# Package 'wsbackfit'

July 22, 2025

Type Package	
Fitle Weighted Smooth Backfitting for Structured Models	
Version 1.0-5	
Date 2021-04-30	
Imports graphics, stats	
<b>Description</b> Non- and semiparametric regression for generalized additive, partial linear, and varying coefficient models as well as their combinations via smoothed backfitting. Based on Roca-Pardinas J and Sperlich S (2010) <doi:10.1007 s11222-009-9130-2="">; Mammen E, Linton O and Nielsen J (1999) <doi:10.1214 1017939138="" aos="">; Lee YK, Mammen E, Park BU (2012) <doi:10.1214 12-aos1026="">.</doi:10.1214></doi:10.1214></doi:10.1007>	
License GPL	
LazyLoad yes	
<b>Depends</b> R (>= $3.5.0$ )	
NeedsCompilation yes	
Author Javier Roca-Pardinas [aut, cre], Maria Xose Rodriguez-Alvarez [aut], Stefan Sperlich [aut], Alan Miller (FORTRAN code lsq.f90: weighted least-squares module) [ctb]	
Maintainer Javier Roca-Pardinas < roca@uvigo.es>	
Repository CRAN	
<b>Date/Publication</b> 2021-05-04 16:50:02 UTC	
Contents	
wsbackfit-package	2
plot.sback	4
predict.sback	5
print.sback	7
residuals.sback	9 10
	12
	17

2 wsbackfit-package

Index 19

wsbackfit-package

Weighted Smooth Backfitting for Structured Models

#### **Description**

Non- and semiparametric regression for generalized additive, partial linear, and varying coefficient models as well as their combinations. Specifically, the package provides estimation procedures for a large class of regression models common in applied statistics. The regression models belong to the class of the so-called generalized structured models, i.e.,

$$E[Y|X,Z] = G(g_0 + \sum_{j} g_j(X_j)Z_j + Z_k'\beta).$$

Note that, up to identification restrictions specified e.g. in Park and Mammen (2006), several of the  $X_j$  and  $Z_j$  can refer to the same variable. For example, all  $X_j$  may be the same but all  $Z_j$  different.

The estimation procedure is based on smoothed backfitting which to our knowledge is the statistically most efficient existing procedure for this model class. Additional weights allow sampling weights, trimming, or efficient estimation under heteroscedasticity. This package also allows to either set the bandwidths or automatically select them using k-fold cross-validation. The option 'offset' facilitates the application of smooth backfitting on aggregated data.

## Details

Package: wsbackfit Type: Package

Version: 1.0-5 Date: 2021-04-30

License: GPL

#### Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez, Stefan Sperlich

Maintainer: Javier Roca-Pardinas <roca@uvigo.es>

## References

Han, K. and Park B.U. (2018). Smooth backfitting for errors-in-variables additive models. Annals of Statistics, 46, 2216-2250.

Lee, Y.K., Mammen, E. and Park, B.U. (2012). Flexible generalized varying coefficient regression models. The Annals of Statistics, 40(3), 1906-1933.

Mammen, E. and Nielsen, J. (2003). Generalised structured models. Biometrika, 90, 551-566.

infect 3

Mammen, E. Linton, O. and Nielsen, J. (1999). The existence and asymptotic properties of a backfitting projection algorithm under weak conditions. Annals of Statistics, 27 (5), 1443-1490.

Mammen, E. and Park, B.U. (2006). A simple smooth backfitting method for additive models. Annals of Statistics, 34 (5), 2252-2271.

Nielsen. J. and Sperlich, S. (2005). Smooth backfitting in practice. Journal of the Royal Statistical Society, B, 67, 43-61.

Roca-Pardinas, J. and Sperlich, S. (2010). Feasible Estimation in Generalized Structured Models. Statistics and Computing, 20, 367-379.

infect

Postoperative Infection Data.

## **Description**

Data from a prospective study conducted at the University Hospital of Santiago de Compostela (Spain). A total of 2318 patients who underwent surgery at this center between January 1996 and March 1997 were characterized post-operatively, in respect of whether they suffered or not post-operative infection.

