

# Package: CMLS (via r-universe)

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**Type** Package

**Title** Constrained Multivariate Least Squares

**Version** 1.0-1

**Date** 2023-03-29

**Author** Nathaniel E. Helwig <helwig@umn.edu>

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**Depends** quadprog, parallel

**Description** Solves multivariate least squares (MLS) problems subject to constraints on the coefficients, e.g., non-negativity, orthogonality, equality, inequality, monotonicity, unimodality, smoothness, etc. Includes flexible functions for solving MLS problems subject to user-specified equality and/or inequality constraints, as well as a wrapper function that implements 24 common constraint options. Also does k-fold or generalized cross-validation to tune constraint options for MLS problems. See ten Berge (1993, ISBN:9789066950832) for an overview of MLS problems, and see Goldfarb and Idnani (1983) <doi:10.1007/BF02591962> for a discussion of the underlying quadratic programming algorithm.

**License** GPL (>= 2)

**NeedsCompilation** no

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CMLS-package	<i>Constrained Multivariate Least Squares</i>
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## Description

Solves multivariate least squares (MLS) problems subject to constraints on the coefficients, e.g., non-negativity, orthogonality, equality, inequality, monotonicity, unimodality, smoothness, etc. Includes flexible functions for solving MLS problems subject to user-specified equality and/or inequality constraints, as well as a wrapper function that implements 24 common constraint options. Also does k-fold or generalized cross-validation to tune constraint options for MLS problems. See ten Berge (1993, ISBN:9789066950832) for an overview of MLS problems, and see Goldfarb and Idnani (1983) <doi:10.1007/BF02591962> for a discussion of the underlying quadratic programming algorithm.

## Details

The DESCRIPTION file:

```
Package:      CMLS
Type:        Package
Title:       Constrained Multivariate Least Squares
Version:     1.0-1
Date:        2023-03-29
Author:      Nathaniel E. Helwig <helwig@umn.edu>
Maintainer:  Nathaniel E. Helwig <helwig@umn.edu>
Depends:    quadprog, parallel
Description: Solves multivariate least squares (MLS) problems subject to constraints on the coefficients, e.g., non-negativity
License:     GPL (>=2)
```

Index of help topics:

CMLS-package	Constrained Multivariate Least Squares
IsplineBasis	I-Spline Basis for Monotonic Polynomial Splines
M splineBasis	M-Spline Basis for Polynomial Splines
cmls	Solve a Constrained Multivariate Least Squares Problem
const	Print or Return Constraint Options for cmls
cv.cmls	Cross-Validation for cmls
mlsei	Multivariate Least Squares with Equality/Inequality Constraints
mlsun	Multivariate Least Squares with Unimodality (and E/I) Constraints

The `cmls` function provides a user-friendly interface for solving the MLS problem with 24 common constraint options (the `const` function prints or returns the different constraint options). The `cv.cmls` function does k-fold or generalized cross-validation to tune the constraint options of the `cmls` function. The `mlsei` function solves the MLS problem subject to user-specified equality and/or inequality (E/I) constraints on the coefficients. The `mlsun` function solves the MLS problem subject to unimodality constraints and user-specified E/I constraints on the coefficients.

### Author(s)

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### References

Goldfarb, D., & Idnani, A. (1983). A numerically stable dual method for solving strictly convex quadratic programs. *Mathematical Programming*, 27, 1-33. doi:10.1007/BF02591962

Helwig, N. E. (in prep). Constrained multivariate least squares in R.

Ten Berge, J. M. F. (1993). *Least Squares Optimization in Multivariate Analysis*. Volume 25 of M & T Series. DSWO Press, Leiden University. ISBN: 9789066950832

Turlach, B. A., & Weingessel, A. (2019). `quadprog`: Functions to solve Quadratic Programming Problems. R package version 1.5-8. <https://CRAN.R-project.org/package=quadprog>

### Examples

```
# See examples for cmls, cv.cmls, mlsei, and mlsun
```

---

cmls

*Solve a Constrained Multivariate Least Squares Problem*

---

### Description

Finds the  $p \times m$  matrix B that minimizes the multivariate least squares problem

$$\text{sum}((Y - X \%*\% B)^2)$$

subject to the specified constraints on the rows of B.

