Package ‘oem’

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Type Package

Title Orthogonalizing EM: Penalized Regression for Big Tall Data

Version 2.0.10

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Description Solves penalized least squares problems for big tall data using the orthogonalizing EM algorithm of Xiong et al. (2016) <doi:10.1080/00401706.2015.1054436>. The main fitting function is oem() and the functions cv.oem() and xval.oem() are for cross validation, the latter being an accelerated cross validation function for linear models. The big.oem() function allows for out of memory fitting.

URL https://arxiv.org/abs/1801.09661,
https://github.com/jaredhuling/oem,
https://jaredhuling.github.io/oem

BugReports https://github.com/jaredhuling/oem/issues

License GPL (>= 2)

Encoding UTF-8

LazyData TRUE

Depends R (>= 3.2.0), bigmemory

Imports Rcpp (>= 0.11.0), Matrix, foreach, methods

LinkingTo Rcpp, RcppEigen, BH, bigmemory, RcppArmadillo

RoxygenNote 7.1.0

Suggests knitr, rmarkdown

VignetteBuilder knitr

NeedsCompilation yes

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big.oem

Orthogonalizing EM for big.matrix objects

Description

Orthogonalizing EM for big.matrix objects

Usage

big.oem(
  x,
  y,
  family = c("gaussian", "binomial"),
  weights = numeric(0),
  lambda = numeric(0),
  nlambda = 100L,
  lambda.min.ratio = NULL,
  alpha = 1,
  gamma = 3,
  tau = 0.5,
  groups = numeric(0),
  penalty.factor = NULL,
  group.weights = NULL,
  standardize = TRUE,
  intercept = TRUE,
  maxit = 500L,
  tol = 1e-07,
big.oem

irls.maxit = 100L,
irls.tol = 0.001,
compute.loss = FALSE,
gigs = 4,
hessian.type = c("full", "upper.bound")

Arguments

x input big.matrix object pointing to design matrix. Each row is an observation, each column corresponds to a covariate.

y numeric response vector of length nobs.

family "gaussian" for least squares problems, "binomial" for binary response. "binomial" currently not available.

penalty Specification of penalty type. Choices include:

- "elastic.net" - elastic net penalty, extra parameters: "alpha"
- "lasso" - lasso penalty
- "ols" - ordinary least squares
- "mcp" - minimax concave penalty, extra parameters: "gamma"
- "scad" - smoothly clipped absolute deviation, extra parameters: "gamma"
- "mcp.net" - minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
- "scad.net" - smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
- "grp.lasso" - group lasso penalty
- "grp.lasso.net" - group lasso penalty + l2 penalty, extra parameters: "alpha"
- "grp.mcp" - group minimax concave penalty, extra parameters: "gamma"
- "grp.scad" - group smoothly clipped absolute deviation, extra parameters: "gamma"
- "grp.mcp.net" - group minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
- "grp.scad.net" - group smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
- "sparse.grp.lasso" - sparse group lasso penalty (group lasso + lasso), extra parameters: "tau"

Careful consideration is required for the group lasso, group MCP, and group SCAD penalties. Groups as specified by the groups argument should be chosen in a sensible manner.

weights observation weights. Not implemented yet. Defaults to 1 for each observation (setting weight vector to length 0 will default all weights to 1)

lambda A user supplied lambda sequence. By default, the program computes its own lambda sequence based on nlambda and lambda.min.ratio. Supplying a value of lambda overrides this.
nlambda
The number of lambda values - default is 100.

lambda.min.ratio
Smallest value for lambda, as a fraction of lambda.max, the (data derived) entry
value (i.e. the smallest value for which all coefficients are zero). The default
depends on the sample size nobs relative to the number of variables nvars. If
nobs > nvars, the default is 0.0001, close to zero. If nobs < nvars, the default
is 0.01. A very small value of lambda.min.ratio will lead to a saturated fit
when nobs < nvars.

alpha
mixing value for elastic.net, mcp.net, scad.net, grp.mcp.net, grp.scad.net.
penalty applied is (1 - alpha) * (ridge penalty) + alpha * (lasso/mcp/mcp/grp.lasso
penalty)

gamma
tuning parameter for SCAD and MCP penalties. must be >= 1

tau
mixing value for sparse.grp.lasso. penalty applied is (1 - tau) * (group lasso
penalty) + tau * (lasso penalty)

groups
A vector of describing the grouping of the coefficients. See the example below.
All unpenalized variables should be put in group 0

penalty.factor
Separate penalty factors can be applied to each coefficient. This is a number that
multiplies lambda to allow differential shrinkage. Can be 0 for some variables,
which implies no shrinkage, and that variable is always included in the model.
Default is 1 for all variables.

group.weights
penalty factors applied to each group for the group lasso. Similar to penalty.factor,
this is a number that multiplies lambda to allow differential shrinkage. Can be 0
for some groups, which implies no shrinkage, and that group is always included
in the model. Default is sqrt(group size) for all groups.

standardize
Logical flag for x variable standardization, prior to fitting the models. The co-
efficients are always returned on the original scale. Default is standardize =
TRUE. If variables are in the same units already, you might not wish to standard-
ize. Keep in mind that standardization is done differently for sparse matrices, so
results (when standardized) may be slightly different for a sparse matrix object
and a dense matrix object

intercept
Should intercept(s) be fitted (default = TRUE) or set to zero (FALSE)

maxit
integer. Maximum number of OEM iterations

tol
convergence tolerance for OEM iterations

irls.maxit
integer. Maximum number of IRLS iterations

irls.tol
convergence tolerance for IRLS iterations. Only used if family != "gaussian"

compute.loss
should the loss be computed for each estimated tuning parameter? Defaults to
FALSE. Setting to TRUE will dramatically increase computational time

gigs
maximum number of gigs of memory available. Used to figure out how to break
up calculations involving the design matrix x

hessian.type
only for logistic regression. if hessian.type = "full", then the full hessian is
used. If hessian.type = "upper.bound", then an upper bound of the hessian is
used. The upper bound can be dramatically faster in certain situations, ie when
n > p
Value

