

Package ‘gss’

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Title General Smoothing Splines

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aids *AIDS Incubation*

Description

A data set collected by Centers for Disease Control and Prevention concerning AIDS patients who were infected with the HIV virus through blood transfusion.

Usage

data(aids)

Format

A data frame containing 295 observations on the following variables.

incu	Time from HIV infection to AIDS diagnosis.
infe	Time from HIV infection to end of data collection (July 1986).
age	Age at time of blood transfusion.

Source

Wang, M.-C. (1989), A semiparametric model for randomly truncated data. *Journal of the American Statistical Association*, **84**, 742–748.

bacteriuria	<i>Treatment of Bacteriuria</i>
-------------	---------------------------------

Description

Bacteriuria patients were randomly assigned to two treatment groups. Weekly binary indicator of bacteriuria was recorded for every patient over 4 to 16 weeks. A total of 72 patients were represented in the data, with 36 each in the two treatment groups.

Usage

```
data(bacteriuria)
```

Format

A data frame containing 820 observations on the following variables.

id	Identification of patients, a factor.
trt	Treatments 1 or 2, a factor.
time	Weeks after randomization.
infect	Binary indicator of bacteriuria (bacteria in urine).

Source

Joe, H. (1997), *Multivariate Models and Dependence Concepts*. London: Chapman and Hall.

References

Gu, C. and Ma, P. (2005), Generalized nonparametric mixed-effect models: computation and smoothing parameter selection. *Journal of Computational and Graphical Statistics*, **14**, 485–504.

buffalo	<i>Buffalo Annual Snowfall</i>
---------	--------------------------------

Description

Annual snowfall accumulations in Buffalo, NY from 1910 to 1973.

Usage

```
data(buffalo)
```

Format

A vector of 63 numerical values.

Source

Scott, D. W. (1985), Average shifted histograms: Effective nonparametric density estimators in several dimensions. *The Annals of Statistics*, **13**, 1024–1040.

cdsscden	<i>Evaluating Conditional PDF, CDF, and Quantiles of Smoothing Spline Conditional Density Estimates</i>
----------	---

Description

Evaluate conditional pdf, cdf, and quantiles of $f(y_1|x, y_2)$ for smoothing spline conditional density estimates $f(y|x)$.

Usage

```
cdsscden(object, y, x, cond, int=NULL)
cpsscden(object, q, x, cond)
cqsscden(object, p, x, cond)
```

Arguments

object	Object of class "sscden" or "sscden1".
x	Data frame of x values on which conditional density $f(y_1 x, y_2)$ is to be evaluated.
y	Data frame or vector of y_1 points on which conditional density $f(y_1 x, y_2)$ is to be evaluated.
cond	One row data frame of conditioning variables y_2 .
q	Vector of points on which cdf is to be evaluated.
p	Vector of probabilities for which quantiles are to be calculated.
int	Vector of normalizing constants.

Details

The arguments x and y are of the same form as the argument newdata in [predict.lm](#), but y in cdsscden can take a vector for 1-D y_1 .

cpsscden and cqsscden naturally only work for 1-D y_1 .

Value

cdssden returns a list object with the following components.

pdf Matrix or vector of conditional pdf $f(y_1|x,y_2)$, with each column corresponding to a distinct x value.

int Vector of normalizing constants.

cpssden and cqssden return a matrix or vector of conditional cdf or quantiles of $f(y_1|x,y_2)$.

Note

If variables other than factors or numerical vectors are involved in y_1 , the normalizing constants can not be computed.

See Also

Fitting function [ssden](#) and [dssden](#).

cdssden	<i>Evaluating Conditional PDF, CDF, and Quantiles of Smoothing Spline Density Estimates</i>
---------	---

Description

Evaluate conditional pdf, cdf, and quantiles for smoothing spline density estimates.

Usage

```
cdssden(object, x, cond, int=NULL)
cpssden(object, q, cond)
cqssden(object, p, cond)
```

Arguments

object	Object of class "ssden".
x	Data frame or vector of points on which conditional density is to be evaluated.
cond	One row data frame of conditioning variables.
int	Normalizing constant.
q	Vector of points on which conditional cdf is to be evaluated.
p	Vector of probabilities for which conditional quantiles are to be calculated.

Details

The argument x in cdssden is of the same form as the argument newdata in [predict.lm](#), but can take a vector for 1-D conditional densities.

cpssden and cqssden naturally only work for 1-D conditional densities of a numerical variable.

Value

cdssden returns a list object with the following components.

pdf Vector of conditional pdf.

int Normalizing constant.

cpsden and cqssden return a vector of conditional cdf or quantiles.

Note

If variables other than factors or numerical vectors are involved in x , the normalizing constant can not be computed.

See Also

Fitting function [ssden](#) and [dssden](#).

clim	<i>Average Temperatures During December 1980 Through February 1981</i>
------	--

Description

Average temperatures at 690 weather stations during December 1980 through February 1981.

Usage

```
data(clim)
```

Format

A data frame containing 690 observations on the following variables.

temp Average temperature, in Celsius.

geog Geographic location (latitude,longitude), in degrees, as a matrix.

Source

This is reformulated from the data frame `climate` in the R package `assist` by Yuedong Wang and Chunlei Ke.

ColoCan	<i>Colorectal Cancer Mortality Rate in Indiana Counties</i>
---------	---

Description

County-wise death counts of colorectal cancer patients in Indiana during years 2000 through 2004.

Usage

```
data(ColoCan)
```

Format

A data frame containing 184 observations on the following variables.

event	Death counts.
pop	Population from Census 2000.
sex	Gender of population.
wrt	Proportion of Whites.
brt	Proportion of Blacks.
ort	Proportion of other minorities.
lat	Latitude.
lon	Longitude.
geog	Geographic location, derived from lat and lon.
scrn	Colorectal cancer screening rate.
name	County name.

Details

geog was generated from lat and lon using the code given in the example section.

Source

Dr. Tonglin Zhang.

References

Zhang, T. and Lin, G. (2009), Cluster detection based on spatial associations and iterated residuals in generalized linear mixed models. *Biometrics*, **65**, 353–360.

Examples

```
## Converting latitude and longitude to x-y coordinates
## The 49th county is Marion, where Indianapolis is located.
## Not run: ltlN2xy <- function(latlon,latlon0) {
  lat <- latlon[,1]*pi/180; lon <- latlon[,2]*pi/180
  lt0 <- latlon0[1]*pi/180; ln0 <- latlon0[2]*pi/180
  x <- cos(lt0)*sin(lon-ln0); y <- sin(lat-lt0)
  cbind(x,y)
}
data(ColoCan)
latlon <- as.matrix(ColoCan[,c("lat", "lon")])
ltln2xy(latlon,latlon[49,])
## Clean up
rm(ltln2xy,ColoCan,latlon)
## End(Not run)
```

dsscden	<i>Evaluating PDF, CDF, and Quantiles of Smoothing Spline Conditional Density Estimates</i>
---------	---

Description

Evaluate pdf, cdf, and quantiles for smoothing spline conditional density estimates.

Usage

```
dsscden(object, y, x)
psscden(object, q, x)
qsscden(object, p, x)
d.ssscden(object, x, y)
d.ssscden1(object, x, y, scale=TRUE)
```

Arguments

object	Object of class "ssscden" or "ssscden1".
x	Data frame of x values on which conditional density $f(y x)$ is to be evaluated.
y	Data frame or vector of points on which conditional density $f(y x)$ is to be evaluated.
q	Vector of points on which cdf is to be evaluated.
p	Vector of probabilities for which quantiles are to be calculated.
scale	Flag indicating whether to use approximate scaling without quadrature.

Details

The arguments x and y are of the same form as the argument newdata in [predict.lm](#), but y in dsscden can take a vector for 1-D responses.

psscden and qsscden naturally only work for 1-D responses.

Value

A matrix or vector of pdf, cdf, or quantiles of $f(y|x)$, with each column corresponding to a distinct x value.

See Also

Fitting function [ssscden](#) and [cdsscden](#).

dssden	<i>Evaluating PDF, CDF, and Quantiles of Smoothing Spline Density Estimates</i>
--------	---

Description

Evaluate pdf, cdf, and quantiles for smoothing spline density estimates.

Usage

```
dssden(object, x)
pssden(object, q)
qssden(object, p)
d.ssden(object, x)
d.ssden1(object, x)
```

Arguments

object	Object of class "ssden".
x	Data frame or vector of points on which density is to be evaluated.
q	Vector of points on which cdf is to be evaluated.
p	Vector of probabilities for which quantiles are to be calculated.

Details

The argument `x` in `dssden` is of the same form as the argument `newdata` in `predict.lm`, but can take a vector for 1-D densities.

`pssden` and `qssden` naturally only work for 1-D densities.

Value

A vector of pdf, cdf, or quantiles.

See Also

Fitting function `ssden` and `cdssden`.

esc *Embryonic Stem Cell from Mouse*

Description

Data concerning mouse embryonic stem cell gene expression and transcription factor association strength.

Usage

data(esc)

Format

A data frame containing 1027 genes with the following variables.

y1	Gene expression after 4 days.
y2	Gene expression after 8 days.
y3	Gene expression after 14 days.
k1f4	Score of TFAS with KLF4.
nanog	Score of TFAS with NANOG.
oct4	Score of TFAS with OCT4.
sox2	Score of TFAS with SOX2.
clusterID	Cluster identification.

References

Cai, J., Xie, D., Fan, Z., Chipperfield, H., Marden, J., Wong, W. H., and Zhong, S. (2010), Modeling co-expression across species for complex traits: insights to the difference of human and mouse embryonic stem cells. *PLoS Computational Biology*, **6**, e1000707.

Ouyang, Z., Zhou, Q., and Wong, W. H. (2009), chip-seq of transcription factors predicts absolute and differential gene expression in embryonic stem cells. *Proceedings of the National Academy of Sciences of USA*, **106**, 21521–21526.

eyetrack *Eyesight Fixation in Eyetracking Experiments*

Description

Eyesight Fixation during some eyetracking experiments in linguistic studies.

Usage

data(eyetrack)

Format

A data frame containing 13891 observations on the following variables.

time	Time, in ms.
color	Binary indicator, 1 if eyesight fixed on target or color competitor, a factor.
object	Binary indicator, 1 if eyesight fixed on target or object competitor, a factor.
id	Identification of homogeneous sessions, a factor.
cnt	Multiplicity count.

Source

Dr. Anouschka Foltz.

References

Gu, C. and Ma, P. (2011), Nonparametric regression with cross-classified responses. Manuscript.

fitted.ssanova	<i>Fitted Values and Residuals from Smoothing Spline ANOVA Fits</i>
----------------	---

Description

Methods for extracting fitted values and residuals from smoothing spline ANOVA fits.

Usage

```
## S3 method for class 'ssanova'
fitted(object, ...)
## S3 method for class 'ssanova'
residuals(object, ...)

## S3 method for class 'gssanova'
fitted(object, ...)
## S3 method for class 'gssanova'
residuals(object, type="working", ...)
```

Arguments

object	Object of class "ssanova" or "gssanova".
type	Type of residuals desired, with two alternatives "working" (default) or "deviance".
...	Ignored.

Details

The fitted values for "gssanova" objects are on the link scale, so are the "working" residuals.

gastric	<i>Gastric Cancer Data</i>
---------	----------------------------

Description

Survival of gastric cancer patients under chemotherapy and chemotherapy-radiotherapy combination.

Usage

```
data(gastric)
```

Format

A data frame containing 90 observations on the following variables.

futime	Follow-up time, in days.
status	Censoring status.
trt	Factor indicating the treatments: 1 – chemotherapy, 2 – combination.

