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**Description**

Efficient procedures for fitting and cross-validating the overlapping group Lasso (implemented in C++) for Cox models with time-dependent covariates. The penalty term is a weighted sum of infinity norms of (overlapping) groups of coefficients, which can select variables structurally with a specific grouping structure.

**Description**

Fit a (time-dependent) Cox model with structured variable selection.

**Usage**

```r
netcox(
  x,
  ID,
  time,
  time2,
  event,
  lambda,
  group,
  group_variable,
  penalty_weights,
  par_init,
  stepsize_init = 1,
  stepsize_shrink = 0.8,
  tol = 1e-05,
)```
Arguments

x
Predictor matrix with dimension \(nm \times p\), where \(n\) is the number of subjects, \(m\) is the maximum observation time, and \(p\) is the number of predictors. See Details.

ID
The ID of each subject, each subject has one ID (many rows in \(x\) share one ID).

time
Represents the start of each time interval.

time2
Represents the stop of each time interval.

event
Indicator of event. \(event = 1\) when event occurs and \(event = 0\) otherwise.

lambda
Sequence of regularization coefficients \(\lambda\)'s.

group
\(G \times G\) matrix describing the relationship between the groups of variables, where \(G\) represents the number of groups. Denote the \(i\)-th group of variables by \(g_i\). The \((i,j)\) entry is 1 if and only if \(i \neq j\) and \(g_i\) is a child group (subset) of \(g_j\), and is 0 otherwise. See Examples and Details.

group_variable
\(p \times G\) matrix describing the relationship between the groups and the variables. The \((i,j)\) entry is 1 if and only if variable \(i\) is in group \(g_j\), but not in any child group of \(g_j\), and is 0 otherwise. See Examples and Details.

penalty_weights
Optional, vector of length \(G\) specifying the group-specific penalty weights. If not specified, the default value is \(1_G\). Modify with caution.

par_init
Optional, vector of initial values of the optimization algorithm. Default initial value is zero for all \(p\) variables.

stepsize_init
Initial value of the stepsize of the optimization algorithm. Default is 1.

stepsize_shrink
Factor in \((0, 1)\) by which the stepsize shrinks in the backtracking linesearch. Default is 0.8.

tol
Convergence criterion. Algorithm stops when the \(l_2\) norm of the difference between two consecutive updates is smaller than \(tol\).

maxit
Maximum number of iterations allowed.

verbose
Logical, whether progress is printed.

Details

The predictor matrix should be of dimension \(nm \times p\). Each row records the values of covariates for one subject at one time, for example, the values at the day from time (Start) to time2 (Stop). An example dataset sim is provided. The dataset has the same format produced by the R package PermAlgo. The specification of arguments group and group_variable for the grouping structure can be found in http://thoth.inrialpes.fr/people/mairal/spams/doc-R/html/doc_spams006.html#sec27, the same as the grouping structure specification in the R package spams.

In the Examples below, \(p = 9\), \(G = 5\), the group structure is:

\[g_1 = \{A_1, A_2, A_1B, A_2B\}\]
\[ g_2 = \{ B, A_1 B, A_2 B, C_1 B, C_2 B \}, \]
\[ g_3 = \{ A_1 B, A_2 B \}, \]
\[ g_4 = \{ C_1, C_2, C_1 B, C_2 B \}, \]
\[ g_5 = \{ C_1 B, C_2 B \}. \]

where \( g_3 \) is a subset of \( g_1 \) and \( g_2 \), and \( g_5 \) is a subset of \( g_2 \) and \( g_4 \).

**Value**

A list with the following three elements.

- `lambdas` The user-specified regularization coefficients \( \lambda \) sorted in decreasing order.
- `estimates` A matrix, with each column corresponding to the coefficient estimates at each \( \lambda \) in `lambdas`.
- `iterations` A vector of number of iterations it takes to converge at each \( \lambda \) in `lambdas`.

**Examples**

### # g3 in g1 -> grp_31 = 1
### # g3 in g2 -> grp_32 = 1
### # g5 in g2 -> grp_52 = 1
### # g5 in g4 -> grp_54 = 1

```
grp <- matrix(c(0, 0, 0, 0, 0,
                 0, 0, 0, 0, 0,
                 1, 1, 0, 0, 0,
                 0, 0, 0, 0, 0,
                 0, 1, 0, 1, 0),
                ncol = 5, byrow = TRUE)
```

### # Variable A1 is in g1 only: grp.var_11 = 1
### # Variable A1B is in g1 and g3, but g3 is a child group of g1, # so grp.var_63 = 1 while grp.var_61 = 0.