An object with S3 class "oem"

Examples

```r
## Not run:
set.seed(123)
nrows <- 50000
ncols <- 100
bkFile <- "bigmat.bk"
descFile <- "bigmatk.desc"
bigmat <- filebacked.big.matrix(nrow=nrows, ncol=ncols, type="double",
                                backingfile=bkFile, backingpath=".",
                                descriptorfile=descFile,
                                dimnames=c(NULL,NULL))

# Each column value with be the column number multiplied by
# samples from a standard normal distribution.
set.seed(123)
for (i in 1:ncols) bigmat[,i] = rnorm(nrows)*i

y <- rnorm(nrows) + bigmat[,1] - bigmat[,2]

fit <- big.oem(x = bigmat, y = y,
                penalty = c("lasso", "elastic.net",
                            "ols",
                            "mcp", "scad",
                            "mcp.net", "scad.net",
                            "grp.lasso", "grp.lasso.net",
                            "grp.mcp", "grp.scad",
                            "sparse.grp.lasso"),
                groups = rep(1:20, each = 5))

fit2 <- oem(x = bigmat[,], y = y,
            penalty = c("lasso", "grp.lasso"),
            groups = rep(1:20, each = 5))

max(abs(fit$beta[[1]] - fit2$beta[[1]]))

layout(matrix(1:2, ncol = 2))
plot(fit)
plot(fit, which.model = 2)

## End(Not run)
```
Description

Cross validation for Orthogonalizing EM

Usage

cv.oem(
x, y,
weights = numeric(0),
lambda = NULL,
type.measure = c("mse", "deviance", "class", "auc", "mae"),
nfolds = 10,
foldid = NULL,
grouped = TRUE,
keep = FALSE,
parallel = FALSE,
ncores = -1,
...)

Arguments

x input matrix of dimension \( n \times p \) or CsparseMatrix objects of the Matrix (sparse not yet implemented. Each row is an observation, each column corresponds to a covariate. The cv.oem() function is optimized for \( n \gg p \) settings and may be very slow when \( p > n \), so please use other packages such as glmnet, ncvreg, grpreg, or gglasso when \( p \gg n \) or \( p \approx n \).
y numeric response vector of length nobs.
penalty Specification of penalty type in lowercase letters. Choices include "lasso", "ols" (Ordinary least squares, no penalty), "elastic.net", "scad", "mcp", "grp.lasso"
weights observation weights. defaults to 1 for each observation (setting weight vector to length 0 will default all weights to 1)
lambda A user supplied lambda sequence. By default, the program computes its own lambda sequence based on nlambdas and lambda.min.ratio. Supplying a value of lambda overrides this.
type.measure measure to evaluate for cross-validation. The default is type.measure = "deviance", which uses squared-error for gaussian models (a.k.a type.measure = "mse" there), deviance for logistic regression. type.measure = "class" applies to binomial only. type.measure = "auc" is for two-class logistic regression only. type.measure = "mse" or type.measure = "mae" (mean absolute error) can be used by all models; they measure the deviation from the fitted mean to the response.
nfolds number of folds for cross-validation. default is 10. 3 is smallest value allowed.
foldid

an optional vector of values between 1 and nfold specifying which fold each observation belongs to.

grouped

Like in glmnet, this is an experimental argument, with default TRUE, and can be ignored by most users. For all models, this refers to computing nfolds separate statistics, and then using their mean and estimated standard error to describe the CV curve. If grouped = FALSE, an error matrix is built up at the observation level from the predictions from the nfold fits, and then summarized (does not apply to type.measure = "auc").

keep

If keep = TRUE, a prevalidated list of array is returned containing fitted values for each observation and each value of lambda for each model. This means these fits are computed with this observation and the rest of its fold omitted. The fold vector is also returned. Default is keep = FALSE

parallel

If TRUE, use parallel foreach to fit each fold. Must register parallel before hand, such as doMC.

ncores

Number of cores to use. If parallel = TRUE, then ncores will be automatically set to 1 to prevent conflicts

... other parameters to be passed to "oem" function

Value

An object with S3 class "cv.oem"

Examples

```r
set.seed(123)
n.obs <- 1e4
n.vars <- 100

true.beta <- c(runif(15, -0.25, 0.25), rep(0, n.vars - 15))

x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta

fit <- cv.oem(x = x, y = y,
               penalty = c("lasso", "grp.lasso"),
               groups = rep(1:20, each = 5))

layout(matrix(1:2, ncol = 2))
plot(fit)
plot(fit, which.model = 2)
```

---

logLik.oem

log likelihood function for fitted oem objects
Description

log likelihood function for fitted oem objects
log likelihood function for fitted cross validation oem objects
log likelihood function for fitted cross validation oem objects

Usage

## S3 method for class 'oem'
logLik(object, which.model = 1, ...)

## S3 method for class 'cv.oem'
logLik(object, which.model = 1, ...)

## S3 method for class 'xval.oem'
logLik(object, which.model = 1, ...)

Arguments

object fitted "oem" model object.
which.model If multiple penalties are fit and returned in the same oem object, the which.model argument is used to specify which model to plot. For example, if the oem object "oemobj" was fit with argument penalty = c("lasso", "grp.lasso"), then which.model = 2 provides a plot for the group lasso model.
...
not used

Examples

set.seed(123)
n.obs <- 2000
n.vars <- 50

true.beta <- c(runif(15, -0.25, 0.25), rep(0, n.vars - 15))
x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta

fit <- oem(x = x, y = y, penalty = c("lasso", "mcp"), compute.loss = TRUE)
logLik(fit)

logLik(fit, which.model = "mcp")

fit <- cv.oem(x = x, y = y, penalty = c("lasso", "mcp"), compute.loss = TRUE,
nlambda = 25)
logLik(fit)

logLik(fit, which.model = "mcp")
fit <- xval.oem(x = x, y = y, penalty = c("lasso", "mcp"), compute.loss = TRUE, nlambda = 25)

logLik(fit)

logLik(fit, which.model = "mcp")