### Usage

```
cmls(X, Y, const = "uncons", struc = NULL,
      z = NULL, df = 10, degree = 3, intercept = TRUE,
      backfit = FALSE, maxit = 1e3, eps = 1e-10,
      del = 1e-6, XtX = NULL, mode.range = NULL)
```

**Arguments**

<code>X</code>	Matrix of dimension $n \times p$ .
<code>Y</code>	Matrix of dimension $n \times m$ .
<code>const</code>	Constraint code. See <code>const</code> for the 24 available options.
<code>struc</code>	Structural constraints (defaults to unstructured). See Note.
<code>z</code>	Predictor values for the spline basis (for smoothness constraints). See Note.
<code>df</code>	Degrees of freedom for the spline basis (for smoothness constraints). See Note.
<code>degree</code>	Polynomial degree for the spline basis (for smoothness constraints). See Note.
<code>intercept</code>	Logical indicating whether the spline basis should contain an intercept (for smoothness constraints). See Note.
<code>backfit</code>	Estimate B via back-fitting (TRUE) or vectorization (FALSE). See Details.
<code>maxit</code>	Maximum number of iterations for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
<code>eps</code>	Convergence tolerance for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
<code>del</code>	Stability tolerance for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
<code>XtX</code>	Crossproduct matrix: $XtX = \text{crossprod}(X)$ .
<code>mode.range</code>	Mode search ranges (for unimodal constraints). See Note.

**Details**

If `backfit = FALSE` (default), a closed-form solution is used to estimate B whenever possible. Otherwise a back-fitting algorithm is used, where the rows of B are updated sequentially until convergence. The backfitting algorithm is determined to have converged when

$$\text{mean}((B.\text{new} - B.\text{old})^2) < \text{eps} * (\text{mean}(B.\text{old}^2) + \text{del}),$$

where `B.old` and `B.new` denote the parameter estimates at iterations  $t$  and  $t + 1$  of the backfitting algorithm.

**Value**

Returns the estimated matrix B with attribute "df" (degrees of freedom), which gives the df for each row of B.

**Note**

Structure constraints (`struc`) should be specified with a  $p \times m$  matrix of logicals (TRUE/FALSE), such that FALSE elements indicate a weight should be constrained to be zero. Default uses unstructured weights, i.e., a  $p \times m$  matrix of all TRUE values.

Inputs `z`, `df`, `degree`, and `intercept` are only applicable when using one of the 12 constraints that involves a spline basis, i.e., "smooth", "smonon", "smoper", "smpeno", "ortsmo", "orsmpe", "monsmo", "mosmno", "unismo", "unsmno", "unsmpe", "unsmpn".

Input `mode.range` is only applicable when using one of the 8 constraints that enforces unimodality: "unimod", "uninon", "uniper", "unpeno", "unismo", "unsmno", "unsmpe", "unsmpn". Mode search ranges (`mode.range`) should be specified with a  $2 \times p$  matrix of integers such that

$$1 \leq \text{mode.range}[1, j] \leq \text{mode.range}[2, j] \leq m \text{ for all } j = 1:p.$$

Default is `mode.range = matrix(c(1, m), 2, p)`.

**Author(s)**

Nathaniel E. Helwig <helwig@umn.edu>

**References**

- Goldfarb, D., & Idnani, A. (1983). A numerically stable dual method for solving strictly convex quadratic programs. *Mathematical Programming*, 27, 1-33. doi:10.1007/BF02591962
- Helwig, N. E. (in prep). Constrained multivariate least squares in R.
- Ten Berge, J. M. F. (1993). *Least Squares Optimization in Multivariate Analysis*. Volume 25 of M & T Series. DSWO Press, Leiden University. ISBN: 9789066950832
- Turlach, B. A., & Weingessel, A. (2019). quadprog: Functions to solve Quadratic Programming Problems. R package version 1.5-8. <https://CRAN.R-project.org/package=quadprog>

**See Also**

- [const](#) prints/returns the constraint options.
- [cv.cmls](#) performs k-fold cross-validation to tune the constraint options.
- [mlsei](#) and [mlsun](#) are used to implement several of the constraints.

**Examples**

```
#####*##### GENERATE DATA #####*#####

# make X
set.seed(2)
n <- 50
m <- 20
p <- 2
Xmat <- matrix(rnorm(n*p), nrow = n, ncol = p)

# make B (which satisfies all constraints except monotonicity)
x <- seq(0, 1, length.out = m)
Bmat <- rbind(sin(2*pi*x), sin(2*pi*x+pi)) / sqrt(4.75)
struc <- rbind(rep(c(TRUE, FALSE), each = m / 2),
               rep(c(FALSE, TRUE), each = m / 2))
Bmat <- Bmat * struc

# make noisy data
set.seed(1)
Ymat <- Xmat %*% Bmat + rnorm(n*m, sd = 0.25)

#####*##### UNCONSTRAINED #####*#####

# unconstrained
Bhat <- cmls(X = Xmat, Y = Ymat, const = "uncons")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")
```

```

# unconstrained and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "uncons", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

#####*##### NON-NEGATIVITY #####*#####

# non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "nonneg")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "nonneg", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

#####*##### PERIODICITY #####*#####

# periodic
Bhat <- cmls(X = Xmat, Y = Ymat, const = "period")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# periodic and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "period", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# periodic and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "pernon")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# periodic and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "pernon", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

#####*##### SMOOTHNESS #####*#####

# smooth
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smooth")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# smooth and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smooth", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