```
grp.var <- matrix(c(1, 0, 0, 0, 0, #A1
                    1, 0, 0, 0, 0, #A2
                    0, 0, 1, 0, 0, #C1
                    0, 0, 1, 0, 0, #C2
                    0, 1, 0, 0, 0, #B
                    0, 0, 1, 0, 0, #A1B
                    0, 0, 1, 0, 0, #A2B
                    0, 0, 0, 0, 1, #C1B
                    0, 0, 0, 1, 0 #C2B
                ), ncol = 5, byrow = TRUE)
```

```
eta_g <- rep(1, 5)
x <- as.matrix(sim[, c("A1","A2","C1","C2","B",
                     "A1B","A2B","C1B","C2B")])
lam.seq <- 10^seq(0, -2, by = -0.2)
```

```
fit <- netcox(x = x,
              ID = sim$Id,
              time = sim$Start,
```
netcox_cv

Conduct cross-validation (cv) for netcox.

netcox_cv(x, ID, time, time2, event, lambda, group, group_variable, penalty_weights, par_init, nfolds = 10, stepsize_init = 1, stepsize_shrink = 0.8, tol = 1e-05, maxit = 1000L, verbose = FALSE)

Arguments

x       Predictor matrix with dimension nm*p, where n is the number of subjects, m is the maximum observation time, and p is the number of predictors. See Details.
ID      The ID of each subjects, each subject has one ID (many rows in x share one ID).
time    Represents the start of each time interval.
time2   Represents the stop of each time interval.
event   Indicator of event. event = 1 when event occurs and event = 0 otherwise.
lambda: Sequence of regularization coefficients λ’s.

group: \( G \times G \) matrix describing the relationship between the groups of variables, where \( G \) represents the number of groups. Denote the \( i \)-th group of variables by \( g_i \). The \((i,j)\) entry is 1 if and only if \( i \neq j \) and \( g_i \) is a child group (subset) of \( g_j \), and is 0 otherwise. See Examples and Details.

group_variable: \( p \times G \) matrix describing the relationship between the groups and the variables. The \((i,j)\) entry is 1 if and only if variable \( i \) is in group \( g_j \), but not in any child group of \( g_j \), and is 0 otherwise. See Examples and Details.

penalty_weights: Optional, vector of length \( G \) specifying the group-specific penalty weights. If not specified, the default value is \( 1_G \). Modify with caution.

par_init: Optional, vector of initial values of the optimization algorithm. Default initial value is zero for all \( p \) variables.

nfolds: Optional, the folds of cross-validation. Default is 10.

stepsize_init: Initial value of the stepsize of the optimization algorithm. Default is 1.

stepsize_shrink: Factor in \((0, 1)\) by which the stepsize shrinks in the backtracking linesearch. Default is 0.8.

tol: Convergence criterion. Algorithm stops when the \( l_2 \) norm of the difference between two consecutive updates is smaller than \( \text{tol} \).

maxit: Maximum number of iterations allowed.

verbose: Logical, whether progress is printed.

Details

For each lambda, 10 folds cross-validation (by default) is performed. The cv error is defined as follows. Suppose we perform \( K \)-fold cross-validation, denote \( \hat{\beta}^{-k} \) by the estimate obtained from the rest of \( K - 1 \) folds (training set). The error of the \( k \)-th fold (test set) is defined as \( 2(P - Q) \) divided by \( R \), where \( P \) is the log partial likelihood evaluated at \( \hat{\beta}^{-k} \) using the entire dataset, \( Q \) is the log partial likelihood evaluated at \( \hat{\beta}^{-k} \) using the training set, and \( R \) is the number of events in the test set. We do not use the negative log partial likelihood evaluated at \( \hat{\beta}^{-k} \) using the test set because the former definition can efficiently use the risk set, and thus it is more stable when the number of events in each test set is small (think of leave-one-out). The cv error is used in parameter tuning. To account for balance in outcomes among the randomly formed test set, we divide the deviance \( 2(P - Q) \) by \( R \). To get the estimated coefficients that has the minimum cv error, use `netcox()$Estimates[netcox()$Lambdas==netcox_cv()$lambda.min]`. To apply the 1-se rule, use `netcox()$Estimates[netcox()$Lambdas==netcox_cv()$lambda.1se]`.

Value

A list.

\( \text{lambdas} \): A vector of lambda used for each cross-validation.

\( \text{cvm} \): The cv error averaged across all folds for each lambda.

\( \text{cvsd} \): The standard error of the cv error for each lambda.
The cv error plus its standard error for each lambda.

cvlo
The cv error minus its standard error for each lambda.

nzero
The number of non-zero coefficients at each lambda.

netcox.fit
A netcox fit for the full data at all lambdas.

lambda.min
The lambda such that the cvm reach its minimum.

lambda.1se
The maximum of lambda such that the cvm is less than the minimum the cvup (the minimum of cvm plus its standard error).

See Also

netcox, plot_netcox_cv.

Examples

grp <- matrix(c(0, 0, 0, 0, 0,
  0, 0, 0, 0, 0,
  1, 1, 0, 0, 0,
  0, 0, 0, 0, 0,
  0, 1, 0, 1, 0),
  ncol = 5, byrow = TRUE)
grp.var <- matrix(c(0, 0, 0, 0, 0, #A1
  1, 0, 0, 0, 0, #A2
  0, 0, 0, 1, 0, #C1
  0, 0, 0, 1, 0, #C2
  0, 1, 0, 0, 0, #B
  0, 0, 1, 0, 0, #A1B
  0, 0, 1, 0, 0, #A2B
  0, 0, 0, 1, 0, #C1B
  0, 0, 0, 0, 1 #C2B
), ncol = 5, byrow = TRUE)
eta_g <- rep(1, 5)
x <- as.matrix(sim[, c("A1","A2","C1","C2","B",
  "A1B","A2B","C1B","C2B")])
lam.seq <- 10^seq(0, -2, by = -0.2)

cv <- netcox_cv(x = x,
  ID = sim$Id,
  time = sim$Start,
  time2 = sim$Stop,
  event = sim$Event,
  lambda = lam.seq,
  group = grp,
  group_variable = grp.var,
  penalty_weights = eta_g,
  nfolds = 5,
  tol = 1e-4,
  maxit = 1e3,
  verbose = FALSE)
**plot_netcox_cv**  

**plots for netcox_cv**  

---

**Description**

Plot the cross-validation curves produced by `netcox_cv`.

**Usage**

`plot_netcox_cv(netcox_cv_obj)`

**Arguments**

- `netcox_cv_obj` The `netcox_cv` object.

**Value**

The plot is the `cvm` (red dot) for each lambda with its standard error (vertical bar). The two vertical dashed lines corresponds to the `lambda.min` and `lambda.1se`.

**See Also**

`netcox`, `netcox_cv`.

**Examples**

