

# Package ‘classmap’

July 25, 2021

**Type** Package

**Title** Visualizing Classification Results

**Date** 2021-07-24

**Version** 1.1.1

**Author** Jakob Raymaekers [aut, cre],  
Peter Rousseeuw [aut]

**Depends** R (>= 3.5.0)

**Suggests** knitr, reshape2, svd, rpart.plot, nnet

**Imports** stats, graphics, ggplot2, robustbase, e1071, cellWise,  
cluster, kernlab, gridExtra, rpart, randomForest

**Maintainer** Jakob Raymaekers <jakob.raymaekers@kuleuven.be>

**Description** Tools to visualize the results of a classification of cases.

The graphical displays include stacked plots, silhouette plots, quasi residual plots, and class maps. Implements the techniques described and illustrated in Raymaekers, Rousseeuw and Hubert (2021),

Class maps for visualizing classification results, Technometrics, appeared online.

<[doi:10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)> (open access) and Raymaekers and Rousseeuw (2021),

Silhouettes and quasi residual plots for neural nets and tree-based classifiers,

<[arXiv:2106.08814](https://arxiv.org/abs/2106.08814)>. Examples can be found in the vignettes: ``Discriminant\_analysis\_examples``, ``K\_nearest\_neighbors\_examples``,

``Support\_vector\_machine\_examples``, ``Rpart\_examples``, ``Random\_forest\_examples``, and ``Neural\_net\_examples``.

**URL** <https://doi.org/10.1080/00401706.2021.1927849>,

<https://arxiv.org/abs/2106.08814>

**License** GPL (>= 2)

**Encoding** UTF-8

**LazyData** true

**VignetteBuilder** knitr

**RoxygenNote** 7.1.1

**NeedsCompilation** no

**Repository** CRAN

**Date/Publication** 2021-07-25 13:40:05 UTC

## R topics documented:

classmap . . . . .	2
confmat.vcr . . . . .	4
data_bookReviews . . . . .	6
data_floralbuds . . . . .	7
data_instagram . . . . .	8
data_titanic . . . . .	9
makeFV . . . . .	10
makeKernel . . . . .	12
silplot . . . . .	13
stackedplot . . . . .	14
vcr.da.newdata . . . . .	16
vcr.da.train . . . . .	18
vcr.forest.newdata . . . . .	20
vcr.forest.train . . . . .	21
vcr.knn.newdata . . . . .	23
vcr.knn.train . . . . .	25
vcr.neural.newdata . . . . .	27
vcr.neural.train . . . . .	28
vcr.rpart.newdata . . . . .	30
vcr.rpart.train . . . . .	32
vcr.svm.newdata . . . . .	34
vcr.svm.train . . . . .	36
<b>Index</b>	<b>39</b>

---

classmap	<i>Draw the class map to visualize classification results.</i>
----------	--

---

### Description

Draw the class map to visualize classification results, based on the output of one of the `vcr.*.*` functions in this package. The vertical axis of the class map shows each case's PAC, the conditional probability that it belongs to an alternative class. The fairness on the horizontal axis is the probability of a member of the given class being at most as far from the class as the case itself.

### Usage

```
classmap(vcrou, whichclass, classLabels = NULL, classCols = NULL,
         main = NULL, cutoff = 0.99, plotcutoff = TRUE, identify = FALSE,
         cex = 1, cex.main=1.2, cex.lab=NULL, cex.axis=NULL, opacity = 1,
         squareplot = TRUE, maxprob = NULL, maxfactor=NULL)
```

**Arguments**

vcrout	output of <code>vcr.*.train</code> or <code>vcr.*.newdata</code> . Required.
whichclass	the number or level of the class to be displayed. Required.
classLabels	the labels (levels) of the classes. If NULL, they are taken from <code>vcrout</code> .
classCols	a list of colors for the class labels. There should be at least as many as there are levels. If NULL the <code>classCols</code> are taken as 2, 3, 4, ...
main	title for the plot.
cutoff	cases with overall farness <code>vcrout\$ofarness &gt; cutoff</code> are flagged as outliers.
plotcutoff	If true, plots the cutoff on the farness values as a vertical line.
identify	if TRUE, invoke <code>graphics::identify</code> after plotting: left-click on a point to get its number, then ESC to exit.
cex	passed on to <code>graphics::plot</code> .
cex.main	same, for title.
cex.lab	same, for labels on horizontal and vertical axes.
cex.axis	same, for axes.
opacity	determines opacity of plotted dots. Value between 0 and 1, where 0 is transparent and 1 is opaque.
squareplot	If TRUE, makes the axes of the plot equally long.
maxprob	draws the farness axis at least upto probability <code>maxprob</code> . If NULL, the limits are obtained automatically.
maxfactor	if not NULL, a number slightly higher than 1 to increase the space at the right hand side of the plot, to make room for marking points.

**Value**

Executing the function plots the class map and returns

coordinates	a matrix with 2 columns containing the coordinates of the plotted points. The first coordinate is the quantile of the farness probability. This makes it easier to add text next to interesting points. If <code>identify = T</code> , the attribute <code>ids</code> of <code>coordinates</code> contains the row numbers of the identified points in the matrix <code>coordinates</code> .
-------------	--

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

- Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)
- Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

```
vcr.da.train, vcr.da.newdata,
vcr.knn.train, vcr.knn.newdata,
vcr.svm.train, vcr.svm.newdata,
vcr.rpart.train, vcr.rpart.newdata,
vcr.forest.train, vcr.forest.newdata,
vcr.neural.train, vcr.neural.newdata
```

**Examples**

```
vcrou = vcr.da.train(iris[,1:4], iris[,5])
classmap(vcrou, "setosa", classCols = 2:4) # tight class
classmap(vcrou, "versicolor", classCols = 2:4) # less tight
# The cases misclassified as virginica are shown in blue.
classmap(vcrou, "virginica", classCols = 2:4)
# The case misclassified as versicolor is shown in green.

# For more examples, we refer to the vignettes:
vignette("Discriminant_analysis_examples")
vignette("K_nearest_neighbors_examples")
vignette("Support_vector_machine_examples")
vignette("Rpart_examples")
vignette("Random_forest_examples")
vignette("Neural_net_examples")
```

---

 confmat.vcr

---

*Build a confusion matrix from the output of a function vcr.\*.\*.*


---

**Description**

Build a confusion matrix from the output of a function vcr.\*.\*. Optionally, a separate column for outliers can be added to the confusion matrix.

**Usage**

```
confmat.vcr(vcrou, cutoff = 0.99, showClassNumbers = FALSE,
            showOutliers = TRUE, silent = FALSE)
```

**Arguments**

vcrou	output of vcr.*.train or vcr.*.newdata.
cutoff	cases with overall farness vcrou\$ofarness > cutoff are flagged as outliers.
showClassNumbers	if TRUE, the row and column names are the number of each level instead of the level itself. Useful for long level names.
showOutliers	if TRUE and some points were flagged as outliers, it adds an extra column on the right of the confusion matrix for these outliers, with label "outl".
silent	if FALSE, the confusion matrix and accuracy are shown on the screen.

