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Description It implements Freund and Schapire's Adaboost.M1 algorithm and Breiman's Bagging algorithm using classification trees as individual classifiers. Once these classifiers have been trained, they can be used to predict on new data. Also, cross validation estimation of the error can be done. Since version 2.0 the function margins() is available to calculate the margins for these classifiers. Also a higher flexibility is achieved giving access to the rpart.control() argument of 'rpart'. Four important new features were introduced on version 3.0, AdaBoost-SAMME (Zhu et al., 2009) is implemented and a new function errorevol() shows the error of the ensembles as a function of the number of iterations. In addition, the ensembles can be pruned using the option 'newmfinal' in the predict.bagging() and predict.boosting() functions and the posterior probability of
each class for observations can be obtained. Version 3.1 modifies the relative importance measure to take into account the gain of the Gini index given by a variable in each tree and the weights of these trees. Version 4.0 includes the margin-based ordered aggregation for Bagging pruning (Guo and Boukir, 2013) and a function to auto prune the 'rpart' tree. Moreover, three new plots are also available importanceplot(), plot.errorevol() and plot.margins(). Version 4.1 allows to predict on unlabeled data. Version 4.2 includes the parallel computation option for some of the functions. Version 5.0 includes the Boosting and Bagging algorithms for label ranking (Albano, Sciandra and Plaia, 2023).

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adabag-package *Applies Multiclass AdaBoost.M1, SAMME and Bagging*

Description

It implements Freund and Schapire's Adaboost.M1 algorithm and Breiman's Bagging algorithm using classification trees as individual classifiers. Once these classifiers have been trained, they can be used to predict on new data. Also, cross validation estimation of the error can be done. Since version 2.0 the function margins() is available to calculate the margins for these classifiers. Also a higher flexibility is achieved giving access to the rpart.control() argument of 'rpart'. Four important new features were introduced on version 3.0, AdaBoost-SAMME (Zhu et al., 2009) is implemented and a new function errorevol() shows the error of the ensembles as a function of the number of iterations. In addition, the ensembles can be pruned using the option 'newmfinal' in the predict.bagging() and predict.boosting() functions and the posterior probability of each class for observations can be obtained. Version 3.1 modifies the relative importance measure to take into account the gain of the Gini index given by a variable in each tree and the weights of these trees. Version 4.0 includes the margin-based ordered aggregation for Bagging pruning (Guo and Boukir, 2013) and a function to auto prune the 'rpart' tree. Moreover, three new plots are also available importanceplot(), plot.errorevol() and plot.margins(). Version 4.1 allows to predict on unlabeled

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Details

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Author(s)

Author: Esteban Alfaro-Cortes, Matias Gamez-Martinez and Noelia Garcia-Rubio,
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References

Albano, A., Sciandra, M., and Plaia, A. (2023): "A weighted distance-based approach with boosted decision trees for label ranking". Expert Systems with Applications.

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Zhu, J., Zou, H., Rosset, S. and Hastie, T. (2009): "Multi-class AdaBoost". Statistics and Its Interface, 2, 349–360.

Reverse cites: To the best of our knowledge this package has been cited by:

Andriyas, S. and McKee, M. (2013). Recursive partitioning techniques for modeling irrigation behavior. Environmental Modelling & Software, 47, 207–217.

Chan, J. C. W. and Paelinckx, D. (2008). Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. Remote Sensing of Environment, 112(6), 2999–3011.

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If you know any other work where this package is cited, please send us an email

See Also

autoprune, bagging, bagging.cv, boosting, boosting.cv, errorevol, importanceplot, margins, MarginOrderedPruning.Bagging, plot.errorevol, plot.margins, predict.bagging, predict.boosting, Ensemble_ranking_IW, errorevol_ranking_vector_IW, prep_data

Examples

```
## rpart library should be loaded
data(iris)
iris.adaboost <- boosting(Species~., data=iris, boos=TRUE,
mfinal=3)
importanceplot(iris.adaboost)

sub <- c(sample(1:50, 35), sample(51:100, 35), sample(101:150, 35))
iris.bagging <- bagging(Species ~ ., data=iris[sub,], mfinal=3)
#Predicting with labeled data
iris.predbagging<-predict.bagging(iris.bagging, newdata=iris[-sub,])
iris.predbagging
#Predicting with unlabeled data
iris.predbagging<- predict.bagging(iris.bagging, newdata=iris[-sub,-5])
iris.predbagging
```

autoprune *Builds automatically a pruned tree of class* rpart

Description

Builds automatically a pruned tree of class rpart looking in the cptable for the minimum cross validation error plus a standard deviation

Usage

```
autoprune(formula, data, subset=1:length(data[,1]), ...)
```

Arguments

formula	a formula, as in the lm function.
data	a data frame in which to interpret the variables named in the formula.
subset	optional expression saying that only a subset of the rows of the data should be used in the fit, as in the rpart function.
...	further arguments passed to or from other methods.

