Package ‘FRESHD’

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Title Fast Robust Estimation of Signals in Heterogeneous Data
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Description Procedure for solving the maximin problem for identical design across heterogeneous data groups. Particularly efficient when the design matrix is either orthogonal or has tensor structure. Orthogonal wavelets can be specified for 1d, 2d or 3d data simply by name. For tensor structured design the tensor components (two or three) may be supplied. The package also provides an efficient implementation of the generic magging estimator.
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Description

This function performs a level J decomposition of the input array (1d, 2d, or 3d) using the pyramid algorithm (Mallat 1989).

Usage

```
iwt(x, wf = "la8", J = NULL)
```

Arguments

- `x`: a 1, 2, or 3 dimensional data array. The size of each dimension must be dyadic.
- `wf`: the type of wavelet family used. See R-package waveslim for options.
- `J`: is the level (depth) of the decomposition. For default NULL the max depth is used making `iwt(x)` equal to multiplying `x` with the inverse of corresponding wavelet matrix.

Details

This is a C++/R wrapper function for a C implementation of the inverse discrete wavelet transform by Brandon Whitcher licensed under the BSD 3 license https://cran.r-project.org/web/licenses/BSD_3_clause, see the Waveslim package; Percival and Walden (2000); Gencay, Selcuk and Whitcher (2001).

Given a data array (1d, 2d or 3d) with dyadic dimensions sizes this transform is computed efficiently via the pyramid algorithm see Mallat (1989).

Value

```
... An array with dimensions equal to those of x.
```

Author(s)

Adam Lund, Brandon Whitcher

References


Examples

### 1d
```r
x <- as.matrix(rnorm(2^3))
range(x - iwt(wt(x)))
```

### 2d
```r
x <- matrix(rnorm(2^(3 + 4)), 2^3, 2^4)
range(x - iwt(wt(x)))
```

### 3d
```r
x <- array(rnorm(2^(3 + 4 + 5)), c(2^3, 2^4, 2^5))
range(x - iwt(wt(x)))
```

---

**magging**

**Maximin Aggregation**

**Description**

R wrapper for a C++ implementation of the generic maximin aggregation procedure.

**Usage**

`magging(B)`

**Arguments**

- `B` array of size `p x G` containing the group parameter estimates where `p` is the number of model parameters and `G` is the number of groups.

**Details**

Following *Buhlmann 2016* this function computes the maximin aggregation estimator for given group estimates. This entails solving a convex quadratic optimization problem. The function wraps a C++ implementation of an algorithm by Goldfarb and Idnani for solving a (convex) quadratic programming problem by means of a dual method.

The underlying C++ program solving the convex quadratic optimization problem, eiquadprog.hpp, copyright (2011) Benjamin Stephens, GPL v2 see https://www.cs.cmu.edu/~bstephe1/eiquadprog.hpp, is based on previous libraries:

QuadProg++, Copyright (C) 2007-2016 Luca Di Gaspero, MIT License. See https://github.com/liuq/QuadProgpp

uQuadProg, Copyright (C) 2006 - 2017 Angelo Furfaro, LGPL v3, a port of QuadProg++ working with ublas data structures. See https://github.com/fx74/uQuadProg/blob/master/README.md

QuadProg Copyright (C) 2014-2015 Gael Guennebaud, LGPL v3, a modification of uQuadProg, working with Eigen data structures. See http://www.labri.fr/perso/guenneba/code/QuadProg/. 
Value

An object with S3 Class "FRESHD".

... A $p$ vector containing the maximin aggregated parameter estimates.