**Value**

A confusion matrix

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

**See Also**

[vcr.da.train](#), [vcr.da.newdata](#),  
[vcr.knn.train](#), [vcr.knn.newdata](#),  
[vcr.svm.train](#), [vcr.svm.newdata](#),  
[vcr.rpart.train](#), [vcr.rpart.newdata](#),  
[vcr.forest.train](#), [vcr.forest.newdata](#),  
[vcr.neural.train](#), [vcr.neural.newdata](#)

**Examples**

```
vcrou = vcr.knn.train(scale(iris[,1:4]), iris[,5], k=5)
# The usual confusion matrix:
confmat.vcr(vcrou, showOutliers = FALSE)

# Cases with ofarness > cutoff are flagged as outliers:
confmat.vcr(vcrou, cutoff = 0.98)

# With the default cutoff = 0.99 only one case is flagged here:
confmat.vcr(vcrou)
# Note that the accuracy is computed before any cases
# are flagged, so it does not depend on the cutoff.

confmat.vcr(vcrou, showClassNumbers=TRUE)
# Shows class numbers instead of labels. This option can
# be useful for long level names.

# For more examples, we refer to the vignettes:
vignette("Discriminant_analysis_examples")
vignette("K_nearest_neighbors_examples")
vignette("Support_vector_machine_examples")
```

---

data_bookReviews	<i>Amazon book reviews data</i>
------------------	---------------------------------

---

## Description

This is a subset of the data used in the paper, which was assembled by Prettenhofer and Stein (2010). It contains 1000 reviews of books on Amazon, of which 500 were selected from the original training data and 500 from the test data.

The full dataset has been used for a variety of things, including classification using svm. The subset was chosen small enough to keep the computation time low, while still containing the examples in the paper.

## Usage

```
data("data_bookReviews")
```

## Format

A data frame with 1000 observations on the following 2 variables.

review the review in text format (character)

sentiment factor indicating the sentiment of the review: negative (1) or positive (2)

## Source

Prettenhofer, P., Stein, B. (2010). Cross-language text classification using structural correspondence learning. *Proceedings of the 48th annual meeting of the association for computational linguistics*, 1118-1127.

## Examples

```
data(data_bookReviews)
# Example review:
data_bookReviews[5, 1]

# The data are used in:
vignette("Support_vector_machine_examples")
```

---

data_floralbuds	<i>Floral buds data</i>
-----------------	-------------------------

---

### Description

This data on floral pear bud detection was first described by Wouters et al. The goal is to classify the instances into buds, branches, scales and support. The numeric vectors resulted from a multispectral vision sensor and describe the scanned images.

### Usage

```
data("data_floralbuds")
```

### Format

A data frame with 550 observations on the following 7 variables.

X1 numeric vector

X2 numeric vector

X3 numeric vector

X4 numeric vector

X5 numeric vector

X6 numeric vector

y a factor with levels branch bud scales support

### Source

Wouters, N., De Ketelaere, B., Deckers, T. De Baerdemaeker, J., Saeys, W. (2015). Multispectral detection of floral buds for automated thinning of pear. *Comput. Electron. Agric.* 113, C, 93–103. <doi:10.1016/j.compag.2015.01.015>

### Examples

```
data("data_floralbuds")
str(data_floralbuds)
summary(data_floralbuds)

# The data are used in:
vignette("Discriminant_analysis_examples")
```

---

data_instagram	<i>Instagram data</i>
----------------	-----------------------

---

### Description

This dataset contains information on fake (spam) accounts on Instagram. The original source is <https://www.kaggle.com/free4ever1/instagram-fake-spammer-genuine-accounts> by Bardiya Bakhshandeh.

The data contains information on 696 Instagram accounts. For each account, 11 variables were recorded describing its characteristics. The goal is to detect fake Instagram accounts, which are used for spamming.

### Usage

```
data("data_instagram")
```

### Format

A data frame with 696 observations on the following variables.

**profile.pic** binary, indicates whether profile has picture.

**nums.length.username** ratio of number of numerical chars in username to its length.

**fullname.words** number of words in full name.

**nums.length.fullname** ratio of number of numerical characters in full name to its length.

**name..username** binary, indicates whether the name and username of the profile are the same.

**description.length** length of the description/biography of the profile (in number of characters).

**external.URL** binary, indicates whether profile has external url.

**private** binary, indicates whether profile is private or not.

**X.posts** number of posts made by profile.

**X.followers** number of followers.

**X.follows** numbers of follows.

**y** whether profile is fake or not.

**dataType** vector taking the values "train" or "test" indicating whether the observation belongs to the training or the test data.

### Source

<https://www.kaggle.com/free4ever1/instagram-fake-spammer-genuine-accounts>

### Examples

```
data(data_instagram)
str(data_instagram)

# The data are used in:
vignette("Random_forest_examples")
```

---

`data_titanic`*Titanic data*

---

## Description

This dataset contains information on 1309 passengers of the RMS Titanic. The goal is to predict survival based on 11 characteristics such as the travel class, age and sex of the passengers.

The original data source is <https://www.kaggle.com/c/titanic/data>

The data is split up in a training data consisting of 891 observations and a test data of 418 observations. The response in the test set was obtained by combining information from other data files, and has been verified by submitting it as a 'prediction' to kaggle and getting perfect marks.

## Usage

```
data("data_titanic")
```

## Format

A data frame with 1309 observations on the following variables.

**PassengerId** a unique identified for each passenger.

**Pclass** travel class of the passenger.

**Name** name of the passenger.

**Sex** sex of the passenger.

**Age** age of the passenger.

**SibSp** number of siblings and spouses traveling with the passenger.

**Parch** number of parents and children traveling with the passenger.

**Ticket** Ticket number of the passenger.

**Fare** fare paid for the ticket.

**Cabin** cabin number of the passenger.

**Embarked** Port of embarkation. Takes the values C (Cherbourg), Q (Queenstown) and S (Southampton).

**y** factor indicating casualty or survivor.

**dataType** vector taking the values "train" or "test" indicating whether the observation belongs to the training or the test data.

## Source

<https://www.kaggle.com/c/titanic/data>

## Examples

```
data("data_titanic")
traindata = data_titanic[which(data_titanic$dataType == "train"), -13]
testdata = data_titanic[which(data_titanic$dataType == "test"), -13]
str(traindata)
table(traindata$y)

# The data are used in:
vignette("Rpart_examples")
```

---

makeFV

*Constructs feature vectors from a kernel matrix.*

---

## Description

Constructs feature vectors from a kernel matrix.

## Usage

```
makeFV(kmat, transformat=NULL, precS=1e-12)
```

## Arguments

kmat	a kernel matrix. If transformat is NULL, we are dealing with training data and then kmat must be a square kernel matrix (of size $n$ by $n$ when there are $n$ cases). Such a PSD matrix kmat can e.g. be produced by <a href="#">makeKernel</a> or by <a href="#">kernlab::kernelMatrix</a> . If on the other hand transformat is not NULL, we are dealing with a test set. See details for the precise working.
transformat	transformation matrix. If not NULL, it is the value transformat of <a href="#">makeFV</a> on training data. It has to be a square matrix, with as many rows as there were training data.
precS	if not NULL, eigenvalues of kmat below precS will be set equal to precS.

## Details

If transformat is non-NULL, we are dealing with a test set. Denote the number of cases in the test set by  $m \geq 1$ . Each row of kmat of the test set then must contain the kernel values of a new case with all cases in the training set. Therefore the kernel matrix kmat must have dimensions  $m$  by  $n$ . The matrix kmat can e.g. be produced by [makeKernel](#). It can also be obtained by running [kernlab::kernelMatrix](#) on the union of the training set and the test set, yielding an  $(n + m)$  by  $(n + m)$  matrix, from which one then takes the  $[(n + 1) : m, 1 : n]$  submatrix.