Details

The cross validation estimation of the error (xerror) has a random component. To avoid this randomness the 1-SE rule (or 1-SD rule) selects the simplest model with a xerror equal or less than the minimum xerror plus the standard deviation of the minimum xerror.

Value

An object of class rpart

Author(s)

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References

Breiman, L., Friedman, J.H., Olshen, R. and Stone, C.J. (1984): "Classification and Regression Trees". Wadsworth International Group. Belmont

Therneau, T., Atkinson, B. and Ripley, B. (2014). rpart: Recursive Partitioning and Regression Trees. R package version 4.1-5

See Also

rpart

Examples

```
## rpart library should be loaded
library(rpart)
data(iris)
iris.prune<-autoprune(Species~., data=iris)
iris.prune

## Comparing the test error of rpart and autoprune
library(mlbench)
data(BreastCancer)
l <- length(BreastCancer[,1])
sub <- sample(1:l,2*l/3)

BC.rpart <- rpart(Class~.,data=BreastCancer[sub,-1],cp=-1, maxdepth=5)
BC.rpart.pred <- predict(BC.rpart,newdata=BreastCancer[-sub,-1],type="class")
tb <-table(BC.rpart.pred,BreastCancer$Class[-sub])
tb
1-(sum(diag(tb))/sum(tb))


BC.prune<-autoprune(Class~.,data=BreastCancer[,-1],subset=sub)
BC.rpart.pred <- predict(BC.prune,newdata=BreastCancer[-sub,-1],type="class")
tb <-table(BC.rpart.pred,BreastCancer$Class[-sub])
tb
1-(sum(diag(tb))/sum(tb))
```

`bagging` *Applies the Bagging algorithm to a data set*

Description

Fits the Bagging algorithm proposed by Breiman in 1996 using classification trees as single classifiers.

Usage

```
bagging(formula, data, mfinal = 100, control, par=FALSE,...)
```

Arguments

`formula`	a formula, as in the `lm` function.
`data`	a data frame in which to interpret the variables named in the `formula`
`mfinal`	an integer, the number of iterations for which boosting is run or the number of trees to use. Defaults to `mfinal=100` iterations.

control	options that control details of the rpart algorithm. See rpart.control for more details.
par	if TRUE, the cross validation process is runned in parallel. If FALSE (by default), the function runs without parallelization.
...	further arguments passed to or from other methods.

Details

Unlike boosting, individual classifiers are independent among them in bagging

Value

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

formula	the formula used.
trees	the trees grown along the iterations.
votes	a matrix describing, for each observation, the number of trees that assigned it to each class.
prob	a matrix describing, for each observation, the posterior probability or degree of support of each class. These probabilities are calculated using the proportion of votes in the final ensemble.
class	the class predicted by the ensemble classifier.
samples	the bootstrap samples used along the iterations.
importance	returns the relative importance of each variable in the classification task. This measure takes into account the gain of the Gini index given by a variable in each tree.

Author(s)

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References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Breiman, L. (1996): "Bagging predictors". Machine Learning, Vol 24, 2, pp.123–140.

Breiman, L. (1998): "Arcing classifiers". The Annals of Statistics, Vol 26, 3, pp. 801–849.

See Also

predict.bagging, bagging.cv

Examples

```
## rpart library should be loaded
#This example has been hidden to fulfill execution time <5s
#library(rpart)
#data(iris)
#iris.bagging <- bagging(Species~., data=iris, mfinal=10)

# Data Vehicle (four classes)
library(rpart)
library(mlbench)
data(Vehicle)
l <- length(Vehicle[,1])
sub <- sample(1:l,2*l/3)
Vehicle.bagging <- bagging(Class ~.,data=Vehicle[sub, ],mfinal=5,
control=rpart.control(maxdepth=5, minsplit=15))
#Using the pruning option
Vehicle.bagging.pred <- predict.bagging(Vehicle.bagging,newdata=Vehicle[-sub, ], newmfinal=3)
Vehicle.bagging.pred$confusion
Vehicle.bagging.pred$error
```

`bagging.cv` *Runs v-fold cross validation with Bagging*

Description

The data are divided into v non-overlapping subsets of roughly equal size. Then, `bagging` is applied on `(v-1)` of the subsets. Finally, predictions are made for the left out subsets, and the process is repeated for each of the v subsets.