Author(s)

Adam Lund, Benjamin Stephens, Gael Guennebaud, Angelo Furfaro, Luca Di Gaspero

Maintainer: Adam Lund, <adam.lund@math.ku.dk>

References

Buhlmann, Peter and Meinshausen, Nicolai (2016). Magging: maximin aggregation for inhomogeneous large-scale data. Proceedings of the IEEE, 1, 104, 126-135


Examples

```r
## size of example
set.seed(42)
G <- 15; n <- c(50, 20, 13); p <- c(7, 5, 4)
nlambda <- 10

## marginal design matrices (Kronecker components)
x <- list()
for(i in 1:length(n)){
x[[i]] <- matrix(rnorm(n[i] * p[i], 0, 1), n[i], p[i])
}

# common features and effects
common_features <- rbinom(prod(p), 1, 0.1)
common_effects <- rnorm(prod(p), 0, 1) * common_features
system.time({
  # group response and fit
  lambda <- exp(seq(-1, -4, length.out = nlambda))
magbeta <- matrix(0, prod(p), nlambda)
  B <- array(NA, c(prod(p), G, nlambda))
  y <- array(NA, c(n, G))
  for(g in 1:G){
    bg <- rnorm(prod(p), 0, 0.1) * (1 - common_features) + common_effects
    Bg <- array(bg, p)
    mu <- RH(x[[3]], RH(x[[2]], RH(x[[1]], Bg)))
    y[, , g] <- array(rnorm(prod(n)), dim = n) + mu
    B[, , g] <- glmlasso::glamlasso(x, y[, , g], lambda = lambda)$coef
  }
  magbeta[, l] <- magging(B[, , l])
})
```
maximin

}  # estimated common effects for specific lambda
modelno <- 10
betafit <- magbeta[, modelno]
plot(common_effects, type = "h", ylim = range(betafit, common_effects), col = "red")
lines(betafit, type = "h")

maximin

Maximin signal estimation

Description

Efficient procedure for solving the maximin estimation problem with identical design across groups, see (Lund, 2022).

Usage

maximin(y,
    x,
    penalty = "lasso",
    alg = "aradmm",
    kappa = 0.99,
    nlambda = 30,
    lambda_min_ratio = 1e-04,
    lambda = NULL,
    penalty_factor = NULL,
    standardize = TRUE,
    tol = 1e-05,
    maxiter = 1000,
    delta = 1,
    gamma = 1,
    eta = 0.1,
    aux_par = NULL)

Arguments

y Array of size $n_1 \times \cdots \times n_d \times G$ containing the response values.
x Either i) the design matrix, ii) a list containing the Kronecker components (2 or 3) if the design matrix has Kronecker structure or iii) a string indicating the name of the wavelet to use (see wt for options)
penalty string specifying the penalty type. Possible values are "lasso".
alg string specifying the optimization algorithm. Possible values are "admm", "aradmm", "tos", "tosacc".
kappa Strictly positive float controlling the maximum sparsity in the solution. Only used with ADMM type algorithms. Should be between 0 and 1.
nlambda

Positive integer giving the number of lambda values. Used when lambda is not specified.

lambda_min_ratio

strictly positive float giving the smallest value for lambda, as a fraction of \( \lambda_{\text{max}} \); the (data dependent) smallest value for which all coefficients are zero. Used when lambda is not specified.

lambda

Sequence of strictly positive floats used as penalty parameters.

penalty_factor

A vector of length \( p \) containing positive floats that are multiplied with each element in lambda to allow differential penalization on the coefficients. For tensor models an array of size \( p_1 \times \cdots \times p_d \).

standardize

Boolean indicating if response \( y \) should be scaled. Default is TRUE to avoid numerical problems.

tol

Strictly positive float controlling the convergence tolerance.

maxiter

Positive integer giving the maximum number of iterations allowed for each lambda value.

delta

Positive float controlling the step size in the algorithm.

gamma

Positive float controlling the relaxation parameter in the algorithm. Should be between 0 and 2.

eta

Scaling parameter for the step size in the accelerated TOS algorithm. Should be between 0 and 1.

aux_par

Auxiliary parameters for the algorithms.

