

Package ‘rdetools’

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Title Relevant Dimension Estimation (RDE) in Feature Spaces

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Description The package provides functions for estimating the relevant dimension of a data set in feature spaces, applications to model selection, graphical illustrations and prediction.

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rdetools-package *Relevant Dimension Estimation (RDE) in Feature Spaces*

Description

Only a finite number of leading kernel PCA components contain the relevant information of a supervised learning problem if the kernel matches the problem. The package provides functions for estimating the relevant dimension in kernel feature spaces. These functions are also able to calculate denoised versions of your label vectors and to estimate the noise levels in your data sets. RDE can also be used for model selection. The package provides functions for this issue and graphical functions to illustrate the results of RDE and model selection. For making predictions kernel projection regression is available.

Details

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Author(s)

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References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_

Examples

```
## rde on a noisy sinc data set
d <- sincdata(100, 0.1) # generate noisy sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
# estimate relevant dimension, denoised ys and noise level in data set
r <- rde(K, d$y, est_y = TRUE, est_noise = TRUE)
r$rd # relevant dimension
r$yh # denoised ys
r$noise # noise level in data set
drawkpc(r) # draw kernel pca coefficients
```

```
## rde for model selection
d <- sincdata(100, 0.1) # generate sinc data
# do model selection
m <- selectmodel(d$X, d$y, sigma = logspace(-3, 3, 100))
m$best # best model
m$rd # relevant dimension for best model
modelimage(m) # graphical illustration of model selection

## kernel projection regression
d <- sincdata(100, 0.1) # generate sinc data
# do model selection
m <- selectmodel(d$X, d$y, sigma = logspace(-3, 3, 100))
f <- kpr(m) # kernel projection regression
plot(f, -4, 4) # draw predicted function
```

denoiselabels

Denoise labels

Description

The function denoises labels of a dataset by projecting them to the d first kernel pca principal directions if d is not 0. If d is 0 the function returns a matrix containing the projected labels for each dimension in each column. The function is primarily an auxiliary function for the rde functions, and it should not be necessary to call it by hand, because rde will do this for you (see examples).

Usage

```
denoiselabels(d, eigvec, kpc, regression = TRUE)
```

Arguments

<code>d</code>	number of leading kernel pca principal directions to project the labels to or 0, if a matrix should be returned which contains the denoised labels for each dimension
<code>eigvec</code>	eigenvectors of the kernel matrix
<code>kpc</code>	kernel pca coefficients
<code>regression</code>	set this to TRUE, if the data should be handled as data of a regression problem and to FALSE in case of a classification problem

Value

denoised version of the labels or a matrix with denoised labels for each dimension in its columns if d was 0.

Author(s)

Jan Saputra Mueller

See Also

[rde](#), [rde_loocv](#), [rde_tcm](#)

Examples

```
## example with sinc data
d <- sincdata(100, 0.7) # generate sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
# rde, return also denoised labels
r <- rde(K, d$y, est_y = TRUE)
r$yh # denoised labels
```

distimage

Distance image

Description

If you've done a model selection with [selectmodel](#), this function can draw you a map, in which the distances of the original label vector and the estimated label vectors are shown. This is done by a [filled.contour](#) plot.

Usage

```
distimage(model,
          color.palette = terrain.colors,
          log = TRUE,
          plottitle = "Distance of Ys",
          ...)
```

Arguments

model	list of model selection data as it has been returned by selectmodel . selectmodel must have been called with <code>ydist</code> parameter set to <code>TRUE</code> !
color.palette	color palette function to use, see rainbow
log	leave this <code>TRUE</code> , if the axis of the model parameter should be logarithmically scaled. Set this to <code>FALSE</code> if you want linear scaling.
plottitle	title of the plot
...	additional parameters for filled.contour

Author(s)

Jan Saputra Mueller

References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_
[https://arxiv.org/abs/0806.1163](#)

See Also

[selectmodel](#), [modelimage](#), [drawkpc](#), [filled.contour](#), [rainbow](#)

Examples

```
## model selection with RBF-kernel and graphical illustration
## of the distances of the labels
d <- sincdata(100, 0.1) # generate sinc data
# do model selection
m <- selectmodel(d$X, d$y, ydist = TRUE, sigma = logspace(-3, 3, 100))
distimage(m) # distance image
```

drawkpc

Draw kernel pca coefficients

Description

The function plots the absolute values of the kernel pca coefficients. The estimated relevant dimension and the estimated noise level (if available) are also drawn. Optionally, it puts a rescaled version of the loo-cv-error/negative-log-likelihood into the plot.