```

```

# smooth and periodic
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smoper")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# smooth and periodic and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smoper", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# smooth and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smonon")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# smooth and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smonon", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# smooth and periodic and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smpeno")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# smooth and periodic and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "smpeno", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

#####**##### ORTHOGONALITY #####**#####

# orthogonal
Bhat <- cmls(X = Xmat, Y = Ymat, const = "orthog")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# orthogonal and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "orthog", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# orthogonal and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "ortnon")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# orthogonal and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "ortnon", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

```

```

# orthogonal and smooth
Bhat <- cmls(X = Xmat, Y = Ymat, const = "ortsmo")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# orthogonal and smooth and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "ortsmo", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# orthogonal and smooth and periodic
Bhat <- cmls(X = Xmat, Y = Ymat, const = "orsmpe")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# orthogonal and smooth and periodic and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "orsmpe", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

#####**##### UNIMODALITY #####**#####

# unimodal
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unimod")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unimod", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "uninon")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "uninon", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and periodic
Bhat <- cmls(X = Xmat, Y = Ymat, const = "uniper")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and periodic and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "uniper", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

```



```

# unimodal and periodic and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unpeno")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and periodic and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unpeno", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

#####**##### UNIMODALITY AND SMOOTHNESS #####**#####

# unimodal and smooth
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unismo")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and smooth and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unismo", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and smooth and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unsmno")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and smooth and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unsmno", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and smooth and periodic
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unsmpe")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and smooth and periodic and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unsmpe", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and smooth and periodic and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unsmpn")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# unimodal and smooth and periodic and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "unsmpn", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

```

```

#####**##### MONOTONICITY #####**#####

# make B
x <- 1:m
Bmat <- rbind(1 / (1 + exp(-(x - quantile(x, 0.5))))),
              1 / (1 + exp(-(x - quantile(x, 0.8))))))
struc <- rbind(rep(c(FALSE, TRUE), c(1 * m, 3 * m) / 4),
               rep(c(FALSE, TRUE), c(m, m) / 2))
Bmat <- Bmat * struc

# make noisy data
set.seed(1)
Ymat <- Xmat %*% Bmat + rnorm(m*n, sd = 0.25)

# monotonic increasing
Bhat <- cmls(X = Xmat, Y = Ymat, const = "moninc")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# monotonic increasing and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "moninc", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# monotonic increasing and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "monnon")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# monotonic increasing and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "monnon", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# monotonic increasing and smooth
Bhat <- cmls(X = Xmat, Y = Ymat, const = "monsmo")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# monotonic increasing and smooth and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "monsmo", struc = struc)
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# monotonic increasing and smooth and non-negative
Bhat <- cmls(X = Xmat, Y = Ymat, const = "mosmno")
mean((Bhat - Bmat)^2)
attr(Bhat, "df")

# monotonic increasing and smooth and non-negative and structured
Bhat <- cmls(X = Xmat, Y = Ymat, const = "mosmno", struc = struc)

```

```
mean((Bhat - Bmat)^2)
attr("Bhat", "df")
```

---

const

*Print or Return Constraint Options for cmls*

---

## Description

Prints or returns six letter constraint codes for [cmls](#), along with corresponding descriptions.

## Usage

```
const(x, print = TRUE)
```

## Arguments

x	Vector of six letter constraint codes. If missing, prints/returns all 24 options.
print	Should constraint information be printed ( <code>print = TRUE</code> ) or returned as a data frame ( <code>print = FALSE</code> ).

## Value

Prints (or returns) constraint codes and descriptions.

## Author(s)

Nathaniel E. Helwig <helwig@umn.edu>

## References

Helwig, N. E. (in prep). Constrained multivariate least squares in R.

## See Also

Constraints are used in the [cmls](#) function.

## Examples

```
# print some constraints
const(c("uncons", "smpeno"))

# return some constraints
const(c("uncons", "smpeno"), print = FALSE)

# print all constraints
const()

# return all constraints
const(print = FALSE)
```

cv.cmls

*Cross-Validation for cmls***Description**

Does k-fold or generalized cross-validation to tune the constraint options for `cmls`. Tunes the model with respect to any combination of the arguments `const`, `df`, `degree`, and/or `intercept`.