**Value**

A list with components:

Xf	When makeKV is applied to the training set, Xf has coordinates of $n$ points (vectors), the plain inner products of which equal the kernel matrix of the training set. That is, $kmat = Xf Xf'$ . The Xf are expressed in an orthogonal basis in which the variance of the coordinates is decreasing, which is useful when plotting the first few coordinates. When <code>makeFV</code> is applied to a test set, Xf are coordinates of the feature vectors of the test set in the same space as those of the training set, and then $kmat = Xf Xf\_training'$ .
transfmat	square matrix for transforming kmat to Xf. The actual transformation needs to be carried out by <code>makeFV</code> because it is not a simple matrix product.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

**See Also**

[makeKernel](#)

**Examples**

```
library(e1071)
set.seed(1); X = matrix(rnorm(200*2),ncol=2)
X[1:100,] = X[1:100,]+2
X[101:150,] = X[101:150,]-2
y = as.factor(c(rep("blue",150),rep("red",50)))
cols = c("deepskyblue3","red")
plot(X,col=cols[as.numeric(y)],pch=19)
# We now fit an SVM with radial basis kernel to the data:
svmfit = svm(y~., data=data.frame(X=X,y=y), scale=FALSE,
             kernel="radial", cost=10, gamma=1, probability=TRUE)
Kxx = makeKernel(X,svfit=svmfit)
outFV = makeFV(Kxx)
Xf = outFV$Xf # The data matrix in this feature space.
dim(Xf) # The feature vectors are high dimensional.
# The inner products of Xf match the kernel matrix:
max(abs(as.vector(Kxx - crossprod(t(Xf), t(Xf))))) # 6.167711e-11 # tiny, OK
range(rowSums(Xf^2)) # all points in Xf lie on the unit sphere.
pairs(Xf[,1:5],col=cols[as.numeric(y)])
# In some of these we see spherical effects, e.g.
plot(Xf[,1],Xf[,5],col=cols[as.numeric(y)],pch=19)
# The data look more separable here than in the original
# two-dimensional space.
```

```
# For more examples, we refer to the vignette:  
vignette("Support_vector_machine_examples")
```

---

makeKernel	<i>Compute kernel matrix</i>
------------	------------------------------

---

### Description

Computes kernel value or kernel matrix, where the kernel type is extracted from an svm trained by [e1071::svm](#).

### Usage

```
makeKernel(X1, X2 = NULL, svfit)
```

### Arguments

X1	first matrix (or vector) of coordinates.
X2	if not NULL, second data matrix or vector. If NULL, X2 is assumed equal to X1.
svfit	output from <a href="#">e1071::svm</a> .

### Value

the kernel matrix, of dimensions  $nrow(X1)$  by  $nrow(X2)$ . When both X1 and X2 are vectors, the result is a single number.

### Author(s)

Raymaekers J., Rousseeuw P.J.

### References

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

### See Also

[makeFV](#)

## Examples

```

library(e1071)
set.seed(1); X = matrix(rnorm(200*2),ncol=2)
X[1:100,] = X[1:100,]+2
X[101:150,] = X[101:150,]-2
y = as.factor(c(rep("blue",150),rep("red",50))) # two classes
# We now fit an SVM with radial basis kernel to the data:
set.seed(1) # to make the result of svm() reproducible.
svmfit = svm(y~., data=data.frame(X=X,y=y), scale=FALSE,
             kernel="radial", cost=10, gamma=1, probability=TRUE)
Kxx = makeKernel(X,svfit=svmfit)
# The result is a square kernel matrix:
dim(Kxx) # 200 200
Kxx[1:5,1:5]

# For more examples, we refer to the vignette:
vignette("Support_vector_machine_examples")

```

---

silplot

*Draw the silhouette plot of a classification*


---

## Description

Draw the silhouette plot to visualize classification results, based on the output of one of the `vcr.*.*` functions in this package. The horizontal axis of the silhouette plot shows each case's  $s(i)$ .

## Usage

```

silplot(vcrout, classLabels = NULL, classCols = NULL,
        showLegend = TRUE, showClassNumbers = FALSE,
        showCases = FALSE, drawLineAtAverage = FALSE,
        topdown = TRUE, main = NULL, summary = TRUE)

```

## Arguments

<code>vcrout</code>	output of <code>vcr.*.train</code> or <code>vcr.*.newdata</code> . Required.
<code>classLabels</code>	the labels (levels) of the classes. If <code>NULL</code> , they are taken from <code>vcrout</code> .
<code>classCols</code>	a list of colors for the classes. There should be at least as many as there are levels. If <code>NULL</code> a default palette is used.
<code>showLegend</code>	if <code>TRUE</code> , a legend is shown to the right of the plot.
<code>showClassNumbers</code>	if <code>TRUE</code> , the legend will show the class numbers instead of the class labels.
<code>showCases</code>	if <code>TRUE</code> , the plot shows the numbers of the cases. They are only readable when the number of cases is relatively small.
<code>topdown</code>	if <code>TRUE</code> (the default), the silhouettes are plotted from top to bottom. Otherwise they are plotted from left to right.

<code>drawLineAtAverage</code>	if TRUE, drwas a line at the average value of the $s(i)$ .
<code>main</code>	title for the plot. If NULL, a default title is used.
<code>summary</code>	if TRUE, puts a summary table on the screen with for each class its number, label, number of class members, and the average of its $s(i)$ .

**Value**

A ggplot object containing the silhouette plot.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

[vcr.da.train](#), [vcr.da.newdata](#),  
[vcr.knn.train](#), [vcr.knn.newdata](#),  
[vcr.svm.train](#), [vcr.svm.newdata](#),  
[vcr.rpart.train](#), [vcr.rpart.newdata](#),  
[vcr.forest.train](#), [vcr.forest.newdata](#),  
[vcr.neural.train](#), [vcr.neural.newdata](#)

**Examples**

```
vcrout = vcr.da.train(iris[,1:4], iris[,5])
silplot(vcrout)
# For more examples, we refer to the vignettes:
vignette("Rpart_examples")
vignette("Forest_examples")
vignette("Neural_net_examples")
```

---

stackedplot

*Make a vertically stacked mosaic plot of class predictions.*

---

**Description**

Make a vertically stacked mosaic plot of class predictions from the output of `vcr.*.train` or `vcr.*.newdata`. Optionally, the outliers for each class can be shown as a gray rectangle at the top.

**Usage**

```
stackedplot(vcrout, cutoff = 0.99, classCols = NULL, classLabels = NULL,  
            separSize=1, minSize=1.5, showOutliers = TRUE, showLegend = FALSE,  
            htitle = NULL, vtitle = NULL)
```

**Arguments**

vcrout	output of vcr.*.train or vcr.*.newdata.
cutoff	cases with overall farness vcrout\$ofarness > cutoff are flagged as outliers.
classCols	user-specified colors for the classes. If NULL a default palette is used.
classLabels	names of given labels. If NULL they are taken from vcrout.
separSize	how much white between rectangles.
minSize	rectangles describing less than minSize percent of the data, are shown as minSize percent.
showOutliers	if TRUE, shows a separate class in gray with the outliers, always at the top.
showLegend	if TRUE, a legend is shown to the right of the plot. Default FALSE, since the legend is not necessary as the colors are already visible in the bottom part of each stack.
htitle	title for horizontal axis (given labels). If NULL, a default title is shown.
vtitle	title for vertical axis (predicted labels). If NULL, a default title is shown.