Usage

```
bagging.cv(formula, data, v = 10, mfinal = 100, control, par=FALSE)
```

Arguments

`formula`	a formula, as in the `lm` function.
`data`	a data frame in which to interpret the variables named in `formula`
`v`	An integer, specifying the type of v-fold cross validation. Defaults to 10. If v is set as the number of observations, leave-one-out cross validation is carried out. Besides this, every value between two and the number of observations is valid and means that roughly every v-th observation is left out.
`mfinal`	an integer, the number of iterations for which boosting is run or the number of trees to use. Defaults to `mfinal=100` iterations.
`control`	options that control details of the rpart algorithm. See rpart.control for more details.
`par`	if `TRUE`, the cross validation process is runned in parallel. If `FALSE` (by default), the function runs without parallelization.

Value

An object of class `bagging.cv`, which is a list with the following components:

`class`	the class predicted by the ensemble classifier.
`confusion`	the confusion matrix which compares the real class with the predicted one.
`error`	returns the average error.

Author(s)

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References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Breiman, L. (1996): "Bagging predictors". Machine Learning, Vol 24, 2, pp. 123–140.

Breiman, L. (1998). "Arcing classifiers". The Annals of Statistics, Vol 26, 3, pp. 801–849.

See Also

`bagging`, `predict.bagging`

Examples

```
## rpart library should be loaded
library(rpart)
data(iris)
iris.baggingcv <- bagging.cv(Species ~ ., v=2, data=iris, mfinal=3,
control=rpart.control(cp=0.01))
iris.baggingcv[-1]


## rpart and mlbench libraries should be loaded
## Data Vehicle (four classes)
#This example has been hidden to keep execution time <5s
#data(Vehicle)
#Vehicle.bagging.cv <- bagging.cv(Class ~.,data=Vehicle,v=5,mfinal=10,
#control=rpart.control(maxdepth=5))
#Vehicle.bagging.cv[-1]
```

`boosting` *Applies the AdaBoost.M1 and SAMME algorithms to a data set*

Description

Fits the AdaBoost.M1 (Freund and Schapire, 1996) and SAMME (Zhu et al., 2009) algorithms using classification trees as single classifiers.

Usage

```
  boosting(formula, data, boos = TRUE, mfinal = 100, coeflearn = 'Breiman',
control,...)
```

Arguments

`formula`	a formula, as in the `lm` function.
`data`	a data frame in which to interpret the variables named in `formula`.
`boos`	if `TRUE` (by default), a bootstrap sample of the training set is drawn using the weights for each observation on that iteration. If `FALSE`, every observation is used with its weights.
`mfinal`	an integer, the number of iterations for which boosting is run or the number of trees to use. Defaults to `mfinal=100` iterations.
`coeflearn`	if 'Breiman'(by default), `alpha=1/2ln((1-err)/err)` is used. If 'Freund' `alpha=ln((1-err)/err)` is used. In both cases the AdaBoost.M1 algorithm is used and `alpha` is the weight updating coefficient. On the other hand, if coeflearn is 'Zhu' the SAMME algorithm is implemented with `alpha=ln((1-err)/err)+ ln(nclasses-1)`.
`control`	options that control details of the rpart algorithm. See rpart.control for more details.
`...`	further arguments passed to or from other methods.

Details

AdaBoost.M1 and SAMME are simple generalizations of AdaBoost for more than two classes. In AdaBoost-SAMME the individual trees are required to have an error lower than 1-1/nclasses instead of 1/2 of the AdaBoost.M1

Value

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

`formula`	the formula used.
`trees`	the trees grown along the iterations.
`weights`	a vector with the weighting of the trees of all iterations.

votes	a matrix describing, for each observation, the number of trees that assigned it to each class, weighting each tree by its alpha coefficient.
prob	a matrix describing, for each observation, the posterior probability or degree of support of each class. These probabilities are calculated using the proportion of votes in the final ensemble.
class	the class predicted by the ensemble classifier.
importance	returns the relative importance of each variable in the classification task. This measure takes into account the gain of the Gini index given by a variable in a tree and the weight of this tree.

Author(s)

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References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Breiman, L. (1998): "Arcing classifiers". The Annals of Statistics, Vol 26, 3, pp. 801–849.

Freund, Y. and Schapire, R.E. (1996): "Experiments with a new boosting algorithm". In Proceedings of the Thirteenth International Conference on Machine Learning, pp. 148–156, Morgan Kaufmann.