---

**oem**  
*Orthogonalizing EM*

**Description**

Orthogonalizing EM

**Usage**

```r
oem(
  x,
  y,
  family = c("gaussian", "binomial"),
  weights = numeric(0),
  lambda = numeric(0),
  nlambda = 100L,
  lambda.min.ratio = NULL,
  alpha = 1,
  gamma = 3,
  tau = 0.5,
  groups = numeric(0),
  penalty.factor = NULL,
  group.weights = NULL,
  standardize = TRUE,
  intercept = TRUE,
  maxit = 500L,
  tol = 1e-07,
  irls.maxit = 100L,
  irls.tol = 0.001,
  accelerate = FALSE,
  ncores = -1,
  compute.loss = FALSE,
  hessian.type = c("upper.bound", "full")
)
```
Arguments

\[x\]
input matrix of dimension \(n \times p\) or \texttt{CsparseMatrix} object of the \texttt{Matrix} package. Each row is an observation, each column corresponds to a covariate. The \texttt{oem()} function is optimized for \(n > p\) settings and may be very slow when \(p > n\), so please use other packages such as \texttt{glmnet}, \texttt{ncvreg}, \texttt{grpreg}, or \texttt{gglasso} when \(p > n\) or \(p \approx n\).

\[y\]
numeric response vector of length \(n_{\text{obs}}\).

\[\text{family}\]
"gaussian" for least squares problems, "binomial" for binary response.

\[\text{penalty}\]
Specification of penalty type. Choices include:

- "elastic.net" - elastic net penalty, extra parameters: "alpha"
- "lasso" - lasso penalty
- "ols" - ordinary least squares
- "mcp" - minimax concave penalty, extra parameters: "gamma"
- "scad" - smoothly clipped absolute deviation, extra parameters: "gamma"
- "mcp.net" - minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
- "scad.net" - smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
- "grp.lasso" - group lasso penalty
- "grp.lasso.net" - group lasso penalty + l2 penalty, extra parameters: "alpha"
- "grp.mcp" - group minimax concave penalty, extra parameters: "gamma"
- "grp.scad" - group smoothly clipped absolute deviation, extra parameters: "gamma"
- "grp.mcp.net" - group minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
- "grp.scad.net" - group smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
- "sparse.grp.lasso" - sparse group lasso penalty (group lasso + lasso), extra parameters: "tau"

Careful consideration is required for the group lasso, group MCP, and group SCAD penalties. Groups as specified by the \texttt{groups} argument should be chosen in a sensible manner.

\[\text{weights}\]
observation weights. Not implemented yet. Defaults to 1 for each observation (setting weight vector to length 0 will default all weights to 1)

\[\text{lambda}\]
A user supplied lambda sequence. By default, the program computes its own lambda sequence based on \texttt{nlambda} and \texttt{lambda.min.ratio}. Supplying a value of lambda overrides this.

\[\text{nlambda}\]
The number of lambda values. The default is 100.

\[\text{lambda.min.ratio}\]
Smallest value for lambda, as a fraction of \texttt{lambda.max}, the (data derived) entry value (i.e. the smallest value for which all coefficients are zero). The default depends on the sample size \(n_{\text{obs}}\) relative to the number of variables \(n_{\text{vars}}\). If
nobs > nvars, the default is 0.0001, close to zero. If nobs < nvars, the default is 0.01. A very small value of lambda.min.ratio will lead to a saturated fit when nobs < nvars.

alpha mixing value for elastic.net, mcp.net, scad.net, grp.mcp.net, grp.scad.net. penalty applied is \((1 - \alpha) \cdot \text{ridge penalty}) + \alpha \cdot \text{lasso/mcp/mcp/grp.lasso penalty)}

gamma tuning parameter for SCAD and MCP penalties. must be \(\geq 1\)

tau mixing value for sparse.grp.lasso. penalty applied is \((1 - \tau) \cdot \text{group lasso penalty}) + \tau \cdot \text{lasso penalty)}

groups A vector of describing the grouping of the coefficients. See the example below. All unpenalized variables should be put in group 0

penalty.factor Separate penalty factors can be applied to each coefficient. This is a number that multiplies lambda to allow differential shrinkage. Can be 0 for some variables, which implies no shrinkage, and that variable is always included in the model. Default is 1 for all variables.

group.weights penalty factors applied to each group for the group lasso. Similar to penalty.factor, this is a number that multiplies lambda to allow differential shrinkage. Can be 0 for some groups, which implies no shrinkage, and that group is always included in the model. Default is sqrt(group size) for all groups.

standardize Logical flag for x variable standardization, prior to fitting the models. The coefficients are always returned on the original scale. Default is standardize = TRUE. If variables are in the same units already, you might not wish to standardize. Keep in mind that standardization is done differently for sparse matrices, so results (when standardized) may be slightly different for a sparse matrix object and a dense matrix object

intercept Should intercept(s) be fitted (default = TRUE) or set to zero (FALSE)

maxit integer. Maximum number of OEM iterations

irls.maxit integer. Maximum number of IRLS iterations

irls.tol convergence tolerance for IRLS iterations. Only used if family != "gaussian"

accelerate boolean argument. Whether or not to use Nesterov acceleration with adaptive restarting

ncores Integer scalar that specifies the number of threads to be used

compute.loss should the loss be computed for each estimated tuning parameter? Defaults to FALSE. Setting to TRUE will dramatically increase computational time

hessian.type only for logistic regression. if hessian.type = "full", then the full hessian is used. If hessian.type = "upper.bound", then an upper bound of the hessian is used. The upper bound can be dramatically faster in certain situations, ie when n » p