Source

Moreau, T., O’Quigley, J., and Mesbah, M. (1985), A global goodness-of-fit statistic for the proportional hazards model. *Applied Statistics*, **34**, 212-218.

gauss.quad	<i>Generating Gauss-Legendre Quadrature</i>
------------	---

Description

Generate Gauss-Legendre quadratures using the FORTRAN routine gaussq.f found on NETLIB.

Usage

```
gauss.quad(size, interval)
```

Arguments

size	Size of quadrature.
interval	Interval to be covered.

Value

gauss.quad returns a list object with the following components.

pt	Quadrature nodes.
wt	Quadrature weights.

gssanova	<i>Fitting Smoothing Spline ANOVA Models with Non-Gaussian Responses</i>
----------	--

Description

Fit smoothing spline ANOVA models in non-Gaussian regression. The symbolic model specification via formula follows the same rules as in [lm](#) and [glm](#).

Usage

```
gssanova(formula, family, type=NULL, data=list(), weights, subset,
         offset, na.action=na.omit, partial=NULL, alpha=NULL, nu=NULL,
         id.basis=NULL, nbasis=NULL, seed=NULL, random=NULL,
         skip.iter=FALSE)
```

Arguments

formula	Symbolic description of the model to be fit.
family	Description of the error distribution. Supported are exponential families "binomial", "poisson", "Gamma", "inverse.gaussian", and "nbinomial". Also supported are accelerated life model families "weibull", "lognorm", and "loglogis".
type	List specifying the type of spline for each variable. See mkterm for details.
data	Optional data frame containing the variables in the model.
weights	Optional vector of weights to be used in the fitting process.
subset	Optional vector specifying a subset of observations to be used in the fitting process.
offset	Optional offset term with known parameter 1.
na.action	Function which indicates what should happen when the data contain NAs.
partial	Optional symbolic description of parametric terms in partial spline models.
alpha	Tuning parameter defining cross-validation; larger values yield smoother fits. Defaults are alpha=1 for family="binomial" and alpha=1.4 otherwise.
nu	Inverse scale parameter in accelerated life model families. Ignored for exponential families.
id.basis	Index designating selected "knots".
nbasis	Number of "knots" to be selected. Ignored when id.basis is supplied.
seed	Seed for reproducible random selection of "knots". Ignored when id.basis is supplied.
random	Input for parametric random effects in nonparametric mixed-effect models. See mkran for details.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See ssanova for notes on skipping theta iteration.

Details

The model specification via formula is intuitive. For example, $y \sim x1 * x2$ yields a model of the form

$$y = C + f_1(x1) + f_2(x2) + f_{12}(x1, x2) + e$$

with the terms denoted by "1", "x1", "x2", and "x1:x2".

The model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

Only one link is implemented for each family. It is the logit link for "binomial", and the log link for "poisson", and "Gamma". For "nbinomial", the working parameter is the logit of the probability p ; see [NegBinomial](#). For "weibull", "lognorm", and "loglogis", it is the location parameter for the log lifetime.

The selection of smoothing parameters is through direct cross-validation. The cross-validation score used for family="poisson" is taken from density estimation as in Gu and Wang (2003), and those used for other families are derived following the lines of Gu and Xiang (2001).

A subset of the observations are selected as "knots." Unless specified via `id.basis` or `nbasis`, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Value

`gssanova` returns a list object of class `c("gssanova", "ssanova")`.

The method `summary.gssanova` can be used to obtain summaries of the fits. The method `predict.ssanova` can be used to evaluate the fits at arbitrary points along with standard errors, on the link scale. The method `project.gssanova` can be used to calculate the Kullback-Leibler projection for model selection. The methods `residuals.gssanova` and `fitted.gssanova` extract the respective traits from the fits.

Responses

For family="binomial", the response can be specified either as two columns of counts or as a column of sample proportions plus a column of total counts entered through the argument `weights`, as in [glm](#).

For family="nbinomial", the response may be specified as two columns with the second being the known sizes, or simply as a single column with the common unknown size to be estimated through the maximum likelihood.

For family="weibull", "lognorm", or "loglogis", the response consists of three columns, with the first giving the follow-up time, the second the censoring status, and the third the left-truncation time. For data with no truncation, the third column can be omitted.

Note

For simpler models and moderate sample sizes, the exact solution of `gssanova0` can be faster.

The results may vary from run to run. For consistency, specify `id.basis` or `set seed`.

In `gss` versions earlier than 1.0, `gssanova` was under the name `gssanova1`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

Gu, C. and Xiang, D. (2001), Cross validating non Gaussian data: generalized approximate cross validation revisited. *Journal of Computational and Graphical Statistics*, **10**, 581–591.

Gu, C. and Wang, J. (2003), Penalized likelihood density estimation: Direct cross-validation and scalable approximation. *Statistica Sinica*, **13**, 811–826.

Gu, C. (2013), *Smoothing Spline ANOVA Models (2nd Ed)*. New York: Springer-Verlag.

Gu, C. (2014), Smoothing Spline ANOVA Models: R Package gss. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## Fit a cubic smoothing spline logistic regression model
test <- function(x)
  {.3*(1e6*(x^11*(1-x)^6)+1e4*(x^3*(1-x)^10))-2}
x <- (0:100)/100
p <- 1-1/(1+exp(test(x)))
y <- rbinom(x,3,p)
logit.fit <- gssanova(cbind(y,3-y)~x,family="binomial")
## The same fit
logit.fit1 <- gssanova(y/3~x,"binomial",weights=rep(3,101),
  id.basis=logit.fit$id.basis)
## Obtain estimates and standard errors on a grid
est <- predict(logit.fit,data.frame(x=x),se=TRUE)
## Plot the fit and the Bayesian confidence intervals
plot(x,y/3,ylab="p")
lines(x,p,col=1)
lines(x,1-1/(1+exp(est$fit)),col=2)
lines(x,1-1/(1+exp(est$fit+1.96*est$se)),col=3)
lines(x,1-1/(1+exp(est$fit-1.96*est$se)),col=3)

## Fit a mixed-effect logistic model
data(bacteriuria)
bact.fit <- gssanova(infect~trt+time,family="binomial",data=bacteriuria,
  id.basis=(1:820)[bacteriuria$id%in%c(3,38)],random=~1|id)
## Predict fixed effects
predict(bact.fit,data.frame(time=2:16,trt=as.factor(rep(1,15))),se=TRUE)
## Estimated random effects
bact.fit$b

## Clean up
## Not run: rm(test,x,p,y,logit.fit,logit.fit1,est,bacteriuria,bact.fit)
dev.off()
## End(Not run)
```

`gssanova0` *Fitting Smoothing Spline ANOVA Models with Non-Gaussian Responses*

Description

Fit smoothing spline ANOVA models in non-Gaussian regression. The symbolic model specification via formula follows the same rules as in [lm](#) and [glm](#).

Usage

```
gssanova0(formula, family, type=NULL, data=list(), weights, subset,
           offset, na.action=na.omit, partial=NULL, method=NULL,
           varht=1, nu=NULL, prec=1e-7, maxiter=30)
```

```
gssanova1(formula, family, type=NULL, data=list(), weights, subset,
           offset, na.action=na.omit, partial=NULL, method=NULL,
           varht=1, alpha=1.4, nu=NULL, id.basis=NULL, nbasis=NULL,
           seed=NULL, random=NULL, skip.iter=FALSE)
```

Arguments

<code>formula</code>	Symbolic description of the model to be fit.
<code>family</code>	Description of the error distribution. Supported are exponential families "binomial", "poisson", "Gamma", "inverse.gaussian", and "nbinomial". Also supported are accelerated life model families "weibull", "lognorm", and "loglogis".
<code>type</code>	List specifying the type of spline for each variable. See mkterm for details.
<code>data</code>	Optional data frame containing the variables in the model.
<code>weights</code>	Optional vector of weights to be used in the fitting process.
<code>subset</code>	Optional vector specifying a subset of observations to be used in the fitting process.
<code>offset</code>	Optional offset term with known parameter 1.
<code>na.action</code>	Function which indicates what should happen when the data contain NAs.
<code>partial</code>	Optional symbolic description of parametric terms in partial spline models.
<code>method</code>	Score used to drive the performance-oriented iteration. Supported are <code>method="v"</code> for GCV, <code>method="m"</code> for GML, and <code>method="u"</code> for Mallows' CL.
<code>varht</code>	Dispersion parameter needed for <code>method="u"</code> . Ignored when <code>method="v"</code> or <code>method="m"</code> are specified.
<code>nu</code>	Inverse scale parameter in accelerated life model families. Ignored for exponential families.
<code>prec</code>	Precision requirement for the iterations.
<code>maxiter</code>	Maximum number of iterations allowed for performance-oriented iteration, and for inner-loop multiple smoothing parameter selection when applicable.

alpha	Tuning parameter modifying GCV or Mallows' CL.
id.basis	Index designating selected "knots".
nbasis	Number of "knots" to be selected. Ignored when id.basis is supplied.
seed	Seed for reproducible random selection of "knots". Ignored when id.basis is supplied.
random	Input for parametric random effects in nonparametric mixed-effect models. See mkran for details.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See ssanova for notes on skipping theta iteration.

Details

The model specification via `formula` is intuitive. For example, `y~x1*x2` yields a model of the form

$$y = C + f_1(x_1) + f_2(x_2) + f_{12}(x_1, x_2) + e$$

with the terms denoted by "1", "x1", "x2", and "x1:x2".

The model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

Only one link is implemented for each family. It is the logit link for "binomial", and the log link for "poisson", "Gamma", and "inverse.gaussian". For "nbinomial", the working parameter is the logit of the probability p ; see [NegBinomial](#). For "weibull", "lognorm", and "loglogis", it is the location parameter for the log lifetime.

The models are fitted by penalized likelihood method through the performance-oriented iteration as described in the reference. For `family="binomial"`, `"poisson"`, `"nbinomial"`, `"weibull"`, `"lognorm"`, and `"loglogis"`, the score driving the performance-oriented iteration defaults to `method="u"` with `varht=1`. For `family="Gamma"` and `"inverse.gaussian"`, the default is `method="v"`.

`gssanova0` uses the algorithm of [ssanova0](#) for the iterated penalized least squares problems, whereas `gssanova1` uses the algorithm of [ssanova](#).

In `gssanova1`, a subset of the observations are selected as "knots." Unless specified via `id.basis` or `nbasis`, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Value

`gssanova0` returns a list object of class `c("gssanova0", "ssanova0", "gssanova")`.

`gssanova1` returns a list object of class `c("gssanova", "ssanova")`.

The method [summary.gssanova0](#) or [summary.gssanova](#) can be used to obtain summaries of the fits. The method [predict.ssanova0](#) or [predict.ssanova](#) can be used to evaluate the fits at arbitrary points along with standard errors, on the link scale. The methods [residuals.gssanova](#) and [fitted.gssanova](#) extract the respective traits from the fits.

Responses

For family="binomial", the response can be specified either as two columns of counts or as a column of sample proportions plus a column of total counts entered through the argument weights, as in `glm`.

For family="nbinomial", the response may be specified as two columns with the second being the known sizes, or simply as a single column with the common unknown size to be estimated through the maximum likelihood.

For family="weibull", "lognorm", or "loglogis", the response consists of three columns, with the first giving the follow-up time, the second the censoring status, and the third the left-truncation time. For data with no truncation, the third column can be omitted.

Note

The direct cross-validation of `gssanova` can be more effective, and more stable for complex models. For large sample sizes, the approximate solutions of `gssanova1` and `gssanova` can be faster than `gssanova0`.

The results from `gssanova1` may vary from run to run. For consistency, specify `id.basis` or set seed.

The method `project` is not implemented for `gssanova0`, nor is the mixed-effect model support through `mkran`.

In *gss* versions earlier than 1.0, `gssanova0` was under the name `gssanova`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

Gu, C. (1992), Cross-validating non Gaussian data. *Journal of Computational and Graphical Statistics*, **1**, 169-179.

Gu, C. (2013), *Smoothing Spline ANOVA Models (2nd Ed)*. New York: Springer-Verlag.

GU, C. (2014), Smoothing Spline ANOVA Models: R Package *gss*. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## Fit a cubic smoothing spline logistic regression model
test <- function(x)
  {.3*(1e6*(x^11*(1-x)^6)+1e4*(x^3*(1-x)^10))-2}
x <- (0:100)/100
p <- 1-1/(1+exp(test(x)))
y <- rbinom(x,3,p)
logit.fit <- gssanova0(cbind(y,3-y)~x,family="binomial")
## The same fit
logit.fit1 <- gssanova0(y/3~x,"binomial",weights=rep(3,101))
## Obtain estimates and standard errors on a grid
est <- predict(logit.fit,data.frame(x=x),se=TRUE)
```

```
## Plot the fit and the Bayesian confidence intervals
plot(x,y/3,ylab="p")
lines(x,p,col=1)
lines(x,1-1/(1+exp(est$fit)),col=2)
lines(x,1-1/(1+exp(est$fit+1.96*est$se)),col=3)
lines(x,1-1/(1+exp(est$fit-1.96*est$se)),col=3)
## Clean up
## Not run: rm(test,x,p,y,logit.fit,logit.fit1,est)
dev.off()
## End(Not run)
```

hzzrate.sshzd

Evaluating Smoothing Spline Hazard Estimates

Description

Evaluate smoothing spline hazard estimates by sshzd.