#### Usage

```
data(infect)
```

#### **Format**

A data frame with 2318 observations on the following 6 variables.

```
age patient's age.
```

sex patient's sex. Coded as 1 = Man and 2 = Woman.

linf lymphocytes (expressed as relative counts (in %) of the white blood cell count)

gluc plasma glucose concentration (measured in mg/dl)

diab diabetes. Coded as 1 = presence and 2 = absence.

inf variable indicating whether the patient suffered (inf = 1) or not (inf = 0) a post-operative infection.

```
data(infect)
summary(infect)
```

4 plot.sback

## Description

Takes a fitted object produced by sback() and plots the estimates of the nonparametric functions on the scale of their respective covariates, no matter whether a particular nonparametric function is an additive component or a varying coefficient.

## Usage

```
## S3 method for class 'sback'
plot(x, composed = TRUE, ask = TRUE, select = NULL, ...)
```

#### **Arguments**

X	an object of class sback as produced by sback().	
composed	a logical value. If TRUE, the default, the function plots the estimates of the composed (linear plus nonlinear) nonparametric functions (see Details).	
ask	a logical value. If TRUE, the default, the user is asked for confirmation, before a new figure is drawn.	
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 = $2$ .	
	other graphics parameters to pass on to plotting commands.	

#### **Details**

For identifiability purposes, the estimating algorithm implemented in the wsbackfit package decomposes each nonparametric function in two components: a linear (parametric) component and a nonlinear (nonparametric) component. For plotting, the user can choose to plot these components either separately in one graph (composed = FALSE), or to only plot the resulting composed function (composed = TRUE). Also, for the varying coefficient terms, the plots show the estimated surface spanned by  $(g_i, X_i, Z_i)$ .

#### Value

None

#### Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez and Stefan Sperlich

#### See Also

```
sback, summary.sback
```

predict.sback 5

#### **Examples**

```
library(wsbackfit)
# Gaussian Simulated Sample
set.seed(123)
# Define the data generating process
n <- 1000
x1 <- runif(n)*4-2
x2 \leftarrow runif(n)*4-2
x3 <- runif(n)*4-2
x4 <- runif(n)*4-2
x5 <- as.numeric(runif(n)>0.6)
f1 <- 2*sin(2*x1)
f2 <- x2^2
f3 <- 0
f4 <- x4
f5 <- 1.5*x5
mu < -f1 + f2 + f3 + f4 + f5
err <- (0.5 + 0.5*x5)*rnorm(n)
y <- mu + err
df \leftarrow data.frame(x1 = x1, x2 = x2, x3 = x3, x4 = x4, x5 = as.factor(x5), y = y)
# Fit the model with a fixed bandwidth for each covariate
m0 \leftarrow sback(formula = y \sim x5 + sb(x1, h = 0.1) + sb(x2, h = 0.13)
 + sb(x3, h = 0.1) + sb(x4, h = 0.1), kbin = 30, data = df)
plot(m0)
```

predict.sback

Predict method for sback fits

## **Description**

Predicted smooth functions and values based on an sback object

## Usage

```
## S3 method for class 'sback'
predict(object, newdata, newoffset = NULL, ...)
```

## Arguments

object

an object of class sback.

6 predict.sback

newdata a data frame containing the values of the covariates at which predictions are

wanted. If not provided then the predictions correspond to the original data.

newoffset an optional numerical vector containing an a priori known component to be

included in the linear predictor for the predictions (offset associated with the

newdata).

... not yet implemented.

#### Value

A list with the following components:

pdata the original supplied newdata argument.

poffset the original supplied newoffset argument.

coeff a numeric vector with the estimated coefficients. This vector includes both the

parametric effects as well as the coefficients associated with the linear compo-

nent of the nonparametric functions.

peffects matrix with the estimated nonparametric functions (only the nonlinear compo-

nent) for each covariate value in the original supplied newdata.

pfitted.values a numeric vector with the fitted values for the supplied newdata.

#### Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez and Stefan Sperlich

#### See Also

```
sback, summary.sback
```

```
library(wsbackfit)
data(infect)

# Generalized varying coefficient model with binary response
m3 <- sback(formula = inf ~ sb(gluc, h = 10) + sb(gluc, by = linf, h = 10),
    data = infect, family = "binomial", kbin = 15)

summary(m3)

# Plot both linear and non linear
# components of nonparametric functions: composed = FALSE
op <- par(no.readonly = TRUE)
par(mfrow = c(1,3))
plot(m3, composed = FALSE)

# Personalized plots
# First obtain predictions in new data
# Create newdata for prediction
ngrid <- 30</pre>
```

print.sback 7

```
gluc0 \leftarrow seq(50, 190, length = ngrid)
linf0 \leftarrow seq(0, 45, length = ngrid)
df <- expand.grid(gluc = gluc0, linf = linf0)</pre>
m3p <- predict(m3, newdata = df)</pre>
par(mfrow = c(1,2))
ii <- order(df[,"gluc"])</pre>
## Parametric coefficients
names(m3p$coeff)
# Nonlinear components
colnames(m3p$peffects)
# Include the linear component
plot(df[ii,"gluc"], m3p$coeff[["gluc"]]*df[ii,"gluc"] +
  m3p$peffects[ii,"sb(gluc, h = 10)"],
  type = 'l', xlab = "Glucose (mg/dl)", ylab = "f_1(gluc)",
  main = "Nonparametric effect of Glucose")
# Include the linear component
plot(df[ii,"gluc"], m3p$coeff[["gluc:linf"]]*df[ii,"gluc"] +
  m3p\$peffects[ii,"sb(gluc, h = 10, by = linf)"],
  type= 'l', xlab = "Glucose (mg/dl)", ylab = "f_2(gluc)",
  main = "Varying coefficients as a function of Glucose")
# Countour plot of the probability of post-opererational infection
n <- sqrt(nrow(df))</pre>
Z <- matrix(m3p$pfitted.values, n, n)</pre>
filled.contour(z = Z, x = gluc0, y = linf0,
  xlab = "Glucose (mg/dl)", ylab = "Lymphocytes (%)",
  main = "Probability of post-opererational infection")
par(op)
```

print.sback

Print a sback object.

#### **Description**

The default print method for a sback object.

## Usage

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

8 print.sback

## Arguments

x an object of class sback as produced by sback.

... further arguments passed to or from other methods. Not yet implemented.

#### Value

None

#### Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez and Stefan Sperlich

#### See Also

```
sback, summary.sback, plot.sback
```

```
library(wsbackfit)
# Gaussian Simulated Sample
set.seed(123)
# Define the data generating process
n <- 1000
x1 <- runif(n)*4-2
x2 <- runif(n)*4-2
x3 <- runif(n)*4-2
x4 <- runif(n)*4-2
x5 <- as.numeric(runif(n)>0.6)
f1 <- 2*sin(2*x1)
f2 <- x2^2
f3 <- 0
f4 <- x4
f5 <- 1.5*x5
mu < -f1 + f2 + f3 + f4 + f5
err <- (0.5 + 0.5*x5)*rnorm(n)
y <- mu + err
df \leftarrow data.frame(x1 = x1, x2 = x2, x3 = x3, x4 = x4, x5 = as.factor(x5), y = y)
# Fit the model with a fixed bandwidth for each covariate
m0 < - sback(formula = y \sim x5 + sb(x1, h = 0.1) + sb(x2, h = 0.1)
 + sb(x3, h = 0.1) + sb(x4, h = 0.1), kbin = 30, data = df)
m0
```

residuals.sback 9

residuals.sback sback residuals

#### **Description**

Returns residuals for a fitted sback object. Deviance, pearson, working and response residuals are available.

#### Usage

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

## **Arguments**

object an object of class sback as produced by sback.

type the type of residuals which should be returned: "deviance" (default), "pearson",

"working" and "response".

... further arguments passed to or from other methods. Not yet implemented.

#### **Details**

For details see residuals.glm.

#### Value

Numeric vector with the residuals.

## Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez and Stefan Sperlich

#### See Also

```
sback, summary.sback, plot.sback.
```

```
library(wsbackfit)
data(infect)

# Generalized varying coefficient model with binary response
m3 <- sback(formula = inf ~ sb(gluc, h = 10) + sb(gluc, by = linf, h = 10),
    data = infect, family = "binomial", kbin = 15)

summary(m3)

# Deviance</pre>
```

10 sb

```
summary(residuals(m3))
# Pearson
summary(residuals(m3, type = "pearson"))
```

sb

Specify a nonparametric and/or a varying coefficient term in a ws-backfit formula

## Description

Function used to indicate nonparametric terms and varying coefficient terms in a sback formula.

## Usage

```
sb(x1 = NULL, by = NULL, h = -1)
```

## Arguments

x1	the univariate predictor
by	numeric predictor of the same dimension as $x1$ . If present, the coefficients of this predictor depend, nonparametrically, on $x1$ , i.e., a varying coefficient term.
h	bandwidth (on the scale of the predictor) for this term. If h = -1, the bandwidth is automatically selected using k-fold cross-validation (see sback). A value of 0 would indicate a linear fit. By default -1.

#### Value

A list with the following components:

cov character vector with the name(s) of the involved predictor(s).

h numeric value with the specified smoothing parameter.

## Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez and Stefan Sperlich

## See Also

```
sback, summary.sback, plot.sback
```

*sb* 11

```
library(wsbackfit)
set.seed(123)
# Gaussian Simulated Sample
set.seed(123)
# Define the data generating process
n <- 1000
x1 <- runif(n)*4-2
x2 <- runif(n)*4-2
x3 <- runif(n)*4-2
x4 <- runif(n)*4-2
x5 <- as.numeric(runif(n)>0.6)
f1 <- 2*sin(2*x1)
f2 <- x2^2
f3 <- 0
f4 <- x4
f5 <- 1.5*x5
mu < -f1 + f2 + f3 + f4 + f5
err <- (0.5 + 0.5*x5)*rnorm(n)
y <- mu + err
df \leftarrow data.frame(x1 = x1, x2 = x2, x3 = x3, x4 = x4, x5 = as.factor(x5), y = y)
# Fit the model with a fixed bandwidth for each covariate
m0 \leftarrow sback(formula = y \sim x5 + sb(x1, h = 0.1) + sb(x2, h = 0.1)
  + sb(x3, h = 0.1) + sb(x4, h = 0.1), kbin = 30, data = df)
summary(m0)
op <- par(no.readonly = TRUE)</pre>
par(mfrow = c(2,2))
plot(m0)
# Fit the model with the bandwidths selected by k-fold cross-validation.
m1 \leftarrow sback(formula = y \sim x5 + sb(x1, h = -1) + sb(x2, h = -1)
  + sb(x3, h = -1) + sb(x4, h = -1), kbin = 30, bw.grid = seq(0.01, 0.99, length = 30),
  data = df
summary(m1)
par(mfrow = c(2,2))
plot(m1)
par(op)
```

sback

Generalized additive and partially linear models

## **Description**

Main function for fitting generalized structured models by using smooth backfitting.

## Usage

```
sback(formula, data, offset = NULL, weights = NULL,
  kernel = c("Gaussian", "Epanechnikov"),
  bw.grid = seq(0.01, 0.99, length = 30), c.bw.factor = FALSE,
  KfoldCV = 5, kbin = 30,
  family = c("gaussian", "binomial", "poisson"))
```

