.5)
intr_keys <- c(1, 2)
intr_values <- list(NULL, c(1, 3))
levels <- c(c(5), rep(1, p-1))
out <- matrix.interaction(X_dense, intr_keys, intr_values, levels)
```

`matrix.kronecker_eye` *Creates a Kronecker product with an identity matrix.*

Description

Creates a Kronecker product with an identity matrix.

Usage

```
matrix.kronecker_eye(mat, K = 1, n_threads = 1)
```

Arguments

mat	The matrix to view as a Kronecker product.
K	Dimension of the identity matrix (default is 1, which does essentially nothing).
n_threads	Number of threads.

Value

Kronecker product with identity matrix. If mat is n x p, the the resulting matrix will be nK x np. The object is an S4 class with methods for efficient computation by adelie.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
p <- 20
K <- 2
mat <- matrix(rnorm(n * p), n, p)
out <- matrix.kronecker_eye(mat, K)
mat <- matrix.dense(mat)
out <- matrix.kronecker_eye(mat, K)
```

---

matrix.lazy_cov *Creates a lazy covariance matrix.*

Description

Creates a lazy covariance matrix.

Usage

```
matrix.lazy_cov(mat, n_threads = 1)
```

Arguments

mat	A dense data matrix to be used with the gaussian_cov() solver.
n_threads	Number of threads.

Value

Lazy covariance matrix. This is essentially the same matrix, but with a setup to create covariance terms as needed on the fly. The object is an S4 class with methods for efficient computation by adelie.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
p <- 20
mat <- matrix(rnorm(n * p), n, p)
out <- matrix.lazy_cov(mat)
```

---

matrix.one_hot *Creates a one-hot encoded matrix.*

Description

Creates a one-hot encoded matrix.

Usage

```
matrix.one_hot(mat, levels = NULL, n_threads = 1)
```

Arguments

`mat`	A dense matrix, which can include factors with levels coded as non-negative integers.
`levels`	Number of levels for each of the columns of `mat`, with `1` representing a quantitative feature. A factor with `K` levels should be represented by the numbers `0,1,...,K-1`.
`n_threads`	Number of threads.

Value

One-hot encoded matrix. All the factor columns, with levels>1, are replaced by a collection of one-hot encoded versions (dummy matrices). The resulting matrix has `sum(levels)` columns. The object is an S4 class with methods for efficient computation by adelie. Note that some of the arguments are transformed to C++ base 0 for internal use, and if the object is examined, it will reflect that.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
p <- 20
mat <- matrix(rnorm(n * p), n, p)
fac <- sample(0:5, n, replace = TRUE)
mat=cbind(fac,mat)
levels <- c(6, rep(1,p))
out <- matrix.one_hot(mat, levels = levels)
```

---

matrix.snp_phased_ancestry

Creates a SNP phased, ancestry matrix.

Description

Creates a SNP phased, ancestry matrix.

Usage

```
matrix.snp_phased_ancestry(io, n_threads = 1)
```

Arguments

io	IO handler.
n_threads	Number of threads.

Value

SNP phased, ancestry matrix.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 123
s <- 423
A <- 8
filename <- paste(tempdir(), "snp_phased_ancestry_dummy.snpdat", sep="/")
handle <- io.snp_phased_ancestry(filename)
calldata <- matrix(
```

```
    as.integer(sample.int(
        2, n * s * 2,
        replace=TRUE,
        prob=c(0.7, 0.3)
    ) - 1),
    n, s * 2
)
ancestries <- matrix(
    as.integer(sample.int(
        A, n * s * 2,
        replace=TRUE,
        prob=rep_len(1/A, A)
    ) - 1),
    n, s * 2
)
handle$write(calldata, ancestries, A, 1)
out <- matrix.snp_phased_ancestry(handle)
file.remove(filename)
```

`matrix.snp_unphased` *Creates a SNP unphased matrix.*

Description

Creates a SNP unphased matrix.

Usage