Usage

```
hzzrate.sshzd(object, x, se=FALSE, include=c(object$terms$labels,object$lab.p))
hzzcurve.sshzd(object, time, covariates=NULL, se=FALSE)
survexp.sshzd(object, time, covariates=NULL, start=0)
```

Arguments

object	Object of class "sshzd".
x	Data frame or vector of points on which hazard is to be evaluated.
se	Flag indicating if standard errors are required.
include	List of model terms to be included in the evaluation.
time	Vector of time points.
covariates	Vector of covariate values.
start	Optional starting times of the intervals.

Value

For se=FALSE, hzzrate.sshzd returns a vector of hazard evaluations, and hzzcurve.sshzd returns a vector or columns of hazard curve(s) evaluated on time points at the covariates values. For se=TRUE, hzzrate.sshzd and hzzcurve.sshzd return a list consisting of the following components.

fit	Vector or columns of hazard.
se.fit	Vector or columns of standard errors for log hazard.

survexp.sshzd returns a vector or columns of expected survivals based on the cumulative hazards over (start, time) at the covariates values, which in fact are the (conditional) survival probabilities $S(time)/S(start)$.

Note

For left-truncated data, `start` must be at or after the earliest truncation point.

See Also

Fitting function [sshzd](#).

 LakeAcidity

Water Acidity in Lakes

Description

Data extracted from the Eastern Lake Survey of 1984 conducted by the United States Environmental Protection Agency, concerning 112 lakes in the Blue Ridge.

Usage

```
data(LakeAcidity)
```

Format

A data frame containing 112 observations on the following variables.

<code>ph</code>	Surface ph.
<code>cal</code>	Calcium concentration.
<code>lat</code>	Latitude.
<code>lon</code>	Longitude.
<code>geog</code>	Geographic location, derived from <code>lat</code> and <code>lon</code>

Details

`geog` was generated from `lat` and `lon` using the code given in the Example section.

Source

Douglas, A. and Delampady, M. (1990), *Eastern Lake Survey – Phase I: Documentation for the Data Base and the Derived Data sets*. Tech Report 160 (SIMS), Dept. Statistics, University of British Columbia.

References

Gu, C. and Wahba, G. (1993), Semiparametric analysis of variance with tensor product thin plate splines. *Journal of the Royal Statistical Society Ser. B*, **55**, 353–368.

Examples

```
## Converting latitude and longitude to x-y coordinates
## Not run: ltl2xy <- function(latlon, latlon0) {
```

```

lat <- latlon[,1]*pi/180; lon <- latlon[,2]*pi/180
lt0 <- latlon0[1]*pi/180; ln0 <- latlon0[2]*pi/180
x <- cos(lt0)*sin(lon-ln0); y <- sin(lat-lt0)
cbind(x,y)
}
data(LakeAcidity)
latlon <- as.matrix(LakeAcidity[,c("lat", "lon")])
m.lat <- (min(latlon[,1])+max(latlon[,1]))/2
m.lon <- (min(latlon[,2])+max(latlon[,2]))/2
ltn2xy(latlon,c(m.lat,m.lon))
## Clean up
rm(ltn2xy,LakeAcidity,latlon,m.lat,m.lon)
## End(Not run)

```

nlm0

Minimizing Univariate Functions on Finite Intervals

Description

Minimize univariate functions on finite intervals using 3-point quadratic fit, with golden-section safe-guard.

Usage

```
nlm0(fun, range, prec=1e-7)
```

Arguments

fun	Function to be minimized.
range	Interval on which the function to be minimized.
prec	Desired precision of the solution.

Value

nlm0 returns a list object with the following components.

estimate	Minimizer.
minimum	Minimum.
evaluations	Number of function evaluations.

 N02

Air Pollution and Road Traffic

Description

A subset of 500 hourly observations collected by the Norwegian Public Roads Administration at Alnabru in Oslo, Norway, between October 2001 and August 2003.

Usage

data(N02)

Format

A data frame containing 500 observations on the following variables.

no2	Concentration of NO ₂ , on log scale.
cars	Traffic volume of the hour, on log scale.
temp	Temperature 2 meters above ground, in Celsius.
wind	wind speed, meters/second.
temp2	Temperature difference between 25 and 2 meters above ground, in Celsius.
wind2	Wind direction, in degrees between 0 and 360.

Source

Statlib Datasets Archive at <http://lib.stat.cmu.edu/datasets>, contributed by Magne Aldrin.

 nox

NO_x in Engine Exhaust

Description

Data from an experiment in which a single-cylinder engine was run with ethanol to see how the NO_x concentration in the exhaust depended on the compression ratio and the equivalence ratio.

Usage

data(nox)

Format

A data frame containing 88 observations on the following variables.

nox	NO _x concentration in exhaust.
comp	Compression ratio.
equi	Equivalence ratio.

Source

Brinkman, N. D. (1981), Ethanol fuel – a single-cylinder engine study of efficiency and exhaust emissions. *SAE Transactions*, **90**, 1410–1424.

References

Cleveland, W. S. and Devlin, S. J. (1988), Locally weighted regression: An approach to regression analysis by local fitting. *Journal of the American Statistical Association*, **83**, 596–610.

Breiman, L. (1991), The pi method for estimating multivariate functions from noisy data. *Technometrics*, **33**, 125–160.

 ozone

Ozone Concentration in Los Angeles Basin

Description

Daily measurements of ozone concentration and eight meteorological quantities in the Los Angeles basin for 330 days of 1976.

Usage

`data(ozone)`

Format

A data frame containing 330 observations on the following variables.

upo3	Upland ozone concentration, in ppm.
vdht	Vandenberg 500 millibar height, in meters.
wdsp	Wind speed, in miles per hour.
hmdt	Humidity.
sbtp	Sandburg Air Base temperature, in Celsius.
ibht	Inversion base height, in foot.
dpgg	Dagget pressure gradient, in mmHg.
ibtp	Inversion base temperature, in Fahrenheit.
vsty	Visibility, in miles.
day	Calendar day, between 1 and 366.

Source

Unknown.

References

Breiman, L. and Friedman, J. H. (1985), Estimating optimal transformations for multiple regression and correlation. *Journal of the American Statistical Association*, **80**, 580–598.

Hastie, T. and Tibshirani, R. (1990), *Generalized Additive Models*. Chapman and Hall.

penny *Thickness of US Lincoln Pennies*

Description

Thickness of US Lincoln pennies minted during years 1945 through 1989.

Usage

```
data(nox)
```

Format

A data frame containing 90 observations on the following variables.

```
year  Year minted.
mil   Thickness in mils.
```

Source

Scott, D. W. (1992), *Multivariate Density Estimation: Theory, Practice and Visualization*. New York: Wiley.

References

Gu, C. (1995), Smoothing spline density estimation: Conditional distribution, *Statistica Sinica*, **5**, 709–726.

Scott, D. W. (1992), *Multivariate Density Estimation: Theory, Practice and Visualization*. New York: Wiley.

predict.ssanova *Predicting from Smoothing Spline ANOVA Fits*

Description

Evaluate terms in a smoothing spline ANOVA fit at arbitrary points. Standard errors of the terms can be requested for use in constructing Bayesian confidence intervals.

Usage

```
## S3 method for class 'ssanova'
predict(object, newdata, se.fit=FALSE,
        include=c(object$terms$labels,object$lab.p), ...)
## S3 method for class 'ssanova0'
predict(object, newdata, se.fit=FALSE,
```



```

                                include=c(object$terms$labels,object$lab.p), ...)
## S3 method for class 'ssanova'
predict1(object, contr=c(1,-1), newdata, se.fit=TRUE,
                                include=c(object$terms$labels,object$lab.p), ...)

```

Arguments

object	Object of class inheriting from "ssanova".
newdata	Data frame or model frame in which to predict.
se.fit	Flag indicating if standard errors are required.
include	List of model terms to be included in the prediction. The offset term, if present, is to be specified by "offset".
contr	Contrast coefficients.
...	Ignored.

Value

For `se.fit=FALSE`, `predict.ssanova` returns a vector of the evaluated fit.

For `se.fit=TRUE`, `predict.ssanova` returns a list consisting of the following components.

fit	Vector of evaluated fit.
se.fit	Vector of standard errors.

Note

For mixed-effect models through `ssanova` or `gssanova`, the Z matrix is set to 0 if not supplied. To supply the Z matrix, add a component `random=I(...)` in `newdata`, where the as-is function `I(...)` preserves the integrity of the Z matrix in data frame.

`predict1.ssanova` takes a list of data frames in `newdata` representing `x1`, `x2`, etc. By default, it calculates $f(x1)-f(x2)$ along with standard errors. While pairwise contrast is the targeted application, all linear combinations can be computed.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

- Gu, C. (1992), Penalized likelihood regression: a Bayesian analysis. *Statistica Sinica*, **2**, 255–264.
- Gu, C. and Wahba, G. (1993), Smoothing spline ANOVA with component-wise Bayesian "confidence intervals." *Journal of Computational and Graphical Statistics*, **2**, 97–117.
- Kim, Y.-J. and Gu, C. (2004), Smoothing spline Gaussian regression: more scalable computation via efficient approximation. *Journal of the Royal Statistical Society, Ser. B*, **66**, 337–356.

See Also

Fitting functions `ssanova`, `ssanova0`, `gssanova`, `gssanova0` and methods `summary.ssanova`, `summary.gssanova`, `summary.gssanova0`, `project.ssanova`, `fitted.ssanova`.

