Package ‘scam’

October 14, 2022

Version 1.2-13
Author  Natalya Pya <nat.pya@gmail.com>
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Title  Shape Constrained Additive Models
Date 2022-09-09
Description  Routines for generalized additive modelling under shape constraints on the component functions of the linear predictor (Pya and Wood, 2015) <doi:10.1007/s11222-013-9448-7>. Models can contain multiple shape constrained (univariate and/or bivariate) and unconstrained terms. The routines of gam() in package ‘mgcv’ are used for setting up the model matrix, printing and plotting the results. Penalized likelihood maximization based on Newton-Raphson method is used to fit a model with multiple smoothing parameter selection by GCV or UBRE/AIC.
Depends  R (>= 2.15.0), mgcv (>= 1.8-2)
Imports  methods, stats, graphics, Matrix, splines
Suggests  nlme
License  GPL (>= 2)
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Description

scam provides functions for generalized additive modelling under shape constraints on the component functions of the linear predictor of the GAM. Models can contain multiple shape constrained and unconstrained terms as well as bivariate smooths with double or single monotonicity. Univariate smooths under eight possible shape constraints such as monotonically increasing/decreasing, convex/concave, increasing/decreasing and convex, increasing/decreasing and concave, are available as model terms.

The model set up is the same as in gam() in package mgcv with the added shape constrained smooths, so the unconstrained smooths can be of more than one variable, and other user defined smooths can be included. Penalized log likelihood maximization is used to fit the model together with the automatic smoothness selection.

Details

Package: scam
Version: 1.2-13
Author: Natalya Pya <nat.pya@gmail.com>
Maintainer: Natalya Pya <nat.pya@gmail.com>
Title: Shape Constrained Additive Models
Date: 2022-09-09
Description: Routines for generalized additive modelling under shape constraints on the component functions of the linear predictor
Depends: R (>= 2.15.0), mgcv (>= 1.8-2)
Imports: methods, stats, graphics, Matrix, splines
Suggests: nlme
License: GPL (>= 2)
LazyLoad: yes

The package provides generalized additive modelling under shape constraints on the component functions of the linear predictor. scam and plot.scam functions are based on the functions of the unconstrained GAM gam() and plot.gam() in package mgcv and similar in use. summary.scam allows to extract the results of the model fitting in the same way as in summary.gam. A Bayesian approach is used to obtain a covariance matrix of the model coefficients and credible intervals for each smooth.

Author(s)

Natalya Pya <nat.pya@gmail.com> based partly on mgcv by Simon Wood
Maintainer: Natalya Pya <nat.pya@gmail.com>
References


The package was part supported by EPSRC grants EP/I000917/1, EP/K005251/1 and the Science Committee of the Ministry of Science and Education of the Republic of Kazakhstan grant #2532/GF3.

Examples

## see examples for scam

### anova.scam

Approximate hypothesis tests related to SCAM fits

Description

Performs hypothesis tests relating to one or more fitted scam objects. The function is a clone of anova.gam of the mgcv package.

The documentation below is similar to that of object anova.gam.

Usage

## S3 method for class 'scam'
anova(object, ..., dispersion = NULL, test = NULL, freq = FALSE,p.type=0)

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

Arguments

object,...

fitted model objects of class scam as produced by scam().

x

an anova.scam object produced by a single model call to anova.scam().

dispersion

a value for the dispersion parameter: not normally used.

test

what sort of test to perform for a multi-model call. One of "Chisq", "F" or "Cp".
anova.scam

freq whether to use frequentist or Bayesian approximations for parametric term p-values. See summary.gam for details.
p.type selects exact test statistic to use for single smooth term p-values. See summary.scam for details.
digits number of digits to use when printing output.

Details

see anova.gam for details.

Value

In the multi-model case anova.scam produces output identical to anova.glm, which it in fact uses.
In the single model case an object of class anova.scam is produced, which is in fact an object returned from summary.scam.
print.anova.scam simply produces tabulated output.

WARNING

If models 'a' and 'b' differ only in terms with no un-penalized components then p values from anova(a,b) are unreliable, and usually much too low.
Default P-values will usually be wrong for parametric terms penalized using 'paraPen': use freq=TRUE to obtain better p-values when the penalties are full rank and represent conventional random effects.
For a single model, interpretation is similar to drop1, not anova.lm.

Author(s)

Simon N. Wood <simon.wood@r-project.org>

References


See Also

scam, predict.scam, scam.check, summary.scam, anova.gam
Examples

```r
library(scam)
set.seed(0)
fac <- rep(1:4,20)
x1 <- runif(80)*5
x2 <- runif(80,-1,2)
x3 <- runif(80, 0, 1)
y <- fac+log(x1)/5
y <- y + exp(-1.3*x2) + rnorm(80)*0.1
fac <- factor(fac)
b <- scam(y ~ fac+s(x1,bs="mpi") +s(x2,bs="mpd") +s(x3))

b1 <- scam(y ~ fac+s(x1,bs="mpi") +s(x2,bs="mpd"))
anova(b,b1,test="F")

## b2 <- scam(y ~ fac +s(x1)+s(x2)+te(x1,x2))
```

---

`bfgs_gcv.ubre` *Multiple Smoothing Parameter Estimation by GCV/UBRE*

**Description**

Function to efficiently estimate smoothing parameters of SCAM by GCV/UBRE score optimization. The procedure is outer to the model fitting by the Newton-Raphson method. The function uses the BFGS method where the Hessian matrix is updated iteratively at each step. Backtracking is included to satisfy the sufficient decrease condition.

The function is not normally called directly, but rather service routines for `scam`.

**Usage**

```r
bfgs_gcv.ubre(fn=gcv.ubre_grad, rho, ini.fd=TRUE, G, gamma=1, env, n.pen=length(rho), typx=rep(1,n.pen), typf=1, control)
```

**Arguments**

- `fn` GCV/UBRE Function which returns the GCV/UBRE value and its derivative wrt log smoothing parameter.
- `rho` log of the initial values of the smoothing parameters.
- `ini.fd` If TRUE, a finite difference to the Hessian is used to find the initial inverse Hessian, otherwise the initial inverse Hessian is a diagonal matrix ‘100*I’.
- `G` A list of items needed to fit a SCAM.
- `gamma` An ad hoc parameter of the GCV/UBRE score.
env  Get the enviroment for the model coefficients, their derivatives and the smoothing parameter.
n.pen  Smoothing parameter dimension.
typx  A vector whose component is a positive scalar specifying the typical magnitude of sp.
typf  A positive scalar estimating the magnitude of the gcv near the minimum.
control  Control option list as returned by `scam.control`.

Value
A list is returned with the following items:

gcv.ubre  The optimal value of GCV/UBRE.
rho  The best value of the log smoothing parameter.
dgcv.ubre  The gradient of the GCV/UBRE.
iterations  The number of iterations taken until convergence.
conv.bfgs  Convergence information indicating why the BFGS terminated (given below).
termcode  An integer code indicating why the optimization process terminated.
1: relative gradient is close to zero, current iterate probably is a solution.
2: scaled distance between last two steps less than ‘steptol’, current iterate probably is a local minimizer, but it’s possible that the algorithm is making very slow progress, or ‘steptol’ is too large.
3: last global step failed to locate a point lower than estimate. Either estimate is an approximate local minimum of the function or steptol is too small.
4: iteration limit exceeded.
5: five consecutive steps of length maxNstep have been taken, it’s possible that ‘maxstep’ is too small.

object  A list of elements returned by the fitting procedure `scam.fit` for an optimal value of the smoothing parameter.

dgcv.ubre.check  If `check.analytical=TRUE` this is the finite-difference approximation of the gradient calculated by `gcv.ubre_grad`, otherwise NULL.
check.grad  If `check.analytical=TRUE` this is the relative difference (in and finite differenced derivatives calculated by `gcv.ubre_grad`, otherwise NULL.

Author(s)
Natalya Pya <nat.pya@gmail.com>

References

See Also

scam

check.analytical  Checking the analytical gradient of the GCV/UBRE score

Description

This function calculates the finite-difference approximation of the GCV/UBRE gradient for the fitted model and compares it with the analytical gradient.

Usage

check.analytical(object, data, del=1e-6,control)

Arguments

object  A fitted scam object.
data  An original data frame or list containing the model response variable and co-

variates.
del  A positive scalar (default is 1e-6) giving an increment for finite difference ap-

proximation.
control  Control option list as returned by scam.control.

Value

A list is returned with the following items:

dgcv.ubre.fd  The finite-difference approximation of the gradient.
check.grad  The relative difference in percentage between the analytical and finite differ-

enced derivatives.

Author(s)

Natalya Pya <nat.pya@gmail.com>

See Also

scam
derivative.scam

Descripti

Function to get derivatives of the smooth model terms (currently only of the univariate smooths). Analytical derivatives for SCOP-splines, finite difference approximation is used for all others

Usage

derivative.scam(object, smooth.number = 1, deriv = 1)

Arguments

object fitted scam object
smooth.number ordered number of the smooth model term (1,2,...), ordered as in the formula, which derivative is needed to be calculated.
deriv either 1 if the 1st derivative is required, or 2 if the 2nd

Value

d values of the derivative of the smooth term.
se.d standard errors of the derivative.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

scam

Examples

c
set.seed(2)
n <- 200
x1 <- runif(n)*4-1;
f1 <- exp(4*x1)/(1+exp(4*x1)) # monotone increasing smooth
x2 <- sort(runif(n)*3-1) # decreasing smooth
f2 <- exp(-1.3*x2)
f <- f1 + f2
y <- f + rnorm(n)*0.2
## fit model, results, and plot...

b <- scam(y ~ s(x1,k=20,bs="mpi") + s(x2,k=15,bs="mpd"),family=gaussian)

d1 <- derivative.scam(b,smooth.number=1,deriv=1)

par(mfrow=c(1,2))

xx <- sort(x1,index=TRUE)
plot(xx$x,d1$d[xx$ix],type="l",xlab=expression(x[1]), ylab=expression(df[1]/dx[1]))

d2 <- derivative.scam(b,smooth.number=2,deriv=1)

xx <- sort(x2,index=TRUE)
plot(xx$x,d2$d[xx$ix],type="l",xlab=expression(x[2]), ylab=expression(df[2]/dx[2]))

---

### formula.scam

**SCAM formula**

#### Description

Description of `scam` formula (see `gam` of the `mgcv` package for Details), and how to extract it from a fitted `scam` object.

The function is a clone of `formula.gam` of the `mgcv` package.

#### Usage

```r
## S3 method for class 'scam'
formula(x,...)
```

#### Arguments

- `x`  
  fitted model objects of class `scam` as produced by `scam()`.  
- `...`  
  un-used in this case

#### Details

see `formula.gam` for details.

#### Value

Returns the model formula, `x$formula`. Provided so that `anova` methods print an appropriate description of the model.

#### See Also

- `scam`
The GCV/UBRE score value and its gradient

Description

For the estimation of the SCAM smoothing parameters the GCV/UBRE score is optimized outer to the Newton-Raphson procedure of the model fitting. This function returns the value of the GCV/UBRE score and calculates its first derivative with respect to the log smoothing parameter using the method of Wood (2009).

The function is not normally called directly, but rather service routines for `bfgs_gcv.ubre`.

Usage

```r
 gcv.ubre_grad(rho, G, gamma, env, control)
```

Arguments

- `rho` log of the initial values of the smoothing parameters.
- `G` a list of items needed to fit a SCAM.
- `gamma` A constant multiplier to inflate the model degrees of freedom in the GCV or UBRE/AIC score.
- `env` Get the environment for the model coefficients, their derivatives and the smoothing parameter.
- `control` A list of fit control parameters as returned by `scam.control`.

Value

A list is returned with the following items:

- `dgcv.ubre` The value of GCV/UBRE gradient.
- `gcv.ubre` The GCV/UBRE score value.
- `scale.est` The value of the scale estimate.
- `object` The elements of the fitting procedure `monogam.fit` for a given value of the smoothing parameter.
- `dgcv.ubre.check` If `check.analytical=TRUE` this returns the finite-difference approximation of the gradient.
- `check.grad` If `check.analytical=TRUE` this returns the relative difference (in and finite differenced derivatives).

Author(s)

Natalya Pya <nat.pya@gmail.com>
References


See Also

scam, scam.fit, bfgs_gcv.ubre

linear.functional.terms

Linear functionals of a smooth in GAMs

Description

Since scam uses the model setup of gam of the mgcv package, in the same way as in gam scam allows the response variable to depend on linear functionals of smooth terms in the s with additional shape constraints.

See linear.functional.terms(mgcv).

Examples

## Not run:
###########################################
## similar to a "signal" regression
## example from mgcv() ...
###########################################
library(scam)
## decreasing smooth...
set.seed(4)
rf <- function(x=seq(-1,3,length=100)) {  
  m <- ceiling(runif(1)*5)  # number of components
  f <- x*0;
  mu <- runif(m,min(x),max(x)); sig <- (runif(m)+.5)*(max(x)-min(x))/10
  for (i in 1:m) f <- f + dnorm(x,mu[i],sig[i])
  f
}

## simulate 200 functions and store in rows of L...
L <- matrix(NA,200,100)
for (i in 1:200) L[i,] <- rf()  ## simulate the functional predictors

x <- seq(-1,3,length=100)  ## evaluation points
f2 <- function(x) {  ## the coefficient function
  return(-4*exp(4*x)/(1+exp(4*x))
}

f <- f2(x)
plot(x,f ,type="l")
y <- L%*%f + rnorm(200)*20  ## simulated response data
X <- matrix(x,200,100,byrow=TRUE)

b <- scam(y~s(X,by=L,k=20,bs="mpdBy"))
par(mfrow=c(1,2))
plot(b,shade=TRUE);lines(x,f,col=2);
## compare with gam() of mgcv package...
g <- gam(y~s(X,by=L,k=20))
plot(g,shade=TRUE);lines(x,f,col=2)

## increasing smooth....
L <- matrix(NA,200,100)
for (i in 1:200) L[i,] <- rf()  ## simulate the functional predictors
x <- seq(-1,3,length=100)  ## evaluation points
f2 <- function(x) {  ## the coefficient function
  return(4*exp(4*x)/(1+exp(4*x))
}

f <- f2(x)
plot(x,f ,type="l")
y <- L%*%f + rnorm(200)*20  ## simulated response data
X <- matrix(x,200,100,byrow=TRUE)

b <- scam(y~s(X,by=L,k=20,bs="mpiBy"))
par(mfrow=c(1,2))
plot(b,shade=TRUE);lines(x,f,col=2);
## compare with unconstrained fit...
g <- scam(y~s(X,by=L,k=20))
plot(g,shade=TRUE);lines(x,f,col=2)

## convex smooth...
## simulate 200 functions and store in rows of L...
set.seed(4)
L <- matrix(NA,200,100)
for (i in 1:200) L[i,] <- rf(x=sort(2*runif(100)-1))  ## simulate the functional predictors

x <- sort(runif(100,-1,1))  ## evaluation points
f2 <- function(x){4*x^2 }  ## the coefficient function

f <- f2(x)
plot(x,f ,type="l")
y <- L%*%f + rnorm(200)*30  ## simulated response data
X <- matrix(x,200,100,byrow=TRUE)

b <- scam(y~s(X,by=L,k=20,bs="cxBy"))
par(mfrow=c(1,2))
plot(b,shade=TRUE);lines(x,f,col=2)
plot(b, shade=TRUE); lines(x, f, col=2);

g <- scam(y~s(X,by=L,k=20))
plot(g, shade=TRUE); lines(x, f, col=2)

## End(Not run)

logLik.scam  

Log likelihood for a fitted SCAM, for AIC

Description

Function to extract the log-likelihood for a fitted scam model (fitted by penalized likelihood maximization). Used by AIC.

The function is a clone of logLik.gam of the mgcv package.

The documentation below is similar to that of object logLik.gam.

Usage

## S3 method for class 'scam'
logLik(object,...)

Arguments

object  
fitted model objects of class scam as produced by scam().

...  
unused in this case

Details

see logLik.gam for details.

Value

Standard logLik object: see logLik.

References


See Also

AIC
marginal.matrices.tescv.ps

Constructs marginal model matrices for "tescv" and "tescx" bivariate smooths in case of B-splines basis functions for both unconstrained marginal smooths

Description

This function returns the marginal model matrices and the list of penalty matrices for the tensor product bivariate smooth with the single concavity or convexity restriction along the second covariate. The marginal smooth functions of both covariates are constructed using the B-spline basis functions.

Usage

marginal.matrices.tescv.ps(x, z, xk, zk, m, q1, q2)

Arguments

x A numeric vector of the values of the first covariate at which to evaluate the B-spline marginal functions. The values in x must be between xk[m[1]+2] and xk[length(xk) - m[1] - 1].

z A numeric vector of the values of the second covariate at which to evaluate the B-spline marginal functions. The values in z must be between zk[m[2]+2] and zk[length(zk) - m[2] - 1].

xk A numeric vector of knot positions for the first covariate, x, with non-decreasing values.

zk A numeric vector of knot positions for the second covariate, z, with non-decreasing values.

m A pair of two numbers where m[i]+1 denotes the order of the basis of the i\textsuperscript{th} marginal smooth (e.g. m[i] = 2 for a cubic spline.)

q1 A number denoting the basis dimension of the first marginal smooth.

q2 A number denoting the basis dimension of the second marginal smooth.

Details

The function is not called directly, but is rather used internally by the constructor smooth.construct.tescv.smooth.spec and smooth.construct.tescx.smooth.spec.

Value

X1 Marginal model matrix for the first unconstrained marginal smooth.

X2 Marginal model matrix for the second monotonic marginal smooth.