Usage

```
drawkpc(model,
         err = TRUE,
         pointcol = "blue",
         rdcol = "red",
         noisecol = "black",
         errcol = "brown",
         ...)
```

Arguments

model	list of rde data returned by rde or selectmodel
err	leave this TRUE, if you want to have a rescaled version of the the loo-cv-error/negative-log-likelihood in the plot
pointcol	color of the kernel pca coefficients
rdcol	color of the relevant dimension line
noisecol	color of the noise level line
errcol	color of the the loo-cv-error/negative-log-likelihood
...	additional parameters to the plotting functions

Author(s)

Jan Saputra Mueller

References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_

See Also

[rde](#), [selectmodel](#), [modelimage](#), [distimage](#)

Examples

```
## draw kernel pca coefficients after calling rde
d <- sincdata(100, 0.1) # generate sinc data
K <- rbfkernel(d$X)
r <- rde(K, d$y, est_noise = TRUE)
drawkpc(r)

## draw kernel pca coefficients after calling selectmodel
d <- sincdata(100, 0.1) # generate sinc data
m <- selectmodel(d$X, d$y, est_noise = TRUE, sigma = logspace(-3, 3, 100))
drawkpc(m)
```

estnoise

Estimate noise level

Description

Estimates the noise level for a label vector 'y' and a denoised version of this label vector 'yh'. Which loss function is used to estimate the noise level depends on the kind of problem (regression problem or classification problem).

Usage

```
estnoise(y, yh, regression = FALSE, nmse = TRUE)
```

Arguments

y	a label vector containing only -1 and 1 for a classification problem, and real numbers in case of regression
yh	a denoised version of y which can be obtained by using e.g. <code>rde</code>
regression	FALSE in case of a classification problem, TRUE in case of a regression problem
nmse	if 'nmse' is TRUE and this is a regression problem, the mean squared error will be normalized

Details

In case of a classification problem, the 0-1-loss is used to estimate the noise level:

$$y = (y_1, \dots, y_n)$$

$$L_{01}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^n \mathbf{I}_{\{y_i \neq \hat{y}_i\}}$$

In case of a regression problem, the mean squared error (mse) or the normalized mean squared error (nmse) is used, depending on whether 'nmse' is FALSE (mse) or TRUE (nmse):

$$L_{mse}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$L_{nmse}(y, \hat{y}) = \frac{L_{mse}(y, \hat{y})}{\frac{1}{n} \sum_{i=1}^n (y_i - \frac{1}{n} \sum_{j=1}^n y_j)^2}$$

Value

Estimated noise level

Author(s)

Jan Saputra Mueller

See Also

[sincdata](#), [rde_loocv](#), [rde_tcm](#), [rbfkernel](#), [drawkpc](#)

Examples

```
## estimate noise of sinc data explicitly
d <- sincdata(100, 0.7) # generate sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
r <- rde(K, d$y, est_y = TRUE) # estimate relevant dimension
noise <- estnoise(d$y, r$yh, regression = TRUE) # estimate noise level

## estimate noise of sinc data implicitly (via rde_loocv)
d <- sincdata(100, 0.7) # generate sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
r <- rde(K, d$y, est_y = TRUE) # estimate relevant dimension AND estimate noise
r$noise # estimated noise level
```

`isregression`*Estimate from labels whether this is a regression problem*

Description

Estimates whether this is a regression or classification problem by looking at the labels. If all labels are only -1 and 1 a classification problem is assumed, otherwise a regression problem. If the argument 'regression' is TRUE, the function always returns TRUE.