Details

For \( n \) heterogeneous data points divided into \( G \) equal sized groups with \( m < n \) data points in each, let \( y_g = (y_{g,1}, \ldots, y_{g,m}) \) denote the vector of observations in group \( g \). For a \( m \times p \) design matrix \( X \) consider the model

\[
y_g = Xb_g + \epsilon_g
\]

for \( b_g \) a random group specific coefficient vector and \( \epsilon_g \) an error term, see Meinshausen and Buhlmann (2015). For the model above following Lund (2022) this package solves the maximin estimation problem

\[
\min_{\beta} -\hat{V}_g(\beta) + \lambda \|\beta\|_1, \lambda \geq 0
\]

where

\[
\hat{V}_g(\beta) := \frac{1}{n}(2\beta^T X^T y_g - \beta^T X^T X \beta),
\]

is the empirical explained variance in group \( g \). See Lund, 2022 for more details and references.

The package solves the problem using different algorithms depending on \( X \):

i) If \( X \) is orthogonal (e.g. the inverse wavelet transform) either an ADMM algorithm (standard or relaxed) or an adaptive relaxed ADMM (ARADMM) with auto tuned step size is used, see Xu et al (2017).

ii) For general \( X \), a three operator splitting (TOS) algorithm is implemented, see Damek and Yin (2017). Note if the design is tensor structured, \( X = \bigotimes_{i=1}^d X_i \) for \( d \in \{1, 2, 3\} \), the procedure accepts a list containing the tensor components (matrices).
Value

An object with S3 Class "FRESHD".

spec
A string indicating the array dimension (1, 2 or 3) and the penalty.

coef
A $p_1 \cdots p_d \times n_{\lambda}$ matrix containing the estimates of the model coefficients ($\beta$) for each $\lambda$ value.

lambda
A vector containing the sequence of penalty values used in the estimation procedure.

df
The number of nonzero coefficients for each value of lambda.

dimcoef
A vector giving the dimension of the model coefficient array $\beta$.

dimobs
A vector giving the dimension of the observation (response) array $Y$.

dim
Integer indicating the dimension of the array model. Equal to 1 for non array.

wf
A string indicating the wavelet name if used.

diagnostics
A list where item iter is a vector containing the number of iterations for each lambda value for which the algorithm converged. Item stop_maxiter is 1 if maximum iterations is reached otherwise zero. Item stop_sparse is 1 if maximum sparsity is reached otherwise zero.

Author(s)

Adam Lund

Maintainer: Adam Lund, <adam.lund@math.ku.dk>

References


Examples

## general 3d tensor design matrix
set.seed(42)
G <- 20; n <- c(65, 26, 13)*3; p <- c(13, 5, 4)*3
sigma <- 1

## marginal design matrices (Kronecker components)
x <- list()
for(i in 1:length(n))(x[[i]] <- matrix(rnorm(n[i] * p[i], 0, sigma), n[i], p[i]))

## common features and effects
common_features <- rbinom(prod(p), 1, 0.1)
comm Effects <- rnorm(prod(p), 0, 0.1) * common_features

# simulate group response
y <- array(NA, c(n, G))
for(g in 1:G){
  bg <- rnorm(prod(p), 0, 0.1) * (1 - common_features) + common_effects
  Bg <- array(bg, p)
  mu <- RH(x[[3]], RH(x[[2]], RH(x[[1]], Bg)))
  y[, , , g] <- array(rnorm(prod(n), 0, var(mu)), dim = n) + mu
}

# fit model for range of lambda
system.time(fit <- maximin(y, x, penalty = "lasso", alg = "tosacc"))

# estimated common effects for specific lambda
modelno <- 10
betafit <- fit$coef[, modelno]
plot(common_effects, type = "h", ylim = range(betafit, common_effects), col = "red")
lines(betafit, type = "h")

# size of example
set.seed(42)
G <- 50; p <- n <- c(2^6, 2^5, 2^6);

# common features and effects
common_features <- rbinom(prod(p), 1, 0.1) # sparsity of comm. feat.
common_effects <- rnorm(prod(p), 0, 1) * common_features