## **Arguments**

_	
formula	a formula object specifying the model to be fitted (see Details).
data	data frame representing the data and containing all needed variables
offset	an optional numerical vector containing priori known components to be included in the linear predictor during fitting. Default is zero.
weights	an optional numeric vector of 'prior weights' to be used in the fitting process. By default, the weights are set to one.
kernel	a character specifying the kernel function. Implemented are: Gaussian and Epanechnikov. By default 'Gaussian'.
bw.grid	numeric vector; a grid for for searching the bandwidth factor $h_c$ when using cross-validation. The bandwidth for dimension (covariate) $j$ is $h_c\sigma_j$ , with $\sigma_j$ being the standard deviation of $X_j$ (see Details). Default is a sequence of length 30 between 0.01 and 0.99.
c.bw.factor	logical; indicates whether the common factor scheme for bandwidth selection proposed by Han and Park (2018) is performed. If TRUE, and provided the user has specified the (marginal) bandwidths for all nonparametric functions, say $h_j$ , the functions searches for the common factor $c_h$ that minimizes the deviance via (k-fold) cross-validation when the bandwidth used for dimension (covariate) $j$ is $c_h h_j$ . The search is done in an equispaced grid of length 15 between 0.5 and 1.5. The default is FALSE.
KfoldCV	number of cross-validation folds to be used for either (1) automatically selecting the optimal bandwidth (in the sequence given in argument bw.grid) for each nonparametric function; or (2) automatically selecting the optimal common bandwidth factor (see argument c.bw.factor). Default is 5.
kbin	an integer value specifying the number of binning knots. Default is 30.
family	a character specifying the distribution family. Implemented are: Gaussian, Bi-

sian'.

nomial and Poisson. In all cases, the link function is the canonical one (logit for binomial, identity for Gaussian and logarithm for Poisson). By default 'gaus-

#### **Details**

The argument formula corresponds to the model for the conditional mean function, i.e.,

$$E[Y|X,Z] = G(g_0 + \sum_{j} g_j(X_j)Z_j + Z_k'\beta).$$

This formula is similar to that used for the glm function, except that nonparametric functions can be added to the additive predictor by means of function sb. For instance, specification  $y \sim x1 + sb(x2, h = -1)$  assumes a parametric effect of x1 (with x1 either numerical or categorical), and a nonparametric effect of x2. h = -1 indicates that the bandwidth should be selected using k-fold cross-validation. Varying coefficient terms get incorporated similarly. For example,  $y \sim sb(x1, by = x2)$  indicates that the coefficients of x2 depend, nonparametrically, on x1. In this case both, x1 and x2, should be numerical predictors.

With respect to the bandwidths associated with each nonparametric function specified using function sb, the user has two options: a) to specify in the formula the desired bandwidth - on the scale of the predictor - through argument h of function sb (followed or not by the common bandwidth factor scheme proposed by Han and Park (2018); see argument c.bw.factor); or, b) to allow the bandwidths to be automatically and data adaptively selected via cross-validation. In the latter case, the estimation procedure tests each of the bandwidth factors supplied in argument bw.grid, and selects the one that minimizes the deviance via (k-fold) cross-validation. The number k of cross-validation folds is specified through argument KfoldCV, with 5 by default. We note that when using crossvalidation, to ensure that the bandwidths associated with the nonparametric functions are on the scale of the predictors, the finally used bandwidth is  $h_i = h\sigma_i$  with  $\sigma_i$  being the standard deviation of  $X_i$ . That is, before fitting the model, each bandwidth factor h provided in bw. grid is multiplied by the standard deviation of the corresponding predictor. Note that the user has also the possibility to specify the bandwidths for some nonparametric function (through argument h), while letting for the remaining nonparametric functions the procedure select the bandwidths by cross-validation. For these functions, argument h should be set to -1. In this case, the common bandwidth factor scheme proposed by Han and Park (2018) cannot be used as it requires that all bandwidths are specified.

Finally, it is worth noting that for identifiability purposes, the estimating algorithm implemented in the wsbackfit package decomposes each nonparametric function in two components: a linear (parametric) component and a nonlinear (nonparametric) component. Note that it implies that for a varying coefficient term  $\sim$  sb(x1, by = x2), the parametric part includes the linear component associated with x1, as well as the linear interaction between x1 and x2.

#### Value

A list with the following components:

call	the matched call.
formula	the original supplied formula argument.
data	the original supplied data argument.
offset	the original supplied offset argument.
weights	the original supplied weights argument.
kernel	the original supplied kernel argument.
kbin	the original supplied kbin argument.

family the original supplied family argument.

effects matrix with the estimated nonparametric functions (only the nonlinear compo-

nent) for each covariate value in the original supplied data.

fitted.values a numeric vector with the fitted values for the supplied data.

residuals a numeric vector with the deviance residuals for the supplied data.

h a numeric vector of the same length as the number of nonparametric functions,

with the bandwidths actually used in the estimation (scaled. See Details).

coeff a numeric vector with the estimated coefficients. This vector includes both the

parametric effects as well as the coefficients associated with the linear compo-

nent of the nonparametric functions.

err.CV matrix with the cross-validated error (deviance) associated with the sequence of

tested (unscaled) bandwidths. Each line corresponds to a particular bandwidth

(unscaled. See Details).

#### Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez and Stefan Sperlich

#### References

Han, K. and Park B.U. (2018). Smooth backfitting for errors-in-variables additive models. Annals of Statistics, 46, 2216-2250.

#### See Also

```
sb, print.sback, summary.sback, plot.sback
```

```
library(wsbackfit)
# Gaussian Simulated Sample
set.seed(123)
# Define the data generating process
n <- 1000
x1 <- runif(n)*4-2
x2 <- runif(n)*4-2
x3 <- runif(n)*4-2
x4 <- runif(n)*4-2
x5 <- as.numeric(runif(n)>0.6)
f1 <- 2*sin(2*x1)
f2 <- x2^2
f3 <- 0
f4 <- x4
f5 <- 1.5*x5
mu < -f1 + f2 + f3 + f4 + f5
```

```
err <- (0.5 + 0.5*x5)*rnorm(n)
y <- mu + err
df \leftarrow data.frame(x1 = x1, x2 = x2, x3 = x3, x4 = x4, x5 = as.factor(x5), y = y)
# Fit the model with a fixed bandwidth for each covariate
m0 \leftarrow sback(formula = y \sim x5 + sb(x1, h = 0.1) + sb(x2, h = 0.1)
 + sb(x3, h = 0.1) + sb(x4, h = 0.1), kbin = 30, data = df)
summary(m0)
op <- par(no.readonly = TRUE)</pre>
par(mfrow = c(2,2))
plot(m0)
# Fit the model with bandwidths selectec using K-fold cross-validation
m0cv \leftarrow sback(formula = y \sim x5 + sb(x1) + sb(x2)
 + sb(x3) + sb(x4), kbin = 30, bw.grid = seq(0.01, 0.99, length = 30), KfoldCV = 5,
 data = df
summary(m0cv)
par(mfrow = c(2,2))
plot(m0cv)
## End(Not run)
# Estimate Variance as a function of x5 (which is binary)
resid <- y - m0$fitted.values</pre>
sig0 \leftarrow var(resid[x5 == 0])
sig1 \leftarrow var(resid[x5 == 1])
w <- x5/sig1 + (1-x5)/sig0
m1 < - sback(formula = y \sim x5 + sb(x1, h = 0.1) + sb(x2, h = 0.1)
 + sb(x3, h = 0.1) + sb(x4, h = 0.1), weights = w, kbin = 30, data = df)
summary(m1)
par(mfrow = c(2,2))
plot(m1)
# Poisson Simulated Data
set.seed(123)
# Define the data generating process
n <- 1000
x1 <- runif(n,-1,1)</pre>
x2 <- runif(n,-1,1)
eta <- 2 + 3*x1^2 + 5*x2^3
```

```
exposure <- round(runif(n, 50, 500))</pre>
y <- rpois(n, exposure*exp(eta))</pre>
df \leftarrow data.frame(y = y, x1 = x1, x2 = x2)
# Fit the model
m2 \leftarrow sback(formula = y \sim sb(x1, h = 0.1) + sb(x2, h = 0.1),
  data = df, offset = log(exposure),
  kbin = 30, family = "poisson")
summary(m2)
par(mfrow = c(1,2))
plot(m2)
# Dataframe and offset for prediction
n.p <- 100
newoffset <- rep(0, n.p)</pre>
df.pred \leftarrow data.frame(x1 = seq(-1, 1, 1 = n.p), x2 = seq(-1, 1, 1 = n.p))
m2p <- predict(m2, newdata = df.pred, newoffset = newoffset)</pre>
# Postoperative Infection Data
data(infect)
# Generalized varying coefficient model with binary response
m3 <- sback(formula = inf \sim sb(gluc, h = 10) + sb(gluc, by = linf, h = 10),
  data = infect, family = "binomial", kbin = 15)
summary(m3)
# Plot both linear and non linear
# components of nonparametric functions: composed = FALSE
par(mfrow = c(1,3))
plot(m3, composed = FALSE)
# Personalized plots
# First obtain predictions in new data
# Create newdata for prediction
ngrid <- 30
gluc0 <- seq(50, 190, length = ngrid)</pre>
linf0 \leftarrow seq(0, 45, length = ngrid)
df <- expand.grid(gluc = gluc0, linf = linf0)</pre>
m3p <- predict(m3, newdata = df)</pre>
par(mfrow = c(1,2))
ii <- order(df[,"gluc"])</pre>
## Parametric coefficients
names(m3p$coeff)
```