Usage

```
isregression(y, regression = FALSE)
```

Arguments

<code>y</code>	label vector for which the kind of problem should be estimated
<code>regression</code>	if regression is TRUE, the function returns always TRUE, if you want an estimation leave this FALSE

Value

TRUE, if this is a regression problem or the argument regression was TRUE, otherwise FALSE

Author(s)

Jan Saputra Mueller

See Also

[rde_loocv](#), [rde_tcm](#), [estnoise](#)

Examples

```
## some examples
y_cl <- c(-1, 1, 1, -1, 1) # label vector for classification problem
y_reg <- runif(5) # label vector for regression problem
isregression(y_cl) # FALSE!
isregression(y_cl, regression = TRUE) # Always TRUE!
isregression(y_reg) # TRUE!
```


Examples

```
## kernel projection regression after
## calling selectmodel (recommended)
d <- sincdata(100, 0.1) # generate sinc data
# do model selection
m <- selectmodel(d$X, d$y, sigma = logspace(-3, 3, 100))
f <- kpr(m)
plot(f, -4, 4)
```

logspace

Logarithmically spaced sequence generation

Description

Function generates a logarithmically spaced sequence of n values between decades 10^l and 10^u .

Usage

```
logspace(l, u, n)
```

Arguments

l	10^l will be the lower value to start from
u	10^u will be the upper value to end with
n	number of values to generate

Value

Logarithmically spaced sequence of length n between 10^l and 10^u .

Author(s)

Jan Saputra Mueller

See Also

[seq](#), [selectmodel](#)

Examples

```
## generate 100 logarithmically spaced values between  $10^{-3}$  and  $10^3$ 
logspace(-3, 3, 100)
```

 modelimage

Model selection image

Description

The function produces a graphical illustration of a model selection which has been done with [selectmodel](#). Strictly speaking it's a [filled.contour](#) plot in which additionally the relevant dimensions for the different models are drawn as a black line. [selectmodel](#) chooses the deepest point in this map, that is the model and the relevant dimension with the smallest loo-cv-error/negative-log-likelihood-value.

Usage

```
modelimage(model,
           color.palette = topo.colors,
           log = TRUE,
           plottitle = "RDE Model Selection",
           ...)
```

Arguments

model	list of model selection data as it has been returned by selectmodel
color.palette	color palette function to use, see rainbow
log	leave this TRUE, if the axis of the model parameter should be logarithmically scaled. Set this to FALSE if you want linear scaling.
plottitle	title of the plot
...	additional parameters for filled.contour

Author(s)

Jan Saputra Mueller

References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_

See Also

[selectmodel](#), [distimage](#), [drawkpc](#), [filled.contour](#), [rainbow](#)

Examples

```
## model selection with RBF-kernel and graphical illustration
d <- sincdata(100, 0.1) # generate sinc data
# do model selection
m <- selectmodel(d$X, d$y, sigma = logspace(-3, 3, 100))
modelimage(m) # draw model selection image
```

 polykernel

 Calculate polynomial kernel matrix

Description

Calculates the polynomial kernel matrix for the dataset contained in the matrix X , where each row of X is a data point. If Y is also a matrix (with the same number of columns as X), the kernel function is evaluated between all data points of X and Y .

Usage

```
polykernel(X, d, Y = NULL)
```

Arguments

X	matrix containing a data point in each column
d	polynomial kernel degree
Y	leave this NULL if the kernel function should be evaluated between the data points only contained in X (which can be regarded as $Y = X$) or to a matrix with same number of columns as X if you want to evaluate the function between the points of X and Y

Details

Each row of X must be a data point, i.e. $X = (x_1, x_2, \dots, x_n)$. The kernel matrix K is then defined as

$$K = (k(x_i, x_j))_{i,j=1,\dots,n}$$

If Y is not NULL and also contains data points in each row, i.e. $Y = (y_1, y_2, \dots, y_m)$, the kernel matrix K of X and Y is defined as

$$K = (k(x_i, y_j))_{i=1,\dots,n,j=1,\dots,m}$$

In this case, k is the polynomial kernel, which is defined as

$$k(x, y) = (\langle x, y \rangle + 1)^d$$

where x, y are data points and d is the polynomial kernel degree.

Value

polynomial kernel matrix K for the given dataset

Author(s)

Jan Saputra Mueller

See Also[rbfkernel](#), [sincdata](#)**Examples**

```
## generate sinc data and calculate polynomial kernel matrix with d = 5
d <- sincdata(100, noise = 0.1)
K <- polykernel(d$X, 5)
```

rbfkernel

*Calculate RBF kernel matrix***Description**

Calculates the RBF kernel matrix for the dataset contained in the matrix X, where each row of X is a data point. If Y is also a matrix (with the same number of columns as X), the kernel function is evaluated between all data points of X and Y.