**Value**

A ggplot object.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

**See Also**

[vcr.da.train](#), [vcr.da.newdata](#),  
[vcr.knn.train](#), [vcr.knn.newdata](#),  
[vcr.svm.train](#), [vcr.svm.newdata](#),  
[vcr.rpart.train](#), [vcr.rpart.newdata](#),  
[vcr.forest.train](#), [vcr.forest.newdata](#),  
[vcr.neural.train](#), [vcr.neural.newdata](#)

## Examples

```

data("data_floralbuds")
X = data_floralbuds[,1:6]; y = data_floralbuds[,7]
vcrou = vcr.da.train(X,y)
cols = c("saddlebrown","orange","olivedrab4","royalblue3")
stackedplot(vcrou, classCols = cols, showLegend=TRUE)

# The legend is not really needed, since we can read the
# color of a class from the bottom of its vertical bar:
stackedplot(vcrou, classCols = cols)

# If we do not wish to show outliers:
stackedplot(vcrou, classCols = cols, showOutliers=FALSE)

# For more examples, we refer to the vignettes:
vignette("Discriminant_analysis_examples")
vignette("K_nearest_neighbors_examples")
vignette("Support_vector_machine_examples")
vignette("Rpart_examples")
vignette("Random_forest_examples")
vignette("Neural_net_examples")

```

---

vcr.da.newdata	<i>Carry out discriminant analysis on new data, and prepare to visualize its results.</i>
----------------	---

---

## Description

Predicts class labels for new data by discriminant analysis, using the output of `vcr.da.train` on the training data. For new data cases whose label in `yintnew` is non-missing, additional output is produced for constructing graphical displays such as the `classmap`.

## Usage

```
vcr.da.newdata(Xnew, ynew=NULL, vcr.da.train.out)
```

## Arguments

<code>Xnew</code>	data matrix of the new data, with the same number of columns as in the training data. Missing values are not allowed.
<code>ynew</code>	factor with class membership of each new case. Can be NA for some or all cases. If NULL, is assumed to be NA everywhere.
<code>vcr.da.train.out</code>	output of <code>vcr.da.train</code> on the training data.

**Value**

A list with components:

yintnew	number of the given class of each case. Can contain NA's.
ynew	given class label of each case. Can contain NA's.
levels	levels of the response, from <code>vcr.da.train.out</code> .
predint	predicted class number of each case. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose ynew is missing.
altlab	label of the alternative class. Is NA for cases whose ynew is missing.
PAC	probability of the alternative class. Is NA for cases whose ynew is missing.
fig	distance of each case $i$ to each class $g$ . Always exists.
farness	farness of each case $i$ from its given class. Is NA for cases whose ynew is missing.
ofarness	For each case $i$ , its lowest <code>fig[i, g]</code> to any class $g$ . Always exists.
classMS	list with center and covariance matrix of each class, from <code>vcr.da.train.out</code> .
lCurrent	log of mixture density of each case in its given class. Is NA for cases with missing ynew.
lPred	log of mixture density of each case in its predicted class. Always exists.
lAlt	log of mixture density of each case in its alternative class. Is NA for cases with missing ynew.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

**See Also**

[vcr.da.train](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
vcr.train = vcr.da.train(iris[,1:4], iris[,5])
inds = c(51:150) # a subset, containing only 2 classes
iris2 = iris[inds,] # fake "new" data
iris2[c(1:10,51:60),5] = NA
vcr.test = vcr.da.newdata(iris2[,1:4],iris2[,5],vcr.train)
```

```

vcr.test$PAC[1:25] # between 0 and 1. Is NA where the response is.
plot(vcr.test$PAC,vcr.train$PAC[inds]); abline(0,1) # match
plot(vcr.test$farness,vcr.train$farness[inds]); abline(0,1) # match
confmat.vcr(vcr.train) # for comparison
confmat.vcr(vcr.test)
stackedplot(vcr.train) # for comparison
stackedplot(vcr.test)
classmap(vcr.train, "versicolor", classCols = 2:4) # for comparison
classmap(vcr.test, "versicolor", classCols = 2:4) # has fewer points

# For more examples, we refer to the vignette:
vignette("Discriminant_analysis_examples")

```

---

vcr.da.train	<i>Carry out discriminant analysis on training data, and prepare to visualize its results.</i>
--------------	--

---

## Description

Custom DA function which prepares for graphical displays such as the [classmap](#). The discriminant analysis itself is carried out by the maximum a posteriori rule, which maximizes the density of the mixture.

## Usage

```
vcr.da.train(X, y, rule = "QDA", estmethod = meancov)
```

## Arguments

X	a numerical matrix containing the predictors in its columns. Missing values are not allowed.
y	a factor with the given class labels.
rule	either "QDA" for quadratic discriminant analysis or "LDA" for linear discriminant analysis.
estmethod	function for location and covariance estimation. Should return a list with the center $\mu$ and the covariance matrix $S$ . The default is meancov (classical mean and covariance matrix), and the option DetMCD (based on <a href="#">robustbase::covMcd</a> ) is also provided.

## Value

A list with components:

yint	number of the given class of each case. Can contain NA's.
y	given class label of each case. Can contain NA's.
levels	levels of y

predint	predicted class number of each case. For each case this is the class with the highest posterior probability. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose y is missing.
altlab	label of the alternative class. Is NA for cases whose y is missing.
PAC	probability of the alternative class. Is NA for cases whose y is missing.
figparams	parameters for computing fig, can be used for new data.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose y is missing.
ofarness	for each case $i$ , its lowest $\text{fig}[i, g]$ to any class $g$ . Always exists.
classMS	list with center and covariance matrix of each class
lCurrent	log of mixture density of each case in its given class. Is NA for cases with missing y.
lPred	log of mixture density of each case in its predicted class. Always exists.
lAlt	log of mixture density of each case in its alternative class. Is NA for cases with missing y.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

**See Also**

[vcr.da.newdata](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
data("data_floralbuds")
X = data_floralbuds[,1:6]; y = data_floralbuds[,7]
vcrou = vcr.da.train(X,y,rule="QDA")
# For linear discriminant analysis, put rule="LDA".
confmat.vcr(vcrou) # There are a few outliers
cols = c("saddlebrown","orange","olivedrab4","royalblue3")
stackedplot(vcrou, classCols = cols)
classmap(vcrou, "bud", classCols = cols)

# For more examples, we refer to the vignettes:
vignette("Discriminant_analysis_examples")
```

---

`vcr.forest.newdata`      *Prepare for visualization of a random forest classification on new data.*

---

### Description

Produces output for the purpose of constructing graphical displays such as the `classmap` on new data. Requires the output of `vcr.forest.train` as an argument.

### Usage

```
vcr.forest.newdata(Xnew, ynew = NULL, vcr.forest.train.out,
                  LOO = FALSE)
```

### Arguments

<code>Xnew</code>	data matrix of the new data, with the same number of columns <code>d</code> as in the training data. Missing values are not allowed.
<code>ynew</code>	factor with class membership of each new case. Can be NA for some or all cases. If NULL, is assumed to be NA everywhere.
<code>vcr.forest.train.out</code>	output of <code>vcr.forest.train</code> on the training data.
<code>LOO</code>	leave one out. Only used when testing this function on a subset of the training data. Default is <code>LOO=FALSE</code> .