Examples

```
## THE FOLLOWING EXAMPLE IS TIME-CONSUMING
## Not run:
## Fit a model with cubic and thin-plate marginals, where geog is 2-D
data(LakeAcidity)
fit <- ssanova(ph~log(cal)*geog,,LakeAcidity)
## Obtain estimates and standard errors on a grid
new <- data.frame(cal=1,geog=I(matrix(0,1,2)))
new <- model.frame(~log(cal)+geog,new)
predict(fit,new,se=TRUE)
## Evaluate the geog main effect
predict(fit,new,se=TRUE,inc="geog")
## Evaluate the sum of the geog main effect and the interaction
predict(fit,new,se=TRUE,inc=c("geog","log(cal):geog"))
## Evaluate the geog main effect on a grid
grid <- seq(-.04,.04,len=21)
new <- model.frame(~geog,list(geog=cbind(rep(grid,21),rep(grid,rep(21,21))))))
est <- predict(fit,new,se=TRUE,inc="geog")
## Plot the fit and standard error
par(pty="s")
contour(grid,grid,matrix(est$fit,21,21),col=1)
contour(grid,grid,matrix(est$se,21,21),add=TRUE,col=2)
## Clean up
rm(LakeAcidity,fit,new,grid,est)
dev.off()

## End(Not run)
```

predict.sscx

Evaluating Smoothing Spline ANOVA Estimate of Relative Risk

Description

Evaluate terms in a smoothing spline ANOVA estimate of relative risk at arbitrary points. Standard errors of the terms can be requested for use in constructing Bayesian confidence intervals.

Usage

```
## S3 method for class 'sscox'
predict(object, newdata, se.fit=FALSE,
        include=c(object$terms$labels,object$lab.p), ...)
```

Arguments

object	Object of class "sscox".
newdata	Data frame or model frame in which to predict.
se.fit	Flag indicating if standard errors are required.
include	List of model terms to be included in the prediction.
...	Ignored.

Value

For `se.fit=FALSE`, `predict.sscox` returns a vector of the evaluated relative risk.

For `se.fit=TRUE`, `predict.sscox` returns a list consisting of the following components.

<code>fit</code>	Vector of evaluated relative risk.
<code>se.fit</code>	Vector of standard errors for log relative risk.

Note

For mixed-effect models through `sscox`, the Z matrix is set to 0 if not supplied. To supply the Z matrix, add a component `random=I(...)` in `newdata`, where the as-is function `I(...)` preserves the integrity of the Z matrix in data frame.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

See Also

Fitting functions `sscox` and method `project.sscox`.

predict.sllrm *Evaluating Log-Linear Regression Model Fits*

Description

Evaluate conditional density in a log-linear regression model fit at arbitrary `x`, or contrast of log conditional density possibly with standard errors for constructing Bayesian confidence intervals.

Usage

```
## S3 method for class 'sllrm'
predict(object, x, y=object$qd.pt, odds=NULL, se.odds=FALSE, ...)
```

Arguments

<code>object</code>	Object of class "sllrm".
<code>x</code>	Data frame of x values.
<code>y</code>	Data frame of y values; y-variables must be factors.
<code>odds</code>	Optional coefficients of contrast.
<code>se.odds</code>	Flag indicating if standard errors are required. Ignored when <code>odds=NULL</code> .
<code>...</code>	Ignored.

Value

For `odds=NULL`, `predict.ssanova` returns a vector/matrix of the estimated $f(y|x)$.

When `odds` is given, it should match `y` in length and the coefficients must add to zero; `predict.ssanova` then returns a vector of estimated "odds ratios" if `se.odds=FALSE` or a list consisting of the following components if `se.odds=TRUE`.

<code>fit</code>	Vector of evaluated fit.
<code>se.fit</code>	Vector of standard errors.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

See Also

Fitting function [ssllrm](#).

print

Print Functions for Smoothing Spline ANOVA Models

Description

Print functions for Smoothing Spline ANOVA models.

Usage

```
## S3 method for class 'ssanova'
print(x, ...)
## S3 method for class 'ssanova0'
print(x, ...)
## S3 method for class 'gssanova'
print(x, ...)
## S3 method for class 'ssden'
print(x, ...)
## S3 method for class 'sscden'
print(x, ...)
## S3 method for class 'sshzd'
print(x, ...)
## S3 method for class 'sscox'
print(x, ...)
## S3 method for class 'ssllrm'
print(x, ...)
## S3 method for class 'summary.ssanova'
print(x, digits=6, ...)
## S3 method for class 'summary.gssanova'
print(x, digits=6, ...)
## S3 method for class 'summary.gssanova0'
print(x, digits=6, ...)
```

Arguments

x	Object of class <code>ssanova</code> , <code>summary.ssanova</code> , <code>summary.gssanova</code> , or <code>ssden</code> .
digits	Number of significant digits to be printed in values.
...	Ignored.

See Also

[ssanova](#), [ssanova0](#), [gssanova](#), [gssanova0](#), [ssden](#), [sllrm](#), [sshzd](#), [summary.ssanova](#), [summary.gssanova](#), [summary.gssanova0](#).

 project

Projecting Smoothing Spline ANOVA Fits for Model Diagnostics

Description

Calculate Kullback-Leibler projection of smoothing spline ANOVA fits for model diagnostics.

Usage

```

project(object, ...)
## S3 method for class 'ssanova'
project(object, include, ...)
## S3 method for class 'ssanova9'
project(object, include, ...)
## S3 method for class 'gssanova'
project(object, include, ...)
## S3 method for class 'ssden'
project(object, include, mesh=FALSE, ...)
## S3 method for class 'ssden1'
project(object, include, drop1=FALSE, ...)
## S3 method for class 'sscden'
project(object, include, ...)
## S3 method for class 'sscden1'
project(object, include, ...)
## S3 method for class 'sshzd'
project(object, include, mesh=FALSE, ...)
## S3 method for class 'ssc Cox'
project(object, include, ...)
## S3 method for class 'sshzd1'
project(object, include, ...)
## S3 method for class 'sllrm'
project(object, include, ...)

```

Arguments

object	Object of class "ssanova", "gssanova", "ssden", "ssden1", "sscden", "sscden1", "sshzd", "sshzd1", or "ssl1rm".
...	Additional arguments. Ignored in <code>project.x</code> .
include	List of model terms to be included in the reduced model space. The <code>partial</code> and <code>offset</code> terms, if present, are to be specified by "partial" and "offset", respectively.
mesh	Flag indicating whether to return evaluations of the projection.
drop1	If TRUE, calculate $p < -\text{length}(\text{include})$ projections with <code>include[-i]</code> , $i=1, \dots, p$.

Details

The entropy $KL(\text{fit0}, \text{null})$ can be decomposed as the sum of $KL(\text{fit0}, \text{fit1})$ and $KL(\text{fit1}, \text{null})$, where `fit0` is the fit to be projected, `fit1` is the projection in the reduced model space, and `null` is the constant fit. The ratio $KL(\text{fit0}, \text{fit1})/KL(\text{fit0}, \text{null})$ serves as a diagnostic of the feasibility of the reduced model.

For regression fits, smoothness safe-guard is used to prevent interpolation, and $KL(\text{fit0}, \text{fit1}) + KL(\text{fit1}, \text{null})$ may not match $KL(\text{fit0}, \text{null})$ perfectly.

For mixed-effect models from `ssanova` and `gssanova`, the estimated random effects are treated as offset.

Value

The functions return a list consisting of the following components.

ratio	$KL(\text{fit0}, \text{fit1})/KL(\text{fit0}, \text{null})$; the smaller the value, the more feasible the reduced model is.
k1	$KL(\text{fit0}, \text{fit1})$.

For regression fits, the list also contains the following component.

check	$KL(\text{fit0}, \text{fit1})/KL(\text{fit0}, \text{null}) + KL(\text{fit1}, \text{null})/KL(\text{fit0}, \text{null})$; a value closer to 1 is preferred.
-------	---

For density and hazard fits, the list may contain the following optional component.

mesh	The evaluations of the projection.
------	------------------------------------

Note

`project.ssden1`, `project.sscden1`, and `project.sshzd1` calculates square error projections.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

Gu, C. (2004), Model diagnostics for smoothing spline ANOVA models. *The Canadian Journal of Statistics*, **32**, 347–358.

See Also

Fitting functions [ssanova](#), [gssanova](#), [ssden](#), [sshzd](#), and [sshzd1](#).

 Sachs

Protein Expression in Human Immune System Cells

Description

Data concerning protein expression levels in human immune system cells under stimulations.

Usage

```
data(Sachs)
```

Format

A data frame containing 7466 cells, with flow cytometry measurements of 11 phosphorylated proteins and phospholipids, on the \log_{10} scale of the original.

praf	Raf phosphorylated at S259.
pmek	Mek1/mek2 phosphorylated at S217/S221.
plcg	Phosphorylation of phospholipase <i>C</i> – γ on Y783.
pip2	Phosphatidylinositol 4,5-biphosphate.
pip3	Phosphatidylinositol 3,4,5-triphosphate.
p44.42	Erk1/erk2 phosphorylated at T202/Y204.
pakts473	AKT phosphorylated at S473.
pka	Phosphorylation of of protein kinase A substrates on 3 sites.
pkc	Phosphorylation of of protein kinase C substrates on S660.
p38	Erk1/erk2 phosphorylated at T180/Y182.
pjnk	Erk1/erk2 phosphorylated at T183/Y185.

Source

Sachs, K., Perez, O., Pe'er, D., Lauffenburger, D. A., and Nolan, G. P. (2005), Causal protein-signaling networks derived from multiparameter single-cell data. *Science*, **308** (5732), 523–529.

 smolyak

Generating Smolyak Cubature

Description

Generate delayed Smolyak cubatures using C routines modified from `smolyak.c` found in Knut Petras' SMOLPACK.

Usage

```
smolyak.quad(d, k)
```

```
smolyak.size(d, k)
```

Arguments

d Dimension of unit cube.

k Depth of algorithm.

Value

smolyak.quad returns a list object with the following components.

pt Quadrature nodes in rows of matrix.

wt Quadrature weights.

smolyak.size returns an integer.

 ssanova

Fitting Smoothing Spline ANOVA Models

Description

Fit smoothing spline ANOVA models in Gaussian regression. The symbolic model specification via formula follows the same rules as in [lm](#).

Usage

```
ssanova(formula, type=NULL, data=list(), weights, subset, offset,
         na.action=na.omit, partial=NULL, method="v", alpha=1.4,
         varht=1, id.basis=NULL, nbasis=NULL, seed=NULL, random=NULL,
         skip.iter=FALSE)
```

Arguments

formula Symbolic description of the model to be fit.

type List specifying the type of spline for each variable. See [mkterm](#) for details.

data Optional data frame containing the variables in the model.

weights Optional vector of weights to be used in the fitting process.

subset Optional vector specifying a subset of observations to be used in the fitting process.

offset Optional offset term with known parameter 1.

na.action Function which indicates what should happen when the data contain NAs.

partial Optional symbolic description of parametric terms in partial spline models.

method	Method for smoothing parameter selection. Supported are method="v" for GCV, method="m" for GML (REML), and method="u" for Mallows' CL.
alpha	Parameter modifying GCV or Mallows' CL; larger absolute values yield smoother fits; negative value invokes a stable and more accurate GCV/CL evaluation algorithm but may take two to five times as long. Ignored when method="m" are specified.
varht	External variance estimate needed for method="u". Ignored when method="v" or method="m" are specified.
id.basis	Index designating selected "knots".
nbasis	Number of "knots" to be selected. Ignored when id.basis is supplied.
seed	Seed to be used for the random generation of "knots". Ignored when id.basis is supplied.
random	Input for parametric random effects in nonparametric mixed-effect models. See mkran for details.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See notes on skipping theta iteration.

Details

The model specification via formula is intuitive. For example, $y \sim x_1 * x_2$ yields a model of the form

$$y = C + f_1(x_1) + f_2(x_2) + f_{12}(x_1, x_2) + e$$

with the terms denoted by "1", "x1", "x2", and "x1:x2".

The model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

A subset of the observations are selected as "knots." Unless specified via id.basis or nbasis, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Using q "knots," ssanova calculates an approximate solution to the penalized least squares problem using algorithms of the order $O(nq^2)$, which for $q \ll n$ scale better than the $O(n^3)$ algorithms of [ssanova0](#). For the exact solution, one may set $q = n$ in ssanova, but [ssanova0](#) would be much faster.