```r
grp <- matrix(c(0, 0, 0, 0, 0,
                0, 0, 0, 0, 0,
                1, 1, 0, 0, 0,
                0, 0, 0, 0, 0,
                0, 1, 0, 1, 0),
               ncol = 5, byrow = TRUE)
grp.var <- matrix(c(1, 0, 0, 0, 0, #A1
                    1, 0, 0, 0, 0, #A2
                    0, 0, 0, 1, 0, #C1
                    0, 0, 0, 1, 0, #C2
                    0, 1, 0, 0, 0, #B
                    0, 0, 1, 0, 0, #A1B
                    0, 0, 1, 0, 0, #A2B
                    0, 0, 0, 1, 1, #C1B
                    0, 0, 0, 0, 1, #C2B
               ), ncol = 5, byrow = TRUE)
eta_g <- rep(1, 5)
x <- as.matrix(sim[, c("A1","A2","C1","C2","B","A1B","A2B","C1B","C2B")])
lam.seq <- 10*seq(0, -2, by = -0.2)

cv <- netcox_cv(x = x,
                 ID = sim$Id,
                 lam.seq = lam.seq)
```

time = sim$Start,
  time2 = sim$Stop,
  event = sim$Event,
  lambda = lam.seq,
  group = grp,
  group_variable = grp.var,
  penalty_weights = eta_g,
  nfolds = 5,
  tol = 1e-4,
  maxit = 1e3,
  verbose = FALSE)

plot_netcox_cv(cv)

plot_netcox_sp

plots for netcox and netcox_cv

Description

Plot the solution path produced by netcox or netcox_cv.

Usage

plot_netcox_sp(
  netcox_obj,
  plot_min = FALSE,
  plot_1se = FALSE,
  type = "l",
  log = "x",
  ...
)

Arguments

netcox_obj The netcox or netcox_cv object.
plot_min Logical, whether a vertical line at lambda.min acquired by netcox_cv is plotted. Not available if netcox_obj is a netcox fit.
plot_1se Logical, whether a vertical line at lambda.1se acquired by netcox_cv is plotted. Not available if netcox_obj is a netcox fit.
type Graphical argument to be passed to matplot, a character string (length 1 vector) or vector of 1-character strings indicating the type of plot for each column of y, see plot.default for all possible types. Default is "l" for lines.
log Graphical argument to be passed to matplot, a character string which contains "x" if the x axis is to be logarithmic, "y" if the y axis is to be logarithmic, "" if neither, "xy" or "yx" if both axes are to be logarithmic. Default is "x".
...

Further arguments of matplot and ultimately of plot.default for some.
Value

Produces a coefficient profile plot of the coefficient paths for a fitted netcox or netcox_cv object.

See Also

netcox, netcox_cv.

Examples

grp <- matrix(c(0, 0, 0, 0, 0,
                0, 0, 0, 0, 0,
                1, 1, 0, 0, 0,
                0, 0, 0, 0, 0,
                0, 1, 0, 1, 0),
               ncol = 5, byrow = TRUE)
grp.var <- matrix(c(1, 0, 0, 0, 0, #A1
                    1, 0, 0, 0, 0, #A2
                    0, 0, 0, 1, 0, #C1
                    0, 0, 1, 0, 0, #C2
                    0, 1, 0, 0, 0, #B
                    0, 0, 1, 0, 0, #A1B
                    0, 0, 0, 0, 1, #A2B
                    0, 1, 0, 0, 0, #C1B
                    0, 0, 0, 1, 0, #C2B
               ), ncol = 5, byrow = TRUE)
eta_g <- rep(1, 5)
x <- as.matrix(sim[, c("A1","A2","C1","C2","B",
                     "A1B","A2B","C1B","C2B")])
lam.seq <- 10^seq(0, -2, by = -0.2)
# plot solution path from a netcox fit
fit <- netcox(x = x,