### Value

A list with components:

<code>yintnew</code>	number of the given class of each case. Can contain NA's.
<code>ynew</code>	given class label of each case. Can contain NA's.
<code>levels</code>	levels of the response, from <code>vcr.forest.train.out</code> .
<code>predint</code>	predicted class number of each case. Always exists.
<code>pred</code>	predicted label of each case.
<code>altint</code>	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose <code>ynew</code> is missing.
<code>altlab</code>	alternative label if <code>yintnew</code> was given, else NA.
<code>PAC</code>	probability of the alternative class. Is NA for cases whose <code>ynew</code> is missing.
<code>fig</code>	distance of each case $i$ from each class $g$ . Always exists.
<code>farness</code>	farness of each case from its given class. Is NA for cases whose <code>ynew</code> is missing.
<code>ofarness</code>	for each case $i$ , its lowest <code>fig[i, g]</code> to any class $g$ . Always exists.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

[vcr.forest.train](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
library(randomForest)
data("data_instagram")
traindata = data_instagram[which(data_instagram$dataType == "train"), -13]
set.seed(71) # randomForest is not deterministic
rfout = randomForest(y ~ ., data=traindata, keep.forest=TRUE)
mytype = list(symm = c(1, 5, 7, 8)) # These 4 columns are
# (symmetric) binary variables. The variables that are not
# listed are interval-scaled by default.
x_train = traindata[, -12]
y_train = traindata[, 12]
vcrtrain = vcr.forest.train(X = x_train, y = y_train,
                           trainfit = rfout, type = mytype)
testdata = data_instagram[which(data_instagram$dataType == "test"), -13]
Xnew = testdata[, -12]
ynew = testdata[, 12]
vcrtest = vcr.forest.newdata(Xnew, ynew, vcrtrain)
confmat.vcr(vcrtest)
stackedplot(vcrtest, classCol = c(4,2))
silplot(vcrtest, classCols = c(4,2))
classmap(vcrtest, "genuine", classCols = c(4,2))
classmap(vcrtest, "fake", classCols = c(4,2))
```

---

vcr.forest.train	<i>Prepare for visualization of a random forest classification on training data</i>
------------------	---

---

**Description**

Produces output for the purpose of constructing graphical displays such as the [classmap](#) and [silplot](#). The user first needs to train a random forest on the data by `randomForest::randomForest`. This then serves as an argument to `vcr.forest.train`.

**Usage**

```
vcr.forest.train(X, y, trainfit, type = list(),
                 k = 5, stand = TRUE)
```

**Arguments**

<code>X</code>	A rectangular matrix or data frame, where the columns (variables) may be of mixed type.
<code>y</code>	factor with the given class labels. It is crucial that <code>X</code> and <code>y</code> are exactly the same as in the call to <code>randomForest::randomForest</code> . <code>y</code> is allowed to contain NA's.
<code>trainfit</code>	the output of a <code>randomForest::randomForest</code> training run.
<code>k</code>	the number of nearest neighbors used in the farness computation.
<code>type</code>	list for specifying some (or all) of the types of the variables (columns) in <code>X</code> , used for computing the dissimilarity matrix, as in <code>cluster::daisy</code> . The list may contain the following components: "ordratio" (ratio scaled variables to be treated as ordinal variables), "logratio" (ratio scaled variables that must be logarithmically transformed), "asymm" (asymmetric binary) and "symm" (symmetric binary variables). Each component's value is a vector, containing the names or the numbers of the corresponding columns of <code>X</code> . Variables not mentioned in the <code>type</code> list are interpreted as usual (see argument <code>X</code> ).
<code>stand</code>	whether or not to standardize numerical (interval scaled) variables by their range as in the original <code>cluster::daisy</code> code for the farness computation. Defaults to TRUE.

**Value**

A list with components:

<code>X</code>	The data used to train the forest.
<code>yint</code>	number of the given class of each case. Can contain NA's.
<code>y</code>	given class label of each case. Can contain NA's.
<code>levels</code>	levels of <code>y</code>
<code>predint</code>	predicted class number of each case. For each case this is the class with the highest posterior probability. Always exists.
<code>pred</code>	predicted label of each case.
<code>altint</code>	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose <code>y</code> is missing.
<code>altlab</code>	label of the alternative class. Is NA for cases whose <code>y</code> is missing.
<code>PAC</code>	probability of the alternative class. Is NA for cases whose <code>y</code> is missing.
<code>figparams</code>	parameters for computing <code>fig</code> , can be used for new data.
<code>fig</code>	distance of each case $i$ from each class $g$ . Always exists.
<code>farness</code>	farness of each case from its given class. Is NA for cases whose <code>y</code> is missing.
<code>ofarness</code>	for each case $i$ , its lowest <code>fig[i, g]</code> to any class $g$ . Always exists.
<code>trainfit</code>	The trained random forest which was given as an input to this function.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

[vcr.forest.newdata](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
library(randomForest)
data("data_instagram")
traindata = data_instagram[which(data_instagram$dataType == "train"), -13]
set.seed(71) # randomForest is not deterministic
rfout = randomForest(y ~ ., data=traindata, keep.forest=TRUE)
mytype = list(symm = c(1, 5, 7, 8)) # These 4 columns are
# (symmetric) binary variables. The variables that are not
# listed are interval-scaled by default.
x_train = traindata[, -12]
y_train = traindata[, 12]
# Prepare for visualization:
vcrtrain = vcr.forest.train(X = x_train, y = y_train,
                           trainfit = rfout, type = mytype)

confmat.vcr(vcrtrain)
stackedplot(vcrtrain, classCols = c(4,2))
silplot(vcrtrain, classCols = c(4,2))
classmap(vcrtrain, "genuine", classCols = c(4,2))
classmap(vcrtrain, "fake", classCols = c(4,2))
```

---

vcr.knn.newdata

*Carry out a k-nearest neighbor classification on new data, and prepare to visualize its results.*

---

**Description**

Predicts class labels for new data by k nearest neighbors, using the output of [vcr.knn.train](#) on the training data. For cases in the new data whose given label ynew is not NA, additional output is produced for constructing graphical displays such as the [classmap](#).

**Usage**

```
vcr.knn.newdata(Xnew, ynew=NULL, vcr.knn.train.out, LOO=FALSE)
```

**Arguments**

Xnew	If the training data was a matrix of coordinates, Xnew must be such a matrix with the same number of columns. If the training data was a set of dissimilarities, Xnew must be a rectangular matrix of dissimilarities, with each row containing the dissimilarities of a new case to all training cases. Missing values are not allowed.
ynew	factor with class membership of each new case. Can be NA for some or all cases. If NULL, is assumed to be NA everywhere.
vcr.knn.train.out	output of <code>vcr.knn.train</code> on the training data.
LOO	leave one out. Only used when testing this function on a subset of the training data. Default is LOO=FALSE.