Value An object with S3 class "oem"
References


Examples

```r
set.seed(123)
n.obs <- 1e4
n.vars <- 50

true.beta <- c(runif(15, -0.25, 0.25), rep(0, n.vars - 15))
x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta

fit <- oem(x = x, y = y,
penalty = c("lasso", "grp.lasso", "sparse.grp.lasso"),
            groups = rep(1:10, each = 5))

layout(matrix(1:3, ncol = 3))
plot(fit)
plot(fit, which.model = 2)
plot(fit, which.model = "sparse.grp.lasso")

# the oem package has support for
# sparse design matrices

library(Matrix)

xs <- rsparsematrix(n.obs * 25, n.vars * 2, density = 0.01)
ys <- rnorm(n.obs * 25, sd = 3) + as.vector(xs %*% c(true.beta, rep(0, n.vars)) )
x.dense <- as.matrix(xs)

system.time(fit <- oem(x = x.dense, y = ys,
penalty = c("lasso", "grp.lasso"),
            groups = rep(1:20, each = 5), intercept = FALSE,
            standardize = FALSE))

system.time(fits <- oem(x = xs, y = ys,
penalty = c("lasso", "grp.lasso"),
            groups = rep(1:20, each = 5), intercept = FALSE,
            standardize = FALSE, lambda = fit$lambda))

max(abs(fit$beta[[1]] - fits$beta[[1]]))
max(abs(fit$beta[[2]] - fits$beta[[2]]))

# logistic
y <- rbinom(n.obs, 1, prob = 1 / (1 + exp(-x %*% true.beta)) )

system.time(res <- oem(x, y, intercept = FALSE,
penalty = c("lasso", "sparse.grp.lasso", "mcp"),
            groups = rep(1:10, each = 5), intercept = FALSE,
            standardize = FALSE, lambda = fit$lambda))
```

family = "binomial",
groups = rep(1:10, each = 5),
nlambda = 10,
irls.tol = 1e-3, tol = 1e-8))

layout(matrix(1:3, ncol = 3))
plot(res)
plot(res, which.model = 2)
plot(res, which.model = "mcp")

# sparse design matrix
xs <- rsparsematrix(n.obs * 2, n.vars, density = 0.01)
x.dense <- as.matrix(xs)
ys <- rbinom(n.obs * 2, 1, prob = 1 / (1 + exp(-x %*% true.beta)))

system.time(res.gr <- oem(x.dense, ys, intercept = FALSE,
penalty = "grp.lasso",
family = "binomial",
nlambda = 10,
groups = rep(1:5, each = 10),
irls.tol = 1e-3, tol = 1e-8))

system.time(res.gr.s <- oem(xs, ys, intercept = FALSE,
penalty = "grp.lasso",
family = "binomial",
nlambda = 10,
groups = rep(1:5, each = 10),
irls.tol = 1e-3, tol = 1e-8))

max(abs(res.gr$beta[[1]] - res.gr.s$beta[[1]]))

---

**oem.xtx**  
*Orthogonalizing EM with precomputed XIX*

**Description**

Orthogonalizing EM with precomputed XIX

**Usage**

```r
oem.xtx(
  xtx, xty,
  family = c("gaussian", "binomial"),
  penalty = c("elastic.net", "lasso", "ols", "mcp", "scad", "mcp.net", "scad.net",
             "grp.lasso", "grp.lasso.net", "grp.mcp", "grp.scad", "grp.mcp.net", "grp.scad.net",
             "sparse.grp.lasso"),
  lambda = numeric(0),
  ...)```

```r
```
nlambda = 100L,
lambda.min.ratio = NULL,
alpha = 1,
gamma = 3,
tau = 0.5,
groups = numeric(0),
scale.factor = numeric(0),
penalty.factor = NULL,
group.weights = NULL,
maxit = 500L,
tol = 1e-07,
irls.maxit = 100L,
irls.tol = 0.001
)

Arguments

xtx input matrix equal to crossprod(x) / nrow(x), where x is the design matrix. It is highly recommended to scale by the number of rows in x. If xtx is scaled, xty must also be scaled or else results may be meaningless!

xty numeric vector of length nvars. Equal to crosprod(x,y) / nobs. It is highly recommended to scale by the number of rows in x.

family "gaussian" for least squares problems, "binomial" for binary response. (only gaussian implemented currently)

penalty Specification of penalty type. Choices include:
  • "elastic.net" - elastic net penalty, extra parameters: "alpha"
  • "lasso" - lasso penalty
  • "ols" - ordinary least squares
  • "mcp" - minimax concave penalty, extra parameters: "gamma"
  • "scad" - smoothly clipped absolute deviation, extra parameters: "gamma"
  • "mcp.net" - minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
  • "scad.net" - smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
  • "grp.lasso" - group lasso penalty
  • "grp.lasso.net" - group lasso penalty + l2 penalty, extra parameters: "alpha"
  • "grp.mcp" - group minimax concave penalty, extra parameters: "gamma"
  • "grp.scad" - group smoothly clipped absolute deviation, extra parameters: "gamma"
  • "grp.mcp.net" - group minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
  • "grp.scad.net" - group smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
  • "sparse.grp.lasso" - sparse group lasso penalty (group lasso + lasso), extra parameters: "tau"
Careful consideration is required for the group lasso, group MCP, and group SCAD penalties. Groups as specified by the groups argument should be chosen in a sensible manner.

**lambda**
A user supplied lambda sequence. By default, the program computes its own lambda sequence based on nlambdas and lambda.min.ratio. Supplying a value of lambda overrides this.

**nlambdas**
The number of lambda values - default is 100.

**lambda.min.ratio**
Smallest value for lambda, as a fraction of lambda.max, the (data derived) entry value (i.e. the smallest value for which all coefficients are zero). The default depends on the sample size nobs relative to the number of variables nvars. The default is 0.0001

**alpha**
mixing value for elastic.net, mcp.net, scad.net, grp.mcp.net, grp.scad.net. penalty applied is (1 - alpha) * (ridge penalty) + alpha * (lasso/mcp/mcp/grp.lasso penalty)

**gamma**
tuning parameter for SCAD and MCP penalties. must be >= 1

**tau**
mixing value for sparse.grp.lasso. penalty applied is (1 - tau) * (group lasso penalty) + tau * (lasso penalty)

**groups**
A vector of describing the grouping of the coefficients. See the example below. All unpenalized variables should be put in group 0

**scale.factor**
of length nvars == ncol(xtx) == length(xty) for scaling columns of x. The standard deviation for each column of x is a common choice for scale.factor. Coefficients will be returned on original scale. Default is no scaling.

**penalty.factor**
Separate penalty factors can be applied to each coefficient. This is a number that multiplies lambda to allow differential shrinkage. Can be 0 for some variables, which implies no shrinkage, and that variable is always included in the model. Default is 1 for all variables.

**group.weights**
penalty factors applied to each group for the group lasso. Similar to penalty.factor, this is a number that multiplies lambda to allow differential shrinkage. Can be 0 for some groups, which implies no shrinkage, and that group is always included in the model. Default is sqrt(group size) for all groups.

**maxit**
integer. Maximum number of OEM iterations

**tol**
convergence tolerance for OEM iterations

**irls.maxit**
integer. Maximum number of IRLS iterations

**irls.tol**
convergence tolerance for IRLS iterations. Only used if family != "gaussian"

**Value**
An object with S3 class "oem"

**Examples**
```r
set.seed(123)
n.obs <- 1e4
n.vars <- 100
```
true.beta <- c(runif(15, -0.25, 0.25), rep(0, n.vars - 15))

x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta

fit <- oem(x = x, y = y,
penalty = c("lasso", "elastic.net",
"ols",
"mcp", "scad",
"mcp.net", "scad.net",
"grp.lasso", "grp.lasso.net",
"grp.mcp", "grp.scad",
"sparse.grp.lasso"),
standardize = FALSE, intercept = FALSE,
groups = rep(1:20, each = 5))

xtx <- crossprod(x) / n.obs
xty <- crossprod(x, y) / n.obs

fit.xtx <- oem.xtx(xtx = xtx, xty = xty,
penalty = c("lasso", "elastic.net",
"ols",
"mcp", "scad",
"mcp.net", "scad.net",
"grp.lasso", "grp.lasso.net",
"grp.mcp", "grp.scad",
"sparse.grp.lasso"),
groups = rep(1:20, each = 5))

max(abs(fit$beta[[1]][-1,] - fit.xtx$beta[[1]]))
max(abs(fit$beta[[2]][-1,] - fit.xtx$beta[[2]]))

layout(matrix(1:2, ncol = 2))
plot(fit.xtx)
plot(fit.xtx, which.model = 2)

---

**oemfit**

**Deprecated functions**

**Description**

These functions have been renamed and deprecated in **oem**: oemfit() (use **oem()**), cv.oemfit() (use **cv.oem()**), print.oemfit(), plot.oemfit(), predict.oemfit(), and coef.oemfit().

**Usage**