Zhu, J., Zou, H., Rosset, S. and Hastie, T. (2009): "Multi-class AdaBoost". Statistics and Its Interface, 2, pp. 349–360.

See Also

predict.boosting, boosting.cv

Examples

```
## rpart library should be loaded
data(iris)
iris.adaboost <- boosting(Species~., data=iris, boos=TRUE, mfinal=3)
iris.adaboost


## Data Vehicle (four classes)
library(mlbench)
data(Vehicle)
l <- length(Vehicle[,1])
sub <- sample(1:l,2*l/3)
mfinal <- 3
maxdepth <- 5
```

```
Vehicle.rpart <- rpart(Class~.,data=Vehicle[sub,],maxdepth=maxdepth)
Vehicle.rpart.pred <- predict(Vehicle.rpart,newdata=Vehicle[-sub, ],type="class")
tb <- table(Vehicle.rpart.pred,Vehicle$Class[-sub])
error.rpart <- 1-(sum(diag(tb))/sum(tb))
tb
error.rpart

Vehicle.adaboost <- boosting(Class ~.,data=Vehicle[sub, ],mfinal=mfinal, coeflearn="Zhu",
control=rpart.control(maxdepth=maxdepth))
Vehicle.adaboost.pred <- predict.boosting(Vehicle.adaboost,newdata=Vehicle[-sub, ])
Vehicle.adaboost.pred$confusion
Vehicle.adaboost.pred$error

#comparing error evolution in training and test set
errorevol(Vehicle.adaboost,newdata=Vehicle[sub, ])->evol.train
errorevol(Vehicle.adaboost,newdata=Vehicle[-sub, ])->evol.test

plot.errorevol(evol.test,evol.train)
```

`boosting.cv` *Runs v-fold cross validation with AdaBoost.M1 or SAMME*

Description

The data are divided into `v` non-overlapping subsets of roughly equal size. Then, `boosting` is applied on `(v-1)` of the subsets. Finally, predictions are made for the left out subsets, and the process is repeated for each of the `v` subsets.

Usage

```
boosting.cv(formula, data, v = 10, boos = TRUE, mfinal = 100,
 coeflearn = "Breiman", control, par=FALSE)
```

Arguments

`formula`	a formula, as in the `lm` function.
`data`	a data frame in which to interpret the variables named in `formula`
`boos`	if `TRUE` (by default), a bootstrap sample of the training set is drawn using the weights for each observation on that iteration. If `FALSE`, every observation is used with its weights.
`v`	An integer, specifying the type of v-fold cross validation. Defaults to 10. If `v` is set as the number of observations, leave-one-out cross validation is carried out. Besides this, every value between two and the number of observations is valid and means that roughly every v-th observation is left out.

mfinal	an integer, the number of iterations for which boosting is run or the number of trees to use. Defaults to mfinal=100 iterations.
coeflearn	if 'Breiman'(by default), alpha=1/2ln((1-err)/err) is used. If 'Freund' alpha=ln((1-err)/err) is used. In both cases the AdaBoost.M1 algorithm is used and alpha is the weight updating coefficient. On the other hand, if coeflearn is 'Zhu' the SAMME algorithm is implemented with alpha=ln((1-err)/err)+ ln(nclasses-1).
control	options that control details of the rpart algorithm. See rpart.control for more details.
par	if TRUE, the cross validation process is runned in parallel. If FALSE (by default), the function runs without parallelization.

Value

An object of class boosting.cv, which is a list with the following components:

class	the class predicted by the ensemble classifier.
confusion	the confusion matrix which compares the real class with the predicted one.
error	returns the average error.

Author(s)

Esteban Alfaro-Cortes <Esteban.Alfaro@uclm.es>, Matias Gamez-Martinez <Matias.Gamez@uclm.es> and Noelia Garcia-Rubio <Noelia.Garcia@uclm.es>

References

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Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Breiman, L. (1998): "Arcing classifiers". The Annals of Statistics, Vol 26, 3, pp. 801–849.

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Zhu, J., Zou, H., Rosset, S. and Hastie, T. (2009): "Multi-class AdaBoost". Statistics and Its Interface, 2, pp. 349–360.