**Value**

A list with components:

yintnew	number of the given class of each case. Can contain NA's.
ynew	given class label of each case. Can contain NA's.
levels	levels of the response, from <code>vcr.knn.train.out</code> .
predint	predicted class number of each case. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose ynew is missing.
altlab	label of the alternative class. Is NA for cases whose ynew is missing.
PAC	probability of the alternative class. Is NA for cases whose ynew is missing.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose ynew is missing.
ofarness	for each case $i$ , its lowest <code>fig[i, g]</code> to any class $g$ . Always exists.
k	the requested number of nearest neighbors, from <code>vcr.knn.train.out</code> .
ktrues	for each case this contains the actual number of elements in its neighborhood. This can be higher than $k$ due to ties.
counts	a matrix with 3 columns, each row representing a case. For the neighborhood of each case it says how many members it has from the given class, the predicted class, and the alternative class. The first and third entry is NA for cases whose ynew is missing.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

## References

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

## See Also

[vcr.knn.train](#), [classmap](#), [silplot](#), [stackedplot](#)

## Examples

```
data("data_floralbuds")
X = data_floralbuds[,1:6]; y = data_floralbuds[,7]
set.seed(12345); trainset = sample(1:550, 275)
vcr.train = vcr.knn.train(X[trainset,],y[trainset], k=5)
vcr.test = vcr.knn.newdata(X[-trainset,],y[-trainset],vcr.train)
confmat.vcr(vcr.train) # for comparison
confmat.vcr(vcr.test)
cols = c("saddlebrown","orange","olivedrab4","royalblue3")
stackedplot(vcr.train, classCols = cols) # for comparison
stackedplot(vcr.test, classCols = cols)
classmap(vcr.train, "bud", classCols = cols) # for comparison
classmap(vcr.test, "bud", classCols = cols)

# For more examples, we refer to the vignette:
vignette("K_nearest_neighbors_examples")
```

---

vcr.knn.train	<i>Carry out a k-nearest neighbor classification on training data, and prepare to visualize its results.</i>
---------------	--

---

## Description

Carries out a k-nearest neighbor classification on the training data. Various additional output is produced for the purpose of constructing graphical displays such as the [classmap](#).

## Usage

```
vcr.knn.train(X,y,k)
```

## Arguments

X	This can be a rectangular matrix or data frame of (already standardized) measurements, or a dist object obtained from <a href="#">stats::dist</a> or <a href="#">cluster::daisy</a> . Missing values are not allowed.
y	factor with the given (observed) class labels. There need to be non-missing y in order to be able to train the classifier.
k	the number of nearest neighbors used. It can be selected by running cross-validation using a different package.

**Value**

A list with components:

yint	number of the given class of each case. Can contain NA's.
y	given class label of each case. Can contain NA's.
levels	levels of y
predint	predicted class number of each case. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose y is missing.
altlab	label of the alternative class. Is NA for cases whose y is missing.
PAC	probability of the alternative class. Is NA for cases whose y is missing.
figparams	parameters used to compute fig.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose y is missing.
ofarness	for each case $i$ , its lowest $\text{fig}[i, g]$ to any class $g$ . Always exists.
k	the requested number of nearest neighbors, from the arguments. Will also be used for classifying new data.
ktrues	for each case this contains the actual number of elements in its neighborhood. This can be higher than k due to ties.
counts	a matrix with 3 columns, each row representing a case. For the neighborhood of each case it says how many members it has from the given class, the predicted class, and the alternative class. The first and third entry is NA for cases whose y is missing.
X	If the argument X was a data frame or matrix of coordinates, <code>as.matrix(X)</code> is returned here. This is useful for classifying new data.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

**See Also**

[vcr.knn.newdata](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```

vcrout = vcr.knn.train(iris[,1:4], iris[,5], k = 5)
confmat.vcr(vcrout)
stackedplot(vcrout)
classmap(vcrout, "versicolor", classCols = 2:4)
# The cases misclassified as virginica are shown in blue.

# For more examples, we refer to the vignette:
vignette("K_nearest_neighbors_examples")

```

---

vcr.neural.newdata	<i>Prepare for visualization of a neural network classification on new data.</i>
--------------------	--

---

**Description**

Prepares graphical display of new data fitted by a neural net that was modeled on the training data, using the output of `vcr.neural.train` on the training data.

**Usage**

```

vcr.neural.newdata(Xnew, ynew = NULL, probs,
                  vcr.neural.train.out)

```

**Arguments**

Xnew	data matrix of the new data, with the same number of columns as in the training data. Missing values in Xnew are not allowed.
ynew	factor with class membership of each new case. Can be NA for some or all cases. If NULL, is assumed to be NA everywhere.
probs	posterior probabilities obtained by running the neural net on the new data.
vcr.neural.train.out	output of <code>vcr.neural.train</code> on the training data.

**Value**

A list with components:

yintnew	number of the given class of each case. Can contain NA's.
ynew	given class label of each case. Can contain NA's.
levels	levels of the response, from <code>vcr.svm.train.out</code> .
predint	predicted class number of each case. Always exists.
pred	predicted label of each case.

altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose ynew is missing.
altlab	alternative label if yintnew was given, else NA.
PAC	probability of the alternative class. Is NA for cases whose ynew is missing.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose ynew is missing.
ofarness	for each case $i$ , its lowest $\text{fig}[i, g]$ to any class $g$ . Always exists.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

[vcr.neural.train](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
# For examples, we refer to the vignette:
vignette("Neural_net_examples")
```

---

vcr.neural.train	<i>Prepare for visualization of a neural network classification on training data.</i>
------------------	---

---

**Description**

Produces output for the purpose of constructing graphical displays such as the [classmap](#). The user first needs train a neural network. The representation of the data in a given layer (e.g. the final layer before applying the softmax function) then serves as the argument  $X$  to [vcr.neural.train](#).

**Usage**

```
vcr.neural.train(X, y, probs, estmethod = meancov)
```

**Arguments**

X	the coordinates of the n objects of the training data, in the layer chosen by the user. Missing values are not allowed.
y	factor with the given class labels of the objects. Make sure that the levels are in the same order as used in the neural net, i.e. the columns of its binary "once-hot-encoded" response vectors.
probs	posterior probabilities obtained by the neural net, e.g. in keras. For each case (row of X), the classes have probabilities that add up to 1. Each row of the matrix probs contains these probabilities. The columns of probs must be in the same order as the levels of y.
estmethod	function for location and covariance estimation. Should return a list with \$m and \$S. Can be meancov (classical mean and covariance matrix) or DetMCD. If one or more classes have a singular covariance matrix, the function automatically switches to the PCA-based farness used in <code>vcr.svm.train</code> .

**Value**

A list with components:

X	the coordinates of the n objects of the training data, in the layer chosen by the user.
yint	number of the given class of each case. Can contain NA's.
y	given class label of each case. Can contain NA's.
levels	levels of y
predint	predicted class number of each case. For each case this is the class with the highest posterior probability. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose y is missing.
altlab	label of the alternative class. Is NA for cases whose y is missing.
ncolX	number of columns in X. Keep??
PAC	probability of the alternative class. Is NA for cases whose y is missing.
computeMD	Whether or not the farness is computed using the Mahalanobis distance.
classMS	list with center and covariance matrix of each class
PCAfits	if not NULL, PCA fits to each class, estimated from the training data but also useful for new data.
figparams	parameters for computing fig, can be used for new data.
fig	distance of each case <i>i</i> from each class <i>g</i> . Always exists.
farness	farness of each case from its given class. Is NA for cases whose y is missing.
ofarness	for each case <i>i</i> , its lowest <code>fig[i, g]</code> to any class <i>g</i> . Always exists.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

[vcr.neural.newdata](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
# For examples, we refer to the vignette:  
vignette("Neural_net_examples")
```

---

`vcr.rpart.newdata`      *Prepare for visualization of an rpart classification on new data.*

---

**Description**

Produces output for the purpose of constructing graphical displays such as the [classmap](#) on new data. Requires the output of [vcr.rpart.train](#) as an argument.

**Usage**