S A list of penalty matrices for this tensor product smooth.
Author(s)
Natalya Pya <nat.pya@gmail.com>

References

See Also

marginal.matrices.tesmi1.ps

Constructs marginal model matrices for "tesmi" and "tesmd1" bivariate smooths in case of B-splines basis functions for both unconstrained marginal smooths

Description
This function returns the marginal model matrices and the list of penalty matrices for the tensor product bivariate smooth with the single monotone increasing or decreasing restriction along the first covariate. The marginal smooth functions of both covariates are constructed using the B-spline basis functions.

Usage
marginal.matrices.tesmi1.ps(x, z, xk, zk, m, q1, q2)

Arguments
x A numeric vector of the values of the first covariate at which to evaluate the B-spline marginal functions. The values in x must be between xk[m[1]+2] and xk[length(xk) - m[1] - 1].
z A numeric vector of the values of the second covariate at which to evaluate the B-spline marginal functions. The values in z must be between zk[m[2]+2] and zk[length(zk) - m[2] - 1].
xk A numeric vector of knot positions for the first covariate, x, with non-decreasing values.
zk A numeric vector of knot positions for the second covariate, z, with non-decreasing values.
m A pair of two numbers where m[i]+1 denotes the order of the basis of the i\textsuperscript{th} marginal smooth (e.g. m[i] = 2 for a cubic spline.)
q1 A number denoting the basis dimension of the first marginal smooth.
q2 A number denoting the basis dimension of the second marginal smooth.
Details

The function is not called directly, but is rather used internally by the constructor
smooth.construct.tesmi1.smooth.spec and smooth.construct.tesmd1.smooth.spec.

Value

X1 Marginal model matrix for the first monotonic marginal smooth.

X2 Marginal model matrix for the second unconstrained marginal smooth.

S A list of penalty matrices for this tensor product smooth.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also


Description

This function returns the marginal model matrices and the list of penalty matrices for the tensor product bivariate smooth with the single monotone increasing or decreasing restriction along the second covariate. The marginal smooth functions of both covariates are constructed using the B-spline basis functions.

Usage

marginal.matrices.tesmi2.ps(x, z, xk, zk, m, q1, q2)
Arguments

x A numeric vector of the values of the first covariate at which to evaluate the B-spline marginal functions. The values in x must be between xk[m[1]+2] and xk[length(xk) - m[1] - 1].

z A numeric vector of the values of the second covariate at which to evaluate the B-spline marginal functions. The values in z must be between zk[m[2]+2] and zk[length(zk) - m[2] - 1].

xk A numeric vector of knot positions for the first covariate, x, with non-decreasing values.

zk A numeric vector of knot positions for the second covariate, z, with non-decreasing values.

m A pair of two numbers where m[i]+1 denotes the order of the basis of the ith marginal smooth (e.g. m[i] = 2 for a cubic spline.)

q1 A number denoting the basis dimension of the first marginal smooth.

q2 A number denoting the basis dimension of the second marginal smooth.

Details

The function is not called directly, but is rather used internally by the constructor smooth.construct.tesmi2.smooth.spec and smooth.construct.tesmd2.smooth.spec.

Value

X1 Marginal model matrix for the first unconstrained marginal smooth.

X2 Marginal model matrix for the second monotonic marginal smooth.

S A list of penalty matrices for this tensor product smooth.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

plot.scam

Description

The function is a clone of the plot.gam of the mgcv package with the differences in the construction of the Bayesian confidence intervals of the shape constrained smooth terms. The function takes a fitted scam object produced by scam() and plots the component smooth functions that make it up, on the scale of the linear predictor. Optionally produces term plots for parametric model components as well.

Note: The fitted shape constrained smooth functions are centred when plotted, which is done in order to be in line with plots of unconstrained smooths (as in gam()). Although 'zeroed intercept' constraints are applied to deal with identifiability of the scop-splines.

Usage

```r
## S3 method for class 'scam'
plot(x, residuals=FALSE, rug=TRUE, se=TRUE, pages=0, select=NULL, scale=-1,
     n=100, n2=40, pers=FALSE, theta=30, phi=30, jit=FALSE, xlab=NULL,
     ylab=NULL, main=NULL, ylim=NULL, xlim=NULL, too.far=0.1,
     all.terms=FALSE, shade=FALSE, shade.col="gray80",
     shift=0, trans=I, seWithMean=FALSE, unconditional = FALSE,
     by.resids = FALSE, scheme=0,...)
```

Arguments

The list of the arguments is the same as in plot.gam of the mgcv package.

- `x` a fitted gam object as produced by gam().
- `residuals` If TRUE then partial residuals are added to plots of 1-D smooths. If FALSE then no residuals are added. If this is an array of the correct length then it is used as the array of residuals to be used for producing partial residuals. If TRUE then the residuals are the working residuals from the IRLS iteration weighted by the IRLS weights. Partial residuals for a smooth term are the residuals that would be obtained by dropping the term concerned from the model, while leaving all other estimates fixed (i.e. the estimates for the term plus the residuals).
- `rug` when TRUE (default) then the covariate to which the plot applies is displayed as a rug plot at the foot of each plot of a 1-d smooth, and the locations of the covariates are plotted as points on the contour plot representing a 2-d smooth.
- `se` when TRUE (default) upper and lower lines are added to the 1-d plots at 2 standard errors above and below the estimate of the smooth being plotted while for 2-d plots, surfaces at +1 and -1 standard errors are contoured and overlayed on the contour plot for the estimate. If a positive number is supplied then this number is multiplied by the standard errors when calculating standard error curves or surfaces. See also shade, below.
pages (default 0) the number of pages over which to spread the output. For example, if pages=1 then all terms will be plotted on one page with the layout performed automatically. Set to 0 to have the routine leave all graphics settings as they are.

select Allows the plot for a single model term to be selected for printing. e.g. if you just want the plot for the second smooth term set select=2.

scale set to -1 (default) to have the same y-axis scale for each plot, and to 0 for a different y axis for each plot. Ignored if ylim supplied.

n number of points used for each 1-d plot - for a nice smooth plot this needs to be several times the estimated degrees of freedom for the smooth. Default value 100.

n2 Square root of number of points used to grid estimates of 2-d functions for contouring.

pers Set to TRUE if you want perspective plots for 2-d terms.

theta One of the perspective plot angles.

phi The other perspective plot angle.

jit Set to TRUE if you want rug plots for 1-d terms to be jittered.

xlab If supplied then this will be used as the x label for all plots.

ylab If supplied then this will be used as the y label for all plots.

main Used as title (or z axis label) for plots if supplied.

ylim If supplied then this pair of numbers are used as the y limits for each plot.

xlim If supplied then this pair of numbers are used as the x limits for each plot.

too.far If greater than 0 then this is used to determine when a location is too far from data to be plotted when plotting 2-D smooths. This is useful since smooths tend to go wild away from data. The data are scaled into the unit square before deciding what to exclude, and too.far is a distance within the unit square.

all.terms if set to TRUE then the partial effects of parametric model components are also plotted, via a call to termplot. Only terms of order 1 can be plotted in this way.

shade Set to TRUE to produce shaded regions as confidence bands for smooths (not available for parametric terms, which are plotted using termplot).

shade.col define the color used for shading confidence bands.

shift constant to add to each smooth (on the scale of the linear predictor) before plotting. Can be useful for some diagnostics, or with trans.

trans function to apply to each smooth (after any shift), before plotting. shift and trans are occasionally useful as a means for getting plots on the response scale, when the model consists only of a single smooth.

seWithMean if TRUE the component smooths are shown with confidence intervals that include the uncertainty about the overall mean. If FALSE then the uncertainty relates purely to the centred smooth itself. An extension of the argument presented in Nychka (1988) suggests that TRUE results in better coverage performance, and this is also suggested by simulation.

unconditional if TRUE then the smoothing parameter uncertainty corrected covariance matrix is used to compute uncertainty bands, if available. Otherwise the bands treat the smoothing parameters as fixed.
Should partial residuals be plotted for terms with by variables? Usually the answer is no, they would be meaningless.

scheme

Integer (0, 1 or 2) or integer vector selecting a plotting scheme for each plot.
scheme == 0 produces a smooth curve with dashed curves indicating 2 standard error bounds. scheme == 1 illustrates the error bounds using a shaded region. For scheme==0, contour plots are produced for 2-d smooths with the x-axes labelled with the first covariate name and the y axis with the second covariate name. For 2-d smooths scheme==1 produces a perspective plot, while scheme==2 produces a heatmap, with overlaid contours.

... other graphics parameters to pass on to plotting commands.

Value

The function generates plots.

Author(s)

Natalya Pya <nat.pya@gmail.com> based on the plot.gam of the mgcv by Simon Wood

References


See Also

scam

Examples

```r
## simulating data...
n <- 200
set.seed(1)
x0 <- rep(1:4,50)
x1 <- runif(n)*6-3
f1 <- 3*exp(-x1^2) # unconstrained smooth term
x2 <- runif(n)*4-1;
f2 <- exp(4*x2)/(1+exp(4*x2)) # monotone increasing smooth
x3 <- runif(n)*5;
f3 <- -log(x3)/5 # monotone decreasing smooth
f <- f1+f2+f3
y <- 2*x0 + f + rnorm(n)*.3
x0 <- factor(x0)

## fit the model and plot ...
b <- scam(y~x0+s(x1,k=15,bs="cr")+s(x2,k=30,bs="mpi") + s(x3,k=30,bs="mpd"))
```
plot(b, pages=1, residuals=TRUE, all.terms=TRUE, shade=TRUE, shade.col=3)

## Not run:
## example with 2-d plots...
## simulating data...
set.seed(2)
n <- 30
x0 <- rep(1:9, 100)
x1 <- sort(runif(n)*4-1)
x2 <- sort(runif(n))
x3 <- runif(n*n, 0, 1)
f <- matrix(0, n, n)
for (i in 1:n) for (j in 1:n)
    { f[i, j] <- -exp(4*x1[i])/(1+exp(4*x1[i]))+2*sin(pi*x2[j])}
f1 <- as.vector(t(f))
f2 <- x3*0
e <- rnorm(length(f1))*0.1
y <- 2*x0 + f1 + f2 + e
x0 <- factor(x0)
x11 <- matrix(0, n, n)
x11[, 1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2, n)
dat <- list(x0=x0, x1=x11, x2=x22, x3=x3, y=y)
## fit model and plot...
b <- scam(y~x0+s(x1, x2, k=c(10, 10), bs=c("tesmd1","ps"), m=2)+s(x3), data=dat, optimizer="efs")
op <- par(mfrow=c(2, 2))
plot(b, all.terms=TRUE)
plot(y, b$fitted.values, xlab="Simulated data", ylab="Fitted data", pch=19, cex=.3)
par(op)

## and use of schemes...
op <- par(mfrow=c(2, 2))
plot(b, all.terms=TRUE, scheme=1)
par(op)
op <- par(mfrow=c(2, 2))
plot(b, all.terms=TRUE, scheme=c(2, 1))
par(op)

## End(Not run)

Predict.matrix.mpi.smooth

Predict matrix method functions for SCAMs

**Description**

The various built in smooth classes for use with scam have associate Predict.matrix method functions to enable prediction from the fitted model.
Usage

```r
## S3 method for class 'mpi.smooth'
Predict.matrix(object, data)
## S3 method for class 'miso.smooth'
Predict.matrix(object, data)
## S3 method for class 'mifo.smooth'
Predict.matrix(object, data)
## S3 method for class 'mpd.smooth'
Predict.matrix(object, data)
## S3 method for class 'cv.smooth'
Predict.matrix(object, data)
## S3 method for class 'cx.smooth'
Predict.matrix(object, data)
## S3 method for class 'micx.smooth'
Predict.matrix(object, data)
## S3 method for class 'micv.smooth'
Predict.matrix(object, data)
## S3 method for class 'mdcx.smooth'
Predict.matrix(object, data)
## S3 method for class 'mdcv.smooth'
Predict.matrix(object, data)
## S3 method for class 'po.smooth'
Predict.matrix(object, data)
## S3 method for class 'mpdBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'mpiBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'cxBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'cvBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'mdcxBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'mdcvBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'micxBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'micvBy.smooth'
Predict.matrix(object, data)
## S3 method for class 'tedmd.smooth'
Predict.matrix(object, data)
## S3 method for class 'tedmi.smooth'
Predict.matrix(object, data)
## S3 method for class 'tesmd1.smooth'
Predict.matrix(object, data)
## S3 method for class 'tesmd2.smooth'
Predict.matrix(object, data)
## S3 method for class 'tesm1.smooth'
```
Predict.matrix(object, data)
## S3 method for class 'tesmi2.smooth'
Predict.matrix(object, data)
## S3 method for class 'temicx.smooth'
Predict.matrix(object, data)
## S3 method for class 'temicv.smooth'
Predict.matrix(object, data)
## S3 method for class 'tedecx.smooth'
Predict.matrix(object, data)
## S3 method for class 'tedecv.smooth'
Predict.matrix(object, data)
## S3 method for class 'tescx.smooth'
Predict.matrix(object, data)
## S3 method for class 'tescv.smooth'
Predict.matrix(object, data)
## S3 method for class 'tecvcv.smooth'
Predict.matrix(object, data)
## S3 method for class 'tecxcv.smooth'
Predict.matrix(object, data)
## S3 method for class 'tecxcx.smooth'
Predict.matrix(object, data)

Arguments

object A smooth object, usually generated by a smooth.construct method having processed a smooth specification object generated by an s term in a scam formula.

data A data frame containing the values of the named covariates at which the smooth term is to be evaluated.

Value

A matrix mapping the coefficients for the smooth term to its values at the supplied data values.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


predict.scam  Prediction from fitted SCAM model

Description

This function is a clone of the mgcv library code `predict.gam` with some modifications to adopt shape preserving smooth terms. It takes a fitted scam object produced by `scam()` and produces predictions given a new set of values for the model covariates or the original values used for the model fit. Predictions can be accompanied by standard errors, based on the posterior distribution of the model coefficients.

It now allows prediction outside the range of knots, and use linear extrapolation in this case.

Usage

```r
## S3 method for class 'scam'
predict(object, newdata, type = "link", se.fit = FALSE, terms = NULL, exclude = NULL,
        block.size = NULL, newdata.guaranteed = FALSE, na.action = na.pass, ...)
```

Arguments

- `object`  a fitted scam object as produced by `scam()`.
- `newdata`  A data frame or list containing the values of the model covariates at which predictions are required. If this is not provided then predictions corresponding to the original data are returned. If `newdata` is provided then it should contain all the variables needed for prediction: a warning is generated if not.
- `type`  When this has the value "link" (default) the linear predictor (possibly with associated standard errors) is returned. When `type="terms"` each component of the linear predictor is returned separately (possibly with standard errors): this includes parametric model components, followed by each smooth component, but excludes any offset and any intercept. `type="iterms"` is the same, except that any standard errors returned for unconstrained smooth components will include the uncertainty about the intercept/overall mean. When `type="response"` predictions on the scale of the response are returned (possibly with approximate standard errors). When `type="lpmatrix"` then a matrix is returned which yields the values of the linear predictor (minus any offset) when postmultiplied by the parameter vector (in this case `se.fit` is ignored). The latter option is most useful for getting variance estimates for quantities derived from the model: for example integrated quantities, or derivatives of smooths. A linear predictor matrix can also be used to implement approximate prediction outside R (see example code, below).
- `se.fit`  when this is TRUE (not default) standard error estimates are returned for each prediction.
- `terms`  if `type="terms"` then only results for the terms given in this array will be returned.
exclude

if type="terms" or type="iterms" then terms (smooth or parametric) named in this array will not be returned. Otherwise any smooth terms named in this array will be set to zero. If NULL then no terms are excluded.

block.size

maximum number of predictions to process per call to underlying code: larger is quicker, but more memory intensive. Set to < 1 to use total number of predictions as this.

newdata.guaranteed

Set to TRUE to turn off all checking of newdata except for sanity of factor levels: this can speed things up for large prediction tasks, but newdata must be complete, with no NA values for predictors required in the model.

na.action

what to do about NA values in newdata. With the default na.pass, any row of newdata containing NA values for required predictors, gives rise to NA predictions (even if the term concerned has no NA predictors). na.exclude or na.omit result in the dropping of newdata rows, if they contain any NA values for required predictors. If newdata is missing then NA handling is determined from object$na.action.

... other arguments.

Details

See predict.gam for details.

Value

If type="lpmatrix" then a matrix is returned which will give a vector of linear predictor values (minus any offset) at the supplied covariate values, when applied to the model coefficient vector. Otherwise, if se.fit is TRUE then a 2 item list is returned with items (both arrays) fit and se.fit containing predictions and associated standard error estimates, otherwise an array of predictions is returned. The dimensions of the returned arrays depends on whether type is "terms" or not: if it is then the array is 2 dimensional with each term in the linear predictor separate, otherwise the array is 1 dimensional and contains the linear predictor/predicted values (or corresponding s.e.s). The linear predictor returned termwise will not include the offset or the intercept.

newdata can be a data frame, list or model.frame: if it’s a model frame then all variables must be supplied.

