

# Package ‘RRF’

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**Title** Regularized Random Forest

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**Suggests** RColorBrewer, MASS

**Description** Feature Selection with Regularized Random Forest. This package is based on the 'randomForest' package by Andy Liaw. The key difference is the RRF() function that builds a regularized random forest. Fortran original by Leo Breiman and Adele Cutler, R port by Andy Liaw and Matthew Wiener, Regularized random forest for classification by Houtao Deng, Regularized random forest for regression by Xin Guan. Reference: Houtao Deng (2013) <[arXiv:1306.0237](https://arxiv.org/abs/1306.0237)>.

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classCenter	<i>Prototypes of groups.</i>
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## Description

Prototypes are ‘representative’ cases of a group of data points, given the similarity matrix among the points. They are very similar to medoids. The function is named ‘classCenter’ to avoid conflict with the function prototype in the methods package.

## Usage

```
classCenter(x, label, prox, nNbr = min(table(label))-1)
```

## Arguments

x	a matrix or data frame
label	group labels of the rows in x
prox	the proximity (or similarity) matrix, assumed to be symmetric with 1 on the diagonal and in [0, 1] off the diagonal (the order of row/column must match that of x)
nNbr	number of nearest neighbors used to find the prototypes.

**Details**

This version only computes one prototype per class. For each case in  $x$ , the  $nNbr$  nearest neighbors are found. Then, for each class, the case that has most neighbors of that class is identified. The prototype for that class is then the medoid of these neighbors (coordinate-wise medians for numerical variables and modes for categorical variables).

This version only computes one prototype per class. In the future more prototypes may be computed (by removing the ‘neighbors’ used, then iterate).

**Value**

A data frame containing one prototype in each row.

**Author(s)**

Andy Liaw

**See Also**

[RRF](#), [MDSplot](#)

**Examples**

```
data(iris)
iris.rf <- RRF(iris[,-5], iris[,5], prox=TRUE)
iris.p <- classCenter(iris[,-5], iris[,5], iris.rf$prox)
plot(iris[,3], iris[,4], pch=21, xlab=names(iris)[3], ylab=names(iris)[4],
     bg=c("red", "blue", "green")[as.numeric(factor(iris$Species))],
     main="Iris Data with Prototypes")
points(iris.p[,3], iris.p[,4], pch=21, cex=2, bg=c("red", "blue", "green"))
```

---

combine

*Combine Ensembles of Trees*

---

**Description**

Combine two more more ensembles of trees into one.

**Usage**

```
combine(...)
```

**Arguments**

... two or more objects of class RRF, to be combined into one.

**Value**

An object of class RRF.

**Note**

The confusion, err.rate, mse and rsq components (as well as the corresponding components in the test component, if exist) of the combined object will be NULL.

**Author(s)**

Andy Liaw <andy\_liaw@merck.com>

**See Also**

[RRF](#), [grow](#)

**Examples**

```
data(iris)
rf1 <- RRF(Species ~ ., iris, ntree=50, norm.votes=FALSE)
rf2 <- RRF(Species ~ ., iris, ntree=50, norm.votes=FALSE)
rf3 <- RRF(Species ~ ., iris, ntree=50, norm.votes=FALSE)
rf.all <- combine(rf1, rf2, rf3)
print(rf.all)
```

---

getTree

*Extract a single tree from a forest.*

---

**Description**

This function extract the structure of a tree from a RRF object.

**Usage**

```
getTree(rfobj, k=1, labelVar=FALSE)
```

**Arguments**

rfobj	a <a href="#">RRF</a> object.
k	which tree to extract?
labelVar	Should better labels be used for splitting variables and predicted class?

**Details**

For numerical predictors, data with values of the variable less than or equal to the splitting point go to the left daughter node.

For categorical predictors, the splitting point is represented by an integer, whose binary expansion gives the identities of the categories that goes to left or right. For example, if a predictor has four categories, and the split point is 13. The binary expansion of 13 is (1, 0, 1, 1) (because  $13 = 1 * 2^0 + 0 * 2^1 + 1 * 2^2 + 1 * 2^3$ ), so cases with categories 1, 3, or 4 in this predictor get sent to the left, and the rest to the right.

**Value**

A matrix (or data frame, if `labelVar=TRUE`) with six columns and number of rows equal to total number of nodes in the tree. The six columns are:

left daughter	the row where the left daughter node is; 0 if the node is terminal
right daughter	the row where the right daughter node is; 0 if the node is terminal
split var	which variable was used to split the node; 0 if the node is terminal
split point	where the best split is; see Details for categorical predictor
status	is the node terminal (-1) or not (1)
prediction	the prediction for the node; 0 if the node is not terminal

**Author(s)**

Andy Liaw <andy\_liaw@merck.com>

**See Also**

[RRF](#)

**Examples**

```
data(iris)
## Look at the third trees in the forest.
getTree(RRF(iris[,-5], iris[,5], ntree=10), 3, labelVar=TRUE)
```

---

grow

*Add trees to an ensemble*

---

**Description**

Add additional trees to an existing ensemble of trees.