```
matrix.snp_unphased(io, n_threads = 1)
```

Arguments

`io`	IO handler.
`n_threads`	Number of threads.

Value

SNP unphased matrix.

Examples

```
n <- 123
s <- 423
filename <- paste(tempdir(), "snp_unphased_dummy.snpdat", sep="/")
handle <- io.snp_unphased(filename)
mat <- matrix(
    as.integer(sample.int(
        3, n * s,
        replace=TRUE,
```

```
        prob=c(0.7, 0.2, 0.1)
    ) - 1),
    n, s
)
impute <- double(s)
handle$write(mat, "mean", impute, 1)
out <- matrix.snp_unphased(handle)
file.remove(filename)
```

`matrix.sparse` *Creates a sparse matrix object.*

Description

Creates a sparse matrix object.

Usage

```
matrix.sparse(mat, method = c("naive", "cov", "constraint"), n_threads = 1)
```

Arguments

`mat`	A sparse matrix.
`method`	Method type, with default `method="naive"`. If `method="cov"`, the matrix is used with the solver `gaussian_cov()`. Used for `glm.gaussian()` and `glm.multigaussian()` families. Generally "naive" is used for wide matrices, and "cov" for tall matrices. If `method="constraint"`, the matrix is used as input to the constraint objects.
`n_threads`	Number of threads.

Value

Sparse matrix object. The object is an S4 class with methods for efficient computation by adelie.

Examples

```
n <- 100
p <- 20
X_dense <- matrix(rnorm(n * p), n, p)
X_sp <- as(X_dense, "dgCMatrix")
out <- matrix.sparse(X_sp, method="naive")
A_dense <- t(X_dense) %*% X_dense
A_sp <- as(A_dense, "dgCMatrix")
out <- matrix.sparse(A_sp, method="cov")
out <- matrix.sparse(X_sp, method="constraint")
```

`matrix.standardize` *Creates a standardized matrix.*

Description

Creates a standardized matrix.

Usage

```
matrix.standardize(
  mat,
  centers = NULL,
  scales = NULL,
  weights = NULL,
  ddof = 0,
  n_threads = 1
)
```

Arguments

`mat`	An `adelie` matrix.
`centers`	The center values. Default is to use the column means.
`scales`	The scale values. Default is to use the sample standard deviations.
`weights`	Observation weight vector, which defaults to 1/n per observation.
`ddof`	Degrees of freedom for standard deviations, with default 0 (1/n). The alternative is 1 leading to 1/(n-1).
`n_threads`	Number of threads.

Value

Standardized matrix. The object is an S4 class with methods for efficient computation by adelie. Conventions depend on the matrix class. For example, if a matrix is constructed using `matrix.onehot()`, only the quantitative variables are standardized.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
p <- 20
X <- matrix(rnorm(n * p), n, p)
out <- matrix.standardize(matrix.dense(X))
```

`matrix.subset` *Creates a subset of the matrix along an axis.*

Description

Creates a subset of the matrix along an axis.

Usage

```
matrix.subset(mat, indices, axis = 1, n_threads = 1)
```

Arguments

`mat`	The `adelie` matrix to subset.
`indices`	Vector of indices to subset the matrix.
`axis`	The axis along which to subset (2 is columns, 1 is rows).
`n_threads`	Number of threads.

Value

Matrix subsetted along the appropriate axis. The object is an S4 class with methods for efficient computation by adelie.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

Examples

```
n <- 100
p <- 20
X <- matrix.dense(matrix(rnorm(n * p), n, p))
indices <- c(1, 3, 10)
out <- matrix.subset(X, indices, axis=1)
out <- matrix.subset(X, indices, axis=2)
```

`plot.cv.glintnet` *plot the cross-validation curve produced by cv.glintnet*

Description

Plots the cross-validation curve, and upper and lower standard deviation curves, as a function of the `lambda` values used.

Plots the cross-validation curve, and upper and lower standard deviation curves, as a function of the `lambda` values used.