# group response
y <- array(NA, c(n, G))
for(g in 1:G){
  bg <- rnorm(prod(p), 0, 0.1) * (1 - common_features) + common_effects
  Bg <- array(bg, p)
  mu <- iwt(Bg)
  y[, , , g] <- array(rnorm(prod(n), 0, 0.5), dim = n) + mu
}

# orthogonal wavelet design with 1d data
G = 50; N1 = 2^10; p = 101; J = 2; amp = 20; sigma2 = 10
y <- matrix(0, N1, G)
z <- seq(0, 2, length.out = N1)
sig <- cos(10 * pi * z) + 1.5 * sin(5 * pi * z)
for (i in 1:G){
  freqs <- sample(1:100, size = J, replace = TRUE)
  y[, i] <- sig * 2 + rnorm(N1, sd = sqrt(sigma2))
  for (j in 1:J){
    y[, i] <- y[, i] + amp * sin(freqs[j] * pi * z + runif(1, -pi, pi))
  }
}

system.time(fit <- maximin(y, "la8", alg = "aradmm", kappa = 0.9))
predict.FRESHD

Make Prediction From a FRESHD Object

Description

Given covariate data this function computes the linear predictors based on the estimated model coefficients in an object produced by the function maximin or magging. Note that the data can be supplied in two different formats: i) for wavelet based models as a string indicating the wavelet used to produce the model object. ii) for models with custom design as a list of one, two or three Kronecker component matrices each of size $n'_i \times p_i, i = 1, 2, 3$. Note $x$ will typically be the original design (covariate data) that was used to produce object using maximin or magging so $n'_i$ is the number of marginal data points in the $i$th dimension i.e. $n'_i = n_i$.

Usage

## S3 method for class 'FRESHD'
predict(object, x, ...)  

Arguments

object An object of class FRESHD, produced with maximin or magging.
x An object that should be like the input to the call that produced object. For models with custom design a list like the one supplied to produce object and for a wavelet design the name of the wavelet used to produce object.

... ignored.

Value

If x is a string indicating a wavelet an array of the same size as the input data used to produce object. Otherwise an array of size $n'_1 \times \cdots \times n'_d$, with $d \in \{1, 2, 3\}$.

Author(s)

Adam Lund

Examples

##size of example
set.seed(42)
G = 50; N1 = 2^10; p = 101; J = 3; amp = 20; sigma2 = 10
y <- matrix(0, N1, G)
z <- seq(0, z, length.out = N1)
sig <- cos(10 * pi * z) + 1.5 * sin(5 * pi * z)
mmy <- predict(fit, "la8")
plot(mmy[,1], type = "l")
lines(sig, col = "red")
for (i in 1:G){
  freqs <- sample(1:100, size = J, replace = TRUE)
  y[, i] <- sig * 2 + rnorm(N1, sd = sqrt(sigma2))
  for (j in 1:J){
    y[, i] <- y[, i] + amp * sin(freqs[j] * pi * z + runif(1, -pi, pi))
  }
  system.time(fitmm <- maximin(y, "la8", alg = "aradmm", kappa = 0.95))
  mmy <- predict(fitmm, "la8")
  plot(mmy[, 2], type = "l")
  lines(sig, col = "red")
}

description

print.FRESHD

Print Function for objects of Class FRESHD

Description

This function will print some information about the FRESHD object.

Usage

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

Arguments

x

a FRESHD object

... ignored

Details

A three-column data.frame with columns ‘sparsity’, ‘Df’ and ‘lambda’. The ‘Df’ column is the number of nonzero coefficients and ‘sparsity’ is the percentage of zeros in the solution.