Author(s)

Natalya Pya <nat.pya@gmail.com> based partly on mgcv by Simon Wood

References

predict.scam

See Also

scam, plot.scam

Examples

## Not run:
library(scam)
set.seed(2)
  n <- 200
  x1 <- runif(n)*6-3
  f1 <- 3*exp(-x1^2)  # unconstrained term
  x2 <- runif(n)*4-1;
  f2 <- exp(4*x2)/(1+exp(4*x2))  # monotone increasing smooth
  f <- f1+f2
  y <- f+rnorm(n)*0.2
  dat <- data.frame(x1=x1,x2=x2,y=y)
  b <- scam(y~s(x1,k=15,bs="cr") + s(x2,k=30,bs="mpi"),
           family=gaussian(link="identity"),data=dat)

  newd <- data.frame(x1=seq(-3,3,length.out=20),x2=seq(-1,3,length.out=20))
  pred <- predict(b,newd)
pred
  predict(b,newd,type="terms",se=TRUE)

## linear extrapolation with predict.scam()...
set.seed(3)
  n <- 100
  x <- sort(runif(n)*3-1)
  f <- exp(-1.3*x)
  y <- rpois(n,exp(f))
  dat <- data.frame(x=x,y=y)
  b <- scam(y~s(x,k=15,bs="mpd"),family=poisson(link="log"),data=dat)
  newd <- data.frame(x=c(2.3,2.7,3.2))
  fe <- predict(b,newd,type="link",se=TRUE)
ylim<-
  plot(c(x,newd[[1]]),c(y,NA,NA,NA),ylim=ylim)
  lines(c(x,newd[[1]]),c(b$fitted,fe),col=3)

## Gaussian model ....
## simulating data...
set.seed(2)
n <- 200
  x <- sort(runif(n)*4-1)
  f <- exp(4*x)/(1+exp(4*x))  # monotone increasing smooth
  y <- f+rnorm(n)*0.1
  dat <- data.frame(x=x,y=y)
  b <- scam(y~ s(x,k=25,bs="mpi"),family=gaussian,data=dat)
  newd <- data.frame(x=c(3.2,3.3,3.6))
  fe <- predict(b,newd)
  plot(c(x,newd[[1]]),c(y,NA,NA,NA))
  lines(c(x,newd[[1]]),c(b$fitted,fe),col=3)
### passing observed data + new data...
newd <- data.frame(x=c(x,3.2,3.3,3.6))
fe <- predict(b,newd,se=TRUE)
plot(newd[[1]],c(y,NA,NA,NA))
lines(newd[[1]],fe$fit,col=2)
lines(newd[[1]],fe$fit+2*fe$se.fit,col=3)
lines(newd[[1]],fe$fit-2*fe$se.fit,col=4)

## prediction with CI...
newd <- data.frame(x=seq(-1.2,3.5,length.out=100))
fe <- predict(b,newd,se=TRUE)
ylim<- c(min(y,fe$se.fit),max(y,fe$se.fit))
plot(newd[[1]],fe$fit,type="l",ylim=ylim)
lines(newd[[1]],fe$fit+2*fe$se.fit,lty=2)
lines(newd[[1]],fe$fit-2*fe$se.fit,lty=2)

## bivariate example...
set.seed(2)
n <- 30
x1 <- sort(runif(n)); x2 <- sort(runif(n)*4-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  { f1[i,j] <- 2*sin(pi*x1[i]) +exp(4*x2[j])/(1+exp(4*x2[j]))}
f <- as.vector(t(f1));
y <- f+rnorm(length(f))*0.1
x11 <- matrix(0,n,n); x11[,1:n] <- x1; x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
b <- scam(y~s(x1,x2,k=c(10,10),bs="tesmi2"),data=dat,optimizer="efs")
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE); plot(b,pers=TRUE,theta = 80, phi = 40)
n.out <- 20
xp <- seq(0,1.4,length.out=n.out)
zp <- seq(-1,3.4,length.out=n.out)
xpl <- matrix(0,n.out,n.out); xpl[,1:n.out] <- xp
xpl <- as.vector(t(xpl)); xp2 <- rep(zp,n.out)
newd <- data.frame(x1=xpl,x2=xp2)
fe <- predict(b,newd)
fc <- t(matrix(fe,n.out,n.out))
persp(xp,zp,fc,expand= 0.85,ticktype = "simple",xlab="x1", ylab="x2",zlab="f",main="", theta = 80, phi = 40)

## obtaining a 'prediction matrix'
newd <- data.frame(x1=c(-2,-1),x2=c(0,1))
Xp <- predict(b,newdata=newd,type="lpmatrix")
fv <- Xp%*% b$beta.t
fv

## End(Not run)
print.scam

Print a SCAM object

Description

The default print method for a scam object. The code is a clone of print.gam of the mgcv package with a slight simplification since only two methods of smoothing parameter selection (by GCV or UBRE) was implemented for scam.

Usage

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

Arguments

x fitted model objects of class scam as produced by scam().

... other arguments.

Details

As for mgcv(gam) prints out the family, model formula, effective degrees of freedom for each smooth term, and optimized value of the smoothness selection criterion used.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

scam, summary.scam
residuals.scam  SCAM residuals

Description

This function is a clone of the mgcv library code residuals.gam. It returns residuals for a fitted scam model object. Pearson, deviance, working and response residuals are available.

Usage

```r
## S3 method for class 'scam'
residuals(object, type = c("deviance", "pearson","scaled.pearson", "working", "response"),...)
```

Arguments

- **object**: a scam fitted model object.
- **type**: the type of residuals wanted.
- **...**: other arguments.

Details

See residuals.gam for details.

Value

An array of residuals.

Author(s)

Natalya Pya <nat.pya@gmail.com>

See Also

scam
**scam**  
*Shape constrained additive models (SCAM) and integrated smoothness selection*

**Description**

This function fits a SCAM to data. Univariate smooths subject to monotonicity, convexity, or monotonicity plus convexity are available as model terms, as well as bivariate smooths with double or single monotonicity. Smoothness selection is estimated as part of the fitting. Confidence/credible intervals are available for each smooth term.

All the shaped constrained smooths have been added to the `gam()` in package mgcv setup using the `smooth.construct` function. The routine calls a `gam()` function for the model set up, but there are separate functions for the model fitting, `scam.fit`, and smoothing parameter selection, `bfgs_gcv.ubre`. Any unconstrained smooth available in `gam` can be taken as model terms.

**Usage**

```r
scam(formula, family = gaussian(), data = list(), gamma = 1,
     sp = NULL, weights = NULL, offset = NULL, optimizer="bfgs",
     optim.method=c("Nelder-Mead","fd"), scale = 0, knots=NULL,
     not.exp=FALSE, start= NULL, etastart=NULL,mustart= NULL,
     control=list(),AR1.rho=0, AR.start=NULL,drop.unused.levels=TRUE)
```

**Arguments**

- **formula**: A SCAM formula. This is exactly like the formula for a GAM (see `formula.gam` of the mgcv library) except that monotone smooth terms, can be added in the expression of the form  
  ```r
  s(x1,k=12,bs="mpi",by=z),
  ```
  where `bs` indicates the basis to use for the constrained smooth: the built in options for the monotonic smooths are described in `shape.constrained.smooth.terms`,
- **family**: A family object specifying the distribution and link to use in fitting etc. See `glm` and `family` for more details.
- **data**: A data frame or list containing the model response variable and covariates required by the formula. By default the variables are taken from environment(formula): typically the environment from which gam is called.
- **gamma**: A constant multiplier to inflate the model degrees of freedom in the GCV or UBRE/AIC score.
- **sp**: A vector of smoothing parameters can be provided here. Smoothing parameters must be supplied in the order that the smooth terms appear in the model formula. The default `sp=NULL` indicates that smoothing parameters should be estimated. If `length(sp)` does not correspond to the number of underlying smoothing parameters or negative values supplied then the vector is ignored and all the smoothing parameters will be estimated.
- **weights**: Prior weights on the data.
offset
Used to supply a model offset for use in fitting. Note that this offset will always be completely ignored when predicting, unlike an offset included in formula. This conforms to the behaviour of lm, glm and gam.

optimizer
The numerical optimization method to use to optimize the smoothing parameter estimation criterion. "bfgs" for the built in to scam package routine bfgs_gcv.ubre, "optim", "nlm", "nlm.fd" (based on finite-difference approximation of the derivatives), "efs" for the extended Fellner Schall method of Wood and Fasiolo (2017) (rather than minimizing REML as in gam(mgcv) this minimizes the GCV criterion).

optim.method
In case of optimizer="optim" this specifies the numerical method to be used in optim in the first element, the second element of optim.method indicates whether the finite difference approximation should be used ("fd") or analytical gradient ("grad"). The default is optim.method=c("Nelder-Mead", "fd").

scale
If this is positive then it is taken as the known scale parameter of the exponential family distribution. Negative value indicates that the scale parameter is unknown. 0 indicates that the scale parameter is 1 for Poisson and binomial and unknown otherwise. This conforms to the behaviour of gam.

knots
An optional list containing user specified knot values to be used for basis construction. Different terms can use different numbers of knots.

not.exp
if TRUE then notExp() function will be used in place of exp (default value) in positivity ensuring beta parameters re-parameterization.

start
Initial values for the model coefficients.

etastart
Initial values for the linear predictor.

mustart
Initial values for the expected values.

control
A list of fit control parameters to replace defaults returned by scam.control. Values not set assume default values.

AR1.rho
The AR1 correlation parameter. An AR1 error model can be used for the residuals of Gaussian-identity link models. Standardized residuals (approximately uncorrelated under correct model) returned in std.rsd if non zero.

AR.start
logical variable of same length as data, TRUE at first observation of an independent section of AR1 correlation. Very first observation in data frame does not need this. If NULL (default) then there are no breaks in AR1 correlation.

drop.unused.levels
as with gam by default unused levels are dropped from factors before fitting.

Details
A shape constrained additive model (SCAM) is a generalized linear model (GLM) in which the linear predictor is given by strictly parametric components plus a sum of smooth functions of the covariates where some of the functions are assumed to be shape constrained. For example,

$$\log(E(Y_i)) = X_i^*b + f_1(x_{1i}) + m_2(x_{2i}) + f_3(x_{3i})$$

where the independent response variables Y_i follow Poisson distribution with log link function, f_1, m_2, and f_3 are smooth functions of the corresponding covariates, and m_2 is subject to monotone increasing constraint.
All available shape constrained smooths are described in `shape.constrained.smooth.terms`.

Residual auto-correlation with a simple AR1 correlation structure can be dealt with, for Gaussian models with identity link. Currently, the AR1 correlation parameter should be supplied (rather than estimated) in `AR1.rho`. `AR1.start` input argument (logical) allows to set independent sections of AR1 correlation. Standardized residuals (approximately uncorrelated under correct model) are returned in `std.rsd` if `AR1.rho` is non zero.

### Value

The function returns an object of class "scam" with the following elements (this agrees with `gamObject`):

- **aic**: AIC of the fitted model: the degrees of freedom used to calculate this are the effective degrees of freedom of the model, and the likelihood is evaluated at the maximum of the penalized likelihood, not at the MLE.
- **assign**: Array whose elements indicate which model term (listed in `pterms`) each parameter relates to: applies only to non-smooth terms.
- **bfgs.info**: If `optimizer="bfgs"`, a list of convergence diagnostics relating to the BFGS method of smoothing parameter selection. The items are: `conv`, indicates why the BFGS algorithm of the smoothness selection terminated; `iter`, number of iterations of the BFGS taken to get convergence; `grad`, the gradient of the GCV/UBRE score at convergence; `score.hist`, the successive values of the score up until convergence.
- **call**: the matched call.
- **coefficients**: the coefficients of the fitted model. Parametric coefficients are first, followed by coefficients for each spline term in turn.
- **coefficients.t**: the parametrized coefficients of the fitted model (exponentiated for the monotonic smooths).
- **conv**: indicates whether or not the iterative fitting method converged.
- **CPU.time**: indicates the real and CPU time (in seconds) taken by the fitting process in case of unknown smoothing parameters.
- **data**: the original supplied data argument. Only included if the `scam` argument `keepData` is set to `TRUE` (default is `FALSE`).
- **deviance**: model deviance (not penalized deviance).
- **df.null**: null degrees of freedom.
- **df.residual**: effective residual degrees of freedom of the model.
- **edf**: estimated degrees of freedom for each model parameter. Penalization means that many of these are less than 1.
- **edf1**: alternative estimate of edf.
- **efs.info**: If `optimizer="efs"`, a list of convergence diagnostics relating to the extended Fellner Schall method for smoothing parameter selection. The items are: `conv`, indicates why the efs algorithm of the smoothness selection terminated; `iter`, number of iterations of the efs taken to get convergence; `score.hist`, the successive values of the score up until convergence.
- **family**: family object specifying distribution and link used.
fitted.values  fitted model predictions of expected value for each datum.
formula  the model formula.
gcv.ubre  the minimized GCV or UBRE score.
dgcv.ubre  the gradient of the GCV or UBRE score.
iter  number of iterations of the Newton-Raphson method taken to get convergence.
linear.predictors  fitted model prediction of link function of expected value for each datum.
method  "GCV" or "UBRE", depending on the fitting criterion used.
min.edf  Minimum possible degrees of freedom for whole model.
model  model frame containing all variables needed in original model fit.
nlm.info  If optimizer="nlm" or optimizer="nlm.fd", a list of convergence diagnostics relating to the BFGS method of smoothing parameter selection. The items are: conv, indicates why the BFGS algorithm of the smoothness selection terminated; iter, number of iterations of BFGS taken to get convergence; grad, the gradient of the GCV/UBRE score at convergence.
not.exp  if TRUE then notExp() function will be used in place of exp (default value) in positivity ensuring beta parameters re-parameterization.
nonsdf  number of parametric, non-smooth, model terms including the intercept.
null.deviance  deviance for single parameter model.
offset  model offset.
optim.info  If optimizer="optim", a list of convergence diagnostics relating to the BFGS method of smoothing parameter selection. The items are: conv, indicates why the BFGS algorithm of the smoothness selection terminated; iter, number of iterations of BFGS taken to get convergence; optim.method, the numerical optimization method used.
prior.weights  prior weights on observations.
pterms  terms object for strictly parametric part of model.
R  Factor R from QR decomposition of weighted model matrix, unpivoted to be in same column order as model matrix.
residuals  the working residuals for the fitted model.
scale.estimated  TRUE if the scale parameter was estimated, FALSE otherwise.
sig2  estimated or supplied variance/scale parameter.
smooth  list of smooth objects, containing the basis information for each term in the model formula in the order in which they appear. These smooth objects are returned by the smooth.construct objects.
sp  estimated smoothing parameters for the model. These are the underlying smoothing parameters, subject to optimization.
std.rsd  Standardized residuals (approximately uncorrelated under correct model) if AR1.rho non zero
termcode  an integer indicating why the optimization process of the smoothness selection terminated (see bfgs_gcv.ubre).
terms  terms object of model model frame.
trA trace of the influence matrix, total number of the estimated degrees of freedom (sum(edf)).
var.summary A named list of summary information on the predictor variables. See `gamObject`.
Ve frequentist estimated covariance matrix for the parameter estimators.
Vp estimated covariance matrix for the parameters. This is a Bayesian posterior covariance matrix that results from adopting a particular Bayesian model of the smoothing process.
Ve.t frequentist estimated covariance matrix for the reparametrized parameter estimators obtained using the delta method. Particularly useful for testing whether terms are zero. Not so useful for CI’s as smooths are usually biased.
Vp.t estimated covariance matrix for the reparametrized parameters obtained using the delta method. Particularly useful for creating credible/confidence intervals.
weights final weights used in the Newton-Raphson iteration.
cmX column means of the model matrix (with elements corresponding to smooths set to zero).
contrasts contrasts associated with a factor.
xlevels levels of a factor variable used in the model.
y response data.

Author(s)
Natalya Pya <nat.pya@gmail.com> based partly on mgcv by Simon Wood

References

See Also
scam-package, shape.constrained.smooth.terms, gam, s.plot.scam, summary.scam, scam.check, predict.scam
Examples

# Gaussian model, two smooth terms: unconstrained and increasing...
# simulating data...
require(scam)
set.seed(4)
n <- 200
x1 <- runif(n)*6-3
f1 <- 3*exp(-x1^2) # unconstrained term
x2 <- runif(n)*4-1;
f2 <- exp(4*x2)/(1+exp(4*x2)) # monotone increasing smooth
y <- f1+f2 + rnorm(n)*.5
dat <- data.frame(x1=x1,x2=x2,y=y)
# fit model, get results, and plot...
b <- scam(y~s(x1,bs="cr") + s(x2,bs="mpi"),data=dat)
print(b)
summary(b)
plot(b,pages=1,shade=TRUE)

# Gaussian model, two smooth terms: increasing and mixed (decreasing and convex)... 
# simulating data...
set.seed(5)
n <- 200
x1 <- runif(n)*4-1;
f1 <- exp(4*x1)/(1+exp(4*x1)) # increasing smooth
x2 <- runif(n)*3-1;
f2 <- exp(-3*x2)/15 # decreasing and convex smooth
y <- f1+f2 + rnorm(n)*.4
dat <- data.frame(x1=x1,x2=x2,y=y)
# fit model, results, and plot...
b <- scam(y~s(x1,bs="mpi") + s(x2,bs="mdcx"),data=dat)
b
summary(b)
plot(b,pages=1, scale=0, shade=TRUE)

# Not run:
# using the extended Fellner-Schall method for smoothing parameter selection...
b0 <- scam(y~s(x1,bs="mpi") + s(x2,bs="mdcx"),data=dat,optimizer="efs")
summary(b0)

# using optim() for smoothing parameter selection...
b1 <- scam(y~s(x1,bs="mpi") + s(x2,bs="mdcx"),data=dat,optimizer="optim")
summary(b1)

b2 <- scam(y~s(x1,bs="mpi") + s(x2,bs="mdcx"),data=dat,optimizer="optim", optim.method=c("BFGS","fd"))
summary(b2)

# using nlm()...
b3 <- scam(y~s(x1,bs="mpi") + s(x2,bs="mdcx"),data=dat,optimizer="nlm"
summary(b3)

## End(Not run)

# Poisson model....
# simulating data...
set.seed(2)
n <- 200
x1 <- runif(n)*6-3
f1 <- 3*exp(-x1^2) # unconstrained term
x2 <- runif(n)*4-1;
f2 <- exp(4*x2)/(1+exp(4*x2)) # monotone increasing smooth
f <- f1+f2
y <- rpois(n,exp(f))
dat <- data.frame(x1=x1,x2=x2,y=y)
# fit model, get results, and plot...
b <- scam(y~s(x1,bs="cr") + s(x2,bs="mpi"),
       family=poisson(link="log"),data=dat,optimizer="efs")
summary(b)
plot(b,pages=1,shade=TRUE)
scam.check(b)