**Usage**

```
cv.cmls(X, Y, nfolds = 2, foldid = NULL, parameters = NULL,
        const = "uncons", df = 10, degree = 3, intercept = TRUE,
        mse = TRUE, parallel = FALSE, cl = NULL, verbose = TRUE, ...)
```

**Arguments**

<code>X</code>	Matrix of dimension $n \times p$ .
<code>Y</code>	Matrix of dimension $n \times m$ .
<code>nfolds</code>	Number of folds for k-fold cross-validation. Ignored if <code>foldid</code> argument is provided. Set <code>nfolds=1</code> for generalized cross-validation (GCV).
<code>foldid</code>	Factor or integer vector of length $n$ giving the fold identification for each observation.
<code>parameters</code>	Parameters for tuning. Data frame with columns <code>const</code> , <code>df</code> , <code>degree</code> , and <code>intercept</code> . See Details.
<code>const</code>	Parameters for tuning. Character vector specifying constraints for tuning. See Details.
<code>df</code>	Parameters for tuning. Integer vector specifying degrees of freedom for tuning. See Details.
<code>degree</code>	Parameters for tuning. Integer vector specifying polynomial degrees for tuning. See Details.
<code>intercept</code>	Parameters for tuning. Logical vector specifying intercepts for tuning. See Details.
<code>mse</code>	If TRUE (default), the mean squared error is used as the CV loss function. Otherwise the mean absolute error is used.
<code>parallel</code>	Logical indicating if <code>parSapply</code> should be used. See Examples.
<code>cl</code>	Cluster created by <code>makeCluster</code> . Only used when <code>parallel = TRUE</code> . Recommended usage: <code>cl = makeCluster(detectCores())</code>
<code>verbose</code>	If TRUE, tuning progress is printed via <code>txtProgressBar</code> . Ignored if <code>parallel = TRUE</code> .
<code>...</code>	Additional arguments to the <code>cmls</code> function, e.g., <code>z</code> , <code>struc</code> , <code>backfit</code> , etc.

## Details

The parameters for tuning can be supplied via one of two options:

(A) Using the `parameters` argument. In this case, the argument `parameters` must be a data frame with columns `const`, `df`, `degree`, and `intercept`, where each row gives a combination of parameters for the CV tuning.

(B) Using the `const`, `df`, `degree`, and `intercept` arguments. In this case, the `expand.grid` function is used to create the `parameters` data frame, which contains all combinations of the arguments `const`, `df`, `degree`, and `intercept`. Duplicates are removed before the CV tuning.

## Value

`best.parameters`  
Best combination of parameters, i.e., the combination that minimizes the `cvloss`.

`top5.parameters`  
Top five combinations of parameters, i.e., the combinations that give the five smallest values of the `cvloss`.

`full.parameters`  
Full set of parameters. Data frame with `cvloss` (GCV, MSE, or MAE) for each combination of parameters.

## Author(s)

Nathaniel E. Helwig <helwig@umn.edu>

## References

Helwig, N. E. (in prep). Constrained multivariate least squares in R.

## See Also

See the `cmls` and `const` functions for further details on the available constraint options.

## Examples

```
# make X
set.seed(1)
n <- 50
m <- 20
p <- 2
Xmat <- matrix(rnorm(n*p), nrow = n, ncol = p)

# make B (which satisfies all constraints except monotonicity)
x <- seq(0, 1, length.out = m)
Bmat <- rbind(sin(2*pi*x), sin(2*pi*x+pi)) / sqrt(4.75)
struc <- rbind(rep(c(TRUE, FALSE), each = m / 2),
               rep(c(FALSE, TRUE), each = m / 2))
Bmat <- Bmat * struc
```

```

# make noisy data
Ymat <- Xmat %*% Bmat + rnorm(n*m, sd = 0.5)

# 5-fold CV: tune df (5,...,15) for const = "smooth"
kcv <- cv.cmls(X = Xmat, Y = Ymat, nfolds = 5,
              const = "smooth", df = 5:15)
kcv$best.parameters
kcv$top5.parameters
plot(kcv$full.parameters$df, kcv$full.parameters$cvloss, t = "b")

## Not run:

# sample foldid for 5-fold CV
set.seed(2)
foldid <- sample(rep(1:5, length.out = n))

# 5-fold CV: tune df (5,...,15) w/ all 20 relevant constraints (no struc)
#           using sequential computation (default)
myconst <- as.character(const(print = FALSE)$label[-c(13:16)])
system.time({
  kcv <- cv.cmls(X = Xmat, Y = Ymat, foldid = foldid,
                const = myconst, df = 5:15)
})
kcv$best.parameters
kcv$top5.parameters

# 5-fold CV: tune df (5,...,15) w/ all 20 relevant constraints (no struc)
#           using parallel package for parallel computations
myconst <- as.character(const(print = FALSE)$label[-c(13:16)])
system.time({
  cl <- makeCluster(2L) # using 2 cores
  kcv <- cv.cmls(X = Xmat, Y = Ymat, foldid = foldid,
                const = myconst, df = 5:15,
                parallel = TRUE, cl = cl)
  stopCluster(cl)
})
kcv$best.parameters
kcv$top5.parameters

# 5-fold CV: tune df (5,...,15) w/ all 20 relevant constraints (w/ struc)
#           using sequential computation (default)
myconst <- as.character(const(print = FALSE)$label[-c(13:16)])
system.time({
  kcv <- cv.cmls(X = Xmat, Y = Ymat, foldid = foldid,
                const = myconst, df = 5:15, struc = struc)
})
kcv$best.parameters
kcv$top5.parameters