Usage

```
## S3 method for class 'cv.glintnet'
plot(x, sign.lambda = -1, ...)

## S3 method for class 'cv.grpnet'
plot(x, sign.lambda = -1, ...)
```

Arguments

`x`	fitted "`cv.grpnet`" object
`sign.lambda`	Either plot against `log(lambda)` or its negative (default) if `sign.lambda=-1`
`...`	Other graphical parameters

Details

A plot is produced, and nothing is returned.

A plot is produced, and nothing is returned.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.
Adelie Python user guide https://jamesyang007.github.io/adelie/

See Also

`grpnet` and `cv.grpnet`.

Examples

```
set.seed(0)
n=500
d_cont = 5     # number of continuous features
d_disc = 5     # number of categorical features
Z_cont = matrix(rnorm(n*d_cont), n, d_cont)
levels = sample(2:5,d_disc, replace = TRUE)
Z_disc = matrix(0,n,d_disc)
for(i in seq(d_disc))Z_disc[,i] = sample(0:(levels[i]-1),n,replace=TRUE)
Z = cbind(Z_cont,Z_disc)
levels = c(rep(1,d_cont),levels)

xmat = model.matrix(~Z_cont[,1]*factor(Z_disc[,2]))
nc=ncol(xmat)
beta = rnorm(nc)
y = xmat%*%beta+rnorm(n)*1.5

cvfit <- cv.glintnet(Z, glm.gaussian(y), levels=levels, intr_keys = 1)
plot(cvfit)


set.seed(1010)
n = 1000
p = 100
nzc = trunc(p/10)
x = matrix(rnorm(n * p), n, p)
beta = rnorm(nzc)
fx = (x[, seq(nzc)] %*% beta)
eps = rnorm(n) * 5
y = drop(fx + eps)
px = exp(fx)
px = px/(1 + px)
ly = rbinom(n = length(px), prob = px, size = 1)
cvob1 = cv.grpnet(x, glm.gaussian(y))
plot(cvob1)
title("Gaussian Family", line = 2.5)
frame()
set.seed(1011)
cvob2 = cv.grpnet(x, glm.binomial(ly))
plot(cvob2)
title("Binomial Family", line = 2.5)
```

`plot.grpnet` *plot coefficients from a "grpnet" object*

Description

Produces a coefficient profile plot of the coefficient paths for a fitted `"grpnet"` object.

Usage

```
## S3 method for class 'grpnet'
plot(x, sign.lambda = -1, glm.name = TRUE, ...)
```

Arguments

x	fitted "grpnet" model
sign.lambda	This determines whether we plot against log(lambda) or its negative. values are -1(default) or 1
glm.name	This is a logical (default TRUE), and causes the glm name of the model to be included in the plot.
...	Other graphical parameters to plot

Details

A coefficient profile plot is produced. If x is a multinomial or multigaussian model, the 2norm of the vector of coefficients is plotted.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.

See Also

grpnet, and print, and coef methods, and cv.grpnet.

Examples

```
x=matrix(rnorm(100*20),100,20)
y=rnorm(100)
fit1=grpnet(x,glm.gaussian(y))
plot(fit1)
g4=diag(4)[sample(1:4,100,replace=TRUE),]
fit2=grpnet(x,glm.multinomial(g4))
plot(fit2,lwd=3)
fit3=grpnet(x,glm.gaussian(y),groups=c(1,5,9,13,17))
plot(fit3)
```

predict.cv.glintnet *make predictions from a "cv.glintnet" object.*

Description

This function makes predictions from a cross-validated glintnet model, using the stored "glintnet.fit" object, and the optimal value chosen for lambda.