Value

ssanova returns a list object of class "ssanova".

The method [summary.ssanova](#) can be used to obtain summaries of the fits. The method [predict.ssanova](#) can be used to evaluate the fits at arbitrary points along with standard errors. The method [project.ssanova](#) can be used to calculate the Kullback-Leibler projection for model selection. The methods [residuals.ssanova](#) and [fitted.ssanova](#) extract the respective traits from the fits.

Skipping Theta Iteration

For the selection of multiple smoothing parameters, `nlm` is used to minimize the selection criterion such as the GCV score. When the number of smoothing parameters is large, the process can be time-consuming due to the great amount of function evaluations involved.

The starting values for the `nlm` iteration are obtained using Algorithm 3.2 in Gu and Wahba (1991). These starting values usually yield good estimates themselves, leaving the subsequent quasi-Newton iteration to pick up the "last 10%" performance with extra effort many times of the initial one. Thus, it is often a good idea to skip the iteration by specifying `skip.iter=TRUE`, especially in high-dimensions and/or with multi-way interactions.

`skip.iter=TRUE` could be made the default in future releases.

Note

To use GCV and Mallows' CL unmodified, set `alpha=1`.

For simpler models and moderate sample sizes, the exact solution of `ssanova0` can be faster.

The results may vary from run to run. For consistency, specify `id.basis` or set `seed`.

In `gss` versions earlier than 1.0, `ssanova` was under the name `ssanova1`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

- Wahba, G. (1990), *Spline Models for Observational Data*. Philadelphia: SIAM.
- Gu, C. and Wahba, G. (1991), Minimizing GCV/GML scores with multiple smoothing parameters via the Newton method. *SIAM Journal on Scientific and Statistical Computing*, **12**, 383–398.
- Kim, Y.-J. and Gu, C. (2004), Smoothing spline Gaussian regression: more scalable computation via efficient approximation. *Journal of the Royal Statistical Society, Ser. B*, **66**, 337–356.
- Gu, C. (2013), *Smoothing Spline ANOVA Models (2nd Ed)*. New York: Springer-Verlag.
- Gu, C. (2014), Smoothing Spline ANOVA Models: R Package `gss`. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## Fit a cubic spline
x <- runif(100); y <- 5 + 3*sin(2*pi*x) + rnorm(x)
cubic.fit <- ssanova(y~x)
## Obtain estimates and standard errors on a grid
new <- data.frame(x=seq(min(x),max(x),len=50))
est <- predict(cubic.fit,new,se=TRUE)
## Plot the fit and the Bayesian confidence intervals
plot(x,y,col=1); lines(new$x,est$fit,col=2)
lines(new$x,est$fit+1.96*est$se,col=3)
lines(new$x,est$fit-1.96*est$se,col=3)
## Clean up
## Not run: rm(x,y,cubic.fit,new,est)
```

```

dev.off()
## End(Not run)

## Fit a tensor product cubic spline
data(nox)
nox.fit <- ssanova(log10(nox)~comp*equi,data=nox)
## Fit a spline with cubic and nominal marginals
nox$comp<-as.factor(nox$comp)
nox.fit.n <- ssanova(log10(nox)~comp*equi,data=nox)
## Fit a spline with cubic and ordinal marginals
nox$comp<-as.ordered(nox$comp)
nox.fit.o <- ssanova(log10(nox)~comp*equi,data=nox)
## Clean up
## Not run: rm(nox,nox.fit,nox.fit.n,nox.fit.o)

```

ssanova0

*Fitting Smoothing Spline ANOVA Models***Description**

Fit smoothing spline ANOVA models in Gaussian regression. The symbolic model specification via formula follows the same rules as in [lm](#).

Usage

```

ssanova0(formula, type=NULL, data=list(), weights, subset,
          offset, na.action=na.omit, partial=NULL, method="v",
          varht=1, prec=1e-7, maxiter=30)

```

Arguments

formula	Symbolic description of the model to be fit.
type	List specifying the type of spline for each variable. See mkterm for details.
data	Optional data frame containing the variables in the model.
weights	Optional vector of weights to be used in the fitting process.
subset	Optional vector specifying a subset of observations to be used in the fitting process.
offset	Optional offset term with known parameter 1.
na.action	Function which indicates what should happen when the data contain NAs.
partial	Optional symbolic description of parametric terms in partial spline models.
method	Method for smoothing parameter selection. Supported are method="v" for GCV, method="m" for GML (REML), and method="u" for Mallows' CL.
varht	External variance estimate needed for method="u". Ignored when method="v" or method="m" are specified.
prec	Precision requirement in the iteration for multiple smoothing parameter selection. Ignored when only one smoothing parameter is involved.
maxiter	Maximum number of iterations allowed for multiple smoothing parameter selection. Ignored when only one smoothing parameter is involved.

Details

The model specification via formula is intuitive. For example, $y \sim x_1 * x_2$ yields a model of the form

$$y = C + f_1(x_1) + f_2(x_2) + f_{12}(x_1, x_2) + e$$

with the terms denoted by "1", "x1", "x2", and "x1:x2".

The model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

ssanova0 and the affiliated methods provide a front end to RKPACK, a collection of RATFOR routines for nonparametric regression via the penalized least squares. The algorithms implemented in RKPACK are of the order $O(n^3)$.

Value

ssanova0 returns a list object of class c("ssanova0", "ssanova").

The method `summary.ssanova0` can be used to obtain summaries of the fits. The method `predict.ssanova0` can be used to evaluate the fits at arbitrary points along with standard errors. The methods `residuals.ssanova` and `fitted.ssanova` extract the respective traits from the fits.

Note

For complex models and large sample sizes, the approximate solution of `ssanova` can be faster.

The method `project` is not implemented for `ssanova0`, nor is the mixed-effect model support through `mkran`.

In `gss` versions earlier than 1.0, `ssanova0` was under the name `ssanova`.

Author(s)

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References

- Wahba, G. (1990), *Spline Models for Observational Data*. Philadelphia: SIAM.
- Gu, C. (2013), *Smoothing Spline ANOVA Models (2nd Ed)*. New York: Springer-Verlag.
- Gu, C. (2014), Smoothing Spline ANOVA Models: R Package `gss`. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## Fit a cubic spline
x <- runif(100); y <- 5 + 3*sin(2*pi*x) + rnorm(x)
cubic.fit <- ssanova0(y~x,method="m")
## Obtain estimates and standard errors on a grid
new <- data.frame(x=seq(min(x),max(x),len=50))
est <- predict(cubic.fit,new,se=TRUE)
## Plot the fit and the Bayesian confidence intervals
plot(x,y,col=1); lines(new$x,est$fit,col=2)
```

```

lines(new$x,est$fit+1.96*est$se,col=3)
lines(new$x,est$fit-1.96*est$se,col=3)
## Clean up
## Not run: rm(x,y,cubic.fit,new,est)
dev.off()
## End(Not run)

## Fit a tensor product cubic spline
data(nox)
nox.fit <- ssanova0(log10(nox)~comp*equi,data=nox)
## Fit a spline with cubic and nominal marginals
nox$comp<-as.factor(nox$comp)
nox.fit.n <- ssanova0(log10(nox)~comp*equi,data=nox)
## Fit a spline with cubic and ordinal marginals
nox$comp<-as.ordered(nox$comp)
nox.fit.o <- ssanova0(log10(nox)~comp*equi,data=nox)
## Clean up
## Not run: rm(nox,nox.fit,nox.fit.n,nox.fit.o)

```

ssanova9

Fitting Smoothing Spline ANOVA Models with Correlated Data

Description

Fit smoothing spline ANOVA models with correlated Gaussian data. The symbolic model specification via formula follows the same rules as in [lm](#).

Usage

```

ssanova9(formula, type=NULL, data=list(), subset, offset,
          na.action=na.omit, partial=NULL, method="v", alpha=1.4,
          varht=1, id.basis=NULL, nbasis=NULL, seed=NULL, cov,
          skip.iter=FALSE)

```

```
para.arma(fit)
```

Arguments

formula	Symbolic description of the model to be fit.
type	List specifying the type of spline for each variable. See mkterm for details.
data	Optional data frame containing the variables in the model.
subset	Optional vector specifying a subset of observations to be used in the fitting process.
offset	Optional offset term with known parameter 1.
na.action	Function which indicates what should happen when the data contain NAs.
partial	Optional symbolic description of parametric terms in partial spline models.

method	Method for smoothing parameter selection. Supported are method="v" for V, method="m" for M, and method="u" for U; see the reference for definitions of U, V, and M.
alpha	Parameter modifying V or U; larger absolute values yield smoother fits. Ignored when method="m" are specified.
varht	External variance estimate needed for method="u". Ignored when method="v" or method="m" are specified.
id.basis	Index designating selected "knots".
nbasis	Number of "knots" to be selected. Ignored when id.basis is supplied.
seed	Seed to be used for the random generation of "knots". Ignored when id.basis is supplied.
cov	Input for covariance functions. See mkcov for details.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See notes on skipping theta iteration.
fit	ssanova9 fit with ARMA error.

Details

The model specification via formula is intuitive. For example, $y \sim x_1 * x_2$ yields a model of the form

$$y = C + f_1(x_1) + f_2(x_2) + f_{12}(x_1, x_2) + e$$

with the terms denoted by "1", "x1", "x2", and "x1:x2".

The model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

A subset of the observations are selected as "knots." Unless specified via `id.basis` or `nbasis`, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Using q "knots," `ssanova` calculates an approximate solution to the penalized least squares problem using algorithms of the order $O(nq^2)$, which for $q \ll n$ scale better than the $O(n^3)$ algorithms of [ssanova0](#). For the exact solution, one may set $q = n$ in `ssanova`, but [ssanova0](#) would be much faster.

Value

`ssanova9` returns a list object of class `c("ssanova9", "ssanova")`.

The method `summary.ssanova9` can be used to obtain summaries of the fits. The method `predict.ssanova9` can be used to evaluate the fits at arbitrary points along with standard errors. The method `project.ssanova9` can be used to calculate the Kullback-Leibler projection for model selection. The methods `residuals.ssanova9` and `fitted.ssanova9` extract the respective traits from the fits.

`para.arma` returns the fitted ARMA coefficients for `cov=list("arma", c(p,q))` in the call to `ssanova9`.

Skipping Theta Iteration

For the selection of multiple smoothing parameters, `nlm` is used to minimize the selection criterion such as the GCV score. When the number of smoothing parameters is large, the process can be time-consuming due to the great amount of function evaluations involved.

The starting values for the `nlm` iteration are obtained using Algorithm 3.2 in Gu and Wahba (1991). These starting values usually yield good estimates themselves, leaving the subsequent quasi-Newton iteration to pick up the "last 10%" performance with extra effort many times of the initial one. Thus, it is often a good idea to skip the iteration by specifying `skip.iter=TRUE`, especially in high-dimensions and/or with multi-way interactions.

`skip.iter=TRUE` could be made the default in future releases.