Usage

```
rbfkernel(X, sigma = 1, Y = NULL)
```

Arguments

X	matrix containing a data point in each row
sigma	kernel width of rbf kernel
Y	leave this NULL if the kernel function should be evaluated between the data points only contained in X (which can be regarded as Y = X) or to a matrix with same number of columns as X if you want to evaluate the function between the points of X and Y

Details

Each row of X must be a data point, i.e. $X = (x_1, x_2, \dots, x_n)$. The kernel matrix K is then defined as

$$K = (k(x_i, x_j))_{i,j=1,\dots,n}$$

If Y is not NULL and also contains data points in each row, i.e. $Y = (y_1, y_2, \dots, y_m)$, the kernel matrix K of X and Y is defined as

$$K = (k(x_i, y_j))_{i=1,\dots,n,j=1,\dots,m}$$

In this case, k is the rbf (radial basis function) kernel, which is defined as

$$k(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma}\right)$$

where x, y are data points and sigma is the rbf kernel width.

Value

RBF kernel matrix K for the given dataset

Author(s)

Jan Saputra Mueller

See Also

[polykernel](#), [sincdata](#)

Examples

```
## generate sinc data and calculate rbf kernel matrix with sigma = 1
d <- sincdata(100, noise = 0.1)
K <- rbfkernel(d$X)
```

rde

Relevant Dimension Estimation (RDE)

Description

The function estimates the relevant dimension in feature space. By default, this is done by fitting a two-component model, but rde by leave-one-out cross-validation is also available. The function is also able to calculate a denoised version of the labels and to estimate the noise level in the data set.

Usage

```
rde(K, y,
     est_y = FALSE,
     alldim = FALSE,
     est_noise = FALSE,
     regression = FALSE,
     nmse = TRUE,
     dim_rest = 0.5,
     tcm = TRUE)
```

Arguments

K	kernel matrix of the inputs (e.g. rbf kernel matrix)
y	label vector which contains the label for each data point
est_y	set this to TRUE if you want a denoised version of the labels
alldim	if this is TRUE denoised labels for all dimensions are calculated (instead of only for relevant dimension)
est_noise	set this to TRUE if you want an estimated noise level

regression	only interesting if one of <code>est_y</code> , <code>alldim</code> , <code>est_noise</code> is TRUE. Set this to TRUE if you want to force the function to handle the data as data for a regression problem. If you leave this FALSE, the function will try to determine itself whether this is a classification or regression problem.
nmse	only interesting if <code>est_noise</code> is TRUE and the function is handling the data as data of a regression problem. If you leave this TRUE, the normalized mean squared error is used for estimating the noise level, otherwise the conventional mean squared error.
dim_rest	percentage of leading dimensions to which the search for the relevant dimensions should be restricted. This is needed due to numerical instabilities. 0.5 should be a good choice in most cases (and is also the default value)
tcm	this is TRUE by default; indicates whether rde should be done by TCM or LOO-CV algorithm

Details

If `est_noise` or `alldim` are TRUE, a denoised version of the labels for the relevant dimension will be returned even if `est_y` is FALSE (so e.g. if you want denoised labels and noise approximation it is enough to set `est_noise` to TRUE).

Value

rd	estimated relevant dimension
err	loo-cv-error/negative-log-likelihood-value for each dimension (the position of the minimum is the relevant dimension)
yh	only returned if <code>est_y</code> , <code>alldim</code> or <code>est_noise</code> is TRUE, contains the denoised labels
Yh	only returned if <code>alldim</code> is TRUE, matrix with denoised labels for each dimension in each column
noise	only returned if <code>est_noise</code> is TRUE, contains the estimated noise level
kpc	kernel pca coefficients
eigvec	eigenvectors of the kernel matrix
eigval	eigenvalues of the kernel matrix
tcm	TRUE if TCM algorithm was used, otherwise (LOO-CV algorithm) FALSE

Author(s)

Jan Saputra Mueller

References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_

See Also

[rde_loocv](#), [rde_tcm](#), [estnoise](#), [isregression](#), [rbfkernel](#), [polykernel](#), [drawkpc](#)