               ID = sim$Id,
               time = sim$Start,
               time2 = sim$Stop,
               event = sim$Event,
               lambda = lam.seq,
               group = grp,
               group_variable = grp.var,
               penalty_weights = eta_g,
               tol = 1e-4,
               maxit = 1e3,
               verbose = FALSE)
plot_netcox_sp(netcox_obj = fit)

# plot solution path from a netcox_cv fit
cv <- netcox_cv(x = x,
                 ID = sim$Id,
                 time = sim$Start,
                 time2 = sim$Stop,
                 event = sim$Event,
                 lambda = lam.seq,
                 group = grp,
sim

A simulated demo dataset sim

Description
A simulated demo dataset sim

Usage
data(sim)

Format
A simulated data frame that is used to illustrate the use of the netcox package. The max follow-up time for each subject is set to be 5. The total number of subject is 50.

- **Id**: The ID of each subject.
- **Event**: During the time from **Start** to **Stop**, if the subject experience the event. We use the function `permalgorithm` in the R package PermAlgo to generate the Event.

**Start**: Start time.

**Stop**: Stop time.

**Fup**: The total follow-up time for the subject.

**Covariates**: A1, A2, C1, C2, B, A1B, A2B, C1B, C2B. The dataset contains 5 variables (9 columns after one-hot encoding). Variable A is a 3-level categorical variable, which results in 2 binary variables (A1 and A2), the same with the variable C. B is a continuous variable. The interaction term AB and CB are also two 3-level categorical variables. The code for generating the covariates is given below.

See Also
PermAlgo

Examples

```r
# generate B
gen_con=function(m){
  X=rnorm(m/5)
  XX=NULL
  for (i in 1:length(X)) {
    if (length(XX)<m){
      ```
```
x.rep = rep(X[i], round(runif(1, 5, 10), 0))
XX = c(XX, X.rep)
}
return(XX[1:m])
}
# generate A and C
gen_cat = function(m){
    X = sample.int(3, m/5, replace = TRUE)
    XX = NULL
    for (i in 1:length(X)) {
        if (length(XX) < m){
            X.rep = rep(X[i], round(runif(1, 5, 10), 0))
            XX = c(XX, X.rep)
        }
    }
    return(XX[1:m])
}
# generate covariate for one subject
gen_X = function(m){
    A = gen_cat(m); B = gen_con(m); C = gen_cat(m)
    A1 = ifelse(A == 1, 1, 0); A2 = ifelse(A == 2, 1, 0)
    C1 = ifelse(C == 1, 1, 0); C2 = ifelse(C == 2, 1, 0)
    A1B = A1 * B; A2B = A2 * B
    C1B = C1 * B; C2B = C2 * B
    return(as.matrix(cbind(A1, A2, C1, C2, B, A1B, A2B, C1B, C2B)))
}
# generate covariate for all subject
gen_X_n = function(m, n){
    Xn = NULL
    for (i in 1:n) {
        X = gen_X(m)
        Xn = rbind(Xn, X)
    }
    return(Xn)
}
n = 50; m = 5
covariates = gen_X_n(m, n)
# generate outcomes
# library(PermAlgo)
# data <- permalgorithm(n, m, covariates,
# # change according to scenario 1/2
# betas = c(rep(log(3), 2), rep(0, 2), log(4), rep(log(3), 2), rep(0, 2)),
# # groupByD=FALSE )
# fit.original = coxph(Surv(Start, Stop, Event) ~ . , data[, c(1, 3)])
```
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