Value

The data.frame above is silently returned

Author(s)

Adam Lund
Examples

```r
##size of example
set.seed(42)
G <- 50; n <- c(65, 26, 13); p <- c(13, 5, 4)
sigma <- 0.1
nlambda = 30
##marginal design matrices (Kronecker components)
x <- list()
for(i in 1:length(n)){x[[i]] <- matrix(rnorm(n[i] * p[i], 0, sigma), n[i], p[i])}
##common features and effects
common_features <- rbinom(prod(p), 1, 0.1)
common_effects <- rnorm(prod(p), 0, 0.1) * common_features
##group response and fit
lambda <- exp(seq(0, -5, length.out = nlambda))
B <- array(NA, c(prod(p), nlambda, G))
y <- array(NA, c(n, G))
for(g in 1:G){
  bg <- rnorm(prod(p), 0, 0.1) * (1 - common_features) + common_effects
  Bg <- array(bg, p)
  mu <- RH(x[[3]], RH(x[[2]], RH(x[[1]], Bg)))
  y[,, g] <- array(rnorm(prod(n), 0, var(mu)), dim = n) + mu
}
##fit model for range of lambda
system.time(fit <- maximin(y, x, penalty = "lasso", alg = "tos"))
Betahat <- fit$coef
##estimated common effects for specific lambda
modelno <- 20;
m <- min(Betahat[, modelno], common_effects)
M <- max(Betahat[, modelno], common_effects)
plot(common_effects, type = "h", ylim = c(m, M), col = "red")
lines(Betahat[, modelno], type = "h")
```

---

**RH**

*The Rotated H-transform of a 3d Array by a Matrix*

**Description**

This function is an implementation of the \( \rho \)-operator found in Currie et al 2006. It forms the basis of the GLAM arithmetic.

**Usage**

```
RH(M, A)
```
Arguments

M  
  a $n \times p_1$ matrix.

A  
  a 3d array of size $p_1 \times p_2 \times p_3$.

Details

For details see Currie et al 2006. Note that this particular implementation is not used in the routines underlying the optimization procedure.

Value

A 3d array of size $p_2 \times p_3 \times n$.

Author(s)

Adam Lund

References


Examples

```r
n1 <- 65; n2 <- 26; n3 <- 13; p1 <- 13; p2 <- 5; p3 <- 4

## marginal design matrices (Kronecker components)
X1 <- matrix(rnorm(n1 * p1), n1, p1)
X2 <- matrix(rnorm(n2 * p2), n2, p2)
X3 <- matrix(rnorm(n3 * p3), n3, p3)

Beta <- array(rnorm(p1 * p2 * p3, 0, 1), c(p1, p2, p3))
max(abs(c(RH(X3, RH(X2, RH(X1, Beta))))) - kronecker(X3, kronecker(X2, X1)) %*% c(Beta))
```

Description

This function performs a level J wavelet transform of the input array (1d, 2d, or 3d) using the pyramid algorithm (Mallat 1989).

Usage

```r
wt(x, wf = "la8", J = NULL)
```
Arguments

- **x**: a 1, 2, or 3 dimensional data array. The size of each dimension must be dyadic.
- **wf**: the type of wavelet family used. See R-package waveslim for options.
- **J**: is the level (depth) of the decomposition. For default NULL the max depth is used making \( wt(x) \) equal to multiplying \( x \) with the corresponding wavelet matrix.

Details

This is a C++/R wrapper function for a C implementation of the discrete wavelet transform by Brandon Whitcher licensed under the BSD 3 license https://cran.r-project.org/web/licenses/BSD_3_clause, see the Waveslim package; Percival and Walden (2000); Gencay, Selcuk and Whitcher (2001).

Given a data array (1d, 2d or 3d) with dyadic sizes this transform is computed efficiently via the pyramid algorithm see Mallat (1989).

Value

... An array with dimensions equal to those of \( x \).

Author(s)

Adam Lund, Brandon Whitcher

References


Examples

```r
###1d
x <- as.matrix(rnorm(2^3))
range(x - iwt(wt(x)))

###2d
x <- matrix(rnorm(2^(3 + 4)), 2^3, 2^4)
range(x - iwt(wt(x)))

###3d
x <- array(rnorm(2^(3 + 4 + 5)), c(2^3, 2^4, 2^5))
range(x - iwt(wt(x)))
```
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