**Usage**

```
## S3 method for class 'RRF'
grow(x, how.many, ...)
```

**Arguments**

x	an object of class RRF, which contains a forest component.
how.many	number of trees to add to the RRF object.
...	currently ignored.

**Value**

An object of class RRF, containing `how.many` additional trees.

**Note**

The confusion, err.rate, mse and rsq components (as well as the corresponding components in the test component, if exist) of the combined object will be NULL.

**Author(s)**

Andy Liaw <andy\_liaw@merck.com>

**See Also**

[combine](#), [RRF](#)

**Examples**

```
data(iris)
iris.rf <- RRF(Species ~ ., iris, ntree=50, norm.votes=FALSE)
iris.rf <- grow(iris.rf, 50)
print(iris.rf)
```

---

importance

*Extract variable importance measure*

---

**Description**

This is the extractor function for variable importance measures as produced by [RRF](#).

**Usage**

```
## S3 method for class 'RRF'
importance(x, type=NULL, class=NULL, scale=TRUE, ...)
```

**Arguments**

x	an object of class <a href="#">RRF</a> .
type	either 1 or 2, specifying the type of importance measure (1=mean decrease in accuracy, 2=mean decrease in node impurity).
class	for classification problem, which class-specific measure to return.
scale	For permutation based measures, should the measures be divided their “standard errors”?
...	not used.

## Details

Here are the definitions of the variable importance measures. The first measure is computed from permuting OOB data: For each tree, the prediction error on the out-of-bag portion of the data is recorded (error rate for classification, MSE for regression). Then the same is done after permuting each predictor variable. The difference between the two are then averaged over all trees, and normalized by the standard deviation of the differences. If the standard deviation of the differences is equal to 0 for a variable, the division is not done (but the average is almost always equal to 0 in that case).

The second measure is the total decrease in node impurities from splitting on the variable, averaged over all trees. For classification, the node impurity is measured by the Gini index. For regression, it is measured by residual sum of squares.

## Value

A matrix of importance measure, one row for each predictor variable. The column(s) are different importance measures.

## See Also

[RRF](#), [varImpPlot](#)

## Examples

```
set.seed(4543)
data(mtcars)
mtcars.rf <- RRF(mpg ~ ., data=mtcars, ntree=1000,
               keep.forest=FALSE, importance=TRUE)
importance(mtcars.rf)
importance(mtcars.rf, type=1)
```

---

imports85

*The Automobile Data*

---

## Description

This is the 'Automobile' data from the UCI Machine Learning Repository.

## Usage

```
data(imports85)
```

## Format

imports85 is a data frame with 205 cases (rows) and 26 variables (columns). This data set consists of three types of entities: (a) the specification of an auto in terms of various characteristics, (b) its assigned insurance risk rating, (c) its normalized losses in use as compared to other cars. The second rating corresponds to the degree to which the auto is more risky than its price indicates.

Cars are initially assigned a risk factor symbol associated with its price. Then, if it is more risky (or less), this symbol is adjusted by moving it up (or down) the scale. Actuaries call this process ‘symboling’. A value of +3 indicates that the auto is risky, -3 that it is probably pretty safe.

The third factor is the relative average loss payment per insured vehicle year. This value is normalized for all autos within a particular size classification (two-door small, station wagons, sports/speciality, etc...), and represents the average loss per car per year.

### Author(s)

Andy Liaw

### Source

Originally created by Jeffrey C. Schlimmer, from 1985 Model Import Car and Truck Specifications, 1985 Ward’s Automotive Yearbook, Personal Auto Manuals, Insurance Services Office, and Insurance Collision Report, Insurance Institute for Highway Safety.

The original data is at <http://www.ics.uci.edu/~mlearn/MLSummary.html>.

### References

1985 Model Import Car and Truck Specifications, 1985 Ward’s Automotive Yearbook.

Personal Auto Manuals, Insurance Services Office, 160 Water Street, New York, NY 10038

Insurance Collision Report, Insurance Institute for Highway Safety, Watergate 600, Washington, DC 20037

### See Also

[RRF](#)

### Examples

```
data(imports85)
imp85 <- imports85[,-2] # Too many NAs in normalizedLosses.
imp85 <- imp85[complete.cases(imp85), ]
## Drop empty levels for factors.
imp85[] <- lapply(imp85, function(x) if (is.factor(x)) x[, drop=TRUE] else x)

stopifnot(require(RRF))
price.rf <- RRF(price ~ ., imp85, do.trace=10, ntree=100)
print(price.rf)
numDoors.rf <- RRF(numOfDoors ~ ., imp85, do.trace=10, ntree=100)
print(numDoors.rf)
```



---

margin

*Margins of RRF Classifier*

---

## Description

Compute or plot the margin of predictions from a RRF classifier.

## Usage

```
## S3 method for class 'RRF'  
margin(x, ...)  
## Default S3 method:  
margin(x, observed, ...)  
## S3 method for class 'margin'  
plot(x, sort=TRUE, ...)
```

## Arguments

x	an object of class <a href="#">RRF</a> , whose type is not regression, or a matrix of predicted probabilities, one column per class and one row per observation. For the plot method, x should be an object returned by <code>margin</code> .
observed	the true response corresponding to the data in x.
sort	Should the data be sorted by their class labels?
...	other graphical parameters to be passed to <code>plot.default</code> .