Note

The results may vary from run to run. For consistency, specify `id.basis` or `set.seed`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

- Han, C. and Gu, C. (2008), Optimal smoothing with correlated data, *Sankhya*, **70-A**, 38–72.
- Gu, C. (2013), *Smoothing Spline ANOVA Models (2nd Ed)*. New York: Springer-Verlag.
- Gu, C. (2014), Smoothing Spline ANOVA Models: R Package `gss`. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
x <- runif(100); y <- 5 + 3*sin(2*pi*x) + rnorm(x)
## independent fit
fit <- ssanova9(y~x,cov=list("known",diag(1,100)))
## AR(1) fit
fit <- ssanova9(y~x,cov=list("arma",c(1,0)))
para.arma(fit)
## MA(1) fit
e <- rnorm(101); e[-1]~.5*e[-101]
x <- runif(100); y <- 5 + 3*sin(2*pi*x) + e
fit <- ssanova9(y~x,cov=list("arma",c(0,1)))
para.arma(fit)
## Clean up
## Not run: rm(x,y,e,fit)
```

 sscden

Estimating Conditional Probability Density Using Smoothing Splines

Description

Estimate conditional probability densities using smoothing spline ANOVA models. The symbolic model specification via formula follows the same rules as in [lm](#).

Usage

```
sscden(formula, response, type=NULL, data=list(), weights, subset,
        na.action=na.omit, alpha=1.4, id.basis=NULL, nbasis=NULL,
        seed=NULL, ydomain=as.list(NULL), yquad=NULL, prec=1e-7,
        maxiter=30, skip.iter=FALSE)
```

```
sscden1(formula, response, type=NULL, data=list(), weights, subset,
         na.action=na.omit, alpha=1.4, id.basis=NULL, nbasis=NULL,
         seed=NULL, rho=list("xy"), ydomain=as.list(NULL), yquad=NULL,
         prec=1e-7, maxiter=30, skip.iter=FALSE)
```

Arguments

formula	Symbolic description of the model to be fit.
response	Formula listing response variables.
type	List specifying the type of spline for each variable. See mkterm for details.
data	Optional data frame containing the variables in the model.
weights	Optional vector of counts for duplicated data.
subset	Optional vector specifying a subset of observations to be used in the fitting process.
na.action	Function which indicates what should happen when the data contain NAs.
alpha	Parameter defining cross-validation scores for smoothing parameter selection.
id.basis	Index of observations to be used as "knots."
nbasis	Number of "knots" to be used. Ignored when id.basis is specified.
seed	Seed to be used for the random generation of "knots." Ignored when id.basis is specified.
ydomain	Data frame specifying marginal support of conditional density.
yquad	Quadrature for calculating integral on Y domain. Mandatory if response variables other than factors or numerical vectors are involved.
prec	Precision requirement for internal iterations.
maxiter	Maximum number of iterations allowed for internal iterations.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See ssanova for notes on skipping theta iteration.
rho	rho function needed for sscden1.

Details

The model is specified via `formula` and `response`, where `response` lists the response variables. For example, `sscden(~y*x, ~y)` prescribe a model of the form

$$\log f(y|x) = g_y(y) + g_{xy}(x, y) + C(x)$$

with the terms denoted by "y", "y:x"; the term(s) not involving response(s) are removed and the constant $C(x)$ is determined by the fact that a conditional density integrates to one on the y axis. `sscden1` does keep terms not involving response(s) during estimation, although those terms cancel out when one evaluates the estimated conditional density.

The model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

A subset of the observations are selected as "knots." Unless specified via `id.basis` or `nbasis`, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Value

`sscden` returns a list object of class "sscden". `sscden1` returns a list object of class `c("sscden1", "sscden")`.

`dsscden` and `cdsscden` can be used to evaluate the estimated conditional density $f(y|x)$ and $f(y1|x, y2)$;

`psscden`, `qsscden`, `cpsscden`, and `cqsscden` can be used to evaluate conditional cdf and quantiles.

The methods `project.sscden` or `project.sscden1` can be used to calculate the Kullback-Leibler or square-error projections for model selection.

Note

Default quadrature on the Y domain will be constructed for numerical vectors on a hyper cube, then outer product with factor levels will be taken if factors are involved. The sides of the hyper cube are specified by `ydomain`; for `ydomain$y` missing, the default is `c(min(y), max(y))+c(-1, 1)*(max(y)-min(y))*0.5`.

On a 1-D interval, the quadrature is the 200-point Gauss-Legendre formula returned from `gauss.quad`.

For multiple numerical vectors, delayed Smolyak cubatures from `smolyak.quad` are used on cubes with the marginals properly transformed; see Gu and Wang (2003) for the marginal transformations.

The results may vary from run to run. For consistency, specify `id.basis` or set `seed`.

For reasonable execution time in high dimensions, set `skip.iter=TRUE`.

Author(s)

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References

Gu, C. (1995), Smoothing spline density estimation: Conditional distribution. *Statistica Sinica*, **5**, 709–726. Springer-Verlag.

Gu, C. (2014), Smoothing Spline ANOVA Models: R Package `gss`. *Journal of Statistical Software*, **58**(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
data(penny); set.seed(5732)
fit <- sscden1(~year*mil,~mil,data=penny,
              ydomain=data.frame(mil=c(49,61)))
yy <- 1944+(0:92)/2
quan <- qsscden(fit,c(.05,.25,.5,.75,.95),
               data.frame(year=yy))
plot(penny$year+.1*rnorm(90),penny$mil,ylim=c(49,61))
for (i in 1:5) lines(yy,quan[i,])
## Clean up
## Not run: rm(penny,yy,quan)
```

 sscox

Estimating Relative Risk Using Smoothing Splines

Description

Estimate relative risk using smoothing spline ANOVA models. The symbolic model specification via formula follows the same rules as in [lm](#), but with the response of a special form.

Usage

```
sscox(formula, type=NULL, data=list(), weights=NULL, subset,
      na.action=na.omit, partial=NULL, alpha=1.4, id.basis=NULL,
      nbasis=NULL, seed=NULL, random=NULL, prec=1e-7, maxiter=30,
      skip.iter=FALSE)
```

Arguments

formula	Symbolic description of the model to be fit, where the response is of the form <code>Surv(futime,status,start=0)</code> .
type	List specifying the type of spline for each variable. See mkterm for details.
data	Optional data frame containing the variables in the model.
weights	Optional vector of counts for duplicated data.
subset	Optional vector specifying a subset of observations to be used in the fitting process.
na.action	Function which indicates what should happen when the data contain NAs.
partial	Optional symbolic description of parametric terms in partial spline models.
alpha	Parameter defining cross-validation score for smoothing parameter selection.
id.basis	Index of observations to be used as "knots."
nbasis	Number of "knots" to be used. Ignored when <code>id.basis</code> is specified.
seed	Seed to be used for the random generation of "knots." Ignored when <code>id.basis</code> is specified.

random	Input for parametric random effects (frailty) in nonparametric mixed-effect models. See mkran for details.
prec	Precision requirement for internal iterations.
maxiter	Maximum number of iterations allowed for internal iterations.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See ssanova for notes on skipping theta iteration.

Details

A proportional hazard model is assumed, and the relative risk is estimated via penalized partial likelihood. The model specification via formula is for the log relative risk. For example, $\text{Suve}(t, d) \sim u * v$ prescribes a model of the form

$$\log f(u, v) = g_u(u) + g_v(v) + g_{u,v}(u, v)$$

with the terms denoted by "u", "v", and "u:v"; relative risk is defined only up to a multiplicative constant, so the constant term is not included in the model.

sscox takes standard right-censored lifetime data, with possible left-truncation and covariates; in $\text{Surv}(\text{fuptime}, \text{status}, \text{start}=0) \sim \dots$, fuptime is the follow-up time, status is the censoring indicator, and start is the optional left-truncation time.

Parallel to those in a [ssanova](#) object, the model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

The selection of smoothing parameters is through a cross-validation mechanism designed for density estimation under biased sampling, with a fudge factor alpha; alpha=1 is "unbiased" for the minimization of Kullback-Leibler loss but may yield severe undersmoothing, whereas larger alpha yields smoother estimates.

A subset of the observations are selected as "knots." Unless specified via `id.basis` or `nbasis`, the number of "knots" q is determined by $\text{max}(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Value

sscox returns a list object of class "sscox".

The method `predict.sscox` can be used to evaluate the fits at arbitrary points along with standard errors. The method `project.sscox` can be used to calculate the Kullback-Leibler projection for model selection.

Note

The function $\text{Surv}(\text{fuptime}, \text{status}, \text{start}=0)$ is defined and parsed inside `sscox`, not quite the same as the one in the `survival` package. The estimation is invariant of monotone transformations of time.

The results may vary from run to run. For consistency, specify `id.basis` or `set seed`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

- Gu, C. (2013), *Smoothing Spline ANOVA Models (2nd Ed)*. New York: Springer-Verlag.
- Gu, C. (2014), Smoothing Spline ANOVA Models: R Package gss. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## Relative Risk
data(stan)
fit.rr <- sscox(Surv(futime,status)~age,data=stan)
est.rr <- predict(fit.rr,data.frame(age=c(35,40)),se=TRUE)
## Base Hazard
risk <- predict(fit.rr,stan)
fit.bh <- sshzd(Surv(futime,status)~futime,data=stan,offset=log(risk))
tt <- seq(0,max(stan$futime),length=51)
est.bh <- hzdcurve.sshzd(fit.bh,tt,se=TRUE)
## Clean up
## Not run: rm(stan,fit.rr,est.rr,risk,fit.bh,tt,est.bh)
```

ssden

Estimating Probability Density Using Smoothing Splines

Description

Estimate probability densities using smoothing spline ANOVA models. The symbolic model specification via formula follows the same rules as in `lm`, but with the response missing.

Usage

```
ssden(formula, type=NULL, data=list(), alpha=1.4, weights=NULL,
      subset, na.action=na.omit, id.basis=NULL, nbasis=NULL, seed=NULL,
      domain=as.list(NULL), quad=NULL, qdsz.depth=NULL, bias=NULL,
      prec=1e-7, maxiter=30, skip.iter=FALSE)