```

```

# 5-fold CV: tune df (5,...,15) w/ all 20 relevant constraints (w/ struc)
#           using parallel package for parallel computations
myconst <- as.character(const(print = FALSE)$label[-c(13:16)])
system.time({
  cl <- makeCluster(2L) # using 2 cores
  kcv <- cv.cmls(X = Xmat, Y = Ymat, foldid = foldid,
               const = myconst, df = 5:15, struc = struc,
               parallel = TRUE, cl = cl)
  stopCluster(cl)
})
kcv$best.parameters
kcv$top5.parameters

## End(Not run)

```

---

IsplineBasis

*I-Spline Basis for Monotonic Polynomial Splines*


---

## Description

Generate the I-spline basis matrix for a monotonic polynomial spline.

## Usage

```
IsplineBasis(x, df = NULL, knots = NULL, degree = 3, intercept = FALSE,
             Boundary.knots = range(x))
```

## Arguments

x	the predictor variable. Missing values are <b>not</b> allowed.
df	degrees of freedom; if specified the number of knots is defined as $df - \text{degree} - \text{ifelse}(\text{intercept}, 1, 0)$ ; the knots are placed at the quantiles of x
knots	the internal breakpoints that define the spline (typically the quantiles of x)
degree	degree of the M-spline basis—default is 3 for cubic splines
intercept	if TRUE, the basis includes an intercept column
Boundary.knots	boundary points for M-spline basis; defaults to min and max of x

## Details

Syntax is adapted from the `bs` function in the **splines** package (R Core Team, 2021).

Used for implementing monotonic smoothness constraints in the `cmls` function.

**Value**

A matrix of dimension  $c(\text{length}(x), \text{df})$  where either  $\text{df}$  was supplied or  $\text{df} = \text{length}(\text{knots}) + \text{degree} + \text{ifelse}(\text{intercept}, 1, 0)$

**Note**

I-spline basis functions are created by integrating M-spline basis functions.

**Author(s)**

Nathaniel E. Helwig <helwig@umn.edu>

**References**

R Core Team (2023). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>

Ramsay, J. O. (1988). Monotone regression splines in action. *Statistical Science*, 3, 425-441. [doi:10.1214/ss/1177012761](https://doi.org/10.1214/ss/1177012761)

**See Also**

[MsplineBasis](#)

**Examples**

```
x <- seq(0, 1, length.out = 101)
I <- IsplineBasis(x, df = 8, intercept = TRUE)
plot(x, I[,1], ylim = c(0, 1), t = "l")
for(j in 2:8) lines(x, I[,j], col = j)
```

---

mlsei

---

*Multivariate Least Squares with Equality/Inequality Constraints*


---

**Description**

Finds the  $q \times p$  matrix  $B$  that minimizes the multivariate least squares problem

$$\text{sum}((Y - X \%*\% t(Z \%*\% B))^2)$$

subject to  $t(A) \%*\% B[, j] \geq b$  for all  $j = 1:p$ . Unique basis functions and constraints are allowed for each column of  $B$ .

**Usage**

```
mlsei(X, Y, Z, A, b, meq,
      backfit = FALSE, maxit = 1000,
      eps = 1e-10, del = 1e-6,
      XtX = NULL, ZtZ = NULL,
      simplify = TRUE, catchError = FALSE)
```



**Arguments**

X	Matrix of dimension $n \times p$ .
Y	Matrix of dimension $n \times m$ .
Z	Matrix of dimension $m \times q$ . Can also input a list (see Note). If missing, then $Z = \text{diag}(m)$ so that $q = m$ .
A	Constraint matrix of dimension $q \times r$ . Can also input a list (see Note). If missing, no constraints are imposed.
b	Constraint vector of dimension $r \times 1$ . Can also input a list (see Note). If missing, then $b = \text{rep}(0, r)$ .
meq	The first meq columns of A are equality constraints, and the remaining $r - \text{meq}$ are inequality constraints. Can also input a vector (see Note). If missing, then $\text{meq} = 0$ .
backfit	Estimate B via back-fitting (TRUE) or vectorization (FALSE). See Details.
maxit	Maximum number of iterations for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
eps	Convergence tolerance for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
del	Stability tolerance for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
XtX	Crossproduct matrix: $XtX = \text{crossprod}(X)$ .
ZtZ	Crossproduct matrix: $ZtZ = \text{crossprod}(Z)$ .
simplify	If Z is a list, should B be returned as a matrix (if possible)? See Note.
catchError	If <code>catchError = FALSE</code> , an error induced by <code>solve.QP</code> will be returned. Otherwise <code>tryCatch</code> will be used in attempt to catch the error.