summary.sback 17

```
# Nonlinear components
colnames(m3p$peffects)
# Include the linear component
plot(df[ii,"gluc"], m3p$coeff[["gluc"]]*df[ii,"gluc"] +
 m3p$peffects[ii, "sb(gluc, h = 10)"],
 type = 'l', xlab = "Glucose (mg/dl)", ylab = "f_1(gluc)",
 main = "Nonparametric effect of Glucose")
# Include the linear component
plot(df[ii,"gluc"], m3p$coeff[["gluc:linf"]]*df[ii,"gluc"] +
 m3p$peffects[ii, "sb(gluc, h = 10, by = linf)"],
 type= 'l', xlab = "Glucose (mg/dl)", ylab = "f_2(gluc)",
 main = "Varying coefficients as a function of Glucose")
# Countour plot of the probability of post-opererational infection
n <- sqrt(nrow(df))</pre>
Z <- matrix(m3p$pfitted.values, n, n)</pre>
filled.contour(z = Z, x = gluc0, y = linf0,
 xlab = "Glucose (mg/dl)", ylab = "Lymphocytes (%)",
 main = "Probability of post-opererational infection")
par(op)
```

summary.sback

Summary for a sback fitted object

## **Description**

Takes a fitted object produced by sback() and produces various useful summaries from it.

## Usage

```
## S3 method for class 'sback'
summary(object, ...)
```

#### **Arguments**

```
object an object of class sback as produced by sback().
... other arguments (not implemented)
```

#### Value

An object of class summary. sback with the information needed to print the results.

## Author(s)

Javier Roca-Pardinas, Maria Xose Rodriguez-Alvarez, Stefan Sperlich

18 summary.sback

#### See Also

```
sback, plot.sback
```

```
library(wsbackfit)
set.seed(123)
# Gaussian Simulated Sample
set.seed(123)
# Define the data generating process
n <- 1000
x1 <- runif(n)*4-2
x2 <- runif(n)*4-2
x3 <- runif(n)*4-2
x4 <- runif(n)*4-2
x5 <- as.numeric(runif(n)>0.6)
f1 <- 2*sin(2*x1)
f2 <- x2^2
f3 <- 0
f4 <- x4
f5 <- 1.5*x5
mu < -f1 + f2 + f3 + f4 + f5
err <- (0.5 + 0.5*x5)*rnorm(n)
y <- mu + err
df \leftarrow data.frame(x1 = x1, x2 = x2, x3 = x3, x4 = x4, x5 = as.factor(x5), y = y)
# Fit the model with a fixed bandwidth for each covariate
m0 \leftarrow sback(formula = y \sim x5 + sb(x1, h = 0.1) + sb(x2, h = 0.13)
 + sb(x3, h = 0.1) + sb(x4, h = 0.1), kbin = 30, data = df)
summary(m0)
```

## **Index**

```
* datasets
infect, 3

formula, 12

glm, 13

infect, 3

plot.sback, 4, 8–10, 14, 18

predict.sback, 5

print.sback, 7, 14

residuals.glm, 9

residuals.sback, 9

sb, 10, 13, 14

sback, 4–6, 8–10, 12, 18

summary.sback, 4, 6, 8–10, 14, 17

wsbackfit (wsbackfit-package), 2

wsbackfit-package, 2
```