ssden1(formula, type=NULL, data=list(), alpha=1.4, weights=NULL,
      subset, na.action=na.omit, id.basis=NULL, nbasis=NULL, seed=NULL,
      domain=as.list(NULL), quad=NULL, prec=1e-7, maxiter=30)
```

Arguments

formula	Symbolic description of the model to be fit.
type	List specifying the type of spline for each variable. See <code>mkterm</code> for details.
data	Optional data frame containing the variables in the model.
alpha	Parameter defining cross-validation score for smoothing parameter selection.
weights	Optional vector of bin-counts for histogram data.

subset	Optional vector specifying a subset of observations to be used in the fitting process.
na.action	Function which indicates what should happen when the data contain NAs.
id.basis	Index of observations to be used as "knots."
nbasis	Number of "knots" to be used. Ignored when id.basis is specified.
seed	Seed to be used for the random generation of "knots." Ignored when id.basis is specified.
domain	Data frame specifying marginal support of density.
quad	Quadrature for calculating integral. Mandatory if variables other than factors or numerical vectors are involved.
qdsz.depth	Depth to be used in smolyak.quad for the generation of quadrature.
bias	Input for sampling bias.
prec	Precision requirement for internal iterations.
maxiter	Maximum number of iterations allowed for internal iterations.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See ssanova for notes on skipping theta iteration.

Details

The model specification via formula is for the log density. For example, $\sim x1*x2$ prescribes a model of the form

$$\log f(x1, x2) = g_1(x1) + g_2(x2) + g_{12}(x1, x2) + C$$

with the terms denoted by "x1", "x2", and "x1:x2"; the constant is determined by the fact that a density integrates to one.

The selective term elimination may characterize (conditional) independence structures between variables. For example, $\sim x1*x2+x1*x3$ yields the conditional independence of x2 and x3 given x1.

Parallel to those in a [ssanova](#) object, the model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

The selection of smoothing parameters is through a cross-validation mechanism described in the references, with a parameter alpha; alpha=1 is "unbiased" for the minimization of Kullback-Leibler loss but may yield severe undersmoothing, whereas larger alpha yields smoother estimates.

A subset of the observations are selected as "knots." Unless specified via id.basis or nbasis, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Value

ssden returns a list object of class "ssden". ssden1 returns a list object of class c("ssden1", "ssden").

[dssden](#) and [cdssden](#) can be used to evaluate the estimated joint density and conditional density; [pssden](#), [qssden](#), [cpssden](#), and [cqssden](#) can be used to evaluate (conditional) cdf and quantiles.

The method [project.ssden](#) can be used to calculate the Kullback-Leibler projection of "ssden" objects for model selection; [project.ssden1](#) can be used to calculate the square error projection of "ssden1" objects.

Note

In `ssden`, default quadrature will be constructed for numerical vectors on a hyper cube, then outer product with factor levels will be taken if factors are involved. The sides of the hyper cube are specified by `domain`; for `domain` missing, the default is $c(\min(x), \max(x)) + c(-1, 1) * (\max(x) - \min(x)) * .05$. In 1-D, the quadrature is the 200-point Gauss-Legendre formula returned from `gauss.quad`. In multi-D, delayed Smolyak cubatures from `smolyak.quad` are used on cubes with the marginals properly transformed; see Gu and Wang (2003) for the marginal transformations.

For reasonable execution time in higher dimensions, set `skip.iter=TRUE` in call to `ssden`.

If you get an error message from `ssden` stating "Newton iteration diverges", try to use a larger `qdsz.depth` which will execute slower, or switch to `ssden1`. The default values of `qdsz.depth` for dimensions 4, 5, 6+ are 12, 11, 10.

`ssden1` does not involve multi-D quadrature but does not perform as well as `ssden`. It can be used in very high dimensions where `ssden` is infeasible.

The results may vary from run to run. For consistency, specify `id.basis` or set `seed`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

- Gu, C. and Wang, J. (2003), Penalized likelihood density estimation: Direct cross-validation and scalable approximation. *Statistica Sinica*, **13**, 811–826.
- Gu, C. (2013), *Smoothing Spline ANOVA Models (2nd Ed)*. New York: Springer-Verlag.
- Gu, C. (2014), Smoothing Spline ANOVA Models: R Package `gss`. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## 1-D estimate: Buffalo snowfall
data(buffalo)
buff.fit <- ssden(~buffalo, domain=data.frame(buffalo=c(0,150)))
plot(xx<-seq(0,150,len=101), dssden(buff.fit,xx), type="l")
plot(xx, pssden(buff.fit,xx), type="l")
plot(qq<-seq(0,1,len=51), qssden(buff.fit,qq), type="l")
## Clean up
## Not run: rm(buffalo, buff.fit, xx, qq)
dev.off()
## End(Not run)

## 2-D with triangular domain: AIDS incubation
data(aids)
## rectangular quadrature
quad.pt <- expand.grid(incu=((1:40)-.5)/40*100, infe=((1:40)-.5)/40*100)
quad.pt <- quad.pt[quad.pt$incu<=quad.pt$infe,]
quad.wt <- rep(1, nrow(quad.pt))
quad.wt[quad.pt$incu==quad.pt$infe] <- .5
quad.wt <- quad.wt/sum(quad.wt)*5e3
```

```

## additive model (pre-truncation independence)
aids.fit <- ssden(~incu+infe,data=aids,subset=age>=60,
                domain=data.frame(incu=c(0,100),infe=c(0,100)),
                quad=list(pt=quad.pt,wt=quad.wt))
## conditional (marginal) density of infe
jk <- cdsden(aids.fit,xx<-seq(0,100,len=51),data.frame(incu=50))
plot(xx,jk$pdf,type="l")
## conditional (marginal) quantiles of infe (TIME-CONSUMING)
## Not run:
cqssden(aids.fit,c(.05,.25,.5,.75,.95),data.frame(incu=50))

## End(Not run)
## Clean up
## Not run: rm(aids,quad.pt,quad.wt,aids.fit,jk,xx)
dev.off()
## End(Not run)

## One factor plus one vector
data(gastric)
gastric$trt
fit <- ssden(~fuptime*trt,data=gastric)
## conditional density
cdsden(fit,c("1","2"),cond=data.frame(fuptime=150))
## conditional quantiles
cqssden(fit,c(.05,.25,.5,.75,.95),data.frame(trt="1"))
## Clean up
## Not run: rm(gastric,fit)

## Sampling bias
## (X,T) is truncated to  $T < X < 1$  for  $T \sim U(0,1)$ , so X is length-biased
rbias <- function(n) {
  t <- runif(n)
  x <- rnorm(n,.5,.15)
  ok <- (x>t)&(x<1)
  while(m<-sum(!ok)) {
    t[!ok] <- runif(m)
    x[!ok] <- rnorm(m,.5,.15)
    ok <- (x>t)&(x<1)
  }
  cbind(x,t)
}
xt <- rbias(100)
x <- xt[,1]; t <- xt[,2]
## length-biased
bias1 <- list(t=1,wt=1,fun=function(t,x){x[,1]})
fit1 <- ssden(~x,domain=list(x=c(0,1)),bias=bias1)
plot(xx<-seq(0,1,len=101),dssden(fit1,xx),type="l")
## truncated
bias2 <- list(t=t,wt=rep(1/100,100),fun=function(t,x){x[,1]>t})
fit2 <- ssden(~x,domain=list(x=c(0,1)),bias=bias2)
plot(xx,dssden(fit2,xx),type="l")
## Clean up
## Not run: rm(rbias,xt,x,t,bias1,fit1,bias2,fit2)

```

Description

Estimate hazard function using smoothing spline ANOVA models. The symbolic model specification via formula follows the same rules as in [lm](#), but with the response of a special form.

Usage

```
sshzd(formula, type=NULL, data=list(), alpha=1.4, weights=NULL,
      subset, offset, na.action=na.omit, partial=NULL, id.basis=NULL,
      nbasis=NULL, seed=NULL, random=NULL, prec=1e-7, maxiter=30,
      skip.iter=FALSE)
```

```
sshzd1(formula, type=NULL, data=list(), alpha=1.4, weights=NULL,
       subset, na.action=na.omit, rho="marginal", partial=NULL,
       id.basis=NULL, nbasis=NULL, seed=NULL, random=NULL, prec=1e-7,
       maxiter=30, skip.iter=FALSE)
```

Arguments

formula	Symbolic description of the model to be fit, where the response is of the form <code>Surv(futime, status, start=0)</code> .
type	List specifying the type of spline for each variable. See mkterm for details.
data	Optional data frame containing the variables in the model.
alpha	Parameter defining cross-validation score for smoothing parameter selection.
weights	Optional vector of counts for duplicated data.
subset	Optional vector specifying a subset of observations to be used in the fitting process.
offset	Optional offset term with known parameter 1.
na.action	Function which indicates what should happen when the data contain NAs.
partial	Optional symbolic description of parametric terms in partial spline models.
id.basis	Index of observations to be used as "knots."
nbasis	Number of "knots" to be used. Ignored when <code>id.basis</code> is specified.
seed	Seed to be used for the random generation of "knots." Ignored when <code>id.basis</code> is specified.
random	Input for parametric random effects (frailty) in nonparametric mixed-effect models. See mkran for details.
prec	Precision requirement for internal iterations.
maxiter	Maximum number of iterations allowed for internal iterations.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See ssanova for notes on skipping theta iteration.
rho	Choice of rho function for <code>sshzd1</code> : "marginal" or "weibull".

Details

The model specification via formula is for the log hazard. For example, `Surv(t, d)~t*u` prescribes a model of the form

$$\log f(t, u) = C + g_t(t) + g_u(u) + g_{t,u}(t, u)$$

with the terms denoted by "1", "t", "u", and "t:u". Replacing `t*u` by `t+u` in the formula, one gets a proportional hazard model with $g_{t,u} = 0$.

`sshzd` takes standard right-censored lifetime data, with possible left-truncation and covariates; in `Surv(futime, status, start=0)~...`, `futime` is the follow-up time, `status` is the censoring indicator, and `start` is the optional left-truncation time. The main effect of `futime` must appear in the model terms specified via `...`

Parallel to those in a `ssanova` object, the model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

The selection of smoothing parameters is through a cross-validation mechanism described in Gu (2002, Sec. 7.2), with a parameter `alpha`; `alpha=1` is "unbiased" for the minimization of Kullback-Leibler loss but may yield severe undersmoothing, whereas larger `alpha` yields smoother estimates.

A subset of the observations are selected as "knots." Unless specified via `id.basis` or `nbasis`, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Value

`sshzd` returns a list object of class "sshzd". `sshzd1` returns a list object of class `c("sshzd1", "sshzd")`.

`hzdrate.sshzd` can be used to evaluate the estimated hazard function. `hzdcurve.sshzd` can be used to evaluate hazard curves with fixed covariates. `survexp.sshzd` can be used to calculate estimated expected survival.

The method `project.sshzd` can be used to calculate the Kullback-Leibler projection of "sshzd" objects for model selection; `project.sshzd1` can be used to calculate the square error projection of "sshzd1" objects.

Note

The function `Surv(futime, status, start=0)` is defined and parsed inside `sshzd`, not quite the same as the one in the `survival` package.

Integration on the time axis is done by the 200-point Gauss-Legendre formula on `c(min(start), max(futime))`, returned from `gauss.quad`.

`sshzd1` can be up to 50 times faster than `sshzd`, at the cost of performance degradation.

The results may vary from run to run. For consistency, specify `id.basis` or `set.seed`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

- Du, P. and Gu, C. (2006), Penalized likelihood hazard estimation: efficient approximation and Bayesian confidence intervals. *Statistics and Probability Letters*, **76**, 244–254.
- Du, P. and Gu, C. (2009), Penalized Pseudo-Likelihood Hazard Estimation: A Fast Alternative to Penalized Likelihood. *Journal of Statistical Planning and Inference*, **139**, 891–899.
- Du, P. and Ma, S. (2010), Frailty Model with Spline Estimated Nonparametric Hazard Function, *Statistica Sinica*, **20**, 561–580.
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- Gu, C. (2014), Smoothing Spline ANOVA Models: R Package gss. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## Model with interaction
data(gastric)
gastric.fit <- sshzd(Surv(futime,status)~futime*trt,data=gastric)
## exp(-Lambda(600)), exp(-(Lambda(1200)-Lambda(600))), and exp(-Lambda(1200))
survexp.sshzd(gastric.fit,c(600,1200,1200),data.frame(trt=as.factor(1)),c(0,600,0))
## Clean up
## Not run: rm(gastric,gastric.fit)
dev.off()
## End(Not run)

## THE FOLLOWING EXAMPLE IS TIME-CONSUMING
## Proportional hazard model
## Not run:
data(stan)
stan.fit <- sshzd(Surv(futime,status)~futime+age,data=stan)
## Evaluate fitted hazard
hzdrate.sshzd(stan.fit,data.frame(futime=c(10,20),age=c(20,30)))
## Plot lambda(t,age=20)
tt <- seq(0,60,leng=101)
hh <- hzdcurve.sshzd(stan.fit,tt,data.frame(age=20))
plot(tt,hh,type="l")
## Clean up
rm(stan,stan.fit,tt,hh)
dev.off()

## End(Not run)
```

Description

Fit smoothing spline log-linear regression models. The symbolic model specification via formula follows the same rules as in [lm](#).

Usage