Usage

```
## S3 method for class 'cv.glintnet'
predict(object, newx, lambda = c("lambda.1se", "lambda.min"), ...)
```

Arguments

object	Fitted "cv.glintnet".
newx	Matrix of new values for x at which predictions are to be made. This matrix is of the same form as in the call to glintnet.
lambda	Value(s) of the penalty parameter lambda at which predictions are required. Default is the entire sequence used to create the model. If values of lambda are supplied, the function uses linear interpolation to make predictions for values of lambda that do not coincide with those used in the fitting algorithm. Note: if newx is a vector (a single row which has lost its matrix dimensions), convert it to a 1-row matrix first, e.g. by supplying t(newx) instead.
...	Other arguments that can be passed to predict.grpnet

Details

This function makes it easier to use the results of cross-validation to make a prediction.

Examples

```
set.seed(0)
n=500
d_cont = 5     # number of continuous features
d_disc = 5     # number of categorical features
Z_cont = matrix(rnorm(n*d_cont), n, d_cont)
levels = sample(2:5,d_disc, replace = TRUE)
Z_disc = matrix(0,n,d_disc)
for(i in seq(d_disc))Z_disc[,i] = sample(0:(levels[i]-1),n,replace=TRUE)
Z = cbind(Z_cont,Z_disc)
levels = c(rep(1,d_cont),levels)

xmat = model.matrix(~Z_cont[,1]*factor(Z_disc[,2]))
nc=ncol(xmat)
beta = rnorm(nc)
y = xmat%*%beta+rnorm(n)*1.5
```

```
cvfit <- cv.glintnet(Z, glm.gaussian(y), levels=levels, intr_keys = 1)
plot(cvfit)
predict(cvfit, newx=Z[1:5,])
```

`predict.cv.grpnet` *make predictions from a "cv.grpnet" object.*

Description

This function makes predictions from a cross-validated grpnet model, using the stored `"grpnet.fit"` object, and the optimal value chosen for `lambda`.

Usage

```
## S3 method for class 'cv.grpnet'
predict(object, newx, lambda = c("lambda.1se", "lambda.min"), ...)
```

Arguments

`object`	Fitted `"cv.grpnet"`.
`newx`	Matrix of new values for `x` at which predictions are to be made. Can be a matrix, a sparse matrix as in `Matrix` package, or else any of the matrix forms allowable in the `adelie` package. This argument is not used for `type="coefficients"`.
`lambda`	Value(s) of the penalty parameter `lambda` at which predictions are required. Default is the value `lambda="lambda.1se"` stored on the CV `object`. Alternatively `lambda="lambda.min"` can be used. If `lambda` is numeric, it is taken as the value(s) of `lambda` to be used.
`...`	Other arguments to `predict.grpnet`, such at `type`.

Details

This function makes it easier to use the results of cross-validation to make a prediction.

Value

The object returned depends on the arguments.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.

See Also

grpnet, and print, and coef methods, and cv.grpnet.

Examples

```
x = matrix(rnorm(100 * 20), 100, 20)
y = rnorm(100)
cv.fit = cv.grpnet(x, glm.gaussian(y))
predict(cv.fit, newx = x[1:5, ])
coef(cv.fit)
coef(cv.fit, lambda = "lambda.min")
predict(cv.fit, newx = x[1:5, ], lambda = c(0.001, 0.002))
```

---

predict.glintnet *make predictions from a "glintnet" object.*

Description

Similar to other predict methods, this functions predicts linear predictors, coefficients and more from a fitted "glintnet" object.

Usage

```
## S3 method for class 'glintnet'
predict(
  object,
  newx,
  lambda = NULL,
  type = c("link", "response", "coefficients", "nonzero"),
  newoffsets = NULL,
  n_threads = 1,
  ...
)
```

Arguments

object	Fitted "glintnet" model.
newx	Matrix of new values for x at which predictions are to be made. This matrix is of the same form as in the call to glintnet.
lambda	Value(s) of the penalty parameter lambda at which predictions are required. Default is the entire sequence used to create the model. If values of lambda are supplied, the function uses linear interpolation to make predictions for values of lambda that do not coincide with those used in the fitting algorithm. Note: if newx is a vector (a single row which has lost its matrix dimensions), convert it to a 1-row matrix first, e.g. by supplying t(newx) instead.