Examples

```
## example with sinc data using tcm algorithm
d <- sincdata(100, 0.1) # generate sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
# rde, return also denoised labels and noise, fit tcm
r <- rde(K, d$y, est_y = TRUE, est_noise = TRUE)
r$rd # estimated relevant dimension
r$noise # estimated noise
drawkpc(r) # draw kernel pca coefficients

## example with sinc data using loo-cv algorithm
d <- sincdata(100, 0.1) # generate sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
# rde, return also denoised labels and noise
r <- rde(K, d$y, est_y = TRUE, est_noise = TRUE, tcm = FALSE)
r$rd # estimated relevant dimension
r$noise # estimated noise
drawkpc(r) # draw kernel pca coefficients
```

rde_loocv

Relevant Dimension Estimation (RDE) by Leave-One-Out Cross-Validation (LOO-CV)

Description

The function estimates the relevant dimension in feature space by leave-one-out cross-validation. It's also able to calculate a denoised version of the labels and to estimate the noise level in the data set.

Usage

```
rde_loocv(K, y,
          est_y = FALSE,
          alldim = FALSE,
          est_noise = FALSE,
          regression = FALSE,
          nmse = TRUE,
          dim_rest = 0.5)
```

Arguments

K	kernel matrix of the inputs (e.g. rbf kernel matrix)
y	label vector which contains the label for each data point
est_y	set this to TRUE if you want a denoised version of the labels
alldim	if this is TRUE denoised labels for all dimensions are calculated (instead of only for relevant dimension)
est_noise	set this to TRUE if you want an estimated noise level

regression	only interesting if one of <code>est_y</code> , <code>alldim</code> , <code>est_noise</code> is TRUE. Set this to TRUE if you want to force the function to handle the data as data for a regression problem. If you leave this FALSE, the function will try to determine itself whether this is a classification or regression problem.
nmse	only interesting if <code>est_noise</code> is TRUE and the function is handling the data as data of a regression problem. If you leave this TRUE, the normalized mean squared error is used for estimating the noise level, otherwise the conventional mean squared error.
dim_rest	percentage of leading dimensions to which the search for the relevant dimensions should be restricted. This is needed due to numerical instabilities. 0.5 should be a good choice in most cases (and is also the default value)

Details

If `est_noise` or `alldim` are TRUE, a denoised version of the labels for the relevant dimension will be returned even if `est_y` is FALSE (so e.g. if you want denoised labels and noise approximation it is enough to set `est_noise` to TRUE).

Value

rd	estimated relevant dimension
err	loo-cv error for each dimension (the position of the minimum is the relevant dimension)
yh	only returned if <code>est_y</code> , <code>alldim</code> or <code>est_noise</code> is TRUE, contains the denoised labels
Yh	only returned if <code>alldim</code> is TRUE, matrix with denoised labels for each dimension in each column
noise	only returned if <code>est_noise</code> is TRUE, contains the estimated noise level
kpc	kernel pca coefficients
eigvec	eigenvectors of the kernel matrix
eigval	eigenvalues of the kernel matrix
tcm	always FALSE; used to tell other functions that loo-cv method was used

Author(s)

Jan Saputra Mueller

References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_

See Also

[rde](#), [rde_tcm](#), [estnoise](#), [isregression](#), [rbfkernel](#), [polykernel](#), [drawkpc](#)

Examples

```
## example with sinc data
d <- sincdata(100, 0.1) # generate sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
# rde, return also denoised labels and noise
r <- rde_loocv(K, d$y, est_y = TRUE, est_noise = TRUE)
r$rd # estimated relevant dimension
r$noise # estimated noise
drawkpc(r) # draw kernel pca coefficients
```

rde_tcm	<i>Relevant Dimension Estimation (RDE) by Fitting a Two-Component Model (TCM)</i>
---------	---

Description

The function estimates the relevant dimension in feature space by fitting a two-component model. It's also able to calculate a denoised version of the labels and to estimate the noise level in the data set.