# Gamma model...
# simulating data...
set.seed(6)
n <- 300
x1 <- runif(n)*6-3
f1 <- 1.5*sin(1.5*x1) # unconstrained term
x2 <- runif(n)*4-1;
f2 <- 1.5/(1+exp(-10*(x2+.75)))+1.5/(1+exp(-5*(x2-.75))) # increasing smooth
x3 <- runif(n)*6-3;
f3 <- 3*exp(-x3^2) # unconstrained term
f <- f1+f2+f3
y <- rgamma(n,shape=1,scale=exp(f))
dat <- data.frame(x1=x1,x2=x2,x3=x3,y=y)
# fit model, get results, and plot...
b <- scam(y~s(x1,bs="ps") + s(x2,k=15,bs="mpi") + s(x3,bs="ps"),
        family=Gamma(link="log"),data=dat,optimizer="efs")
b
summary(b)
par(mfrow=c(2,2))
plot(b,shade=TRUE)

## Not run:
## bivariate example...
## simulating data...
set.seed(2)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(runif(n))
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
\begin{verbatim}
  \( f_{i,j} \leftarrow -\exp(4x_{1[i]})/(1+\exp(4x_{1[i]})) + 2\sin(\pi x_{2[j]}) \)
  f <- as.vector(t(f1))
  y <- f + rnorm(length(f)) * .2
  x11 <- matrix(0,n,n)
  x11[1:n] <- x1
  x11 <- as.vector(t(x11))
  x22 <- rep(x2,n)
  dat <- list(x1=x11,x2=x22,y=y)

  # fit model and plot...
  b <- scam(y~s(x1,x2,k=c(10,10),bs=c("tesmd1","ps"),data=dat,optimizer="efs")
  summary(b)
  par(mfrow=c(2,2),mar=c(4,4,2,2))
  plot(b,se=TRUE)
  plot(b,pers=TRUE,theta = 30, phi = 40)
  plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data",pch=".",cex=3)

  # example with random effect smoother...
  set.seed(2)
  n <- 200
  x1 <- runif(n)*6-3
  f1 <- 3*exp(-x1^2) # unconstrained term
  x2 <- runif(n)*4-1;
  f2 <- exp(4*x2)/(1+exp(4*x2)) # increasing smooth
  f <- f1+f2
  a <- factor(sample(1:10,200,replace=TRUE))
  Xa <- model.matrix(~a-1) # random main effects
  y <- f + Xa%*%rnorm(length(levels(a)))*.5 + rnorm(n)*.4
  dat <- data.frame(x1=x1,x2=x2,y=y,a=a)
  # fit model and plot...
  b <- scam(y~s(x1,bs="cr") + s(x2,bs="mpi") + s(a,bs="re"), data=dat)
  summary(b)
  scam.check(b)
  plot(b,pages=1,shade=TRUE)

  # example with AR1 errors...
  set.seed(8)
  n <- 500
  x1 <- runif(n)*6-3
  f1 <- 3*exp(-x1^2) # unconstrained term
  x2 <- runif(n)*4-1;
  f2 <- exp(4*x2)/(1+exp(4*x2)) # increasing smooth
  f <- f1+f2
  e <- rnorm(n,0,sd=2)
  for (i in 2:n) e[i] <- .6*e[i-1] + e[i]
  y <- f + e
  dat <- data.frame(x1=x1,x2=x2,y=y)
  b <- scam(y~s(x1,bs="cr") + s(x2,k=25,bs="mpi"),
            data=dat, AR1.rho=.6, optimizer="efs")
  b
  ## Raw residuals still show correlation...
  acf(residuals(b))
  ## But standardized are now fine...
  x11()
\end{verbatim}
Some diagnostics for a fitted scam object

Description

Takes a fitted scam object produced by scam() and produces some diagnostic information about the fitting procedure and results. This function is almost the same as gam.check of the mgcv library.

Usage

scam.check(b, rl.col=3, pch=".", ... )

Arguments

- b: a fitted scam object as produced by scam().
- rl.col: color for the reference line on the quantile-quantile plot.
- pch: plot character to use for the quantile-quantile plot. 19 is good.
- ... extra graphics parameters to pass to plotting functions.

Details

As for mgcv(gam) plots 4 standard diagnostic plots, and some other convergence diagnostics. The printed information relates to the optimization process used to select smoothing parameters.

Author(s)

Natalya Pya <nat.pya@gmail.com> based partly on mgcv by Simon Wood

References


See Also

scam
### Examples

```r
## Not run:
library(scam)
set.seed(2)
n <- 200
x1 <- runif(n)*4-1;
f1 <- exp(4*x1)/(1+exp(4*x1)) # monotone increasing smooth
x2 <- runif(n)*3-1;
f2 <- exp(-3*x2)/15 # monotone decreasing and convex smooth
f <- f1+f2
y <- f + rnorm(n)*0.2
data <- data.frame(x1=x1,x2=x2,y=y)
b <- scam(y ~ s(x1,k=25,bs="mpi",m=2)+s(x2,k=25,bs="mdcx",m=2),
family=gaussian(link="identity"),data=data)
plot(b,pages=1)
scam.check(b,pch=19,cex=.3)

## End(Not run)
```

### scam.control

Setting GAM fitting defaults

#### Description

This is an internal function of package scam which allows control of the numerical options for fitting a SCAM.

#### Usage

```r
scam.control(maxit = 200, maxHalf=30, devtol.fit=1e-7, steptol.fit=1e-7, keepData=FALSE, efs.lspmax=15, efs.tol=.1, nlm=list(), optim=list(), bfgs=list(), trace =FALSE, print.warn=FALSE)
```

#### Arguments

- **maxit**: Maximum number of IRLS iterations to perform used in `scam.fit`.
- **maxHalf**: If a step of the BFGS optimization method leads to a worse penalized deviance, then the step length of the model coefficients is halved. This is the number of halvings to try before giving up used in `bfgs_gcv.ubre`.
- **devtol.fit**: A positive scalar giving the convergence control for the model fitting algorithm in `scam.fit`.
- **steptol.fit**: A positive scalar giving the tolerance at which the scaled distance between two successive iterates is considered close enough to zero to terminate the model fitting algorithm in `scam.fit`.
- **keepData**: Should a copy of the original data argument be kept in the `scam` object?
- **efs.lspmax**: maximum log smoothing parameters to allow under extended Fellner Schall smoothing parameter optimization.
change in GCV to count as negligible when testing for EFS convergence. If the step is small and the last 3 steps led to a GCV change smaller than this, then stop.

list of control parameters to pass to nlm if this is used for outer estimation of smoothing parameters (not default).

list of control parameters to pass to optim if this is used for outer estimation of smoothing parameters (not default).

list of control parameters to pass to default BFGS optimizer used for outer estimation of log smoothing parameters.

turns on or off some de-bugging information.

when set to FALSE turns off printing warning messages for step halving under non-finite exponentiated coefficients, non-finite deviance and/or if mu or eta are out of bounds.

Outer iteration is used to estimate smoothing parameters of SCAM by GCV/UBRE score optimization. The default procedure is the built-in BFGS method which is controlled by the list bfgs with the following elements: steptol.bfgs (default 1e-7) is the relative convergence tolerance; gradtol.bfgs (default 6.0554*1e-6) is a tolerance at which the gradient is considered to be close enough to 0 to terminate the BFGS algorithm; maxNstep is a positive scalar which gives the maximum allowable step length (default 5); maxHalf gives the maximum number of step halving in “backtracking” to permit before giving up (default 30); check.analytical is logical whether the analytical gradient of GCV/UBRE should be checked numerically (default FALSE); del is an increment for finite differences when checking analytical gradients (default 1e-4).

If outer iteration using nlm is used for fitting, then the control list nlm stores control arguments for calls to routine nlm. As in gam.control the list has the following named elements: ndigit is the number of significant digits in the GCV/UBRE score; gradtol is the tolerance used to judge convergence of the gradient of the GCV/UBRE score to zero (default 1e-6); stepmax is the maximum allowable log smoothing parameter step (default 2); steptol is the minimum allowable step length (default 1e-4); iterlim is the maximum number of optimization steps allowed (default 200); check.analytical indicates whether the built in exact derivative calculations should be checked numerically (default FALSE). Any of these which are not supplied and named in the list are set to their default values.

Outer iteration using optim is controlled using list optim, which currently has one element: factr which takes default value 1e7.

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See Also

c scam, scam.fit, gam.control

scam.fit

Newton-Raphson method to fit SCAM

Description

This routine estimates SCAM coefficients given log smoothing parameters using the Newton-Raphson method. The estimation of the smoothing parameters by the GCV/UBRE score optimization is outer to the model fitting. Routine gcv.ubre_grad evaluates the first derivatives of the smoothness selection scores with respect to the log smoothing parameters. Routine bfgs.gcv.ubre estimates the smoothing parameters using the BFGS method.

The function is not normally called directly, but rather service routines for scam.

Usage

scam.fit(G, sp, gamma=1, etastart=NULL, mustart=NULL, env=env, null.coef=rep(0,ncol(G$X)), control=scam.control())

Arguments

G
A list of items needed to fit a SCAM.

sp
The vector of smoothing parameters.

gamma
This constant allows to inflate the model degrees of freedom in the GCV or UBRE/AIC score.

etastart
Initial values for the linear predictor.

mustart
Initial values for the expected values.

env
Get the environment for the model coefficients, their derivatives and the smoothing parameter.

null.coef
coefficients for a null model, needed for an ability to check for immediate divergence.

ccontrol
A list of fit control parameters returned by scam.control. It includes: maxit, a positive scalar which gives the maximum number of iterations for Newton’s method; devtol.fit, a scalar giving the tolerance at which the relative penalized deviance is considered to be close enough to 0 to terminate the algorithm; steptol.fit, a scalar giving the tolerance at which the scaled distance between two successive iterates is considered close enough to zero to terminate the algorithm; trace turns on or off some de-bugging information; print.warn, when set to FALSE turns off printing warning messages for step halving under non-finite exponentiated coefficients, non-finite deviance and/or if mu or eta are out of bounds.
Details

The routine applies step halving to any step that increases the penalized deviance substantially.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

scam

Description

As in mgcv(gam), shape preserving smooth terms are specified in a scam formula using s terms. All the shape constrained smooth terms are constructed using the B-splines basis proposed by Eilers and Marx (1996) with a discrete penalty on the basis coefficients.

The univariate single penalty built in shape constrained smooth classes are summarized as follows

- Monotone increasing P-splines bs="mpi". To achieve monotone increasing smooths these reparametrize the coefficients so that they form an increasing sequence. For details see smooth.construct.mpi.smooth.spec.

- Monotone decreasing P-splines bs="mpd". To achieve monotone decreasing smooths these reparametrize the coefficients so that they form a decreasing sequence. A first order difference penalty applied to the basis coefficients starting with the second is used for the monotone increasing and decreasing cases.

- Convex P-splines bs="cx". These reparametrize the coefficients so that the second order differences of the basis coefficients are greater than zero. For details see smooth.construct.cx.smooth.spec.

- Concave P-splines bs="cv". These reparametrize the coefficients so that the second order differences of the basis coefficients are less than zero. For details see smooth.construct.cv.smooth.spec.
• Monotone increasing and convex P-splines bs="micx". These reparametrize the coefficients so that the first and the second order differences of the basis coefficients are greater than zero. For details see smooth.construct.micx.smooth.spec.

• Monotone increasing and concave P-splines bs="micv". These reparametrize the coefficients so that the first order differences of the basis coefficients are greater than zero while the second order difference are less than zero.

• Monotone decreasing and convex P-splines bs="mdcx". These reparametrize the coefficients so that the first order differences of the basis coefficients are less than zero while the second order difference are greater. For details see smooth.construct.mdcx.smooth.spec.

• Monotone decreasing and concave P-splines bs="mdcv". These reparametrize the coefficients so that the first and the second order differences of the basis coefficients are less than zero. For all four types of the mixed constrained smoothing a first order difference penalty applied to the basis coefficients starting with the third one is used.

Using the concept of the tensor product spline bases bivariate smooths under monotonicity constraint where monotonicity may be assumed on only one of the covariates (single monotonicity) or both of them (double monotonicity) are added as the smooth terms of the SCAM. Bivariate B-spline is constructed by expressing the coefficients of one of the marginal univariate B-spline bases as the B-spline of the other covariate. Double or single monotonicity is achieved by the corresponding re-parametrization of the bivariate basis coefficients to satisfy the sufficient conditions formulated in terms of the first order differences of the coefficients. The following explains the built in bivariate monotonic smooth classes.

• Double monotone increasing P-splines bs="tedmi". See smooth.construct.tedmi.smooth.spec for details.

• Double monotone decreasing P-splines bs="tedmd".

• Single monotone increasing P-splines along the first covariate direction bs="tesmi1".

• Single monotone increasing P-splines along the second covariate direction bs="tesmi2".

• Single monotone decreasing P-splines along the first covariate direction bs="tesmd1".

• Single monotone decreasing P-splines along the second covariate direction bs="tesmd2".

Double penalties for the monotonic tensor product smooths are obtained from the penalties of the marginal smooths.

Author(s)
Natalya Pya <nat.pya@gmail.com>

References


See Also

Examples

```r
## see examples for scam
```

---

### smooth.construct.cv.smooth.spec

**Constructor for concave P-splines in SCAMs**

#### Description

This is a special method function for creating smooths subject to concavity constraint which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using concave P-splines. This smooth is specified via model terms such as `s(x,k,bs="cv",m=2)`, where `k` denotes the basis dimension and `m+1` is the order of the B-spline basis.

cvBy.smooth.spec works similar to cv.smooth.spec but without applying an identifiability constraint ('zero intercept' constraint). cvBy.smooth.spec should be used when the smooth term has a numeric by variable that takes more than one value. In such cases, the smooth terms are fully identifiable without a 'zero intercept' constraint, so they are left unconstrained. This smooth is specified as `s(x,by=z,bs="cvBy")`. See an example below.

However a factor by variable requires identifiability constraints, so `s(x,by=fac,bs="cv")` is used in this case.

#### Usage

```r
## S3 method for class 'cv.smooth.spec'
smooth.construct(object, data, knots)
## S3 method for class 'cvBy.smooth.spec'
smooth.construct(object, data, knots)
```
Arguments

- **object**: A smooth specification object, generated by an s term in a GAM formula.
- **data**: A data frame or list containing the data required by this term, with names given by `object$term`. The by variable is the last element.
- **knots**: An optional list containing the knots supplied for basis setup. If it is NULL then the knot locations are generated automatically.

Value

An object of class "cv.smooth", "cvBy.smooth".

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also


Examples

```r
## Not run:
## Concave P-splines example
## simulating data...
require(scam)
set.seed(1)
n <- 100
x <- sort(2*runif(n)-1)
f <- -4*x^2
y <- f + rnorm(n)*0.45
dat <- data.frame(x=x,y=y)
b <- scam(y~s(x,k=15,bs="cv"),family=gaussian,data=dat,not.exp=FALSE)
## fit unconstrained model...
b1 <- scam(y~s(x,k=15,bs="cr"),family=gaussian, data=dat,not.exp=FALSE)
## plot results ...
plot(x,y,xlab="x",ylab="y",cex=.5)
lines(x,f) ## the true function
lines(x,b$fitted,col=2) ## constrained fit
lines(x,b1$fitted,col=3) ## unconstrained fit
## Poisson version...
y <- rpois(n,15*exp(f))
```
dat <- data.frame(x=x, y=y)
## fit model ...
b <- scam(y~s(x,k=15,bs="cv"),family=poisson(link="log"),data=dat,not.exp=FALSE)
## fit unconstrained model...
b1<-scam(y~s(x,k=15,bs="cr"),family=poisson(link="log"), data=dat,not.exp=FALSE)
## plot results ...
plot(x,y,xlab="x",ylab="y",cex=.5)
lines(x,15*exp(f)) ## the true function
lines(x,b$fitted,col=2) ## constrained fit
lines(x,b1$fitted,col=3) ## unconstrained fit
## plotting on log scale...
plot(x,log(15*exp(f)),type="l",cex=.5) ## the true function
lines(x,log(b$fitted),col=2) ## constrained fit
lines(x,log(b1$fitted),col=3) ## unconstrained fit
## 'by' factor example...
set.seed(9)
n <- 400
x <- sort(runif(n,-.5,.5))
f1 <- -.7*x+cos(x)-3
f2 <- -20*x^2
par(mfrow=c(1,2))
plot(x,f1,type="l");plot(x,f2,type="l")
e <- rnorm(n, 0, 1.5)
fac <- as.factor(sample(1:2,n,replace=TRUE))
fac.1 <- as.numeric(fac==1)
fac.2 <- as.numeric(fac==2)
y <- f1*fac.1 + f2*fac.2 + e
dat <- data.frame(y=y,x=x,fac=fac,f1=f1,f2=f2)
b2 <- scam(y ~ fac+s(x,by=fac,bs="cv"),data=dat,optimizer="efs")
plot(b2,pages=1,scale=0,shade=TRUE)
summary(b2)
x11()
vis.scam(b2,theta=50,color="terrain",cond=list(z=1))
## numeric 'by' variable example...
set.seed(6)
n <- 100
x <- sort(2*runif(n)-1)
z <- runif(n,-2,3)
f <- -4*x^2
y <- f*z + rnorm(n)*0.6
dat <- data.frame(x=x,z=z,y=y)
b <- scam(y~s(x,k=15,by=z,bs="cvBy"),data=dat)
summary(b)
par(mfrow=c(1,2))
plot(b,shade=TRUE)
## unconstrained fit...
b1 <- scam(y~s(x,k=15,by=z),data=dat)
plot(b1,shade=TRUE)
summary(b1)
Description

This is a special method function for creating smooths subject to convexity constraint which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using convex P-splines. This smooth is specified via model terms such as $s(x,k,bs="cx",m=2)$, where $k$ denotes the basis dimension and $m+1$ is the order of the B-spline basis.

cxBy.smooth.spec works similar to cx.smooth.spec but without applying an identifiability constraint ('zero intercept' constraint). cxBy.smooth.spec should be used when the smooth term has a numeric by variable that takes more than one value. In such cases, the smooth terms are fully identifiable without a 'zero intercept' constraint, so they are left unconstrained. This smooth is specified as $s(x,by=z,bs="cxBy")$. See an example below.