type	Type of prediction required. Type "link" is the default, and gives the linear predictors. Type "response" applies the inverse link to these predictions. Type "coefficients" extracts the coefficients, intercepts and the active-set sizes. Type "nonzero" returns a list of active groups along the path, indexed from 1 to number of groups.
newoffsets	If an offset is used in the fit, then one must be supplied for making predictions (except for type="coefficients".
n_threads	Number of threads, default 1.
...	Other arguments that can be passed to predict.grpnet

Value

The object returned depends on type.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie <hastie@stanford.edu>

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.
Adelie Python user guide https://jamesyang007.github.io/adelie/

See Also

grpnet, and print, and coef methods, and cv.grpnet.

Examples

```
set.seed(0)
n=500
d_cont = 5     # number of continuous features
d_disc = 5     # number of categorical features
Z_cont = matrix(rnorm(n*d_cont), n, d_cont)
levels = sample(2:5,d_disc, replace = TRUE)
Z_disc = matrix(0,n,d_disc)
for(i in seq(d_disc))Z_disc[,i] = sample(0:(levels[i]-1),n,replace=TRUE)
Z = cbind(Z_cont,Z_disc)
levels = c(rep(1,d_cont),levels)

xmat = model.matrix(~Z_cont[,1]*factor(Z_disc[,2]))
nc=ncol(xmat)
beta = rnorm(nc)
y = xmat%*%beta+rnorm(n)*1.5

fit <- glintnet(Z, glm.gaussian(y), levels=levels, intr_keys = 1)
predict(fit, lambda = c(.1,.01), newx = Z[1:4,])
predict(fit, lambda = c(0.1,0.01), type="nonzero")
```

predict.grpnet *make predictions from a "grpnet" object.*

Description

Similar to other predict methods, this functions predicts linear predictors, coefficients and more from a fitted "grpnet" object. Note that if the default standardize=TRUEE was used in fitting the grpnet object, the coefficients reported are for the standardized inputs. However, the predict function will apply the stored standardization to newx and give the correct predictions.

Usage

```
## S3 method for class 'grpnet'
predict(
  object,
  newx,
  lambda = NULL,
  type = c("link", "response", "coefficients", "nonzero"),
  newoffsets = NULL,
  n_threads = 1,
  ...
)

## S3 method for class 'grpnet'
coef(object, lambda = NULL, ...)
```

Arguments

object	Fitted "grpnet" model.
newx	Matrix of new values for x at which predictions are to be made. Can be a matrix, a sparse matrix as in Matrix package, or else any of the matrix forms allowable in the adelie package. The number of columns must match that of the input matrix used in fitting object. If the model object was fit with standardize=TRUE, the saved centers and scaling will be applied to this matrix. This argument is not used for type="coefficients"
lambda	Value(s) of the penalty parameter lambda at which predictions are required. Default is the entire sequence used to create the model. If values of lambda are supplied, the function uses linear interpolation to make predictions for values of lambda that do not coincide with those used in the fitting algorithm. Note: if newx is a vector (a single row which has lost its matrix dimensions), convert it to a 1-row matrix first, e.g. by supplying t(newx) instead.
type	Type of prediction required. Type "link" is the default, and gives the linear predictors. Type "response" applies the inverse link to these predictions. Type "coefficients" extracts the coefficients, intercepts and the active-set sizes. Type "nonzero" returns a list of active groups along the path, indexed from 1 to number of groups.

newoffsets	If an offset is used in the fit, then one must be supplied for making predictions (except for type="coefficients".
n_threads	Number of threads, default 1.
...	Currently ignored.

Details

The shape of the objects returned are different for "multinomial" and "multigaussian" objects. coef(...) is equivalent to predict(type="coefficients",...)

Value

The object returned depends on type.

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie <hastie@stanford.edu>

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.
Adelie Python user guide https://jamesyang007.github.io/adelie/

See Also

grpnet, and print, and coef methods, and cv.grpnet.