Usage

```
rde_tcm(K, y,
        est_y = FALSE,
        alldim = FALSE,
        est_noise = FALSE,
        regression = FALSE,
        nmse = TRUE,
        dim_rest = 0.5)
```

Arguments

K	kernel matrix of the inputs (e.g. rbf kernel matrix)
y	label vector which contains the label for each data point
est_y	set this to TRUE if you want a denoised version of the labels
alldim	if this is TRUE denoised labels for all dimensions are calculated (instead of only for relevant dimension)
est_noise	set this to TRUE if you want an estimated noise level
regression	only interesting if one of est_y, alldim, est_noise is TRUE. Set this to TRUE if you want to force the function to handle the data as data for a regression problem. If you leave this FALSE, the function will try to determine itself whether this is a classification or regression problem.
nmse	only interesting if est_noise is TRUE and the function is handling the data as data of a regression problem. If you leave this TRUE, the normalized mean squared error is used for estimating the noise level, otherwise the conventional mean squared error.

`dim_rest` percentage of leading dimensions to which the search for the relevant dimensions should be restricted. This is needed due to numerical instabilities. 0.5 should be a good choice in most cases (and is also the default value)

Details

If `est_noise` or `alldim` are TRUE, a denoised version of the labels for the relevant dimension will be returned even if `est_y` is FALSE (so e.g. if you want denoised labels and noise approximation it is enough to set `est_noise` to TRUE).

Value

`rd` estimated relevant dimension
`err` negative log-likelihood for each dimension (the position of the minimum is the relevant dimension)
`yh` only returned if `est_y`, `alldim` or `est_noise` is TRUE, contains the denoised labels
`Yh` only returned if `alldim` is TRUE, matrix with denoised labels for each dimension in each column
`noise` only returned if `est_noise` is TRUE, contains the estimated noise level
`kpc` kernel pca coefficients
`eigvec` eigenvectors of the kernel matrix
`eigval` eigenvalues of the kernel matrix
`tcm` always TRUE; used to tell other functions that tcm method was used

Author(s)

Jan Saputra Mueller

References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_

See Also

[rde](#), [rde_loocv](#), [estnoise](#), [isregression](#), [rbfkernel](#), [polykernel](#), [drawkpc](#)

Examples

```
## example with sinc data
d <- sincdata(100, 0.1) # generate sinc data
K <- rbfkernel(d$X) # calculate rbf kernel matrix
# rde, return also denoised labels and noise
r <- rde_tcm(K, d$y, est_y = TRUE, est_noise = TRUE)
r$rd # estimated relevant dimension
r$noise # estimated noise
drawkpc(r) # draw kernel pca coefficients
```

selectmodel

*Model selection***Description**

The function can be used for selecting the kernel from a number of possible candidates which fits the problem best. You need a parametrized kernel function and a number of possible parameters. A relevant dimension estimation will be done for all parameter combinations and the one with the smallest loo-cv-error/negative-log-likelihood on its estimated relevant dimension will be chosen.

Usage

```
selectmodel(X, y,
            kernel = rbfkernel,
            est_y = FALSE,
            ydist = FALSE,
            est_noise = FALSE,
            regression = FALSE,
            nmse = TRUE,
            tcm = TRUE,
            Xname = "X",
            ...)
```

Arguments

X	matrix containing a data point in each row
y	label vector which contains the label for each data point
kernel	parametrized kernel function which should be used
est_y	set this to TRUE if you want a denoised version of the labels for the best model
ydist	set this to TRUE if you want a matrix, which contains the distances between the denoised labels and the original labels for all dimensions and all parameter combinations (each line in the matrix contains the distances for one parameter combination. This is needed for distimage)
est_noise	set this to TRUE if you want an estimated noise level (for the best model)
regression	only interesting if est_y or est_noise is TRUE. Set this to TRUE if you want to force the function to handle the data as data for a regression problem. If you leave this FALSE, the function will try to determine itself whether this is a classification or regression problem.
nmse	only interesting if est_noise is TRUE and the function is handling the data as data of a regression problem. If you leave this TRUE, the normalized mean squared error is used for estimating the noise level, otherwise the conventional mean squared error.
tcm	this is TRUE by default; indicates whether rde should be done by TCM or LOO-CV algorithm

Xname	the name of the parameter of the kernel function which should contain the data points. This is X by default and can be left as it is if you use rbfkernel or polykernel .
...	for each parameter of the kernel function you should give a list of parameters to select the best parameter combination from (e.g. for rbfkernel this is only the parameter sigma of for polykernel it's only the parameter d. See examples.)