## Value

For `margin`, the *margin* of observations from the [RRF](#) classifier (or whatever classifier that produced the predicted probability matrix given to `margin`). The margin of a data point is defined as the proportion of votes for the correct class minus maximum proportion of votes for the other classes. Thus under majority votes, positive margin means correct classification, and vice versa.

## Author(s)

Robert Gentleman, with slight modifications by Andy Liaw

## See Also

[RRF](#)

## Examples

```
set.seed(1)  
data(iris)  
iris.rf <- RRF(Species ~ ., iris, keep.forest=FALSE)  
plot(margin(iris.rf))
```

---

**MDSplot***Multi-dimensional Scaling Plot of Proximity matrix from RRF*

---

**Description**

Plot the scaling coordinates of the proximity matrix from RRF.

**Usage**

```
MDSplot(rf, fac, k=2, palette=NULL, pch=20, ...)
```

**Arguments**

<code>rf</code>	an object of class <a href="#">RRF</a> that contains the proximity component.
<code>fac</code>	a factor that was used as response to train <code>rf</code> .
<code>k</code>	number of dimensions for the scaling coordinates.
<code>palette</code>	colors to use to distinguish the classes; length must be the equal to the number of levels.
<code>pch</code>	plotting symbols to use.
<code>...</code>	other graphical parameters.

**Value**

The output of [cmdscale](#) on `1 - rf$proximity` is returned invisibly.

**Note**

If `k > 2`, [pairs](#) is used to produce the scatterplot matrix of the coordinates.

**Author(s)**

Robert Gentleman, with slight modifications by Andy Liaw

**See Also**

[RRF](#)

**Examples**

```
set.seed(1)
data(iris)
iris.rf <- RRF(Species ~ ., iris, proximity=TRUE,
              keep.forest=FALSE)
MDSplot(iris.rf, iris$Species)
## Using different symbols for the classes:
MDSplot(iris.rf, iris$Species, palette=rep(1, 3), pch=as.numeric(iris$Species))
```

---

na.roughfix	<i>Rough Imputation of Missing Values</i>
-------------	---

---

**Description**

Impute Missing Values by median/mode.

**Usage**

```
na.roughfix(object, ...)
```

**Arguments**

object	a data frame or numeric matrix.
...	further arguments special methods could require.

**Value**

A completed data matrix or data frame. For numeric variables, NAs are replaced with column medians. For factor variables, NAs are replaced with the most frequent levels (breaking ties at random). If object contains no NAs, it is returned unaltered.

**Note**

This is used as a starting point for imputing missing values by random forest.

**Author(s)**

Andy Liaw

**See Also**

[rrfImpute](#), [RRF](#).

**Examples**

```
data(iris)
iris.na <- iris
set.seed(111)
## artificially drop some data values.
for (i in 1:4) iris.na[sample(150, 20), i] <- NA
iris.roughfix <- na.roughfix(iris.na)
iris.narf <- RRF(Species ~ ., iris.na, na.action=na.roughfix)
print(iris.narf)
```

---

`outlier`*Compute outlying measures*

---

### Description

Compute outlying measures based on a proximity matrix.

### Usage

```
## Default S3 method:  
outlier(x, cls=NULL, ...)  
## S3 method for class 'RRF'  
outlier(x, ...)
```

### Arguments

<code>x</code>	a proximity matrix (a square matrix with 1 on the diagonal and values between 0 and 1 in the off-diagonal positions); or an object of class <code>RRF</code> , whose type is not regression.
<code>cls</code>	the classes the rows in the proximity matrix belong to. If not given, all data are assumed to come from the same class.
<code>...</code>	arguments for other methods.

### Value

A numeric vector containing the outlying measures. The outlying measure of a case is computed as  $n / \text{sum}(\text{squared proximity})$ , normalized by subtracting the median and divided by the MAD, within each class.

### See Also

[RRF](#)

### Examples

```
set.seed(1)  
iris.rf <- RRF(iris[,-5], iris[,5], proximity=TRUE)  
plot(outlier(iris.rf), type="h",  
      col=c("red", "green", "blue")[as.numeric(iris$Species)])
```

---

partialPlot	<i>Partial dependence plot</i>
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---

### Description

Partial dependence plot gives a graphical depiction of the marginal effect of a variable on the class probability (classification) or response (regression).

### Usage

```
## S3 method for class 'RRF'
partialPlot(x, pred.data, x.var, which.class,
            w, plot = TRUE, add = FALSE,
            n.pt = min(length(unique(pred.data[, xname])), 51),
            rug = TRUE, xlab=deparse(substitute(x.var)), ylab="",
            main=paste("Partial Dependence on", deparse(substitute(x.var))),
            ...)
```

### Arguments

<code>x</code>	an object of class RRF, which contains a forest component.
<code>pred.data</code>	a data frame used for constructing the plot, usually the training data used to construct the random forest.
<code>x.var</code>	name of the variable for which partial dependence is to be examined.
<code>which.class</code>	For classification data, the class to focus on (default the first class).
<code>w</code>	weights to be used in averaging; if not supplied, mean is not weighted
<code>plot</code>	whether the plot should be shown on the graphic device.
<code>add</code>	whether to add to existing plot (TRUE).
<code>n.pt</code>	if <code>x.var</code> is continuous, the number of points on the grid for evaluating partial dependence.
<code>rug</code>	whether to draw hash marks at the bottom of the plot indicating the deciles of <code>x.var</code> .
<code>xlab</code>	label for the x-axis.
<code>ylab</code>	label for the y-axis.
<code>main</code>	main title for the plot.
<code>...</code>	other graphical parameters to be passed on to plot or lines.