However a factor by variable requires identifiability constraints, so $s(x,by=fac,bs="cx")$ is used in this case.

Usage

## S3 method for class 'cx.smooth.spec'
smooth.construct(object, data, knots)
## S3 method for class 'cxBy.smooth.spec'
smooth.construct(object, data, knots)

Arguments

- **object**: A smooth specification object, generated by an s term in a GAM formula.
- **data**: A data frame or list containing the data required by this term, with names given by object$term. The by variable is the last element.
- **knots**: An optional list containing the knots supplied for basis setup. If it is NULL then the knot locations are generated automatically.

Value

An object of class "cx.smooth", "cxBy.smooth".

Author(s)

Natalya Pya <nat.pya@gmail.com>
smooth.construct.cx.smooth.spec

References


See Also


Examples

## Not run:
## Convex SCOP-splines example...
## simulating data...
require(scam)
set.seed(16)
n <- 100
x <- sort(2*runif(n)-1)
f <- 4*x^2
y <- f + rnorm(n)*0.4
dat <- data.frame(x=x,y=y)
b <- scam(y~s(x,k=15,bs="cx"),family=gaussian,data=dat)
## unconstrained fit...
b1 <- scam(y~s(x,k=15),family=gaussian, data=dat)
## plot results ....
plot(x,y,xlab="x",ylab="y")
lines(x,f) ## the true function
lines(x,b$fitted,col=2) ## constrained fit
lines(x,b1$fitted,col=3) ## unconstrained fit

## Poisson version...
set.seed(18)
y <- rpois(n,exp(f))
dat <- data.frame(x=x,y=y)
## fit shape constrained model ...
b <- scam(y~s(x,k=15,bs="cx"),family=poisson(link="log"),data=dat,optimizer="efs")
## unconstrained fit...
b1 <- scam(y~s(x,k=15),family=poisson(link="log"), data=dat,optimizer="efs")
## plot results ...
plot(x,y,xlab="x",ylab="y")
lines(x,exp(f)) ## the true function
lines(x,b$fitted,col=2) ## constrained fit
lines(x,b1$fitted,col=3) ## unconstrained fit

## 'by' factor example...
set.seed(9)
n <- 400
x <- sort(runif(n,-.5,.5))
smooth.construct.mdcv.smooth.spec

Constructor for monotone decreasing and concave P-splines in SCAMs

Description

This is a special method function for creating smooths subject to both monotone decreasing and concavity constraints which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using mixed constrained P-splines. This smooth is specified via model terms such as s(x,k,bs="mdcv",m=2), where k denotes the basis dimension and m+1 is the order of the B-spline basis.

mdcvBy.smooth.spec works similar to mdcv.smooth.spec but without applying an identifiability constraint ("zero intercept" constraint). mdcvBy.smooth.spec should be used when the smooth
term has a numeric by variable that takes more than one value. In such cases, the smooth terms are fully identifiable without a 'zero intercept' constraint, so they are left unconstrained. This smooth is specified as s(x, by=z, bs="mdcvBy"). See an example below.

However a factor by variable requires identifiability constraints, so s(x, by=fac, bs="mdcv") is used in this case.

Usage

## S3 method for class 'mdcv.smooth.spec'
smooth.construct(object, data, knots)
## S3 method for class 'mdcvBy.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the data required by this term, with names given by object$term. The by variable is the last element.
knots An optional list containing the knots supplied for basis setup. If it is NULL then the knot locations are generated automatically.

Value

An object of class "mdcv.smooth", "mdcvBy.smooth".

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also


Examples

## Not run:
## Monotone decreasing and concave SCOP-splines example
## simulating data...
require(scam)
set.seed(2)
n <- 100
x <- sort(runif(n))
f <- -x^4
y <- f+rnorm(n)*.2
dat <- data.frame(x=x,y=y)
## fit model ...
b <- scam(y~s(x,bs="mdcv"),family=gaussian(),data=dat)

## fit unconstrained model ...
b1 <- scam(y~s(x,bs="ps"),family=gaussian(),data=dat)
## plot results ...
plot(x,y,xlab="x",ylab="y",cex=.5)
lines(x,f) ## the true function
lines(x,b$fitted.values,col=2) ## mixed constrained fit
lines(x,b1$fitted.values,col=3) ## unconstrained fit

## numeric 'by' variable example...
set.seed(6)
n <- 100
x <- sort(runif(n))
z <- runif(n,-2,3)
f <- -x^4
y <- f*z + rnorm(n)*0.4
dat <- data.frame(x=x,z=z,y=y)
b <- scam(y~s(x,k=15,by=z,bs="mdcvBy"),data=dat)
summary(b)
par(mfrow=c(1,2))
plot(b,shade=TRUE)
## unconstrained fit...
b1 <- scam(y~s(x,k=15,by=z),data=dat)
plot(b1,shade=TRUE)
summary(b1)

## End(Not run)
fully identifiable without a 'zero intercept' constraint, so they are left unconstrained. This smooth is specified as \( s(x, by=z, bs="mdcxBy") \). See an example below.

However a factor by variable requires identifiability constraints, so \( s(x, by=fac, bs="mdcx") \) is used in this case.

**Usage**

```r
## S3 method for class 'mdcx.smooth.spec'
smooth.construct(object, data, knots)
## S3 method for class 'mdcxBy.smooth.spec'
smooth.construct(object, data, knots)
```

**Arguments**

- `object` A smooth specification object, generated by an \( s \) term in a GAM formula.
- `data` A data frame or list containing the data required by this term, with names given by `object$term`. The by variable is the last element.
- `knots` An optional list containing the knots supplied for basis setup. If it is `NULL` then the knot locations are generated automatically.

**Value**

An object of class "mdcx.smooth", "mdcxBy.smooth".

**Author(s)**

Natalya Pya <nat.pya@gmail.com>

**References**


**See Also**

- `smooth.construct.mpi.smooth.spec`
- `smooth.construct.mpd.smooth.spec`
- `smooth.construct.cx.smooth.spec`
- `smooth.construct.cv.smooth.spec`
- `smooth.construct.mdcv.smooth.spec`
- `smooth.construct.micx.smooth.spec`
- `smooth.construct.micv.smooth.spec`

**Examples**

```r
## Not run:
## Monotone decreasing and convex SCOP-splines example
## simulating data...
require(scam)
set.seed(2)
N <- 100
```
smooth.construct.micv.smooth.spec

Constructor for monotone increasing and concave P-splines in SCAMs

Description

This is a special method function for creating smooths subject to both monotone increasing and concavity constraints which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using mixed constrained P-splines. This smooth is specified via model terms such as s(x, k, bs="micv", m=2), where k denotes the basis dimension and m+1 is the order of the B-spline basis.

micvBy.smooth.spec works similar to micv.smooth.spec but without applying an identifiability constraint (‘zero intercept’ constraint). micvBy.smooth.spec should be used when the smooth term has a numeric by variable that takes more than one value. In such cases, the smooth terms are fully identifiable without a ‘zero intercept’ constraint, so they are left unconstrained. This smooth is specified as s(x, by=z, bs="micvBy"). See an example below.
However a factor by variable requires identifiability constraints, so \( s(x, \text{by=fac, bs="micv"} ) \) is used in this case.

**Usage**

```r
## S3 method for class 'micv.smooth.spec'
smooth.construct(object, data, knots)
## S3 method for class 'micvBy.smooth.spec'
smooth.construct(object, data, knots)
```

**Arguments**

- `object` A smooth specification object, generated by an `s` term in a GAM formula.
- `data` A data frame or list containing the data required by this term, with names given by `object$term`. The by variable is the last element.
- `knots` An optional list containing the knots supplied for basis setup. If it is `NULL` then the knot locations are generated automatically.

**Value**

An object of class "micv.smooth", "micvBy.smooth".

**Author(s)**

Natalya Pya <nat.pya@gmail.com>

**References**


**See Also**

- `smooth.construct.mpi.smooth.spec`
- `smooth.construct.cx.smooth.spec`
- `smooth.construct.cv.smooth.spec`
- `smooth.construct.mdcv.smooth.spec`
- `smooth.construct.mdcx.smooth.spec`
- `smooth.construct.micx.smooth.spec`
- `smooth.construct.mpd.smooth.spec`

**Examples**

```r
## Not run:
## Monotone increasing and concave SCOP-splines example
## simulating data...
set.seed(3)
n <- 100
x <- sort(runif(n)*99+1)
f <- log(x)/2
y <- f+rnorm(n)*.3
dataframe(x=x, y=y)
```
smooth.construct.micx.smooth.spec

Constructor for monotone increasing and convex P-splines in SCAMs

Description

This is a special method function for creating smooths subject to both monotone increasing and convexity constraints which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using the mixed constrained P-splines. This smooth is specified via model terms such as `s(x,k,bs="micx",m=2)`, where `k` denotes the basis dimension and `m+1` is the order of the B-spline basis.

`micxBy.smooth.spec` works similar to `micx.smooth.spec` but without applying an identifiability constraint (‘zero intercept’ constraint). `micxBy.smooth.spec` should be used when the smooth term has a numeric by variable that takes more than one value. In such cases, the smooth terms are fully identifiable without a ‘zero intercept’ constraint, so they are left unconstrained. This smooth is specified as `s(x,by=z,bs="micvBy")`. See an example below.

However a factor by variable requires identifiability constraints, so `s(x,by=fac,bs="micx")` is used in this case.

---

```r
## fit model ...
b <- scam(y~s(x,k=15,bs="micv"), data=dat)
summary(b)
## fit unconstrained model ...
b1 <- scam(y~s(x,k=15,bs="ps"),data=dat)
## plot results ...
plot(x,y,xlab="x",ylab="y",cex=.5)
lines(x,f)  ## the true function
lines(x,b$fitted.values,col=2)  ## mixed constrained fit
lines(x,b1$fitted.values,col=3)  ## unconstrained fit

## numeric 'by' variable example...
set.seed(3)
n <- 100
x <- sort(runif(n)*99+1)
f <- log(x)/2
z <- runif(n,-2,3)
y <- f*z + rnorm(n)*0.3
dat <- data.frame(x=x,z=z,y=y)
b <- scam(y~s(x,k=15,by=z,bs="micvBy")-1,data=dat)
summary(b)
par(mfrow=c(1,2))
plot(b,shade=TRUE)
## unconstrained fit...
b1 <- scam(y~s(x,k=15,by=z)-1,data=dat)
plot(b1,shade=TRUE)
summary(b1)

## End(Not run)
```
Usage

## S3 method for class 'micx.smooth.spec'
smooth.construct(object, data, knots)

## S3 method for class 'micBy.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object  A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the data required by this term, with names given by object$term. The by variable is the last element.
knots An optional list containing the knots supplied for basis setup. If it is NULL then the knot locations are generated automatically.

Value

An object of class "micx.smooth", "micBy.smooth".

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also


Examples

## Not run:
## Monotone increasing and convex SCOP-splines example
## simulating data...
set.seed(1)
n <- 100
x <- runif(n)*2
f <- 5*x^2/8
y <- rpois(n,exp(f))
dat <- data.frame(x=x,y=y)
## fit model ...
b <- scam(y=s(x,bs="micx"),family=poisson(link="log"), data=dat)
## fit unconstrained model ...
b1 <- scam(y~s(x,bs="cr"),family=poisson(link="log"),
data=dat)

## plot results ....
plot(x,y,xlab="x",ylab="y",cex=.5)
x1 <- sort(x,index=TRUE)
lines(x1$x,exp(f)[x1$ix])  ## the true function
lines(x1$x,b$fitted.values[x1$ix],col=2)  ## mixed constrained fit
lines(x1$x,b1$fitted.values[x1$ix],col=3)  ## unconstrained fit

## numeric 'by' variable example...
set.seed(10)
n <- 100
x <- runif(n)*2
f <- x^2
z <- runif(n,-2,3)
y <- f*z + rnorm(n)*0.4
dat <- data.frame(x=x,z=z,y=y)
b <- scam(y~s(x,by=z,bs="micxBy"),data=dat)
summary(b)
par(mfrow=c(1,2))
plot(b,shade=TRUE)

## unconstrained fit...
b1 <- scam(y~s(x,by=z),data=dat)
plot(b1,shade=TRUE)
summary(b1)

## End(Not run)
Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the data required by this term, with names given by object$term. The by variable is the last element.
knots An optional list containing the knots supplied for basis setup. If it is NULL then the knot locations are generated automatically.

Details

The constructor is not called directly, but as with gam(mgcv) is used internally.

A ‘finish at zero’ constraint is achieved by setting the last (m+1) spline coefficients to zero. According to the B-spline basis functions properties, the value of the spline, f(x), is determined by m+2 non-zero basis functions, and only m+1 B-splines are non-zero at knots. Only m+2 B-splines are non-zero on any [k_i, k_{i+1}], and the sum of these m+2 basis functions is 1.

If the knots of the spline are not supplied, then they are placed evenly throughout the covariate values with an exception of the m inner knots preceding the last inner knot that are joined with that last knot. This is done in order to avoid an otherwise plateau fit at the right-end region. If the knots are supplied, then the number of supplied knots should be k+m+2, and the range of the middle k-m knots must include all the covariate values.

Note: when a plateau region is expected at the right-end covariate region, the smooth might result in some decrease when approaching to zero.

Value

An object of class “mifo.smooth”.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

smooth.construct.miso.smooth.spec

Examples

```r
## Monotone increasing SCOP-spline examples with a finish at zero constraint...
set.seed(53)
n <- 100;x <- runif(n);z <- runif(n)
pc <- max(x)
y <- exp(3*x)/10-exp(3*pc)/10 + z*(1-z)*5 + rnorm(100)*.4
m1 <- scam(y~s(x,bs="miso") + s(z)) #,knots=knots)
plot(m1,pages=1,scale=0)
summary(m1)
newd<- data.frame(x=pc,z=0)
predict(m1,newd, type='terms')
```

smooth.construct.miso.smooth.spec

Constructor for monotone increasing SCOP-splines with an additional 'start at zero' constraint

Description

This is a special method function for creating smooths subject to a monotone increasing constraint plus the smooths should pass through zero at the left-end point of the covariate range. This is similar to the `pc` argument to `s` in `mgcv(gam)` when `pc=min(x)`, where x is a covariate. The smooth is built by the `mgcv` constructor function for smooth terms, `smooth.construct`. 'Zero intercept' identifiability constraints used for univariate SCOP-splines are substituted with a 'start at zero' constraint here. This smooth is specified via model terms such as `s(x,k,bs="miso",m=2)`, where k denotes the basis dimension and m+1 is the order of the B-spline basis.

Usage

```r
## S3 method for class 'miso.smooth.spec'
smooth.construct(object, data, knots)
```

Arguments

- **object**: A smooth specification object, generated by an `s` term in a GAM formula.
- **data**: A data frame or list containing the data required by this term, with names given by `object$term`. The `by` variable is the last element.
- **knots**: An optional list containing the knots supplied for basis setup. If it is `NULL` then the knot locations are generated automatically.
smooth.construct.miso.smooth.spec

Details

The constructor is not called directly, but as with gam(mgcv) is used internally.

A 'start at zero' constraint is achieved by setting the first \((m+1)\) spline coefficients to zero. According to the B-spline basis functions properties, the value of the spline, f(x), is determined by \(m+2\) non-zero basis functions, and only \(m+1\) B-splines are non-zero at knots. Only \(m+2\) B-splines are non-zero on any \([k_i, k_{i+1})\), and the sum of these \(m+2\) basis functions is 1.

If the knots of the spline are not supplied, then they are placed evenly throughout the covariate values with an exception of the \(m\) inner knots following the first inner knot that are joined with that first knot. This is done in order to avoid an otherwise plateau fit at the left-end region. If the knots are supplied, then the number of supplied knots should be \(k+m+2\), and the range of the middle \(k-m\) knots must include all the covariate values.

Value

An object of class "miso.smooth".

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also


Examples

```r
## Monotone increasing SCOP-spline examples with a start at zero constraint...
## passing through 0 at -1...
require(scan)
set.seed(7)
n <- 100;
x <- c(-1,runif(n-1)*4-1);  # starting at -1 for a function to be zero at a start
z <- runif(n)
y <- exp(4*x)/(1+exp(4*x)) -0.01798621+ z*(1-z)*5 + rnorm(100)*.4
m1 <- scam(y~s(x,bs='miso')+s(z))
plot(m1,pages=1)
newd<- data.frame(x=-1,z=0)
predict(m1,newd, type='terms')
```
## Not run:
### passing through 0 at 0...

```r
set.seed(53)
n <- 100;
x <- c(0,runif(n-1)); ## starting at 0 for a function to be zero at a start
z <- runif(n)
y <- exp(3*x)/10-.1 + z*(1-z)*5 + rnorm(100)*.4
m2 <- scam(y~s(x,bs='miso')+s(z))
plot(m2,pages=1)
newd<- data.frame(x=0,z=0)
predict(m2,newd, type='terms')
```

## End(Not run)

---

smooth.construct.mpd.smooth.spec

**Constructor for monotone decreasing P-splines in SCAMs**

### Description

This is a special method function for creating smooths subject to monotone decreasing constraints which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using monotonic P-splines. This smooth is specified via model terms such as `s(x,k,bs="mpd",m=2)`, where `k` denotes the basis dimension and `m+1` is the order of the B-spline basis.