```
vcr.rpart.newdata(Xnew, ynew = NULL, vcr.rpart.train.out,  
                  LOO = FALSE)
```

**Arguments**

<code>Xnew</code>	data matrix of the new data, with the same number of columns <code>d</code> as in the training data. Missing values are not allowed.
<code>ynew</code>	factor with class membership of each new case. Can be NA for some or all cases. If NULL, is assumed to be NA everywhere.
<code>vcr.rpart.train.out</code>	output of <a href="#">vcr.rpart.train</a> on the training data.
<code>LOO</code>	leave one out. Only used when testing this function on a subset of the training data. Default is <code>LOO=FALSE</code> .

**Value**

A list with components:

yintnew	number of the given class of each case. Can contain NA's.
ynew	given class label of each case. Can contain NA's.
levels	levels of the response, from <code>vcr.rpart.train.out</code> .
predint	predicted class number of each case. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose ynew is missing.
altlab	alternative label if yintnew was given, else NA.
PAC	probability of the alternative class. Is NA for cases whose ynew is missing.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose ynew is missing.
ofarness	for each case $i$ , its lowest <code>fig[i, g]</code> to any class $g$ . Always exists.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

[vcr.rpart.train](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
library(rpart)
# load("data_titanic.rdata")
data("data_titanic")
traindata = data_titanic[which(data_titanic$dataType == "train"), -13]
str(traindata); table(traindata$y)
set.seed(123) # rpart is not deterministic
rpart.out = rpart(y ~ Pclass + Sex + SibSp +
                  Parch + Fare + Embarked,
                  data=traindata, method='class', model=TRUE)
y_train = traindata[, 12]
x_train = traindata[,-12]
mytype = list(nominal=c("Name", "Sex", "Ticket", "Cabin", "Embarked"),
              ordratio=c("Pclass"))
# These are 5 nominal columns, and one ordinal.
```

```
# The variables not listed are by default interval-scaled.
vcrtrain = vcr.rpart.train(x_train, y_train, rpart.out, mytype)
testdata = data_titanic[which(data_titanic$dataType == "test"), -13]
dim(testdata)
x_test = testdata[, -12]
y_test = testdata[, 12]
vcrtest = vcr.rpart.newdata(x_test, y_test, vcrtrain)
confmat.vcr(vcrtest)
silplot(vcrtest, classCols = c(2,4))
classmap(vcrtest, "casualty", classCols = c(2,4))
classmap(vcrtest, "survived", classCols = c(2,4))
```

---

vcr.rpart.train	<i>Prepare for visualization of an rpart classification on training data.</i>
-----------------	---

---

### Description

Produces output for the purpose of constructing graphical displays such as the [classmap](#). The user first needs to train a classification tree on the data by [rpart::rpart](#). This then serves as an argument to [vcr.rpart.train](#).

### Usage

```
vcr.rpart.train(X, y, trainfit, type = list(),
               k = 5, stand = TRUE)
```

### Arguments

X	A rectangular matrix or data frame, where the columns (variables) may be of mixed type and may contain NA's.
y	factor with the given class labels. It is crucial that X and y are exactly the same as in the call to <a href="#">rpart::rpart</a> . y is allowed to contain NA's.
k	the number of nearest neighbors used in the farness computation.
trainfit	the output of an <a href="#">rpart::rpart</a> training cycle.
type	list for specifying some (or all) of the types of the variables (columns) in X, used for computing the dissimilarity matrix, as in <a href="#">cluster::daisy</a> . The list may contain the following components: "ordratio" (ratio scaled variables to be treated as ordinal variables), "logratio" (ratio scaled variables that must be logarithmically transformed), "asymm" (asymmetric binary) and "symm" (symmetric binary variables). Each component's value is a vector, containing the names or the numbers of the corresponding columns of X. Variables not mentioned in the type list are interpreted as usual (see argument X).
stand	whether or not to standardize numerical (interval scaled) variables by their range as in the original <a href="#">cluster::daisy</a> code for the farness computation. Defaults to TRUE.

**Value**

A list with components:

X	The input data X. Keep??
yint	number of the given class of each case. Can contain NA's.
y	given class label of each case. Can contain NA's.
levels	levels of y
predint	predicted class number of each case. For each case this is the class with the highest posterior probability. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose y is missing.
altlab	label of the alternative class. Is NA for cases whose y is missing.
PAC	probability of the alternative class. Is NA for cases whose y is missing.
figparams	parameters for computing fig, can be used for new data.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose y is missing.
ofarness	for each case $i$ , its lowest $\text{fig}[i, g]$ to any class $g$ . Always exists.
trainfit	the trainfit used to build the VCR object.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J.(2021). Silhouettes and quasi residual plots for neural nets and tree-based classifiers. ([link to open access pdf](#))

**See Also**

[vcr.rpart.newdata](#), [classmap](#), [silplot](#), [stackedplot](#)

**Examples**

```
library(rpart)
# load("data_titanic.rdata")
data("data_titanic")
traindata = data_titanic[which(data_titanic$dataType == "train"), -13]
str(traindata); table(traindata$y)
set.seed(123) # rpart is not deterministic
rpart.out = rpart(y ~ Pclass + Sex + SibSp +
                  Parch + Fare + Embarked,
                  data=traindata, method='class', model=TRUE)
```

```

y_train = traingdata[, 12]
x_train = traingdata[,-12]
mytype = list(nominal=c("Name", "Sex", "Ticket", "Cabin", "Embarked"),
              ordratio=c("Pclass"))
# These are 5 nominal columns, and one ordinal.
# The variables not listed are by default interval-scaled.
vcrtrain = vcr.rpart.train(x_train, y_train, rpart.out, mytype)
confmat.vcr(vcrtrain)
silplot(vcrtrain, classCols = c(2,4))
# Quasi residual plot:
xm = x_train$Age[which(x_train$Sex == "male")]
ym = vcrtrain$PAC[which(x_train$Sex == "male")]
plot(xm, ym, main = "quasi residual plot for males",
     xlab = "Age (years)", ylab = "P[alternative class]")
lom = loess(ym ~ xm)
lines(0:82, predict(lom, 0:82), col="red", lwd = 2)
text(x=17,y=0.56,"loess curve",col="red", cex = 1)
classmap(vcrtrain, "casualty", classCols = c(2,4))
classmap(vcrtrain, "survived", classCols = c(2,4))

```

---

vcr.svm.newdata	<i>Prepare for visualization of a support vector machine classification on new data.</i>
-----------------	--

---

### Description

Carries out a support vector machine classification of new data using the output of `vcr.svm.train` on the training data, and computes the quantities needed for its visualization.

### Usage

```
vcr.svm.newdata(Xnew, ynew=NULL, vcr.svm.train.out)
```

### Arguments

Xnew	data matrix of the new data, with the same number of columns as in the training data. Missing values in Xnew are not allowed.
ynew	factor with class membership of each new case. Can be NA for some or all cases. If NULL, is assumed to be NA everywhere.
vcr.svm.train.out	output of <code>vcr.svm.train</code> on the training data.

### Value

A list with components:

yintnew	number of the given class of each case. Can contain NA's.
ynew	given class label of each case. Can contain NA's.

levels	levels of the response, from <code>vcr.svm.train.out</code> .
predint	predicted class number of each case. Always exists.
pred	predicted label of each case.
altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose <code>ynew</code> is missing.
altlab	alternative label if <code>yintnew</code> was given, else NA.
PAC	probability of the alternative class. Is NA for cases whose <code>ynew</code> is missing.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose <code>ynew</code> is missing.
ofarness	for each case $i$ , its lowest <code>fig[i, g]</code> to any class $g$ . Always exists.

**Author(s)**

Raymaekers J., Rousseeuw P.J.