```r
oemfit(
  formula,
```
data = list(),
lambda = NULL,
nlambda = 100,
lambda.min.ratio = NULL,
tolerance = 0.001,
maxIter = 1000,
standardized = TRUE,
numGroup = 1,
penalty = c("lasso", "scad", "ols", "elastic.net", "ngarrote", "mcp"),
alpha = 3,
evaluate = 0,
condition = -1
)

cv.oemfit(
    formula,
    data = list(),
    lambda = NULL,
type.measure = c("mse", "mae"),
    ...
)

## S3 method for class 'oemfit'
plot(
    x,
    xvar = c("norm", "lambda", "loglambda", "dev"),
    xlab = iname,
    ylab = "Coefficients",
    ...
)

## S3 method for class 'oemfit'
predict(
    object,
    newx,
    s = NULL,
    type = c("response", "coefficients", "nonzero"),
    ...
)

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

formula

an object of '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 under 'Details'.

data

an optional data frame, list or environment (or object coercible by 'as.data.frame'
to a data frame) containing the variables in the model. If not found in 'data',
the variables are taken from 'environment(formula)', typically the environment
from which 'oemfit' is called.

lambda

A user supplied lambda sequence. Typical usage is to have the program compute
its own lambda sequence based on nlambda and lambda.min.ratio. Supplying
a value of lambda overrides this. WARNING: use with care. Do not supply
a single value for lambda (for predictions after CV use predict() instead).
Supply instead a decreasing sequence of lambda values. oemfit relies on its
warms starts for speed, and its often faster to fit a whole path than compute a
single fit.

nlambda

The number of lambda values - default is 100.

lambda.min.ratio

Smallest value for lambda, as a fraction of lambda.max, the (data derived) entry
value (i.e. the smallest value for which all coefficients are zero). The default
depends on the sample size nobs relative to the number of variables nvars. If
nobs > nvars, the default is 0.0001, close to zero. If nobs < nvars, the default
is 0.01. A very small value of lambda.min.ratio will lead to a saturated fit in
the nobs < nvars case.

tolerance

Convergence tolerance for OEM. Each inner OEM loop continues until the max-
imum change in the objective after any coefficient update is less than tolerance.
Defaults value is 1E-3.

maxIter

Maximum number of passes over the data for all lambda values; default is 1000.

standardized

Logical flag for x variable standardization, prior to fitting the model sequence.
The coefficients are always returned on the original scale. Default is standardize=TRUE.
If variables are in the same units already, you might not wish to standardize.

numGroup

Integer value for the number of groups to use for OEM fitting. Default is 1.

penalty

type in lower letters. Different types include 'lasso', 'scad', 'ols' (ordinary least
square), 'elastic-net', 'ngarrote' (non-negative garrote) and 'mcp'.

alpha

alpha value for scad and mcp.

evaluate

debugging argument

condition

Debugging for different ways of calculating OEM.

type.measure

type.measure measure to evaluate for cross-validation. type.measure = "mse"
(mean squared error) or type.measure = "mae" (mean absolute error)

... arguments to be passed to oemfit()

nfolds

number of folds for cross-validation. default is 10.

foldid

an optional vector of values between 1 and nfolds specifying which fold each
observation belongs to.

x

fitted oemfit object
`plot.oem`  

what is on the X-axis. "norm" plots against the L1-norm of the coefficients, "lambda" against the log-lambda sequence, and "dev" against the percent deviance explained.

- **xlab**: x-axis label
- **ylab**: y-axis label
- **object**: fitted oemfit object
- **newx**: matrix of new values for x at which predictions are to be made. Must be a matrix.
- **s**: Value(s) of the penalty parameter lambda at which predictions are required. Default is the entire sequence used to create the model.
- **type**: not used.
- **digits**: significant digits in print out.

**Details**

The sequence of models implied by 'lambda' is fit by OEM algorithm.

**Author(s)**

Bin Dai

---

**plot.oem**  

*Plot method for Orthogonalizing EM fitted objects*

**Description**

Plot method for Orthogonalizing EM fitted objects

Plot method for Orthogonalizing EM fitted objects

**Usage**