`mpdBy.smooth.spec` works similar to `mpd.smooth.spec` but without applying an identifiability constraint (`'zero intercept' constraint). `mpdBy.smooth.spec` should be used when the smooth term has a numeric by variable that takes more than one value. In such cases, the smooth terms are fully identifiable without a `'zero intercept' constraint, so they are left unconstrained. This smooth is specified as `s(x,by=z,bs="mpdBy")`. See an example below.

However a factor by variable requires identifiability constraints, so `s(x,by=fac,bs="mpd")` is used in this case.

### Usage

```r
## S3 method for class 'mpd.smooth.spec'
smooth.construct(object, data, knots)
## S3 method for class 'mpdBy.smooth.spec'
smooth.construct(object, data, knots)
```

### Arguments

- **object**
  A smooth specification object, generated by an `s` term in a GAM formula.

- **data**
  A data frame or list containing the data required by this term, with names given by `object$term`. The by variable is the last element.

- **knots**
  An optional list containing the knots supplied for basis setup. If it is NULL then the knot locations are generated automatically.
**Value**

An object of class "mpd.smooth", "mpdBy.smooth".

**Author(s)**

Natalya Pya <nat.pya@gmail.com>

**References**


**See Also**


**Examples**

```r
## Not run:
## Monotone decreasing SCOP-splines example...
## simulating data...
require(scam)
set.seed(3)
n <- 100
x <- runif(n)*3-1
f <- exp(-1.3*x)
y <- rpois(n,exp(f))
dat <- data.frame(x=x, y=y)
## fit model...
b <- scam(y~s(x,k=15,bs="mpd"),family=poisson(link="log"),
data=dat)
## unconstrained model fit for comparison...
b1 <- scam(y~s(x,k=15,bs="ps"),family=poisson(link="log"),
data=dat)
## plot results...
plot(x,y,xlab="x",ylab="y",cex=.5)
x1 <- sort(x,index=TRUE)
lines(x1$x,exp(f)[x1$ix])  ## the true function
lines(x1$x,b$fitted.values[x1$ix],col=2)  ## decreasing fit
lines(x1$x,b1$fitted.values[x1$ix],col=3)  ## unconstrained fit
## 'by' factor example...
set.seed(3)
n <- 400
x <- runif(n, 0, 1)
## all three smooths are decreasing...
f1 <- -log(x *5)
```
f2 <- -exp(2 * x) + 4
f3 <- -5 * sin(x)
e <- rnorm(n, 0, 2)
fac.1 <- as.numeric(fac==1)
fac.2 <- as.numeric(fac==2)
fac.3 <- as.numeric(fac==3)
y <- f1*fac.1 + f2*fac.2 + f3*fac.3 + e
dat <- data.frame(y=y,x=x,fac=fac,f1=f1,f2=f2,f3=f3)
b2 <- scam(y ~ fac+s(x,by=fac,bs="mpd"),data=dat)
summary(b2)
vis.scam(b2,theta=120,color="terrain",cond=list(z=1))

## comparing with unconstrained fit...
b3 <- scam(y ~ fac+s(x,by=fac),data=dat)
x11()
plot(b3,pages=1,shade=TRUE)
summary(b3)

## Note that in mgcv::gam() when using factor 'by' variables, 'centering'
## constraints are applied to the smooths, which usually means that the 'by'
## factor variable should be included as a parametric term, as well.
## The difference with scam() is that here a 'zero intercept' constraint is
## applied in place of 'centering' (although scam’s fitted smooths are centred for plotting).
## compare with a fit of the model without 'fac' parametric term...
b4 <- scam(y ~ s(x,by=fac,bs="mpd"),data=dat)
summary(b4)
summary(b2)

## 'by' variable example...
set.seed(3)
n <- 100
x <- sort(runif(n,-1,2))
z <- runif(n,-2,3)
f <- exp(-1.3*x)
y <- f*x + rnorm(n)*0.4
dat <- data.frame(x=x,y=y,z=z)
b <- scam(y~s(x,k=15,by=z,bs="mpdBy"),data=dat,optimizer="efs")
plot(b,shade=TRUE)
summary(b)

## unconstrained fit...
b1 <- scam(y=s(x,k=15,by=z),data=dat)
plot(b1,shade=TRUE)
summary(b1)

## End(Not run)
smooth.construct.mpi.smooth.spec

Constructor for monotone increasing P-splines in SCAMs

Description

This is a special method function for creating smooths subject to a monotone increasing constraint which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using monotonic P-splines. This smooth is specified via model terms such as \( s(x, k, bs=\text{"mpi"}, m=2) \), where \( k \) denotes the basis dimension and \( m+1 \) is the order of the B-spline basis.

mpiBy.smooth.spec works similar to mpi.smooth.spec but without applying an identifiability constraint (‘zero intercept’ constraint). mpiBy.smooth.spec should be used when the smooth term has a numeric by variable that takes more than one value. In such cases, the smooth terms are fully identifiable without a ‘zero intercept’ constraint, so they are left unconstrained. This smooth is specified as \( s(x, by=z, bs=\text{"mpiBy"}) \). See an example below.

However a factor by variable requires identifiability constraints, so \( s(x, by=fac, bs=\text{"mpi"}) \) is used in this case.

Usage

```r
## S3 method for class 'mpi.smooth.spec'
smooth.construct(object, data, knots)
## S3 method for class 'mpiBy.smooth.spec'
smooth.construct(object, data, knots)
```

Arguments

- `object` A smooth specification object, generated by an \( s \) term in a GAM formula.
- `data` A data frame or list containing the data required by this term, with names given by `object$term`. The by variable is the last element.
- `knots` An optional list containing the knots supplied for basis setup. If it is `NULL` then the knot locations are generated automatically.

Details

The constructor is not called directly, but as with `gam(mgcv)` is used internally.

If the knots of the spline are not supplied, then they are placed evenly throughout the covariate values. If the knots are supplied, then the number of supplied knots should be \( k+m+2 \), and the range of the middle \( k-m \) knots must include all the covariate values.

Value

An object of class "mpi.smooth", "mpiBy.smooth".

Author(s)

Natalya Pya <nat.pya@gmail.com>
References


See Also

Examples

```
## Monotone increasing P-splines example
## simulating data...
require(scam)
set.seed(12)
n <- 100
x <- runif(n)*4-1
f <- 4*exp(4*x)/(1+exp(4*x))
y <- rpois(n,exp(f))
dat <- data.frame(x=x,y=y)
## fit model ...
b <- scam(y~s(x,k=15,bs="mpi"),family=poisson(link="log"), data=dat)
## fit unconstrained model...
b1 <- scam(y~s(x,k=15,bs="ps"),family=poisson(link="log"), data=dat)
## plot results ...
plot(x,y,xlab="x",ylab="y")
x1 <- sort(x,index=TRUE)
lines(x1$x,exp(f)[x1$ix])  ## the true function
lines(x1$x,b$fitted.values[x1$ix],col=2)  ## monotone fit
lines(x1$x,b1$fitted.values[x1$ix],col=3)  ## unconstrained fit
## example with supplied knots...
knots <- list(x=c (-1.5, -1.2, -0.99, -0.97, -0.7, -0.5, -0.3, 0, 0.7, 0.9, 1.1, 1.22, 1.5, 2.2, 2.7, 2.93, 2.99, 3.2, 3.6))
b2 <- scam(y~s(x,k=15,bs="mpi"),knots=knots, family=poisson(link="log"), data=dat)
summary(b2)
plot(b2,shade=TRUE)
## Not run:
## example with two terms...
set.seed(0)
n <- 200
x1 <- runif(n)*6-3
f1 <- 3*exp(-x1^2)  # unconstrained term
```
x2 <- runif(n)*4-1;
f2 <- exp(4*x2)/(1+exp(4*x2)) # monotone increasing smooth
f <- f1+f2
y <- f+rnorm(n)*.7
data <- data.frame(x1=x1,x2=x2,y=y)
knots <- list(x1=c(-4,-3.5,-2.99,-2.7,-2.5,-1.9,-1.1,-.9,-.3,0.3,.8,1.2,1.9,2.3,
2.7,2.99,3.5,4,1,4.5), x2=c(-1.5,-1.2,-1.1,-.89,-.69,-.5,-.3,0,.7,
0.9,1,1.2,1.5,1.7,2.2,2.77,2.99,3.1,3.2,3.6))
b3 <- scam(y~s(x1,k=15)+s(x2,bs="mpi", k=15),
  knots=knots,data=data)
save(b3)
plot(b3,pages=1,shade=TRUE)
## setting knots for f(x2) only...
knots <- list(x2=c(-1.5,-1.2,-1.1,-.89,-.69,-.5,-.3,
  0,0.7,0.9,1,1.1,1.2,1.5,2.2,2.77,2.99,3.1,3.2,3.6))
b4 <- scam(y~s(x1,k=15)+s(x2,bs="bs") + s(x2,bs="mpi", k=15),
  knots=knots,data=data)
save(b4)
plot(b4,pages=1,shade=TRUE)

## 'by' factor example...
scale.seed(2)
n <- 400
x <- runif(n, 0, 1)
## all three smooths are increasing...
f1 <- log(x * 5)
f2 <- exp(2*x) - 4
f3 <- 5*sin(x)
e <- rnorm(n, 0, 2)
factor <- as.factor(sample(1:3, n, replace=TRUE))
factor.1 <- as.numeric(factor==1)
factor.2 <- as.numeric(factor==2)
factor.3 <- as.numeric(factor==3)
y <- f1*factor.1 + f2*factor.2 + f3*factor.3 + e
data <- data.frame(y=y, x=x, fac=factor, f1=f1, f2=f2, f3=f3)
b5 <- scam(y ~ fac+s(x,by=fac,bs="mpi"), data=data)
plot(b5,pages=1, scale=0, shade=TRUE)
save(b5)
vis.scam(b5,theta=50,color="terrain", cond=list(z=1))

## comparing with unconstrained fit...
b6 <- scam(y ~ fac+s(x,by=fac),data=data)
x11()
plot(b6,pages=1, scale=0, shade=TRUE)
save(b6)

## Note that in mgcv::gam() when using factor 'by' variables, 'centering'
## constraints are applied to the smooths, which usually means that the 'by'
## factor variable should be included as a parametric term, as well.
## The difference with scam() is that here a 'zero intercept' constraint is
## applied in place of 'centering' (although scam's fitted smooths are centred for plotting).
## Compare with a fit of the model without 'fac' parametric term...
b7 <- scam(y ~ s(x,by=fac,bs="mpi"),data=data)
smooth.construct.po.smooth.spec

Constructor for monotone increasing P-splines in SCAMs

Description

This is a special method function for creating univariate smooths subject to a positivity constraint which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed using monotonic P-splines. This smooth is specified via model terms such as \texttt{s(x, k, bs=’po’, m=2)}, where \texttt{k} denotes the basis dimension and \texttt{m+1} is the order of the B-spline basis.

Note: Models that include this smooth should not have an intercept. See examples below.

Usage

\texttt{## S3 method for class ‘po.smooth.spec’
smooth.construct(object, data, knots)}

Arguments

\texttt{object} \hspace{1cm} A smooth specification object, generated by an \texttt{s} term in a GAM formula.
\texttt{data} \hspace{1cm} A data frame or list containing the data required by this term, with names given by \texttt{object$term}. The by variable is the last element.
\texttt{knots} \hspace{1cm} An optional list containing the knots supplied for basis setup. If it is \texttt{NULL} then the knot locations are generated automatically.
Value

An object of class "po.smooth".

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also


Examples

## SCOP-splines example with positivity constraint...
## simulating data...
## Not run:
require(scam)
set.seed(3)
n <- 100
x <- seq(-3,3,length.out=n)
f <- dnorm(x)
y <- f + rnorm(n)*0.1
b <- scam(y~s(x,bs="po")-1)

b1 <- scam(y~s(x)) ## unconstrained model
plot(x,y)
lines(x,f)
lines(x,fitted(b),col=2)
lines(x,fitted(b1),col=3)

## two-term example...
set.seed(3)
n <- 200
x1 <- seq(-3,3,length.out=n)
f1 <- 3*exp(-x1^2) ## positively constrained smooth
x2 <- runif(n)*3-1;
f2 <- exp(4*x2)/(1+exp(4*x2)) # monotone increasing smooth
f <- f1+f2
y <- f+rnorm(n)*0.3
dat <- data.frame(x1=x1,x2=x2,y=y)
## fit model, results, and plot...
b2 <- scam(y~s(x1,bs="po") + s(x2,bs="mpi") - 1, data = dat)
summary(b2)
plot(b2, pages = 1)

b3 <- scam(y~s(x1,bs="ps") + s(x2,bs="ps"), data = dat) ## unconstrained model
summary(b3)
plot(b3, pages = 1)

## End(Not run)

smooth.construct.tecvcv.smooth.spec

Tensor product smoothing constructor for bivariate function subject to
double concavity constraint

Description

This is a special method function for creating tensor product bivariate smooths subject to double
concavity constraint, i.e. concavity constraint wrt both the first and the second covariates. This is
built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from
a pair of single penalty marginal smooths which are represented using the B-spline basis functions.
This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="tecvcv",m=c(2,2)),
where q1 and q2 denote the basis dimensions for the marginal smooths.

Usage

## S3 method for class 'tecvcv.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object
A smooth specification object, generated by an s term in a GAM formula.

data
A data frame or list containing the values of the elements of object$term, with
names given by object$term.

knots
An optional list containing the knots corresponding to object$term. If it is
NULL then the knot locations are generated automatically.

Value

An object of class "tecvcv.smooth". In addition to the usual elements of a smooth class docu-
mented under smooth.construct of the mgcv library, this object contains:

p.ident
A vector of 0's and 1's for model parameter identification: 1's indicate param-
ters which will be exponentiated, 0's - otherwise.

Zc
A matrix of identifiability constraints.
Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also


Examples

```r
## Not run:
## tensor product 'tecvcv' example
## simulating data...
set.seed(3)
n <- 30
x1 <- sort(2*runif(n)-1)
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f1[i,j] <- -4*(x1[i]^2+x2[j]^2)
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.05
x11 <- matrix(0,n,n)
x11[1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="tecvcv"), data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b, theta=30,phi=40)
## plotting the truth...
x11()
x1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n) f1[i,j] <- -4*(x1[i]^2+x2[j]^2)
persp(x1,x2,f1,theta = 30, phi = 40)
## End(Not run)
```
Tensor product smoothing constructor for bivariate function subject to mixed constraints: convexity constraint wrt the first covariate and concavity wrt the second one

Description

This is a special method function for creating tensor product bivariate smooths subject to mixed constraints, convexity constraint wrt the first covariate and concavity wrt the second one. This is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths which are represented using the B-spline basis functions. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="tecxcv",m=c(2,2)), where q1 and q2 denote the basis dimensions for the marginal smooths.

Usage

## S3 method for class 'tecxv.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the values of the elements of object$term, with names given by object$term.
knots An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class "tecxv.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

p.ident A vector of 0's and 1's for model parameter identification: 1's indicate parameters which will be exponentiated, 0's - otherwise.
Zc A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References

smooth.construct.tecxcx.smooth.spec

See Also


Examples

```r
## Not run:
## tensor product teccv example
## simulating data...
set.seed(5)
n <- 30
x1 <- sort(2*runif(n)-1)
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
    f1[i,j] <- 2*x1[i]^2 - 4*x2[j]^2
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.05
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x11 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="tecxcv"), data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b,theta=30,phi=40)
```

## plotting the truth...

```r
x1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
    f1[i,j] <- 2*x1[i]^2 - 4*x2[j]^2
persp(x1,x2,f1,theta = 30, phi = 40)
```

## End(Not run)

---

smooth.construct.tecxcx.smooth.spec

Tensor product smoothing constructor for bivariate function subject to double convexity constraint
smooth.construct.tecx.x.smooth.spec

Description

This is a special method function for creating tensor product bivariate smooths subject to double convexity constraint, convexity constraint wrt both the first and the second covariates. This is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths which are represented using the B-spline basis functions. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="tecx.x",m=c(2,2)), where q1 and q2 denote the basis dimensions for the marginal smooths.

Usage

## S3 method for class 'tecx.x.smooth.spec'
smooth.construct(object, data, knots)

Arguments

- **object** A smooth specification object, generated by an s term in a GAM formula.
- **data** A data frame or list containing the values of the elements of object$term, with names given by object$term.
- **knots** An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class "tecx.x.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

- **p.ident** A vector of 0’s and 1’s for model parameter identification: 1’s indicate parameters which will be exponentiated, 0’s - otherwise.
- **Zc** A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

Examples

## Not run:
## tensor product 'tecxcx' example
## simulating data...
set.seed(1)

n <- 30
x1 <- sort(2*runif(n)-1)
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  { f1[i,j] <- 2*(x1[i]^2 + x2[j]^2) }
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.05
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="tecxcx"), data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b,theta=20,phi=20)
## plotting the truth...
x11()
x1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n) f1[i,j] <- 2*(x1[i]^2 + x2[j]^2)
persp(x1,x2,f1,theta = 30, phi = 40)

## End(Not run)

**smooth.construct.tedecv.smooth.spec**

Tensor product smoothing constructor for bivariate function subject to mixed constraints: monotone decreasing constraint wrt the first covariate and concavity wrt the second one

**Description**

This is a special method function for creating tensor product bivariate smooths subject to mixed constraints, monotone decreasing constraint wrt the first covariate and concavity wrt the second one,
which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths which are represented using the B-spline basis functions. This tensor product is specified by model terms such as \( s(x_1,x_2,k=c(q_1,q_2),bs="tedecv",m=c(2,2)) \), where \( q_1 \) and \( q_2 \) denote the basis dimensions for the marginal smooths.