```
ssllrm(formula, response, type=NULL, data=list(), weights, subset,
       na.action=na.omit, alpha=1, id.basis=NULL, nbasis=NULL,
       seed=NULL, random=NULL, prec=1e-7, maxiter=30, skip.iter=FALSE)
```

Arguments

formula	Symbolic description of the model to be fit.
response	Formula listing response variables.
type	List specifying the type of spline for each variable. See mkterm for details.
data	Optional data frame containing the variables in the model.
weights	Optional vector of weights to be used in the fitting process.
subset	Optional vector specifying a subset of observations to be used in the fitting process.
na.action	Function which indicates what should happen when the data contain NAs.
alpha	Parameter modifying GCV or Mallows' CL; larger absolute values yield smoother fits; negative value invokes a stable and more accurate GCV/CL evaluation algorithm but may take two to five times as long. Ignored when method="m" are specified.
id.basis	Index designating selected "knots".
nbasis	Number of "knots" to be selected. Ignored when id.basis is supplied.
seed	Seed to be used for the random generation of "knots". Ignored when id.basis is supplied.
random	Input for parametric random effects in nonparametric mixed-effect models. See mkran for details.
prec	Precision requirement for internal iterations.
maxiter	Maximum number of iterations allowed for internal iterations.
skip.iter	Flag indicating whether to use initial values of theta and skip theta iteration. See ssanova for notes on skipping theta iteration.

Details

The model is specified via `formula` and `response`, where `response` lists the response variables. For example, `ssllrm(~y1*y2*x, ~y1+y2)` prescribe a model of the form

$$\log f(y1, y2|x) = g_1(y1) + g_2(y2) + g_{12}(y1, y2) + g_{x1}(x, y1) + g_{x2}(x, y2) + g_{x12}(x, y1, y2) + C(x)$$

with the terms denoted by "y1", "y2", "y1:y2", "y1:x", "y2:x", and "y1:y2:x"; the term(s) not involving response(s) are removed and the constant $C(x)$ is determined by the fact that a conditional density integrates (adds) to one on the y axis.

The model terms are sums of unpenalized and penalized terms. Attached to every penalized term there is a smoothing parameter, and the model complexity is largely determined by the number of smoothing parameters.

A subset of the observations are selected as "knots." Unless specified via `id.basis` or `nbasis`, the number of "knots" q is determined by $\max(30, 10n^{2/9})$, which is appropriate for the default cubic splines for numerical vectors.

Value

ssllrm returns a list object of class "ssllrm".

The method `predict.ssllrm` can be used to evaluate $f(y|x)$ at arbitrary x , or contrasts of $\log\{f(y|x)\}$ such as the odds ratio along with standard errors. The method `project.ssllrm` can be used to calculate the Kullback-Leibler projection for model selection.

Note

The responses, or y -variables, must be factors, and there must be at least one numerical x 's. For response, there is no difference between $\sim y_1+y_2$ and $\sim y_1*y_2$.

The results may vary from run to run. For consistency, specify `id.basis` or `set.seed`.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

Gu, C. and Ma, P. (2011), Nonparametric regression with cross-classified responses. *The Canadian Journal of Statistics*, **39**, 591–609.

Gu, C. (2014), Smoothing Spline ANOVA Models: R Package `gss`. *Journal of Statistical Software*, 58(5), 1-25. URL <http://www.jstatsoft.org/v58/i05/>.

Examples

```
## Simulate data
test <- function(x)
  {.3*(1e6*(x^11*(1-x)^6)+1e4*(x^3*(1-x)^10))-2}
x <- (0:100)/100
p <- 1-1/(1+exp(test(x)))
y <- rbinom(x,3,p)
y1 <- as.ordered(y)
y2 <- as.factor(rbinom(x,1,p))
## Fit model
fit <- ssllrm(~y1*y2*x,~y1+y2)

## Evaluate f(y|x)
est <- predict(fit,data.frame(x=x),
  data.frame(y1=as.factor(0:3),y2=as.factor(rep(0,4))))
## f(y|x) at all y values (fit$qd.pt)
est <- predict(fit,data.frame(x=x))

## Evaluate contrast of log f(y|x)
est <- predict(fit,data.frame(x=x),odds=c(-1,.5,.5,0),
  data.frame(y1=as.factor(0:3),y2=as.factor(rep(0,4))),se=TRUE)
## Odds ratio log{f(0,0|x)/f(3,0|x)}
est <- predict(fit,data.frame(x=x),odds=c(1,-1),
  data.frame(y1=as.factor(c(0,3)),y2=as.factor(c(0,1))),se=TRUE)

## KL projection
```

```

k1 <- project(fit,include=c("y2:x","y1:y2","y1:x","y2:x"))

## Clean up
## Not run: rm(test,x,p,y,y1,y2,fit,est,k1)
dev.off()
## End(Not run)

```

stan	<i>Stanford Heart Transplant Data</i>
------	---------------------------------------

Description

Survival of patients from the Stanford heart transplant program.

Usage

```
data(stan)
```

Format

A data frame containing 184 observations on the following variables.

time	Follow-up time after transplant, in days.
status	Censoring status.
age	Age at transplant.
futime	Square root of time.

Source

Miller, R. G. and Halpern, J. (1982), Regression with censored data. *Biometrika*, **69**, 521–531.

summary.gssanova	<i>Assessing Smoothing Spline ANOVA Fits with Non-Gaussian Responses</i>
------------------	--

Description

Calculate various summaries of smoothing spline ANOVA fits with non-Gaussian responses.

Usage

```

## S3 method for class 'gssanova'
summary(object, diagnostics=FALSE, ...)

```

Arguments

object	Object of class "gssanova".
diagnostics	Flag indicating if diagnostics are required.
...	Ignored.

Details

Similar to the iterated weighted least squares fitting of [glm](#), penalized likelihood regression fit can be calculated through iterated penalized weighted least squares.

The diagnostics are based on the "pseudo" Gaussian response model behind the weighted least squares problem at convergence.

Value

summary.gssanova returns a list object of class "summary.gssanova" consisting of the following components. The entries pi, kappa, cosines, and roughness are only calculated if diagnostics=TRUE.

call	Fitting call.
family	Error distribution.
alpha	Parameter used to define cross-validation in model fitting.
fitted	Fitted values on the link scale.
dispersion	Assumed or estimated dispersion parameter.
residuals	Working residuals on the link scale.
rss	Residual sum of squares.
dev.resid	Deviance residuals.
deviance	Deviance of the fit.
dev.null	Deviance of the null model.
penalty	Roughness penalty associated with the fit.
pi	"Percentage decomposition" of "explained variance" into model terms.
kappa	Concurvity diagnostics for model terms. Virtually the square roots of variance inflation factors of a retrospective linear model.
cosines	Cosine diagnostics for practical significance of model terms.
roughness	Percentage decomposition of the roughness penalty penalty into model terms.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

Gu, C. (1992), Diagnostics for nonparametric regression models with additive terms. *Journal of the American Statistical Association*, **87**, 1051–1058.

See Also

Fitting function [gssanova](#) and methods [predict.ssanova](#), [project.gssanova](#), [fitted.gssanova](#).

summary.gssanova0	<i>Assessing Smoothing Spline ANOVA Fits with Non-Gaussian Responses</i>
-------------------	--

Description

Calculate various summaries of smoothing spline ANOVA fits with non-Gaussian responses.

Usage

```
## S3 method for class 'gssanova0'
summary(object, diagnostics=FALSE, ...)
```

Arguments

object	Object of class "gssanova".
diagnostics	Flag indicating if diagnostics are required.
...	Ignored.

Details

Similar to the iterated weighted least squares fitting of [glm](#), penalized likelihood regression fit can be calculated through iterated penalized weighted least squares.

The diagnostics are based on the "pseudo" Gaussian response model behind the weighted least squares problem at convergence.

Value

summary.gssanova0 returns a list object of [class](#) "summary.gssanova0" consisting of the following components. The entries pi, kappa, cosines, and roughness are only calculated if diagnostics=TRUE.

call	Fitting call.
family	Error distribution.
method	Method for smoothing parameter selection.
dispersion	Assumed or estimated dispersion parameter.
iter	Number of performance-oriented iterations performed.
fitted	Fitted values on the link scale.
residuals	Working residuals on the link scale.
rss	Residual sum of squares.
dev.resid	Deviance residuals.
deviance	Deviance of the fit.
dev.null	Deviance of the null model.

alpha	Estimated size for family="nbinomial" with one column responses. Estimated inverse scale of log life time for family="nbinomial", "lognorm", or "loglogis".
penalty	Roughness penalty associated with the fit.
pi	"Percentage decomposition" of "explained variance" into model terms.
kappa	Concurvity diagnostics for model terms. Virtually the square roots of variance inflation factors of a retrospective linear model.
cosines	Cosine diagnostics for practical significance of model terms.
roughness	Percentage decomposition of the roughness penalty into model terms.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

Gu, C. (1992), Diagnostics for nonparametric regression models with additive terms. *Journal of the American Statistical Association*, **87**, 1051–1058.

See Also

Fitting function [gssanova0](#) and methods [predict.ssanova0](#), [fitted.gssanova](#).

summary.ssanova

Assessing Smoothing Spline ANOVA Fits

Description

Calculate various summaries of smoothing spline ANOVA fits.

Usage

```
## S3 method for class 'ssanova'
summary(object, diagnostics=FALSE, ...)
## S3 method for class 'ssanova0'
summary(object, diagnostics=FALSE, ...)
## S3 method for class 'ssanova9'
summary(object, diagnostics=FALSE, ...)
```

Arguments

object	Object of class "ssanova".
diagnostics	Flag indicating if diagnostics are required.
...	Ignored.

Value

`summary.ssanova` returns a list object of class "summary.ssanova" consisting of the following components. The entries `pi`, `kappa`, `cosines`, and `roughness` are only calculated if `diagnostics=TRUE`; see the reference below for details concerning the diagnostics.

<code>call</code>	Fitting call.
<code>method</code>	Method for smoothing parameter selection.
<code>fitted</code>	Fitted values.
<code>residuals</code>	Residuals.
<code>sigma</code>	Assumed or estimated error standard deviation.
<code>r.squared</code>	Fraction of "explained variance" by the fitted model.
<code>rss</code>	Residual sum of squares.
<code>penalty</code>	Roughness penalty associated with the fit.
<code>pi</code>	"Percentage decomposition" of "explained variance" into model terms.
<code>kappa</code>	Concurvity diagnostics for model terms. Virtually the square roots of variance inflation factors of a retrospective linear model.
<code>cosines</code>	Cosine diagnostics for practical significance of model terms.
<code>roughness</code>	Percentage decomposition of the roughness penalty penalty into model terms.

Author(s)

Chong Gu, <chong@stat.purdue.edu>

References

Gu, C. (1992), Diagnostics for nonparametric regression models with additive terms. *Journal of the American Statistical Association*, **87**, 1051–1058.

See Also

Fitting functions `ssanova`, `ssanova0` and methods `predict.ssanova`, `project.ssanova`, `fitted.ssanova`.

wesdr

Progression of Diabetic Retinopathy

Description

Data derived from the Wisconsin Epidemiological Study of Diabetic Retinopathy.

Usage

`data(wesdr)`

Format

A data frame containing 669 observations on the following variables.

dur Duration of diabetes at baseline, in years.
gly Percent of glycosylated hemoglobin at baseline.
bmi Body mass index at baseline.
ret Binary indicator of retinopathy progression at first follow-up.

Source

Wang, Y. (1997), GRKPACK: Fitting smoothing spline ANOVA models for exponential families. *Communications in Statistics – Simulations and Computation*, **26**, 765–782.

References

Klein, R., Klein, B. E. K., Moss, S. E., Davis, M. D., and DeMets, D. L. (1988), Glycosylated hemoglobin predicts the incidence and progression of diabetic retinopathy. *Journal of the American Medical Association*, **260**, 2864–2871.

Klein, R., Klein, B. E. K., Moss, S. E., Davis, M. D., and DeMets, D. L. (1989), The Wisconsin Epidemiologic Study of Diabetic Retinopathy. X. Four incidence and progression of diabetic retinopathy when age at diagnosis is 30 or more years. *Archive Ophthalmology*, **107**, 244–249.

Wahba, G., Wang, Y., Gu, C., Klein, R., and Klein, B. E. K. (1995), Smoothing spline ANOVA for exponential families, with application to the Wisconsin Epidemiological Study of Diabetic Retinopathy. *The Annals of Statistics*, **23**, 1865–1895.

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