**References**

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

**See Also**

[vcr.svm.train](#), [classmap](#), [silplot](#), [stackedplot](#), [e1071::svm](#)

**Examples**

```
library(e1071)
set.seed(1); X = matrix(rnorm(200*2), ncol=2)
X[1:100,] = X[1:100,]+2
X[101:150,] = X[101:150,]-2
y = as.factor(c(rep("blue",150),rep("red",50)))
# We now fit an SVM with radial basis kernel to the data:
set.seed(1) # to make the result of svm() reproducible.
svmfit = svm(y~., data=data.frame(X=X, y=y), scale=FALSE, kernel="radial",
             cost=10, gamma=1, probability=TRUE)
vcr.train = vcr.svm.train(X, y, svfit=svmfit)
# As "new" data we take a subset of the training data:
inds = c(1:25, 101:125, 151:175)
vcr.test = vcr.svm.newdata(X[inds,], y[inds], vcr.train)
plot(vcr.test$PAC, vcr.train$PAC[inds]); abline(0,1) # match
plot(vcr.test$farness, vcr.train$farness[inds]); abline(0,1)
confmat.vcr(vcr.test)
cols = c("deepskyblue3", "red")
stackedplot(vcr.test, classCols = cols)
classmap(vcr.train, "blue", classCols = cols) # for comparison
classmap(vcr.test, "blue", classCols = cols)
classmap(vcr.train, "red", classCols = cols) # for comparison
```

```
classmap(vcr.test, "red", classCols = cols)
```

```
# For more examples, we refer to the vignettes:
vignette("Support_vector_machine_examples")
```

---

vcr.svm.train	<i>Prepare for visualization of a support vector machine classification on training data.</i>
---------------	---

---

## Description

Produces output for the purpose of constructing graphical displays such as the `classmap`. The user first needs to run a support vector machine classification on the data by `e1071::svm`, with the option `probability = TRUE`. This classification can be with two or more classes. The output of `e1071::svm` is then an argument to `vcr.svm.train`. As `e1071::svm` does not output the data itself, it needs to be given as well, in the arguments `X` and `y`.

## Usage

```
vcr.svm.train(X, y, svfit, ortho = FALSE)
```

## Arguments

<code>X</code>	matrix of data coordinates, as used in <code>e1071::svm</code> . Missing values are not allowed.
<code>y</code>	factor with the given (observed) class labels. It is crucial that <code>X</code> and <code>y</code> are exactly the same as in the call to <code>e1071::svm</code> .
<code>svfit</code>	an object returned by <code>e1071::svm</code> , called with exactly the same <code>X</code> and <code>y</code> as above.
<code>ortho</code>	If <code>TRUE</code> , will compute fairness in the orthogonal complement of the vector beta given by <code>e1071::svm</code> . Is only possible for 2 classes, else there would be several beta vectors.

## Value

A list with components:

<code>yint</code>	number of the given class of each case. Can contain NA's.
<code>y</code>	given class label of each case. Can contain NA's.
<code>levels</code>	levels of the response <code>y</code> .
<code>predint</code>	predicted class number of each case. Always exists.
<code>pred</code>	predicted label of each case.

altint	number of the alternative class. Among the classes different from the given class, it is the one with the highest posterior probability. Is NA for cases whose y is missing.
altlab	label of the alternative class. Is NA for cases whose y is missing.
PAC	probability of the alternative class. Is NA for cases whose y is missing.
figparams	parameters used in fig, can be used for new data.
fig	distance of each case $i$ from each class $g$ . Always exists.
farness	farness of each case from its given class. Is NA for cases whose y is missing.
ofarness	for each case $i$ , its lowest $\text{fig}[i, g]$ to any class $g$ . Always exists.
svfit	as it was input, will be useful for new data.
X	the matrix of data coordinates from the arguments. This is useful for classifying new data.

### Author(s)

Raymaekers J., Rousseeuw P.J.

### References

Raymaekers J., Rousseeuw P.J., Hubert M. (2021). Class maps for visualizing classification results. *Technometrics*, appeared online. doi: [10.1080/00401706.2021.1927849](https://doi.org/10.1080/00401706.2021.1927849)(link to open access pdf)

### See Also

[vcr.knn.newdata](#), [classmap](#), [silplot](#), [stackedplot](#), [e1071::svm](#)

### Examples

```
library(e1071)
set.seed(1); X = matrix(rnorm(200*2),ncol=2)
X[1:100,] = X[1:100,]+2
X[101:150,] = X[101:150,]-2
y = as.factor(c(rep("blue",150),rep("red",50)))
cols = c("deepskyblue3","red")
plot(X,col=cols[as.numeric(y)],pch=19)
# We now fit an SVM with radial basis kernel to the data:
set.seed(1) # to make the result of svm() reproducible.
svfmit = svm(y~.,data=data.frame(X=X,y=y),scale=FALSE,kernel="radial",
            cost=10, gamma=1, probability=TRUE)
plot(svfmit$decision.values,col=cols[as.numeric(y)]); abline(h=0)
# so the decision values separate the classes reasonably well.
plot(svfmit,data=data.frame(X=X,y=y),X.2~X.1,col=cols)
# The boundary is far from linear (but in feature space it is).
vcr.train = vcr.svm.train(X, y, svfmit=svfmit)
confmat.vcr(vcr.train)
stackedplot(vcr.train, classCols = cols)
classmap(vcr.train, "blue", classCols = cols)
classmap(vcr.train, "red", classCols = cols)
```

```
# For more examples, we refer to the vignettes:  
vignette("Support_vector_machine_examples")
```

# Index

`classmap`, 2, 16–21, 23, 25, 26, 28, 30–33, 35–37  
`cluster::daisy`, 22, 25, 32  
`confmat.vcr`, 4  
  
`data_bookReviews`, 6  
`data_floralbuds`, 7  
`data_instagram`, 8  
`data_titanic`, 9  
  
`e1071::svm`, 12, 35–37  
  
`graphics::identify`, 3  
`graphics::plot`, 3  
  
`kernlab::kernelMatrix`, 10  
  
`makeFV`, 10, 10, 11, 12  
`makeKernel`, 10, 11, 12  
  
`randomForest::randomForest`, 21, 22  
`robustbase::covMcd`, 18  
`rpart::rpart`, 32  
  
`silplot`, 13, 17, 19, 21, 23, 25, 26, 28, 30, 31, 33, 35, 37  
`stackedplot`, 14, 17, 19, 21, 23, 25, 26, 28, 30, 31, 33, 35, 37  
`stats::dist`, 25  
  
`vcr.da.newdata`, 4, 5, 14, 15, 16, 19  
`vcr.da.train`, 4, 5, 14–17, 18  
`vcr.forest.newdata`, 4, 5, 14, 15, 20, 23  
`vcr.forest.train`, 4, 5, 14, 15, 20, 21, 21  
`vcr.knn.newdata`, 4, 5, 14, 15, 23, 26, 37  
`vcr.knn.train`, 4, 5, 14, 15, 23–25, 25  
`vcr.neural.newdata`, 4, 5, 14, 15, 27, 30  
`vcr.neural.train`, 4, 5, 14, 15, 27, 28, 28  
`vcr.rpart.newdata`, 4, 5, 14, 15, 30, 33  
`vcr.rpart.train`, 4, 5, 14, 15, 30–32, 32  
`vcr.svm.newdata`, 4, 5, 14, 15, 34  
`vcr.svm.train`, 4, 5, 14, 15, 29, 34–36, 36