```r
## S3 method for class 'oem'
plot(
x,  
which.model = 1,  
xvar = c("norm", "lambda", "loglambda", "dev"),  
labsize = 0.6,  
xlab = iname,  
ylab = NULL,  
main = x$penalty[which.model],  
...  )

## S3 method for class 'cv.oem'
plot(x, which.model = 1, sign.lambda = 1, ...)
```
## S3 method for class 'xval.oem'
plot(
  x,
  which.model = 1,
  type = c("cv", "coefficients"),
  xvar = c("norm", "lambda", "loglambda", "dev"),
  labsize = 0.6,
  xlab = iname,
  ylab = NULL,
  main = x$penalty[which.model],
  sign.lambda = 1,
  ...
)

Arguments

- **x**: fitted "oem" model object
- **which.model**: If multiple penalties are fit and returned in the same oem object, the which.model argument is used to specify which model to plot. For example, if the oem object "oemobj" was fit with argument penalty = c("lasso","grp.lasso"), then which.model = 2 provides a plot for the group lasso model.
- **xvar**: What is on the X-axis. "norm" plots against the L1-norm of the coefficients, "lambda" against the log-lambda sequence, and "dev" against the percent deviance explained.
- **labsize**: size of labels for variable names. If labsize = 0, then no variable names will be plotted
- **xlab**: label for x-axis
- **ylab**: label for y-axis
- **main**: main title for plot
- **...**: other graphical parameters for the plot
- **sign.lambda**: Either plot against log(lambda) (default) or its negative if sign.lambda = -1.
- **type**: one of "cv" or "coefficients". type = "cv" will produce a plot of cross validation results like plot.cv.oem. type = "coefficients" will produce a coefficient path plot like plot.oem()

Examples

```r
set.seed(123)
n.obs <- 1e4
n.vars <- 100
n.obs.test <- 1e3

true.beta <- c(runif(15, -0.5, 0.5), rep(0, n.vars - 15))

x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta
```
fit <- oem(x = x, y = y, penalty = c("lasso", "grp.lasso"), groups = rep(1:10, each = 10))

layout(matrix(1:2, ncol = 2))
plot(fit, which.model = 1)
plot(fit, which.model = 2)

set.seed(123)
n.obs <- 1e4
n.vars <- 100
n.obs.test <- 1e3

true.beta <- c(runif(15, -0.5, 0.5), rep(0, n.vars - 15))
x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta

fit <- cv.oem(x = x, y = y, penalty = c("lasso", "grp.lasso"), groups = rep(1:10, each = 10))

layout(matrix(1:2, ncol = 2))
plot(fit, which.model = 1)
plot(fit, which.model = "grp.lasso")

set.seed(123)
n.obs <- 1e4
n.vars <- 100
n.obs.test <- 1e3

true.beta <- c(runif(15, -0.5, 0.5), rep(0, n.vars - 15))
x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta

fit <- xval.oem(x = x, y = y, penalty = c("lasso", "grp.lasso"), groups = rep(1:10, each = 10))

layout(matrix(1:4, ncol = 2))
plot(fit, which.model = 1)
plot(fit, which.model = "grp.lasso")

plot(fit, which.model = 1, type = "coef")
plot(fit, which.model = 2, type = "coef")

---

**predict.cv.oem**

**Prediction function for fitted cross validation oem objects**

**Description**

Prediction function for fitted cross validation oem objects
predict.cv.oem

Usage

```
## S3 method for class 'cv.oem'
predict(
  object, 
  newx, 
  which.model = "best.model",
  s = c("lambda.min", "lambda.1se"),
  ...)
```

Arguments

- **object**: fitted "cv.oem" model object
- **newx**: Matrix of new values for x at which predictions are to be made. Must be a matrix; can be sparse as in the CsparseMatrix objects of the Matrix package. This argument is not used for type = c("coefficients", "nonzero")
- **which.model**: If multiple penalties are fit and returned in the same oem object, the which.model argument is used to specify which model to make predictions for. For example, if the oem object "oemobj" was fit with argument penalty = c("lasso", "grp.lasso"), then which.model = 2 provides predictions for the group lasso model. For predict.cv.oem(), can specify "best.model" to use the best model as estimated by cross-validation.
- **s**: Value(s) of the penalty parameter lambda at which predictions are required. Default is the entire sequence used to create the model. For predict.cv.oem(), can also specify "lambda.1se" or "lambda.min" for best lambdas estimated by cross-validation.
- **...**: used to pass the other arguments for predict.oem

Value

An object depending on the type argument

Examples