### Details

The function being plotted is defined as:

$$\tilde{f}(x) = \frac{1}{n} \sum_{i=1}^n f(x, x_{iC}),$$

where  $x$  is the variable for which partial dependence is sought, and  $x_{iC}$  is the other variables in the data. The summand is the predicted regression function for regression, and logits (i.e., log of fraction of votes) for which `class` for classification:

$$f(x) = \log p_k(x) - \frac{1}{K} \sum_{j=1}^K \log p_j(x),$$

where  $K$  is the number of classes,  $k$  is which `class`, and  $p_j$  is the proportion of votes for class  $j$ .

### Value

A list with two components: `x` and `y`, which are the values used in the plot.

### Note

The RRF object must contain the forest component; i.e., created with `RRF(..., keep.forest=TRUE)`.

This function runs quite slow for large data sets.

### Author(s)

Andy Liaw <andy\_liaw@merck.com>

### References

Friedman, J. (2001). Greedy function approximation: the gradient boosting machine, *Ann. of Stat.*

### See Also

[RRF](#)

### Examples

```
data(airquality)
airquality <- na.omit(airquality)
set.seed(131)
ozone.rf <- RRF(Ozone ~ ., airquality)
partialPlot(ozone.rf, airquality, Temp)
```

```
data(iris)
set.seed(543)
iris.rf <- RRF(Species~., iris)
partialPlot(iris.rf, iris, Petal.Width, "versicolor")
```

---

`plot.RRF`*Plot method for RRF objects*

---

**Description**

Plot the error rates or MSE of a RRF object

**Usage**

```
## S3 method for class 'RRF'  
plot(x, type="l", main=deparse(substitute(x)), ...)
```

**Arguments**

<code>x</code>	an object of class RRF.
<code>type</code>	type of plot.
<code>main</code>	main title of the plot.
<code>...</code>	other graphical parameters.

**Value**

Invisibly, the error rates or MSE of the RRF object. If the object has a non-null test component, then the returned object is a matrix where the first column is the out-of-bag estimate of error, and the second column is for the test set.

**Note**

This function does not work for RRF objects that have `type=unsupervised`.  
If the `x` has a non-null test component, then the test set errors are also plotted.

**Author(s)**

Andy Liaw

**See Also**

[RRF](#)

**Examples**

```
data(mtcars)  
plot(RRF(mpg ~ ., mtcars, keep.forest=FALSE, ntree=100), log="y")
```

---

predict.RRF	<i>predict method for random forest objects</i>
-------------	---

---

## Description

Prediction of test data using random forest.

## Usage

```
## S3 method for class 'RRF'
predict(object, newdata, type="response",
        norm.votes=TRUE, predict.all=FALSE, proximity=FALSE, nodes=FALSE,
        cutoff, ...)
```

## Arguments

object	an object of class RRF, as that created by the function RRF.
newdata	a data frame or matrix containing new data. (Note: If not given, the out-of-bag prediction in object is returned.)
type	one of response, prob. or votes, indicating the type of output: predicted values, matrix of class probabilities, or matrix of vote counts. class is allowed, but automatically converted to "response", for backward compatibility.
norm.votes	Should the vote counts be normalized (i.e., expressed as fractions)? Ignored if object\$type is regression.
predict.all	Should the predictions of all trees be kept?
proximity	Should proximity measures be computed? An error is issued if object\$type is regression.
nodes	Should the terminal node indicators (an n by ntree matrix) be return? If so, it is in the "nodes" attribute of the returned object.
cutoff	(Classification only) A vector of length equal to number of classes. The 'winning' class for an observation is the one with the maximum ratio of proportion of votes to cutoff. Default is taken from the forest\$cutoff component of object (i.e., the setting used when running RRF).
...	not used currently.

## Value

If object\$type is regression, a vector of predicted values is returned. If predict.all=TRUE, then the returned object is a list of two components: aggregate, which is the vector of predicted values by the forest, and individual, which is a matrix where each column contains prediction by a tree in the forest.

If object\$type is classification, the object returned depends on the argument type:

response	predicted classes (the classes with majority vote).
----------	---



prob	matrix of class probabilities (one column for each class and one row for each input).
vote	matrix of vote counts (one column for each class and one row for each new input); either in raw counts or in fractions (if norm.votes=TRUE).

If `predict.all=TRUE`, then the `individual` component of the returned object is a character matrix where each column contains the predicted class by a tree in the forest.