**Details**

If `backfit = FALSE` (default), a closed-form solution is used to estimate B whenever possible. Otherwise a back-fitting algorithm is used, where the columns of B are updated sequentially until convergence. The backfitting algorithm is determined to have converged when

$$\text{mean}((B.\text{new} - B.\text{old})^2) < \text{eps} * (\text{mean}(B.\text{old}^2) + \text{del}),$$

where B.old and B.new denote the parameter estimates at iterations  $t$  and  $t + 1$  of the backfitting algorithm.

**Value**

If Z is a list with  $q_j = q$  for all  $j = 1, \dots, p$ , then...

B	is returned as a $q \times p$ matrix when <code>simplify = TRUE</code>
B	is returned as a list of length $p$ when <code>simplify = FALSE</code>

If Z is a list with  $q_j \neq q$  for some  $j$ , then B is returned as a list of length  $p$ .

Otherwise B is returned as a  $q \times p$  matrix.

**Note**

The Z input can also be a list of length  $p$  where  $Z[[j]]$  contains a  $m \times q_j$  matrix. If  $q_j = q$  for all  $j = 1, \dots, p$  and `simplify = TRUE`, the output B will be a matrix. Otherwise B will be a list of length  $p$  where  $B[[j]]$  contains a  $q_j \times 1$  vector.

The A and b inputs can also be lists of length  $p$  where  $t(A[[j]]) \%*\% B[,j] \geq b[[j]]$  for all  $j = 1, \dots, p$ . If A and b are lists of length  $p$ , the meq input should be a vector of length  $p$  indicating the number of equality constraints for each element of A.

**Author(s)**

Nathaniel E. Helwig <helwig@umn.edu>

**References**

Goldfarb, D., & Idnani, A. (1983). A numerically stable dual method for solving strictly convex quadratic programs. *Mathematical Programming*, 27, 1-33. doi:10.1007/BF02591962

Helwig, N. E. (in prep). Constrained multivariate least squares in R.

Ten Berge, J. M. F. (1993). *Least Squares Optimization in Multivariate Analysis*. Volume 25 of M & T Series. DSWO Press, Leiden University. ISBN: 9789066950832

Turlach, B. A., & Weingessel, A. (2019). quadprog: Functions to solve Quadratic Programming Problems. R package version 1.5-8. <https://CRAN.R-project.org/package=quadprog>

**See Also**

[cmls](#) calls this function for several of the constraints.

**Examples**

```
#####**##### GENERATE DATA #####**#####

# make X
set.seed(2)
n <- 50
m <- 20
p <- 2
Xmat <- matrix(rnorm(n*p), nrow = n, ncol = p)

# make B (which satisfies all constraints except monotonicity)
x <- seq(0, 1, length.out = m)
Bmat <- rbind(sin(2*pi*x), sin(2*pi*x+pi)) / sqrt(4.75)
struc <- rbind(rep(c(TRUE, FALSE), each = m / 2),
               rep(c(FALSE, TRUE), each = m / 2))
Bmat <- Bmat * struc

# make noisy data
set.seed(1)
Ymat <- Xmat \%*\% Bmat + rnorm(n*m, sd = 0.25)
```

```

#####**##### UNCONSTRAINED #####**#####

# unconstrained
Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "uncons")
Bhat.mlsei <- t(mlsei(X = Xmat, Y = Ymat))
mean((Bhat.cmls - Bhat.mlsei)^2)

# unconstrained and structured (note: cmls is more efficient)
Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "uncons", struc = struc)
Amat <- vector("list", p)
meq <- rep(0, p)
for(j in 1:p){
  meq[j] <- sum(!struc[j,])
  if(meq[j] > 0){
    A <- matrix(0, nrow = m, ncol = meq[j])
    A[!struc[j,],] <- diag(meq[j])
    Amat[[j]] <- A
  } else {
    Amat[[j]] <- matrix(0, nrow = m, ncol = 1)
  }
}
Bhat.mlsei <- t(mlsei(X = Xmat, Y = Ymat, A = Amat, meq = meq))
mean((Bhat.cmls - Bhat.mlsei)^2)

#####**##### NON-NEGATIVITY #####**#####

# non-negative
Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "nonneg")
Bhat.mlsei <- t(mlsei(X = Xmat, Y = Ymat, A = diag(m)))
mean((Bhat.cmls - Bhat.mlsei)^2)

# non-negative and structured (note: cmls is more efficient)
Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "nonneg", struc = struc)
eye <- diag(m)
meq <- rep(0, p)
for(j in 1:p){
  meq[j] <- sum(!struc[j,])
  Amat[[j]] <- eye[,sort(struc[j,], index.return = TRUE)$ix]
}
Bhat.mlsei <- t(mlsei(X = Xmat, Y = Ymat, A = Amat, meq = meq))
mean((Bhat.cmls - Bhat.mlsei)^2)

# see internals of cmls.R for further examples

```

**Description**

Finds the  $q \times p$  matrix  $B$  that minimizes the multivariate least squares problem

$$\text{sum}((Y - X \%*\% t(Z \%*\% B) )^2)$$

subject to  $Z \%*\% B[, j]$  is unimodal and  $t(A) \%*\% B[, j] \geq b$  for all  $j = 1:p$ . Unique basis functions and constraints are allowed for each column of  $B$ .