```
set.seed(123)
n.obs <- 1e4
n.vars <- 100
n.obs.test <- 1e3
true.beta <- c(rnorm(15, -0.5, 0.5), rep(0, n.vars - 15))
x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x * true.beta
x.test <- matrix(rnorm(n.obs.test * n.vars), n.obs.test, n.vars)
y.test <- rnorm(n.obs.test, sd = 3) + x.test * true.beta

fit <- cv.oem(x = x, y = y, 
              penalty = c("lasso", "grp.lasso"), 
              groups = rep(1:10, each = 10), 
```

nlambda = 10)
preds.best <- predict(fit, newx = x.test, type = "response", which.model = "best.model")
apply(preds.best, 2, function(x) mean((y.test - x) ^ 2))
preds.gl <- predict(fit, newx = x.test, type = "response", which.model = "grp.lasso")
apply(preds.gl, 2, function(x) mean((y.test - x) ^ 2))
preds.l <- predict(fit, newx = x.test, type = "response", which.model = 1)
apply(preds.l, 2, function(x) mean((y.test - x) ^ 2))

predict.oem  Prediction method for Orthogonalizing EM fitted objects

Description

Prediction method for Orthogonalizing EM fitted objects

Usage

## S3 method for class 'oem'
predict(
  object,
  newx,
  s = NULL,
  which.model = 1,
  type = c("link", "response", "coefficients", "nonzero", "class"),
  ...
)

Arguments

  object  fitted "oem" model object
  newx  Matrix of new values for x at which predictions are to be made. Must be a
temporal matrix; can be sparse as in the CsparseMatrix objects of the Matrix package.
  This argument is not used for type="coefficients", "nonzero"
  s  Value(s) of the penalty parameter lambda at which predictions are required. De-
temporal is the entire sequence used to create the model.
  which.model  If multiple penalties are fit and returned in the same oem object, the which.model argument is used to specify which model to make predictions for. For example, if the oem object oemobj was fit with argument penalty = c("lasso","grp.lasso"), then which.model = 2 provides predictions for the group lasso model.
type

Type of prediction required. type = "link" gives the linear predictors for the "binomial" model; for "gaussian" models it gives the fitted values. type = "response" gives the fitted probabilities for "binomial". type = "coefficients" computes the coefficients at the requested values for s. type = "class" applies only to "binomial" and produces the class label corresponding to the maximum probability.

Value

An object depending on the type argument

Examples

```r
set.seed(123)
n.obs <- 1e4
n.vars <- 100
n.obs.test <- 1e3

true.beta <- c(runif(15, -0.5, 0.5), rep(0, n.vars - 15))
x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta
x.test <- matrix(rnorm(n.obs.test * n.vars), n.obs.test, n.vars)
y.test <- rnorm(n.obs.test, sd = 3) + x.test %*% true.beta

fit <- oem(x = x, y = y,
           penalty = c("lasso", "grp.lasso"),
           groups = rep(1:10, each = 10),
           nlambda = 10)
preds.lasso <- predict(fit, newx = x.test, type = "response", which.model = 1)
preds.grp.lasso <- predict(fit, newx = x.test, type = "response", which.model = 2)

apply(preds.lasso, 2, function(x) mean((y.test - x) ^ 2))
apply(preds.grp.lasso, 2, function(x) mean((y.test - x) ^ 2))
```

predict.xval.oem  Prediction function for fitted cross validation oem objects

Description

Prediction function for fitted cross validation oem objects
Usage

## S3 method for class 'xval.oem'
predict(
  object,
  newx,
  which.model = "best.model",
  s = c("lambda.min", "lambda.1se"),
  ...
)

Arguments

- **object**: fitted "cv.oem" model object
- **newx**: Matrix of new values for x at which predictions are to be made. Must be a matrix; can be sparse as in the CsparseMatrix objects of the Matrix package. This argument is not used for type=c("coefficients","nonzero")
- **which.model**: If multiple penalties are fit and returned in the same oem object, the which.model argument is used to specify which model to make predictions for. For example, if the oem object "oemobj" was fit with argument penalty = c("lasso","grp.lasso"), then which.model = 2 provides predictions for the group lasso model. For predict.cv.oem(), can specify "best.model" to use the best model as estimated by cross-validation
- **s**: Value(s) of the penalty parameter lambda at which predictions are required. Default is the entire sequence used to create the model. For predict.cv.oem, can also specify "lambda.1se" or "lambda.min" for best lambdas estimated by cross validation
- **...**: used to pass the other arguments for predict.oem()

Value

An object depending on the type argument

Examples

```r
set.seed(123)
n.obs <- 1e4
n.vars <- 100
n.obs.test <- 1e3

true.beta <- c(runif(15, -0.5, 0.5), rep(0, n.vars - 15))

x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta
x.test <- matrix(rnorm(n.obs.test * n.vars), n.obs.test, n.vars)
y.test <- rnorm(n.obs.test, sd = 3) + x.test %*% true.beta

fit <- xval.oem(x = x, y = y,
  penalty = c("lasso", "grp.lasso"),
  groups = rep(1:10, each = 10),
```
nlambda = 10)
preds.best <- predict(fit, newx = x.test, type = "response", which.model = "best.model")
apply(preds.best, 2, function(x) mean((y.test - x) ^ 2))
preds.gl <- predict(fit, newx = x.test, type = "response", which.model = "grp.lasso")
apply(preds.gl, 2, function(x) mean((y.test - x) ^ 2))
preds.l <- predict(fit, newx = x.test, type = "response", which.model = 1)
apply(preds.l, 2, function(x) mean((y.test - x) ^ 2))
Arguments

- `object`: fitted "cv.oem" object
- `...`: not used

Description

Fast cross validation for Orthogonalizing EM

Usage