If `proximity=TRUE`, the returned object is a list with two components: `pred` is the prediction (as described above) and `proximity` is the proximity matrix. An error is issued if `object$type` is regression.

If `nodes=TRUE`, the returned object has a “nodes” attribute, which is an n by ntree matrix, each column containing the node number that the cases fall in for that tree.

NOTE: If the object inherits from `RRF.formula`, then any data with NA are silently omitted from the prediction. The returned value will contain NA correspondingly in the aggregated and individual tree predictions (if requested), but not in the proximity or node matrices.

NOTE2: Any ties are broken at random, so if this is undesirable, avoid it by using odd number ntree in `RRF()`.

### Author(s)

Andy Liaw <andy\_liaw@merck.com> and Matthew Wiener <matthew\_wiener@merck.com>, based on original Fortran code by Leo Breiman and Adele Cutler.

### References

Breiman, L. (2001), *Random Forests*, Machine Learning 45(1), 5-32.

### See Also

[RRF](#)

### Examples

```
data(iris)
set.seed(111)
ind <- sample(2, nrow(iris), replace = TRUE, prob=c(0.8, 0.2))
iris.rf <- RRF(Species ~ ., data=iris[ind == 1,])
iris.pred <- predict(iris.rf, iris[ind == 2,])
table(observed = iris[ind==2, "Species"], predicted = iris.pred)
## Get prediction for all trees.
predict(iris.rf, iris[ind == 2,], predict.all=TRUE)
## Proximities.
predict(iris.rf, iris[ind == 2,], proximity=TRUE)
## Nodes matrix.
str(attr(predict(iris.rf, iris[ind == 2,], nodes=TRUE), "nodes"))
```

**Description**

RRF implements the regularized random forest algorithm. It is based on the randomForest R package by Andy Liaw, Matthew Wiener, Leo Breiman and Adele Cutler.

**Usage**

```
## S3 method for class 'formula'
RRF(formula, data=NULL, ..., subset, na.action=na.fail)
## Default S3 method:
RRF(x, y=NULL, xtest=NULL, ytest=NULL, ntree=500,
     mtry=if (!is.null(y) && !is.factor(y))
           max(floor(ncol(x)/3), 1) else floor(sqrt(ncol(x))),
     replace=TRUE, classwt=NULL, cutoff, strata,
     sampsize = if (replace) nrow(x) else ceiling(.632*nrow(x)),
     nodesize = if (!is.null(y) && !is.factor(y)) 5 else 1,
     maxnodes = NULL,
     importance=FALSE, localImp=FALSE, nPerm=1,
     proximity, oob.prox=proximity,
     norm.votes=TRUE, do.trace=FALSE,
     keep.forest=!is.null(y) && is.null(xtest), corr.bias=FALSE,
     keep.inbag=FALSE, coefReg=NULL, flagReg=1, feaIni=NULL,...)
## S3 method for class 'RRF'
print(x, ...)
```

**Arguments**

data	an optional data frame containing the variables in the model. By default the variables are taken from the environment which RRF is called from.
subset	an index vector indicating which rows should be used. (NOTE: If given, this argument must be named.)
na.action	A function to specify the action to be taken if NAs are found. (NOTE: If given, this argument must be named.)
x, formula	a data frame or a matrix of predictors, or a formula describing the model to be fitted (for the print method, an RRF object).
y	A response vector. If a factor, classification is assumed, otherwise regression is assumed. If omitted, RRF will run in unsupervised mode.
xtest	a data frame or matrix (like x) containing predictors for the test set.
ytest	response for the test set.
ntree	Number of trees to grow. This should not be set to too small a number, to ensure that every input row gets predicted at least a few times.

mtry	Number of variables randomly sampled as candidates at each split. Note that the default values are different for classification ( $\sqrt{p}$ where $p$ is number of variables in $x$ ) and regression ( $p/3$ )
replace	Should sampling of cases be done with or without replacement?
classwt	Priors of the classes. Need not add up to one. Ignored for regression.
cutoff	(Classification only) A vector of length equal to number of classes. The ‘winning’ class for an observation is the one with the maximum ratio of proportion of votes to cutoff. Default is $1/k$ where $k$ is the number of classes (i.e., majority vote wins).
strata	A (factor) variable that is used for stratified sampling.
samplesize	Size(s) of sample to draw. For classification, if samplesize is a vector of the length the number of strata, then sampling is stratified by strata, and the elements of samplesize indicate the numbers to be drawn from the strata.
nodesize	Minimum size of terminal nodes. Setting this number larger causes smaller trees to be grown (and thus take less time). Note that the default values are different for classification (1) and regression (5).
maxnodes	Maximum number of terminal nodes trees in the forest can have. If not given, trees are grown to the maximum possible (subject to limits by nodesize). If set larger than maximum possible, a warning is issued.
importance	Should importance of predictors be assessed?
localImp	Should casewise importance measure be computed? (Setting this to TRUE will override importance.)
nPerm	Number of times the OOB data are permuted per tree for assessing variable importance. Number larger than 1 gives slightly more stable estimate, but not very effective. Currently only implemented for regression.
proximity	Should proximity measure among the rows be calculated?
oob.prox	Should proximity be calculated only on “out-of-bag” data?
norm.votes	If TRUE (default), the final result of votes are expressed as fractions. If FALSE, raw vote counts are returned (useful for combining results from different runs). Ignored for regression.
do.trace	If set to TRUE, give a more verbose output as RRF is run. If set to some integer, then running output is printed for every do.trace trees.
keep.forest	If set to FALSE, the forest will not be retained in the output object. If xtest is given, defaults to FALSE.
corr.bias	perform bias correction for regression? Note: Experimental. Use at your own risk.
keep.inbag	Should an $n$ by $n_{tree}$ matrix be returned that keeps track of which samples are “in-bag” in which trees (but not how many times, if sampling with replacement)
coefReg	the coefficient(s) of regularization. A smaller coefficient may lead to a smaller feature subset, i.e. there are fewer variables with non-zero importance scores. coefReg must be either a single value (all variables have the same coefficient) or a numeric vector of length equal to the number of predictor variables. default: 0.8