**Usage**

```
mlsun(X, Y, Z, A, b, meq,
      mode.range = NULL, maxit = 1000,
      eps = 1e-10, del = 1e-6,
      XtX = NULL, ZtZ = NULL,
      simplify = TRUE, catchError = FALSE)
```

**Arguments**

<code>X</code>	Matrix of dimension $n \times p$ .
<code>Y</code>	Matrix of dimension $n \times m$ .
<code>Z</code>	Matrix of dimension $m \times q$ . Can also input a list (see Note). If missing, then $Z = \text{diag}(m)$ so that $q = m$ .
<code>A</code>	Constraint matrix of dimension $q \times r$ . Can also input a list (see Note). If missing, no equality/inequality (E/I) constraints are imposed.
<code>b</code>	Constraint vector of dimension $r \times 1$ . Can also input a list (see Note). If missing, then $b = \text{rep}(0, r)$ .
<code>meq</code>	The first <code>meq</code> columns of $A$ are equality constraints, and the remaining $r - \text{meq}$ are inequality constraints. Can also input a vector (see Note). If missing, then $\text{meq} = 0$ .
<code>mode.range</code>	Mode search ranges, which should be a $2 \times p$ matrix of integers such that $1 \leq \text{mode.range}[1, j] \leq \text{mode.range}[2, j] \leq m$ for all $j = 1:p$ . Default is $\text{mode.range} = \text{matrix}(c(1, m), 2, p)$ .
<code>maxit</code>	Maximum number of iterations for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
<code>eps</code>	Convergence tolerance for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
<code>del</code>	Stability tolerance for back-fitting algorithm. Ignored if <code>backfit = FALSE</code> .
<code>XtX</code>	Crossproduct matrix: $XtX = \text{crossprod}(X)$ .
<code>ZtZ</code>	Crossproduct matrix: $ZtZ = \text{crossprod}(Z)$ .
<code>simplify</code>	If $Z$ is a list, should $B$ be returned as a matrix (if possible)? See Note.
<code>catchError</code>	If <code>catchError = FALSE</code> , an error induced by <a href="#">solve.QP</a> will be returned. Otherwise <a href="#">tryCatch</a> will be used in attempt to catch the error.

## Details

A back-fitting algorithm is used to estimate B, where the columns of B are updated sequentially until convergence (outer loop). For each column of B, (the inner loop of) the algorithm searches for the  $j$ -th mode across the search range specified by the  $j$ -th column of `mode.range`. The backfitting algorithm is determined to have converged when

$$\text{mean}((\text{B.new} - \text{B.old})^2) < \text{eps} * (\text{mean}(\text{B.old}^2) + \text{del}),$$

where `B.old` and `B.new` denote the parameter estimates at outer iterations  $t$  and  $t + 1$  of the back-fitting algorithm.

## Value

If Z is a list with  $q_j = q$  for all  $j = 1, \dots, p$ , then...

B is returned as a  $q \times p$  matrix when `simplify = TRUE`

B is returned as a list of length  $p$  when `simplify = FALSE`

If Z is a list with  $q_j \neq q$  for some  $j$ , then B is returned as a list of length  $p$ .

Otherwise B is returned as a  $q \times p$  matrix.

## Note

The Z input can also be a list of length  $p$  where `Z[[j]]` contains a  $m \times q_j$  matrix. If  $q_j = q$  for all  $j = 1, \dots, p$  and `simplify = TRUE`, the output B will be a matrix. Otherwise B will be a list of length  $p$  where `B[[j]]` contains a  $q_j \times 1$  vector.

The A and b inputs can also be lists of length  $p$  where `t(A[[j]]) %>% B[, j] >= b[[j]]` for all  $j = 1, \dots, p$ . If A and b are lists of length  $p$ , the `meq` input should be a vector of length  $p$  indicating the number of equality constraints for each element of A.

## Author(s)

Nathaniel E. Helwig <helwig@umn.edu>

## References

Goldfarb, D., & Idnani, A. (1983). A numerically stable dual method for solving strictly convex quadratic programs. *Mathematical Programming*, 27, 1-33. doi:10.1007/BF02591962

Helwig, N. E. (in prep). Constrained multivariate least squares in R.