Usage

## S3 method for class 'tedecv.smooth.spec'
smooth.construct(object, data, knots)

Arguments

- **object**: A smooth specification object, generated by an \( s \) term in a GAM formula.
- **data**: A data frame or list containing the values of the elements of \( \text{object}\$term \), with names given by \( \text{object}\$term \).
- **knots**: An optional list containing the knots corresponding to \( \text{object}\$term \). If it is NULL then the knot locations are generated automatically.

Value

An object of class "tedecv.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

- **p.ident**: A vector of 0’s and 1’s for model parameter identification: 1’s indicate parameters which will be exponentiated, 0’s - otherwise.
- **Zc**: A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

smooth.construct.tedmd.smooth.spec smooth.construct.temicx.smooth.spec smooth.construct.tedecx.smooth.spec

Examples

## Not run:
## tensor product 'tedecv' example
## simulating data...
set.seed(2)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n) 
    { f1[i,j] <- -exp(4*x1[i])/(1+exp(4*x1[i]))- 4*x2[j]^2 } 

f = as.vector(t(f1)) 
y = f+rnorm(length(f))*0.1 
x11 = matrix(0,n,n) 
x11[,1:n] = x1 
x11 = as.vector(t(x11)) 
x22 = rep(x2,n) 
dat = list(x1=x11,x2=x22,y=y) 

## fit model ... 
b = scam(y=s(x1,x2,k=c(10,10),bs="tedecv",m=2), data=dat) 

## plot results ... 
par(mfrow=c(2,2),mar=c(4,4,2,2)) 
plot(b,se=TRUE) 
plot(b,pers=TRUE,theta = 30, phi = 40) 
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data") 
x11() 
vis.scam(b, theta=30) 

## plotting the truth... 
x11() 
x1 = seq(min(x1),max(x1),length.out=30) 
x2 = seq(min(x2),max(x2),length.out=30) 
f1 = matrix(0,n,n) 
for (i in 1:n) for (j in 1:n) f1[i,j] <- -exp(4*x1[i])/(1+exp(4*x1[i]))- 4*x2[j]^2 
persp(x1,x2,f1,theta = 30, phi = 40) 

## End(Not run)
Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the values of the elements of object$term, with names given by object$term.
knots An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class "tedecx.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

p.ident A vector of 0's and 1's for model parameter identification: 1's indicate parameters which will be exponentiated, 0's - otherwise.
Zc A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

smooth.construct.tedmd.smooth.spec smooth.construct.tedecv.smooth.spec

Examples

```r
## Not run:
## tensor product 'tedecx' example
## simulating data...

set.seed(2)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f1[i,j] <- -exp(4*x1[i])/(1+exp(4*x1[i])) + 2*x2[j]^2
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.05
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
```
b <- scam(y~s(x1,x2,k=c(10,10),bs="tedecx",m=2), not.exp=TRUE, data=dat)
## b1 <- scam(y~s(x1,bs="mpd",m=2)+s(x2,bs="cx",m=2), data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b,theta=20,phi=20)
## plotting the truth...
x11()
#1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n) f1[i,j] <- -exp(4*x1[i])/(1+exp(4*x1[i])) + 2*x2[j]^2
persp(x1,x2,f1,theta = 30, phi = 40)
## End(Not run)

smooth.construct.tedmd.smooth.spec

Tensor product smoothing constructor for bivariate function subject to
double monotone decreasing constraint

Description

This is a special method function for creating tensor product bivariate smooths subject to double
monotone decreasing constraints which is built by the mgcv constructor function for smooth terms,
smooth.construct. It is constructed from a pair of single penalty marginal smooths which are
represented using the B-spline basis functions. This tensor product is specified by model terms such
as s(x1,x2,k=c(q1,q2),bs="tedmd",m=c(2,2)), where q1 and q2 denote the basis dimensions
for the marginal smooths.

Usage

## S3 method for class 'tedmd.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the values of the elements of object$term, with
names given by object$term.
knots An optional list containing the knots corresponding to object$term. If it is
NULL then the knot locations are generated automatically.
Value

An object of class "tedmd.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

- **p.ident**: A vector of 0’s and 1’s for model parameter identification: 1’s indicate parameters which will be exponentiated, 0’s - otherwise.
- **Zc**: A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

smooth.construct.tedmi.smooth.spec

Examples

```r
## Not run:
## tensor product `tedmd' example
## simulating data...
require(scam)
set.seed(2)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(runif(n))
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  { f1[i,j] <- -exp(4*x1[i])/(1+exp(4*x1[i]))-2*exp(x2[j]-0.5)}
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.1
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ... b <- scam(y~s(x1,x2,k=c(10,10),bs="tedmd",m=2),
        family=gaussian(link="identity"), data=dat)
## plot results ... par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 80, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
```
smooth.construct.tedmi.smooth.spec

Tensor product smoothing constructor for bivariate function subject to double monotone increasing constraint

Description

This is a special method function for creating tensor product bivariate smooths subject to double monotone increasing constraints which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths which are represented using the B-spline basis functions. This tensor product is specified by model terms such as \( s(x_1, x_2, k=\text{c}(q_1, q_2), bs=\text{"tedmi"}, m=\text{c}(2, 2)) \), where \( q_1 \) and \( q_2 \) denote the basis dimensions for the marginal smooths.

Usage

## S3 method for class 'tedmi.smooth.spec'
smooth.construct(object, data, knots)

Arguments

- **object**: A smooth specification object, generated by an s term in a GAM formula.
- **data**: A data frame or list containing the values of the elements of \( \text{object}\$\text{term} \), with names given by \( \text{object}\$\text{term} \).
- **knots**: An optional list containing the knots corresponding to \( \text{object}\$\text{term} \). If it is NULL then the knot locations are generated automatically.

Value

An object of class "tedmi.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

- **p.ident**: A vector of 0’s and 1’s for model parameter identification: 1’s indicate parameters which will be exponentiated, 0’s - otherwise.
- **Zc**: A matrix of identifiability constraints.

Author(s)

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References


smooth.construct.temicv.smooth.spec

Tensor product smoothing constructor for bivariate function subject to mixed constraints: monotone increasing constraint wrt the first covariate and concavity wrt the second one

Description

This is a special method function for creating tensor product bivariate smooths subject to mixed constraints, monotone increasing constraint wrt the first covariate and concavity wrt the second one, which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths which are represented using the B-spline basis functions. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="temicv",m=c(2,2)), where q1 and q2 denote the basis dimensions for the marginal smooths.

See Also

smooth.construct.tedmd.smooth.spec

Examples

```r
## Not run:
## tensor product 'tedmi' example
## simulating data...
set.seed(1)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(runif(n))
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  { f1[i,j] <- exp(4*x1[i])/(1+exp(4*x1[i]))+2*exp(x2[j]-0.5)}
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.1
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="tedmi",m=2),family=gaussian, data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
## End(Not run)
```
Usage

## S3 method for class 'temicv.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object       A smooth specification object, generated by an s term in a GAM formula.
data         A data frame or list containing the values of the elements of object$term, with names given by object$term.
knots       An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class "temicv.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

p.ident      A vector of 0’s and 1’s for model parameter identification: 1’s indicate parameters which will be exponentiated, 0’s - otherwise.
Zc            A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

smooth.construct.tedmd.smooth.spec smooth.construct.temicx.smooth.spec

Examples

## Not run:
## tensor product 'temicv' example
## simulating data...
set.seed(4)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f1[i,j] <- exp(4*x1[i])/(1+exp(4*x1[i])) - 4*x2[j]^2
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.1
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="temicv",m=2), data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b, theta=30, phi = 40)
## plotting the truth...
x11()
x1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n) f1[i,j] <- exp(4*x1[i])/(1+exp(4*x1[i])) - 4*x2[j]^2
persp(x1,x2,f1,theta = 30, phi = 40)

## End(Not run)

smooth.construct.temicx.smooth.spec

Tensor product smoothing constructor for bivariate function subject to mixed constraints: monotone increasing constraint wrt the first covariate and convexity wrt the second one

Description

This is a special method function for creating tensor product bivariate smooths subject to mixed constraints, monotone increasing constraint wrt the first covariate and convexity wrt the second one, which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths which are represented using the B-spline basis functions. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="temicx",m=c(2,2)), where q1 and q2 denote the basis dimensions for the marginal smooths.

Usage

## S3 method for class 'temicx.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the values of the elements of object$term, with names given by object$term.
knots An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.
Value

An object of class "temicx.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

pident A vector of 0's and 1's for model parameter identification: 1's indicate parameters which will be exponentiated, 0's - otherwise.
Zc A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

smooth.construct.tedmd.smooth.spec

Examples

## Not run:
## tensor product 'temicx' example
## simulating data...
set.seed(1)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f1[i,j] <- exp(4*x1[i])/(1+exp(4*x1[i])) + 2*x2[j]^2
f <- as.vector(t(f1))
y <- f+rnorm(length(f))*0.1
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="temicx",m=2), data=dat)
## plot results ... 
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b,theta = 30, phi = 40)
## plotting the truth...
x11()}
x1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n) f1[i,j] <- exp(4*x1[i])/(1+exp(4*x1[i])) + 2*x2[j]^2
persp(x1,x2,f1,theta = 30, phi = 40)

## End(Not run)

smooth.construct.tescv.smooth.spec

Tensor product smoothing constructor for a bivariate function concave in the second covariate

Description

This is a special method function for creating tensor product bivariate smooths concave in the second covariate which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="tescv",m=c(2,2)), where the basis for the first marginal smooth is specified in the second element of bs.

Usage

## S3 method for class 'tescv.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the values of the elements of object$term, with names given by object$term.
knots An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class "tescv.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

p.ident A vector of 0's and 1's for model parameter identification: 1's indicate parameters which will be exponentiated, 0's - otherwise.
Zc A matrix of identifiability constraints.

Author(s)

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References


See Also

smooth.construct.temicv.smooth.spec smooth.construct.tedicv.smooth.spec smooth.construct.tedecv.smooth.spec
smooth.construct.tedecx.smooth.spec smooth.construct.tescx.smooth.spec smooth.construct.tescv.smooth.spec

Examples

```r
## Not run:
## tensor product 'tescv' example
## simulating data...
set.seed(5)
n <- 30
x1 <- sort(runif(n))
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f1[i,j] <- sin(2*pi*x1[i]) - 4*x2[j]^2
f1 <- as.vector(t(f1))
f <- (f1-min(f1))/(max(f1)-min(f1))
y <- f+rnorm(length(f))*0.1
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="tescv",m=2),
          family=gaussian(), data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE, theta = 50, phi = 20)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b, theta = 50, phi = 20)
## plotting the truth...
x11()
x1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f1[i,j] <- sin(2*pi*x1[i]) - 4*x2[j]^2
persp(x1,x2,f1,theta = 50, phi = 20)
## End(Not run)
```
smooth.construct.tescx.smooth.spec

 Tensor product smoothing constructor for a bivariate function convex in the second covariate

Description

This is a special method function for creating tensor product bivariate smooths convex in the second covariate which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="tescx",m=c(2,2)), where the basis for the first marginal smooth is specified in the second element of bs.

Usage

## S3 method for class 'tescx.smooth.spec'
smooth.construct(object, data, knots)

Arguments

- **object**: A smooth specification object, generated by an s term in a GAM formula.
- **data**: A data frame or list containing the values of the elements of object$term, with names given by object$term.
- **knots**: An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class "tescx.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

- **p.ident**: A vector of 0's and 1's for model parameter identification: 1's indicate parameters which will be exponentiated, 0's - otherwise.
- **Zc**: A matrix of identifiability constraints.

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

Examples

```r
## Not run:
## tensor product `tescx' example
## simulating data...
set.seed(2)
n <- 30
x1 <- sort(runif(n))
x2 <- sort(2*runif(n)-1)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f1[i,j] <- sin(x1[i]) + 2*x2[j]^2
f1 <- as.vector(t(f1))
f <- (f1-min(f1))/(max(f1)-min(f1))
y <- f+rnorm(length(f))*0.1
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,k=c(10,10),bs="tescx",m=2),
  family=gaussian(), data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE, theta = 50, phi = 20)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
vis.scam(b, theta = 50, phi = 20)
## plotting the truth...
x11()
x1 <- seq(min(x1),max(x1),length.out=30)
x2 <- seq(min(x2),max(x2),length.out=30)
f1 <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n) f1[i,j] <- sin(x1[i]) + 2*x2[j]^2
persp(x1,x2,f1,theta = 50, phi = 20)
## End(Not run)
```

smooth.construct.tesmd1.smooth.spec

Tensor product smoothing constructor for a bivariate function monotone decreasing in the first covariate

Description

This is a special method function for creating tensor product bivariate smooths monotone decreasing in the first covariate which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths. This tensor
product is specified by model terms such as \( s(x_1, x_2, k=q_1, q_2, bs="tesmd1", m=2) \). The default basis for the second marginal smooth is P-spline. Note: currently only cyclic cubic regression spline ("cc") is implemented in addition to P-spline.

Usage

```r
## S3 method for class 'tesmd1.smooth.spec'
smooth.construct(object, data, knots)
```

Arguments

- **object**: A smooth specification object, generated by an \( s \) term in a GAM formula.
- **data**: A data frame or list containing the values of the elements of **object$term**, with names given by **object$term**.
- **knots**: An optional list containing the knots corresponding to **object$term**. If it is NULL then the knot locations are generated automatically.

Value

An object of class "tesmd1.smooth". In addition to the usual elements of a smooth class documented under `smooth.construct` of the `mgcv` library, this object contains:

- **p.ident**: A vector of 0’s and 1’s for model parameter identification: 1’s indicate parameters which will be exponentiated, 0’s - otherwise.
- **Zc**: A matrix of identifiability constraints.
- **margin.bs**: A two letter character string indicating the (penalized) smoothing basis to use for the second unconstrained marginal smooth. (eg "ps" for P-splines).

Author(s)

Natalya Pya <nat.pya@gmail.com>

References


See Also

`smooth.construct.tesmd2.smooth.spec`
Examples

```
## Not run:
## tensor product `tesmd1' example
## simulating data...
require(scam)
set.seed(2)
n <- 30
x1 <- sort(rnorm(n)*4-1); x2 <- sort(rnorm(n))
f <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
    f[i,j] <- -exp(4*x1[i])/(1+exp(4*x1[i]))+2*sin(pi*x2[j])
f <- as.vector(t(f))
y <- f+rnorm(length(f))*2
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,bs="tesmd1",k=10),data=dat)
## plot results ...
par(mfrow=c(2,2),mar=c(4,4,2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
vis.scam(b)
## example with cyclic cubic regression spline along the second covariate...
set.seed(2)
n <- 30
x1 <- sort(rnorm(n)*4-1); x2 <- sort(rnorm(n))
f <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
    f[i,j] <- -exp(4*x1[i])/(1+exp(4*x1[i]))+sin(2*pi*x2[j])
f <- as.vector(t(f))
y <- f+rnorm(length(f))*2
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b1 <- scam(y~s(x1,x2,bs="tesmd1",xt="cc",k=10),data=dat)
## plot results ...
par(mfrow=c(2,2))
plot(b1,se=TRUE)
plot(b1,pers=TRUE,theta = 30, phi = 40)
plot(y,b1$fitted.values,xlab="Simulated data",ylab="Fitted data")
vis.scam(b1)
```

smooth.construct.tesmd2.smooth.spec

Tensor product smoothing constructor for a bivariate function monotone decreasing in the second covariate

Description

This is a special method function for creating tensor product bivariate smooths monotone decreasing in the second covariate which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths. This tensor product is specified by model terms such as \( s(x_1, x_2, k=c(q_1, q_2), bs="tesmd2", m=c(2, 2)) \). The default basis for the first marginal smooth is P-spline. Note: currently only cyclic cubic regression spline ("cc") is implemented in addition to P-spline.

Usage

## S3 method for class 'tesmd2.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an \( s \) term in a GAM formula.
data A data frame or list containing the values of the elements of object$term, with names given by object$term.knots An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class “tesmd2.smooth”. In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

p.ident A vector of 0’s and 1’s for model parameter identification: 1’s indicate parameters which will be exponentiated, 0’s - otherwise.
Zc A matrix of identifiability constraints.
margin.bs A two letter character string indicating the (penalized) smoothing basis to use for the first unconstrained marginal smooth. (eg "ps" for P-splines).

Author(s)

Natalya Pya <nat.pya@gmail.com>
References


See Also

smooth.construct.tesmd1.smooth.spec

Examples

## Not run:
## tensor product `tesmd2' example
## simulating data...
  require(scam)
  set.seed(2)
  n <- 30
  x1 <- sort(runif(n)); x2 <- sort(runif(n)*4-1)
  f <- matrix(0,n,n)
  for (i in 1:n) for (j in 1:n)
    f[i,j] <- 2*sin(pi*x1[i])-exp(4*x2[j])/(1+exp(4*x2[j]))
  f <- as.vector(t(f))
  y <- f+rnorm(length(f))*0.2
  x11 <- matrix(0,n,n)
  x11[,1:n] <- x1
  x11 <- as.vector(t(x11))
  x22 <- rep(x2,n)
  dat <- list(x1=x11,x2=x22,y=y)
  ## fit model ...
  b <- scam(y~s(x1,x2,bs="tesmd2",k=10),data=dat)
  ## plot results ...
  par(mfrow=c(2,2),mar=c(4,4,2,2))
  plot(b,se=TRUE)
  plot(b,pers=TRUE,theta = 30, phi = 40)
  plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
  vis.scam(b,theta = 40, phi = 20)
## example with cyclic cubic regression spline along the 1st covariate...
  set.seed(4)
  n <- 30
  x1 <- sort(runif(n)); x2 <- sort(runif(n)*4-1)
  f <- matrix(0,n,n)
  for (i in 1:n) for (j in 1:n)
    f[i,j] <- sin(2*pi*x1[i])-exp(4*x2[j])/(1+exp(4*x2[j]))
  f <- as.vector(t(f))
  y <- f+rnorm(length(f))*0.2
  x11 <- matrix(0,n,n)
  x11[,1:n] <- x1
  x11 <- as.vector(t(x11))
  x22 <- rep(x2,n)
dat <- list(x1=x11, x2=x22, y=y)
## fit model ...
b1 <- scam(y~s(x1,x2,bs="tesmd2",xt="cc",k=10), data=dat)
## plot results ...
par(mfrow=c(2,2))
plot(b1,se=TRUE)
plot(b1,pers=TRUE,theta = 30, phi = 40)
plot(y,b1$fitted.values,xlab="Simulated data",ylab="Fitted data")
vis.scam(b1,theta=40,phi=20)

## End(Not run)

smooth.construct.tesmi1.smooth.spec

Tensor product smoothing constructor for a bivariate function monotone increasing in the first covariate

Description

This is a special method function for creating tensor product bivariate smooths monotone increasing in the first covariate which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="tesmi1",m=2). The basis for the second marginal smooth can be specified as a two letter character string of the argument xt (eg xt="cc" to specify cyclic cubic regression spline). See example below. The default basis for the second marginal smooth is P-spline. Note: currently only cyclic cubic regression spline is implemented in addition to P-spline.