Examples

```
set.seed(0)
n <- 100
p <- 200
X <- matrix(rnorm(n * p), n, p)
y <- X[,1] * rnorm(1) + rnorm(n)
groups <- c(1, sample(2:199, 60, replace = FALSE))
groups <- sort(groups)
fit <- grpnet(X, glm.gaussian(y), groups = groups)
coef(fit)
predict(fit,newx = X[1:5,], lambda = c(0.1, 0.05))
predict(fit, type="nonzero", lambda = c(0.1, 0.05))
```

`print.cv.grpnet` *print a cross-validated grpnet object*

Description

Print a summary of the results of cross-validation for a grpnet model.

Usage

```
## S3 method for class 'cv.grpnet'
print(x, digits = max(3, getOption("digits") - 3), ...)
```

Arguments

`x`	fitted 'cv.grpnet' object
`digits`	significant digits in printout
`...`	additional print arguments

Author(s)

James Yang, Trevor Hastie, and Balasubramanian Narasimhan
Maintainer: Trevor Hastie hastie@stanford.edu

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.

See Also

`grpnet`, `predict` and `coef` methods.

Examples

```
x = matrix(rnorm(100 * 20), 100, 20)
y = rnorm(100)
fit1 = cv.grpnet(x, glm.gaussian(y))
print(fit1)
```

`print.glintnet` *Print a summary of the glintnet path at each step along the path.*

Description

Print a summary of the grpnet path at each step along the path.

Usage

```
## S3 method for class 'glintnet'
print(x, digits = max(3, getOption("digits") - 3), ...)
```

Arguments

`x`	fitted glintnet object
`digits`	significant digits in printout
`...`	additional print arguments

Details

The call that produced the object `x` is printed, followed by a five-column matrix with columns `N_main`, `N_int`, `Df`, `%Dev` and `Lambda`. The `N_main` column is the number of main-effect terms in the solution, and `N_int` the number of interaction terms. Since an interaction term implies both main effects, the former is always at least as large as the latter. The `Df` column is the number of nonzero coefficients (Df is a reasonable name only for lasso fits). `%Dev` is the percent deviance explained (relative to the null deviance).

Value

The matrix above is silently returned

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.

See Also

`grpnet`, `predict`, `plot` and `coef` methods.

Examples

```
x = matrix(rnorm(100 * 20), 100, 20)
y = rnorm(100)
fit1 = grpnet(x, glm.gaussian(y), groups = c(1:5,7,9))
print(fit1)
```

`print.grpnet` *print a grpnet object*

Description

Print a summary of the grpnet path at each step along the path.

Usage

```
## S3 method for class 'grpnet'
print(x, digits = max(3, getOption("digits") - 3), ...)
```

Arguments

`x`	fitted grpnet object
`digits`	significant digits in printout
`...`	additional print arguments

Details

The call that produced the object `x` is printed, followed by a four-column matrix with columns `Groups`, `Df`, `%Dev` and `Lambda`. The `Groups` column is the number of active groups in the solution. The `Df` column is the number of nonzero coefficients (Df is a reasonable name only for lasso fits). `%Dev` is the percent deviance explained (relative to the null deviance).

Value

The matrix above is silently returned

References

Yang, James and Hastie, Trevor. (2024) A Fast and Scalable Pathwise-Solver for Group Lasso and Elastic Net Penalized Regression via Block-Coordinate Descent. arXiv doi:10.48550/arXiv.2405.08631.

See Also

`grpnet`, `predict`, `plot` and `coef` methods.

Examples

```
x = matrix(rnorm(100 * 20), 100, 20)
y = rnorm(100)
fit1 = grpnet(x, glm.gaussian(y), groups = c(1:5,7,9))
print(fit1)
```

`set_configs` *Set configuration settings.*

Description

Set configuration settings.

Usage

```
set_configs(name, value = NULL)
```

Arguments

`name`	Configuration variable name.
`value`	Value to assign to the configuration variable.

Value

Assigned value.

Examples

```
set_configs("hessian_min", 1e-6)
set_configs("hessian_min")
```

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