Ten Berge, J. M. F. (1993). *Least Squares Optimization in Multivariate Analysis*. Volume 25 of M & T Series. DSWO Press, Leiden University. ISBN: 9789066950832

Turlach, B. A., & Weingessel, A. (2019). *quadprog: Functions to solve Quadratic Programming Problems*. R package version 1.5-8. <https://CRAN.R-project.org/package=quadprog>

## See Also

`mls` calls this function for the unimodality constraints.

## Examples

```
#####**##### GENERATE DATA #####**#####

# make X
set.seed(2)
n <- 50
m <- 20
p <- 2
Xmat <- matrix(rnorm(n*p), nrow = n, ncol = p)

# make B (which satisfies all constraints except monotonicity)
x <- seq(0, 1, length.out = m)
Bmat <- rbind(sin(2*pi*x), sin(2*pi*x+pi)) / sqrt(4.75)
struc <- rbind(rep(c(TRUE, FALSE), each = m / 2),
               rep(c(FALSE, TRUE), each = m / 2))
Bmat <- Bmat * struc

# make noisy data
set.seed(1)
Ymat <- Xmat %>% Bmat + rnorm(n*m, sd = 0.25)

#####**##### UNIMODALITY #####**#####

# unimodal
Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "unimod")
Bhat.mlsun <- t(mlsun(X = Xmat, Y = Ymat))
mean((Bhat.cmls - Bhat.mlsun)^2)

# unimodal and structured
Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "unimod", struc = struc)
Amat <- vector("list", p)
meq <- rep(0, p)
for(j in 1:p){
  meq[j] <- sum(!struc[,j])
  if(meq[j] > 0){
    A <- matrix(0, nrow = m, ncol = meq[j])
    A[!struc[j,],] <- diag(meq[j])
    Amat[[j]] <- A
  } else {
    Amat[[j]] <- matrix(0, nrow = m, ncol = 1)
  }
}
Bhat.mlsun <- t(mlsun(X = Xmat, Y = Ymat, A = Amat, meq = meq))
mean((Bhat.cmls - Bhat.mlsun)^2)

# unimodal and non-negative
Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "uninon")
Bhat.mlsun <- t(mlsun(X = Xmat, Y = Ymat, A = diag(m)))
mean((Bhat.cmls - Bhat.mlsun)^2)

# unimodal and non-negative and structured
```

```

Bhat.cmls <- cmls(X = Xmat, Y = Ymat, const = "uninon", struc = struc)
eye <- diag(m)
meq <- rep(0, p)
for(j in 1:p){
  meq[j] <- sum(!struc[j,])
  Amat[[j]] <- eye[,sort(struc[j,], index.return = TRUE)$ix]
}
Bhat.mlsun <- t(mlsun(X = Xmat, Y = Ymat, A = Amat, meq = meq))
mean((Bhat.cmls - Bhat.mlsun)^2)

# see internals of cmls.R for further examples

```

---

MsplineBasis

*M-Spline Basis for Polynomial Splines*


---

### Description

Generate the M-spline basis matrix for a polynomial spline.

### Usage

```

MsplineBasis(x, df = NULL, knots = NULL, degree = 3, intercept = FALSE,
             Boundary.knots = range(x), periodic = FALSE)

```

### Arguments

<code>x</code>	the predictor variable. Missing values are <b>not</b> allowed.
<code>df</code>	degrees of freedom; if specified the number of knots is defined as <code>df - degree - ifelse(intercept, 1, 0)</code> ; the knots are placed at the quantiles of <code>x</code>
<code>knots</code>	the internal breakpoints that define the spline (typically the quantiles of <code>x</code> )
<code>degree</code>	degree of the piecewise polynomial—default is 3 for cubic splines
<code>intercept</code>	if TRUE, the basis includes an intercept column
<code>Boundary.knots</code>	boundary points for M-spline basis; defaults to min and max of <code>x</code>
<code>periodic</code>	if TRUE, the M-spline basis is constrained to be periodic

### Details

Syntax is adapted from the `bs` function in the **splines** package (R Core Team, 2021).

Used for implementing various types of smoothness constraints in the `cmls` function.

### Value

A matrix of dimension `c(length(x), df)` where either `df` was supplied or `df = length(knots) + degree + ifelse(intercept, 1, 0)`

**Author(s)**

Nathaniel E. Helwig <helwig@umn.edu>

**References**

R Core Team (2023). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>

Ramsay, J. O. (1988). Monotone regression splines in action. *Statistical Science*, 3, 425-441. [doi:10.1214/ss/1177012761](https://doi.org/10.1214/ss/1177012761)

**See Also**

[IsplineBasis](#)

**Examples**

```
x <- seq(0, 1, length.out = 101)
M <- MsplineBasis(x, df = 8, intercept = TRUE)
M <- scale(M, center = FALSE)
plot(x, M[,1], ylim = range(M), t = "l")
for(j in 2:8) lines(x, M[,j], col = j)
```



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