Usage

## S3 method for class 'tesmi1.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an s term in a GAM formula.
data A data frame or list containing the values of the elements of object$term, with names given by object$term.
knots An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value

An object of class "tesmi1.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

p.ident A vector of 0's and 1's for model parameter identification: 1's indicate parameters which will be exponentiated, 0's - otherwise.
Zc  A matrix of identifiability constraints.

margin.bs  A two letter character string indicating the (penalized) smoothing basis to use for the second unconstrained marginal smooth. (eg "cc" for cyclic cubic regression spline).

Author(s)
Natalya Pya <nat.pya@gmail.com>

References


See Also

smooth.construct.tesmi2.smooth.spec

Examples

## Not run:
## tensor product `tesmi1' example...
## simulating data...
require(scam)
set.seed(2)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(runif(n))
f <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f[i,j] <- exp(4*x1[i])/(1+exp(4*x1[i]))+2*sin(pi*x2[j])
f <- as.vector(t(f))
y <- f+rnorm(length(f))*0.3
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b <- scam(y~s(x1,x2,bs="tesmi1",k=c(10,10)), data=dat)
## plot results ...
par(mfrow=c(2,2))
plot(b,se=TRUE)
plot(b,pers=TRUE,theta = 30, phi = 40)
plot(y,b$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b,theta=40,phi=20)

## example with cyclic cubic regression spline along the second covariate...
set.seed(2)
n <- 30
x1 <- sort(runif(n)*4-1)
x2 <- sort(runif(n))
f <- matrix(0,n,n)
for (i in 1:n) for (j in 1:n)
  f[i,j] <- exp(4*x1[i])/(1+exp(4*x1[i]))+sin(2*pi*x2[j])
f <- as.vector(t(f))
y <- f+rnorm(length(f))*0.2
x11 <- matrix(0,n,n)
x11[,1:n] <- x1
x11 <- as.vector(t(x11))
x22 <- rep(x2,n)
dat <- list(x1=x11,x2=x22,y=y)
## fit model ...
b1 <- scam(y~s(x1,x2,bs="tesmi1",xt="cc",k=10), data=dat)
## plot results ...
par(mfrow=c(2,2))
plot(b1,se=TRUE)
plot(b1,pers=TRUE,theta = 30, phi = 40)
plot(y,b1$fitted.values,xlab="Simulated data",ylab="Fitted data")
x11()
vis.scam(b1,theta=40,phi=20)

## End(Not run)

smooth.construct.tesmi2.smooth.spec

Tensor product smoothing constructor for a bivariate function monotone increasing in the second covariate

Description

This is a special method function for creating tensor product bivariate smooths monotone increasing in the second covariate which is built by the mgcv constructor function for smooth terms, smooth.construct. It is constructed from a pair of single penalty marginal smooths. This tensor product is specified by model terms such as s(x1,x2,k=c(q1,q2),bs="tesmi2",m=c(2,2)). The default basis for the first marginal smooth is P-spline. Note: currently only cyclic cubic regression spline ("cc") is implemented in addition to P-spline.

Usage

## S3 method for class 'tesmi2.smooth.spec'
smooth.construct(object, data, knots)

Arguments

object A smooth specification object, generated by an s term in a GAM formula.
Data frame or list containing the values of the elements of object$term, with names given by object$term.

knots
An optional list containing the knots corresponding to object$term. If it is NULL then the knot locations are generated automatically.

Value
An object of class "tesmi2.smooth". In addition to the usual elements of a smooth class documented under smooth.construct of the mgcv library, this object contains:

p.ident A vector of 0's and 1's for model parameter identification: 1's indicate parameters which will be exponentiated, 0's - otherwise.

Zc A matrix of identifiability constraints.

margin.bs A two letter character string indicating the (penalized) smoothing basis to use for the first unconstrained marginal smooth. (eg "cc" for cyclic cubic regression spline).

Author(s)
Natalya Pya <nat.pya@gmail.com>

References

See Also
smooth.construct.tesmi1.smooth.spec

Examples

## Not run:
## tensor product 'tesmi2' example
## simulating data...
  set.seed(2)
  n <- 30
  x1 <- sort(runif(n)); x2 <- sort(runif(n)*4-1)
  f <- matrix(0,n,n)
  for (i in 1:n) for (j in 1:n)
    f[i,j] <- 2*sin(pi*x1[i]) +exp(4*x2[j])/(1+exp(4*x2[j]))
  f <- as.vector(t(f))
  y <- f+rnorm(length(f))*3
  x11 <- matrix(0,n,n)
  x11[,1:n] <- x1
  x11 <- as.vector(t(x11))
  x22 <- rep(x2,n)
  dat <- list(x1=x11,x2=x22,y=y)
## fit model ...

\[ \text{b} \leftarrow \text{scam}(y \sim s(x_1, x_2, bs=\text{"tesmi2"}, k=c(10, 10)), \text{data=dat}) \]

## plot results ...

\[ \text{par(mfrow=c(2,2),mar=c(4,4,2,2))} \]

\[ \text{plot(b, se=TRUE)} \]

\[ \text{plot(b, pers=TRUE, theta = 50, phi = 20)} \]

\[ \text{plot(y, b$fitted.values, xlab=\"Simulated data\", ylab=\"Fitted data\")} \]

\[ \text{x11()} \]

\[ \text{vis.scam(b, theta=50, phi=20)} \]

## example with cyclic cubic regression spline along the 1st covariate...

\[ \text{set.seed(2)} \]

\[ \text{n} \leftarrow 30 \]

\[ \text{x1} \leftarrow \text{sort(\text{runif(n))}; \text{x2} \leftarrow \text{sort(\text{runif(n)}*4-1)} \]

\[ \text{f} \leftarrow \text{matrix(0, n,n)} \]

\[ \text{for (i in 1:n) for (j in 1:n)} \]

\[ \quad \text{f[i,j] \leftarrow \sin(2*\pi*x1[i])+ exp(4*x2[j])/(1+exp(4*x2[j]))} \]

\[ \text{f} \leftarrow \text{as.vector(t(f))} \]

\[ \text{y} \leftarrow \text{f+rnorm(\text{length(f)})*.3} \]

\[ \text{x11} \leftarrow \text{matrix(0, n,n)} \]

\[ \text{x11[,1:n] \leftarrow x1} \]

\[ \text{x11} \leftarrow \text{as.vector(t(x11))} \]

\[ \text{x22} \leftarrow \text{rep(x2,n)} \]

\[ \text{dat} \leftarrow \text{list(x1=x11, x2=x22, y=y)} \]

## fit model ...

\[ \text{b1} \leftarrow \text{scam}(y \sim s(x_1, x_2, bs=\text{"tesmi2"}, xt=\text{"cc"}, k=10), \text{data=dat}) \]

## plot results ...

\[ \text{par(mfrow=c(2,2))} \]

\[ \text{plot(b1, se=TRUE)} \]

\[ \text{plot(b1, pers=TRUE, theta = 50, phi = 20)} \]

\[ \text{plot(y, b1$fitted.values, xlab=\"Simulated data\", ylab=\"Fitted data\")} \]

\[ \text{vis.scam(b1, theta=40, phi=20)} \]

## End(Not run)

---

**summary.scam**

**Summary for a SCAM fit**

**Description**

Takes a fitted scam object produced by scam() and produces various useful summaries from it. The same code as in `summary.gam` of the mgcv package is used here with slight modifications to accept the exponentiated parameters of the shape constrained smooth terms and the corresponding covariance matrix.

**Usage**

```r
# S3 method for class 'scam'
summary(object, dispersion=NULL, freq=FALSE, ...)
```
### S3 method for class 'summary.scam'

```r
print(x, digits = max(3, getOption("digits") - 3),
      signif.stars = getOption("show.signif.stars"),...)
```

**Arguments**

- `object` a fitted `scam` object as produced by `scam()`.
- `x` a `summary.scam` object produced by `summary.scam()`.
- `dispersion` A known dispersion parameter. NULL to use estimate or default (e.g. 1 for Poisson).
- `freq` By default p-values for individual terms are calculated using the Bayesian estimated covariance matrix of the parameter estimators. If this is set to TRUE then the frequentist covariance matrix of the parameters is used instead.
- `digits` controls number of digits printed in output.
- `signif.stars` Should significance stars be printed alongside output.
- `...` other arguments.

**Value**

`summary.scam` produces the same list of summary information for a fitted `scam` object as in the unconstrained case `summary.gam` except for the last element BFGS termination condition.

- `p.coeff` is an array of estimates of the strictly parametric model coefficients.
- `p.t` is an array of the `p.coeff`’s divided by their standard errors.
- `p.pv` is an array of p-values for the null hypothesis that the corresponding parameter is zero. Calculated with reference to the t distribution with the estimated residual degrees of freedom for the model fit if the dispersion parameter has been estimated, and the standard normal if not.
- `m` The number of smooth terms in the model.
- `chi.sq` An array of test statistics for assessing the significance of model smooth terms. See details.
- `s.pv` An array of approximate p-values for the null hypotheses that each smooth term is zero. Be warned, these are only approximate.
- `se` array of standard error estimates for all parameter estimates.
- `r.sq` The adjusted r-squared for the model. Defined as the proportion of variance explained, where original variance and residual variance are both estimated using unbiased estimators. This quantity can be negative if your model is worse than a one parameter constant model, and can be higher for the smaller of two nested models! Note that proportion null deviance explained is probably more appropriate for non-normal errors.
- `dev.expl` The proportion of the null deviance explained by the model.
- `edf` array of estimated degrees of freedom for the model terms.
- `residual.df` estimated residual degrees of freedom.
- `n` number of data.
summary.scam

gcv       minimized GCV score for the model, if GCV used.
ubre      minimized UBRE score for the model, if UBRE used.
scale     estimated (or given) scale parameter.
family    the family used.
formula   the original scam formula.
dispersion the scale parameter.
pTerms.df the degrees of freedom associated with each parametric term (excluding the constant).
pTerms.chi.sq a Wald statistic for testing the null hypothesis that the each parametric term is zero.
pTerms.pv  p-values associated with the tests that each term is zero. For penalized fits these are approximate. The reference distribution is an appropriate chi-squared when the scale parameter is known, and is based on an F when it is not.
cov.unscaled The estimated covariance matrix of the parameters (or estimators if freq=TRUE), divided by scale parameter.
cov.scaled The estimated covariance matrix of the parameters (estimators if freq=TRUE).
p.table    significance table for parameters
s.table    significance table for smooths
p.Terms    significance table for parametric model terms
BFGS termination condition
the value of the maximum component of the scaled GCV/UBRE gradient used as stopping condition. This value is printed if the termination code of the BFGS optimization process is not ‘1’ (not full convergence) (see bfgs_gcv.ubre for details)

WARNING
The p-values are approximate.

Author(s)
Natalya Pya <nat.pya@gmail.com> based on mgcv by Simon Wood

References

See Also
scam
Examples

```r
## Not run:
## simulating data...
n <- 200
set.seed(1)
x1 <- runif(n)*6-3
f1 <- 3*exp(-x1^2) # unconstrained smooth term
x2 <- runif(n)*4-1;
f2 <- exp(4*x2)/(1+exp(4*x2)) # monotone increasing smooth
x3 <- runif(n)*5;
f3 <- -log(x3)/5 # monotone decreasing smooth
f <- f1+f2+f3
y <- f + rnorm(n)*.3
dat <- data.frame(x1=x1,x2=x2,x3=x3,y=y)
## fit model ...
b <- scam(y~s(x1,k=15,bs="cr",m=2)+s(x2,k=30,bs="mpi",m=2)+s(x3,k=30,bs="mpd",m=2),
data=dat)
summary(b)
plot(b,pages=1,shade=TRUE)
## End(Not run)
```

---

**vis.scam**  
*Visualization of SCAM objects*

**Description**

Produces perspective or contour plot views of scam model predictions. The code is a clone of `vis.gam` of the mgcv package.

**Usage**

```r
vis.scam(x,view=NULL,cond=list(),n.grid=30,too.far=0,col=NA,
color="heat",contour.col=NULL,se=-1,type="link",
plot.type="persp",zlim=NULL,nCol=50,...)
```

**Arguments**

The documentation below is the same as in documentation object `vis.gam`.

- **view**
  - an array containing the names of the two main effect terms to be displayed on the x and y dimensions of the plot. If omitted the first two suitable terms will be used.

- **cond**
  - a named list of the values to use for the other predictor terms (not in `view`). Variables omitted from this list will have the closest observed value to the median for continuous variables, or the most commonly occurring level for factors. Parametric matrix variables have all the entries in each column set to the observed column entry closest to the column median.
n.grid  The number of grid nodes in each direction used for calculating the plotted surface.

too.far  plot grid nodes that are too far from the points defined by the variables given in view can be excluded from the plot. too.far determines what is too far. The grid is scaled into the unit square along with the view variables and then grid nodes more than too.far from the predictor variables are excluded.

col  The colours for the facets of the plot. If this is NA then if se>0 the facets are transparent, otherwise the colour scheme specified in color is used. If col is not NA then it is used as the facet colour.

color  the colour scheme to use for plots when se<=0. One of "topo", "heat", "cm", "terrain", "gray" or "bw". Schemes "gray" and "bw" also modify the colors used when se>0.

contour.col  sets the colour of contours when using plot.type="contour". Default scheme used if NULL.

se  if less than or equal to zero then only the predicted surface is plotted, but if greater than zero, then 3 surfaces are plotted, one at the predicted values minus se standard errors, one at the predicted values and one at the predicted values plus se standard errors.

type  "link" to plot on linear predictor scale and "response" to plot on the response scale.

plot.type  one of "contour" or "persp".

zlim  a two item array giving the lower and upper limits for the z-axis scale. NULL to choose automatically.

nCol  The number of colors to use in color schemes.

...  other options to pass on to persp, image or contour.

Value

Simply produces a plot.

Author(s)

Simon Wood <simon.wood@r-project.org>

See Also

persp, vis.gam, and scam.

Examples

library(scam)

# Example with factor variable
set.seed(0)
fac<-rep(1:4,20)
x <- runif(80)*5;
y <- fac+log(x)/5+rnorm(80)*0.1
vis.scam

```r
fac <- factor(fac)
b <- scam(y~fac+s(x,bs="mpi"))
vis.scam(b,theta=-35,color="heat") # factor example

# Example with "by" variable
z<-rnorm(80)*0.4
y<-as.numeric(fac)+log(x)*z+rnorm(80)*0.1
b<-scam(y~fac+s(x,by=z))
g <- gam(y~fac+s(x,by=z))
vis.scam(b,theta=-35,color="terrain",cond=list(z=1)) # by variable example
vis.scam(b,view=c("z","x"),theta= 65) # plot against by variable
## compare with gam(mgcv)...
vis.gam(g,theta=-35,color="terrain",cond=list(z=1)) # by variable example
vis.gam(g,view=c("z","x"),theta= 65) # plot against by variable

## all three smooths are increasing...
set.seed(2)
n <- 400
x <- runif(n, 0, 1)
f1 <- log(x *5)
f2 <- exp(2 * x) - 4
f3 <- 5* sin(x)
e <- rnorm(n, 0, 2)
fac <- as.factor(sample(1:3,n,replace=TRUE))
fac.1 <- as.numeric(fac==1)
fac.2 <- as.numeric(fac==2)
fac.3 <- as.numeric(fac==3)
y <- f1*fac.1 + f2*fac.2 + f3*fac.3 + e
dat <- data.frame(y=y,x=x,fac=fac,f1=f1,f2=f2,f3=f3)

b1 <- scam(y ~ s(x,by=fac,bs="mpi"),data=dat,optimizer="efs")
plot(b1,pages=1,scale=0,shade=TRUE)
summary(b1)
vis.scam(b1,theta=-40,color="terrain",cond=list(z=1))

## note that the preceding, b1, fit is the same as....

b2 <- scam(y ~ s(x,by=as.numeric(fac==1),bs="mpi") + s(x,by=as.numeric(fac==2),bs="mpi") +
             s(x,by=as.numeric(fac==3),bs="mpi"),data=dat,optimizer="efs")
summary(b2)

## Note that as in gam() when using factor 'by' variables, centering
## constraints are applied to the smooths, which usually means that the 'by'
## variable should be included as a parametric term, as well.
## The difference with scam() is that here a 'zero intercept' constraint is
## applied in place of 'centering' (although scam's fitted smooths are centred for plotting).
## compare with the gam() fits...
g1 <- gam(y ~ fac+s(x,by=fac),data=dat)
g2 <- gam(y ~ s(x,by=fac),data=dat)
summary(g1)
summary(g2)
```
plot(g1, pages=1, scale=0, shade=TRUE)
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