<code>flagReg</code>	1: with regularization; 0: without regularization. default: 1
<code>feaIni</code>	initial feature subset, useful only when <code>flagReg = 1</code>
<code>...</code>	optional parameters to be passed to the low level function <code>RRF</code> . default: <code>t</code> .

**Value**

An object of class `RRF`, which is a list with the following components:

<code>call</code>	the original call to <code>RRF</code>
<code>type</code>	one of regression, classification, or unsupervised.
<code>predicted</code>	the predicted values of the input data based on out-of-bag samples.
<code>importance</code>	a matrix with <code>nclass + 2</code> (for classification) or two (for regression) columns. For classification, the first <code>nclass</code> columns are the class-specific measures computed as mean decrease in accuracy. The <code>nclass + 1</code> st column is the mean decrease in accuracy over all classes. The last column is the mean decrease in Gini index. For Regression, the first column is the mean decrease in accuracy and the second the mean decrease in MSE. If <code>importance=FALSE</code> , the last measure is still returned as a vector.
<code>importanceSD</code>	The “standard errors” of the permutation-based importance measure. For classification, a <code>p</code> by <code>nclass + 1</code> matrix corresponding to the first <code>nclass + 1</code> columns of the importance matrix. For regression, a length <code>p</code> vector.
<code>localImp</code>	a <code>p</code> by <code>n</code> matrix containing the casewise importance measures, the <code>[i,j]</code> element of which is the importance of <code>i</code> -th variable on the <code>j</code> -th case. NULL if <code>localImp=FALSE</code> .
<code>ntree</code>	number of trees grown.
<code>mtry</code>	number of predictors sampled for splitting at each node.
<code>forest</code>	(a list that contains the entire forest; NULL if <code>RRF</code> is run in unsupervised mode or if <code>keep.forest=FALSE</code> ).
<code>err.rate</code>	(classification only) vector error rates of the prediction on the input data, the <code>i</code> -th element being the (OOB) error rate for all trees up to the <code>i</code> -th.
<code>confusion</code>	(classification only) the confusion matrix of the prediction (based on OOB data).
<code>votes</code>	(classification only) a matrix with one row for each input data point and one column for each class, giving the fraction or number of (OOB) ‘votes’ from the random forest.
<code>oob.times</code>	number of times cases are ‘out-of-bag’ (and thus used in computing OOB error estimate)
<code>proximity</code>	if <code>proximity=TRUE</code> when <code>RRF</code> is called, a matrix of proximity measures among the input (based on the frequency that pairs of data points are in the same terminal nodes).
<code>feaSet</code>	features selected
<code>mse</code>	(regression only) vector of mean square errors: sum of squared residuals divided by <code>n</code> .
<code>rsq</code>	(regression only) “pseudo R-squared”: $1 - \text{mse} / \text{Var}(y)$ .

`test` if test set is given (through the `xtest` or additionally `ytest` arguments), this component is a list which contains the corresponding predicted, `err.rate`, confusion, votes (for classification) or predicted, `mse` and `rsq` (for regression) for the test set. If `proximity=TRUE`, there is also a component, `proximity`, which contains the proximity among the test set as well as proximity between test and training data.

### Note

For large data sets, especially those with large number of variables, calling RRF via the formula interface is not advised: There may be too much overhead in handling the formula.

### Author(s)

Houtao Deng <softwareheng@gmail.com>, based on the randomForest R package by Andy Liaw, Matthew Wiener, Leo Breiman and Adele Cutler.

### References

- Houtao Deng and George C. Runger (2013), *Gene Selection with Guided Regularized Random Forest*, Pattern Recognition 46(12): 3483-3489.
- Houtao Deng and George C. Runger (2012), *Feature Selection via Regularized Trees*, the 2012 International Joint Conference on Neural Networks (IJCNN).
- Houtao Deng (2013), *Guided Random Forest in the RRF Package*, arXiv:1306.0237.