```r
xval.oem(
  x,
  y,
  nfolds = 10L,
  foldid = NULL,
  type.measure = c("mse", "deviance", "class", "auc", "mae"),
  ncores = -1,
  family = c("gaussian", "binomial"),
  penalty = c("elastic.net", "lasso", "ols", "mcp", "scad", "mcp.net", "scad.net",
             "grp.lasso", "grp.lasso.net", "grp.mcp", "grp.scad", "grp.mcp.net", "grp.scad.net",
             "sparse.grp.lasso"),
  weights = numeric(0),
  lambda = numeric(0),
  nlambda = 100L,
  lambda.min.ratio = NULL,
  alpha = 1,
  gamma = 3,
  tau = 0.5,
  groups = numeric(0),
  penalty.factor = NULL,
  group.weights = NULL,
  standardize = TRUE,
  intercept = TRUE,
  maxit = 500L,
  tol = 1e-07,
  irls.maxit = 100L,
  irls.tol = 0.001,
  compute.loss = FALSE
)
```
Arguments

x  
input matrix of dimension n x p (sparse matrices not yet implemented). Each row is an observation, each column corresponds to a covariate. The xval.oem() function is optimized for n » p settings and may be very slow when p > n, so please use other packages such as glmnet, ncvreg, grpreg, or gglasso when p > n or p approx n.

y  
numeric response vector of length nobs = nrow(x).

nfolds  
integer number of cross validation folds. 3 is the minimum number allowed. defaults to 10

foldid  
an optional vector of values between 1 and nfold specifying which fold each observation belongs to.

type.measure  
measure to evaluate for cross-validation. The default is type.measure = "deviance", which uses squared-error for gaussian models (a.k.a type.measure = "mse" there), deviance for logistic regression. type.measure = "class" applies to binomial only. type.measure = "auc" is for two-class logistic regression only. type.measure="mse" or type.measure="mae" (mean absolute error) can be used by all models; they measure the deviation from the fitted mean to the response.

ncores  
Integer scalar that specifies the number of threads to be used

family  
"gaussian" for least squares problems, "binomial" for binary response (not implemented yet).

penalty  
Specification of penalty type. Choices include:

• "elastic.net" - elastic net penalty, extra parameters: "alpha"
• "lasso" - lasso penalty
• "ols" - ordinary least squares
• "mcp" - minimax concave penalty, extra parameters: "gamma"
• "scad" - smoothly clipped absolute deviation, extra parameters: "gamma"
• "mcp.net" - minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
• "scad.net" - smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
• "grp.lasso" - group lasso penalty
• "grp.lasso.net" - group lasso penalty + l2 penalty, extra parameters: "alpha"
• "grp.mcp" - group minimax concave penalty, extra parameters: "gamma"
• "grp.scad" - group smoothly clipped absolute deviation, extra parameters: "gamma"
• "grp.mcp.net" - group minimax concave penalty + l2 penalty, extra parameters: "gamma", "alpha"
• "grp.scad.net" - group smoothly clipped absolute deviation + l2 penalty, extra parameters: "gamma", "alpha"
• "sparse.grp.lasso" - sparse group lasso penalty (group lasso + lasso), extra parameters: "tau"
Careful consideration is required for the group lasso, group MCP, and group SCAD penalties. Groups as specified by the `groups` argument should be chosen in a sensible manner.

**weights**
observation weights. defaults to 1 for each observation (setting weight vector to length 0 will default all weights to 1)

**lambda**
A user supplied lambda sequence. By default, the program computes its own lambda sequence based on `nlambda` and `lambda.min.ratio`. Supplying a value of lambda overrides this.

**nlambda**
The number of lambda values - default is 100.

**lambda.min.ratio**
Smallest value for lambda, as a fraction of `lambda.max`, the (data derived) entry value (i.e. the smallest value for which all coefficients are zero). The default depends on the sample size `nobs` relative to the number of variables `nvars`. If `nobs > nvars`, the default is 0.0001, close to zero.

**alpha**
mixing value for `elastic.net`, `mcp.net`, `scad.net`, `grp.mcp.net`, `grp.scad.net`, penalty applied is \((1 - \alpha) * (\text{ridge penalty}) + \alpha * (\text{lasso/mcp/mcp/grp.lasso penalty})\)

**gamma**
tuning parameter for SCAD and MCP penalties. must be \(>= 1\)

**tau**
mixing value for `sparse.grp.lasso`. penalty applied is \((1 - \tau) * (\text{group lasso penalty}) + \tau * (\text{lasso penalty})\)

**groups**
A vector of describing the grouping of the coefficients. See the example below. All unpenalized variables should be put in group 0

**penalty.factor**
Separate penalty factors can be applied to each coefficient. This is a number that multiplies lambda to allow differential shrinkage. Can be 0 for some variables, which implies no shrinkage, and that variable is always included in the model. Default is 1 for all variables.

**group.weights**
penalty factors applied to each group for the group lasso. Similar to `penalty.factor`, this is a number that multiplies lambda to allow differential shrinkage. Can be 0 for some groups, which implies no shrinkage, and that group is always included in the model. Default is `sqrt(group size)` for all groups.

**standardize**
Logical flag for \(x\) variable standardization, prior to fitting the models. The coefficients are always returned on the original scale. Default is `standardize = TRUE`. If variables are in the same units already, you might not wish to standardize.

**intercept**
Should intercept(s) be fitted (default = `TRUE`) or set to zero (FALSE)

**maxit**
integer. Maximum number of OEM iterations

**tol**
convergence tolerance for OEM iterations

**irls.maxit**
integer. Maximum number of IRLS iterations

**irls.tol**
convergence tolerance for IRLS iterations. Only used if `family` != "gaussian"

**compute.loss**
should the loss be computed for each estimated tuning parameter? Defaults to FALSE. Setting to TRUE will dramatically increase computational time

**Value**
An object with S3 class "xval.oem"
Examples

```r
set.seed(123)
n.obs <- 1e4
n.vars <- 100

true.beta <- c(runif(15, -0.25, 0.25), rep(0, n.vars - 15))

x <- matrix(rnorm(n.obs * n.vars), n.obs, n.vars)
y <- rnorm(n.obs, sd = 3) + x %*% true.beta

system.time(fit <- oem(x = x, y = y,
    penalty = c("lasso", "grp.lasso"),
    groups = rep(1:20, each = 5)))

system.time(xfit <- xval.oem(x = x, y = y,
    penalty = c("lasso", "grp.lasso"),
    groups = rep(1:20, each = 5)))

system.time(xfit2 <- xval.oem(x = x, y = y,
    penalty = c("lasso", "grp.lasso",
        "mcp", "scad",
        "mcp.net", "scad.net",
        "grp.lasso", "grp.lasso.net",
        "grp.mcp", "grp.scad",
        "sparse.grp.lasso"),
    groups = rep(1:20, each = 5)))
```
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