Value

rd	estimated relevant dimension for best model
best	the best parameter combination which has been found through model selection
yh	only returned if est_y, alldim or est_noise is TRUE, contains the denoised labels for the best model
noise	only returned if est_noise is TRUE, contains the estimated noise level for the best model
Yd	contains the distances of the denoised labels and the original labels; needed for distimage
rds	estimated relevant dimensions for each model
err	loo-cv-error/negative-log-likelihood-value for each dimension for the best model
errs	loo-cv-error/negative-log-likelihood-value for each dimension for all models (in each line is the error for one model)
kpc	kernel pca coefficients for best model
eigvec	eigenvectors of the kernel matrix for best model
eigval	eigenvalues of the kernel matrix for best model
params	list of parameters for the kernel function which has been given to the function
tcm	TRUE if TCM algorithm was used, otherwise (LOO-CV algorithm) FALSE
kernel	kernel function which has been used
Xname	the name of the parameter of the kernel function which should contain the data points as it has been given to the function
X	matrix with the data points as it has been given to the function
regression	TRUE, if the data are data of a regression problem, FALSE in case of a classification problem

Author(s)

Jan Saputra Mueller

References

M. L. Braun, J. M. Buhmann, K. R. Mueller (2008) _On Relevant Dimensions in Kernel Feature Spaces_

See Also

[rde](#), [modelimage](#), [distimage](#), [drawkpc](#)

Examples

```
## model selection with RBF-kernel
d <- sincdata(100, 0.1) # generate sinc data
# do model selection, calculate also denoised labels
m <- selectmodel(d$X, d$y, est_y = TRUE, sigma = logspace(-3, 3, 100))
m$best # best model
m$rd # relevant dimension for best model
modelimage(m) # draw model selection image

## model selection with polynomial kernel
d <- sincdata(100, 0.1) # generate sinc data
# do model selection, calculate also denoised labels
m <- selectmodel(d$X, d$y, kernel = polykernel, est_y = TRUE, d = 1:20)
m$best # best model
m$rd # relevant dimension for best model
modelimage(m, log = FALSE) # draw model selection image
```

sinc

*Calculate sinc values***Description**

Calculates (normalized) sinc values for each element of a vector/matrix/... etc.,

$$\text{sinc}(x) = \frac{\sin(\pi x)}{\pi x}, x \neq 0$$

If $x = 0$, $\text{sinc}(x)$ is defined as 1 (removable singularity in zero).

Usage

```
sinc(X)
```

Arguments

X an arbitrary vector/matrix/... containing numbers

Value

an vector/matrix/... of same size as the argument containing the sinc values for each element

Author(s)

Jan Saputra Mueller

References

http://en.wikipedia.org/wiki/Sinc_function

See Also[sincdata](#)**Examples**

```
## calculate sinc values of a vector
v <- 1:10
sinc(v)
```

sincdata	<i>Generate random sinc data</i>
----------	----------------------------------

Description

Function draws n points uniformly from the interval $[a, b]$, calculates the sinc (normalized sinc function) values for that points and adds a normal noise with a standard deviation of `noise` to these values.

Usage

```
sincdata(n, noise = 0, a = -4, b = 4)
```

Arguments

<code>n</code>	number of points to generate
<code>noise</code>	noise level to add to sinc values, i.e. standard deviation of normal noise
<code>a</code>	left bound of interval from which the x s are drawn, a must be smaller than b
<code>b</code>	right bound of interval from which the y s are drawn, b must be larger than a

Value

Randomly generated sinc data

<code>x</code>	matrix with one column (i.e. a vector, but returned object is a matrix) containing the x -values
<code>y</code>	matrix with one row (i.e. a vector, but returned object is a matrix) containing the y -values

Author(s)

Jan Saputra Mueller

References

http://en.wikipedia.org/wiki/Sinc_function

See Also[sinc](#)**Examples**

```
## generate 100 data points with noise level 0
## drawn from the interval [-4,4]
sincedata(100)

## generate 1000 data points with noise level 0.7
## drawn from the interval [-10, 10]
sincedata(1000, 0.7, a = -10, b = 10)
```

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