### Examples

```
#-----Example 1 -----
library(RRF);set.seed(1)

#only the first feature and last feature are truly useful
X <- matrix(runif(50*50), ncol=50)
class <- (X[,1])^2 + (X[,50])^2
class[class>median(class)] <- 1;
class[class<=median(class)] <- 0

#ordinary random forest.
rf <- RRF(X,as.factor(class), flagReg = 0)
impRF <- rf$importance
impRF <- impRF[, "MeanDecreaseGini"]
rf$feaSet

#regularized random forest
rrf <- RRF(X,as.factor(class), flagReg = 1)
rrf$feaSet

#guided regularized random forest
imp <- impRF/(max(impRF))#normalize the importance score
gamma <- 0.5
coefReg <- (1-gamma)+gamma*imp #weighted average
grrf <- RRF(X,as.factor(class),coefReg=coefReg, flagReg=1)
```

```

grrf$feaSet

#guided random forest
gamma <- 1
coefReg <- (1-gamma)+gamma*imp
grf <- RRF(X,as.factor(class),coefReg=coefReg, flagReg=0)
grf$feaSet

#-----Example 2 XOR learning-----
#only the first 3 features are needed
#and each individual feature is not useful
#bSample <- sample(0:1,20000,replace=TRUE)
#X <- matrix(bSample,ncol=40)
#class <- xor(xor(X[,1],X[,2]),X[,3])

```

---

rrfcv

*Random Forest Cross-Validation for feature selection*


---

## Description

This function shows the cross-validated prediction performance of models with sequentially reduced number of predictors (ranked by variable importance) via a nested cross-validation procedure.

## Usage

```

rrfcv(trainx, trainy, cv.fold=5, scale="log", step=0.5,
      mtry=function(p) max(1, floor(sqrt(p))), recursive=FALSE, ...)

```

## Arguments

trainx	matrix or data frame containing columns of predictor variables
trainy	vector of response, must have length equal to the number of rows in trainx
cv.fold	number of folds in the cross-validation
scale	if "log", reduce a fixed proportion (step) of variables at each step, otherwise reduce step variables at a time
step	if log=TRUE, the fraction of variables to remove at each step, else remove this many variables at a time
mtry	a function of number of remaining predictor variables to use as the mtry parameter in the RRF call
recursive	whether variable importance is (re-)assessed at each step of variable reduction
...	other arguments passed on to RRF

**Value**

A list with the following components:

```
list(n.var=n.var, error.cv=error.cv, predicted=cv.pred)
```

n.var	vector of number of variables used at each step
error.cv	corresponding vector of error rates or MSEs at each step
predicted	list of n.var components, each containing the predicted values from the cross-validation

**Author(s)**

Andy Liaw

**References**

Svetnik, V., Liaw, A., Tong, C. and Wang, T., "Application of Breiman's Random Forest to Modeling Structure-Activity Relationships of Pharmaceutical Molecules", MCS 2004, Roli, F. and Windeatt, T. (Eds.) pp. 334-343.

**See Also**

[RRF](#), [importance](#)

**Examples**

```
## The following can take a while to run, so if you really want to try
## it, copy and paste the code into R.

set.seed(647)
myiris <- cbind(iris[1:4], matrix(runif(508 * nrow(iris)), nrow(iris), 508))
result <- rrfcv(myiris, iris$Species)
with(result, plot(n.var, error.cv, log="x", type="o", lwd=2))

result <- replicate(5, rrfcv(myiris, iris$Species), simplify=FALSE)
error.cv <- sapply(result, "[[", "error.cv")
matplot(result[[1]]$n.var, cbind(rowMeans(error.cv), error.cv), type="l",
        lwd=c(2, rep(1, ncol(error.cv))), col=1, lty=1, log="x",
        xlab="Number of variables", ylab="CV Error")
```

---

`rrfImpute`*Missing Value Imputations by RRF*

---

**Description**

Impute missing values in predictor data using proximity from RRF.

**Usage**

```
## Default S3 method:  
rrfImpute(x, y, iter=5, ntree=300, ...)  
## S3 method for class 'formula'  
rrfImpute(x, data, ..., subset)
```

**Arguments**

<code>x</code>	A data frame or matrix of predictors, some containing NAs, or a formula.
<code>y</code>	Response vector (NA's not allowed).
<code>data</code>	A data frame containing the predictors and response.
<code>iter</code>	Number of iterations to run the imputation.
<code>ntree</code>	Number of trees to grow in each iteration of RRF.
<code>...</code>	Other arguments to be passed to <a href="#">RRF</a> .
<code>subset</code>	A logical vector indicating which observations to use.

**Details**

The algorithm starts by imputing NAs using [na.roughfix](#). Then [RRF](#) is called with the completed data. The proximity matrix from the RRF is used to update the imputation of the NAs. For continuous predictors, the imputed value is the weighted average of the non-missing observations, where the weights are the proximities. For categorical predictors, the imputed value is the category with the largest average proximity. This process is iterated `iter` times.

Note: Imputation has not (yet) been implemented for the unsupervised case. Also, Breiman (2003) notes that the OOB estimate of error from RRF tend to be optimistic when run on the data matrix with imputed values.

**Value**

A data frame or matrix containing the completed data matrix, where NAs are imputed using proximity from RRF. The first column contains the response.

**Author(s)**

Andy Liaw



## References

Leo Breiman (2003). Manual for Setting Up, Using, and Understanding Random Forest V4.0.  
[https://www.stat.berkeley.edu/~breiman/Using\\_random\\_forests\\_v4.0.pdf](https://www.stat.berkeley.edu/~breiman/Using_random_forests_v4.0.pdf)

## See Also

[na.roughfix.](#)

## Examples

```
data(iris)
iris.na <- iris
set.seed(111)
## artificially drop some data values.
for (i in 1:4) iris.na[sample(150, 20), i] <- NA
set.seed(222)
iris.imputed <- rrfImpute(Species ~ ., iris.na)
set.seed(333)
iris.rf <- RRF(Species ~ ., iris.imputed)
print(iris.rf)
```

---

rrfNews

*Show the NEWS file*

---

## Description

Show the NEWS file of the RRF package.

## Usage

```
rrfNews()
```

## Value

None.

---

treeseize

*Size of trees in an ensemble*

---

## Description

Size of trees (number of nodes) in and ensemble.

## Usage

```
treeseize(x, terminal=TRUE)
```

**Arguments**

x                    an object of class RRF, which contains a forest component.  
 terminal            count terminal nodes only (TRUE) or all nodes (FALSE)

**Value**

A vector containing number of nodes for the trees in the RRF object.

**Note**

The RRF object must contain the forest component; i.e., created with `RRF(..., keep.forest=TRUE)`.

**Author(s)**

Andy Liaw <andy\_liaw@merck.com>

**See Also**

[RRF](#)

**Examples**

```
data(iris)
iris.rf <- RRF(Species ~ ., iris)
hist(treesize(iris.rf))
```

---

tuneRRF

*Tune RRF for the optimal mtry parameter*

---

**Description**

Starting with the default value of `mtry`, search for the optimal value (with respect to Out-of-Bag error estimate) of `mtry` for RRF.

**Usage**

```
tuneRRF(x, y, mtryStart, ntreeTry=50, stepFactor=2, improve=0.05,
        trace=TRUE, plot=TRUE, doBest=FALSE, ...)
```

**Arguments**

x                    matrix or data frame of predictor variables  
 y                    response vector (factor for classification, numeric for regression)  
 mtryStart           starting value of `mtry`; default is the same as in [RRF](#)  
 ntreeTry            number of trees used at the tuning step  
 stepFactor          at each iteration, `mtry` is inflated (or deflated) by this value

improve	the (relative) improvement in OOB error must be by this much for the search to continue
trace	whether to print the progress of the search
plot	whether to plot the OOB error as function of mtry
doBest	whether to run a forest using the optimal mtry found
...	options to be given to <a href="#">RRF</a>

**Value**

If doBest=FALSE (default), it returns a matrix whose first column contains the mtry values searched, and the second column the corresponding OOB error.

If doBest=TRUE, it returns the [RRF](#) object produced with the optimal mtry.

**See Also**

[RRF](#)

**Examples**

```
data(fgl, package="MASS")
fgl.res <- tuneRRF(fgl[, -10], fgl[, 10], stepFactor=1.5)
```

---

varImpPlot	<i>Variable Importance Plot</i>
------------	---------------------------------

---

**Description**

Dotchart of variable importance as measured by a Random Forest

**Usage**

```
varImpPlot(x, sort=TRUE, n.var=min(30, nrow(x$importance)),
           type=NULL, class=NULL, scale=TRUE,
           main=deparse(substitute(x)), ...)
```

**Arguments**

x	An object of class RRF.
sort	Should the variables be sorted in decreasing order of importance?
n.var	How many variables to show? (Ignored if sort=FALSE.)
type, class, scale	arguments to be passed on to <a href="#">importance</a>
main	plot title.
...	Other graphical parameters to be passed on to <a href="#">dotchart</a> .

**Value**

Invisibly, the importance of the variables that were plotted.

**Author(s)**

Andy Liaw <andy\_liaw@merck.com>

**See Also**

[RRF](#), [importance](#)

**Examples**

```
set.seed(4543)
data(mtcars)
mtcars.rf <- RRF(mpg ~ ., data=mtcars, ntree=1000, keep.forest=FALSE,
                importance=TRUE)
varImpPlot(mtcars.rf)
```

---

varUsed

*Variables used in a random forest*

---

**Description**

Find out which predictor variables are actually used in the random forest.

**Usage**

```
varUsed(x, by.tree=FALSE, count=TRUE)
```

**Arguments**

x	An object of class RRF.
by.tree	Should the list of variables used be broken down by trees in the forest?
count	Should the frequencies that variables appear in trees be returned?

**Value**

If count=TRUE and by.tree=FALSE, a integer vector containing frequencies that variables are used in the forest. If by.tree=TRUE, a matrix is returned, breaking down the counts by tree (each column corresponding to one tree and each row to a variable).

If count=FALSE and by.tree=TRUE, a list of integer indices is returned giving the variables used in the trees, else if by.tree=FALSE, a vector of integer indices giving the variables used in the entire forest.

**Author(s)**

Andy Liaw

**See Also**

[RRF](#)

**Examples**

```
data(iris)
set.seed(17)
varUsed(RRF(Species~., iris, ntree=100))
```

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