See Also

boosting, predict.boosting

Examples

```
## rpart library should be loaded
data(iris)
iris.boostcv <- boosting.cv(Species ~ ., v=2, data=iris, mfinal=5,
control=rpart.control(cp=0.01))
iris.boostcv[-1]

## rpart and mlbench libraries should be loaded
## Data Vehicle (four classes)
#This example has been hidden to fulfill execution time <5s
#data(Vehicle)
#Vehicle.boost.cv <- boosting.cv(Class ~.,data=Vehicle,v=5, mfinal=10, coeflearn="Zhu",
#control=rpart.control(maxdepth=5))
#Vehicle.boost.cv[-1]
```

Ensemble_ranking_IW *Ensemble methods for ranking data: Item-Weighted Boosting and Bagging Algorithms*

Description

The `Ensemble_ranking_IW` function applies the item-weighted Boosting and Bagging algorithms to ranking data (Albano et al., 2023). These algorithms utilize classification trees as base classifiers to perform item-weighted ensemble methods for rankings.

Usage

```
Ensemble_ranking_IW(formula, data, iw, algo = "boosting",
  mfinal = 100, coeflearn = "Breiman", control, bin = FALSE,
  trace= TRUE, ...)
```

Arguments

`formula`	a formula specifying the response ranking variable and predictors, similar to the `lm` function. The response variable must be the "Label" column of the object generated by the `prep_data` function.
`data`	An N by (K+1) data frame containing the prepared item-weighted ranking data. The column "Label" should contain the transformed ranking responses, and the remaining columns should contain the predictors. Continuous variables are allowed, while the dummy coding should be used for categorical variables. The data frame must be the output of the `prep_data` function.

iw	a vector or matrix representing the item weights or dissimilarities for the ranking data. For a vector, it should be a row vector of length M, where M is the number of items. For a matrix, it should be a symmetric M by M matrix representing item dissimilarities. For coherence, iw should be the same vector/matrix used in prep_data(...).
algo	the ensemble method to use. Possible values are "bagging" or "boosting". Defaults to "boosting".
mfinal	the number of trees to use for boosting or bagging. Defaults to 100 iterations.
coeflearn	the coefficient learning method to use. Possible values are "Breiman", "Freund", or "Zhu". Defaults to "Breiman".
control	an optional argument to control details of the classification tree algorithm. See rpart.control for more information.
bin	a logical value indicating whether to use the binary logarithm function for updating weights at each iteration. Defaults to FALSE. When set to TRUE, it corresponds to utilizing the AdaBoost.R.M2 algorithm as defined by Albano et al. (2023).
trace	a logical value controling the display of additional information (the number of trees and the average weighted tau_x) during execution. Defaults to TRUE.
...	additional arguments passed to or from other methods.

Details

The Ensemble_ranking_IW function extends the Boosting and Bagging algorithms to handle item-weighted ranking data. It allows for the application of these ensemble methods to improve ranking predicting performance using classification trees as base classifiers.

Value

An object of class boosting or bagging, which is a list with the following components:

formula	the used formula.
trees	the trees grown during the iterations.
weights	a vector of weights for each tree in all iterations.
importance	a measure of the relative importance of each predictor in the ranking task, taking into account the weighted gain of the variable's contribution in each tree.

Author(s)

Alessandro Albano <alessandro.albano@unipa.it>, Mariangela Sciandra <mariangela.sciandra@unipa.it>, and Antonella Plaia <antonella.plaia@unipa.it>

References

Albano, A., Sciandra, M., and Plaia, A. (2023): "A weighted distance-based approach with boosted decision trees for label ranking." *Expert Systems with Applications*.

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Zhu, J., Zou, H., Rosset, S., and Hastie, T. (2009): "Multi-class AdaBoost." *Statistics and Its Interface*, 2, pp. 349–360.

Examples

```
## Not run:
  # Load simulated ranking data
  data(simulatedRankingData)
  x <- simulatedRankingData$x
  y <- simulatedRankingData$y

  # Prepare the data with item weights
  dati <- prep_data(y, x, iw = c(2, 5, 5, 2))

  # Divide the data into training and test sets
  set.seed(12345)
  samp <- sample(nrow(dati))
  l <- length(dati[, 1])
  sub <- sample(1:l, 2 * l / 3)
  data_sub1 <- dati[sub, ]
  data_test1 <- dati[-sub, ]

  # Apply ensemble ranking with AdaBoost.M1
  boosting_1 <- Ensemble_ranking_IW(
    Label ~ .,
    data = data_sub1,
    iw = c(2, 5, 5, 2),
    mfinal = 3,
    coeflearn = "Breiman",
    control = rpart.control(maxdepth = 4, cp = -1),
    algo = "boosting",
    bin = FALSE
  )

  # Evaluate the performance
  test_boosting1 <- errorevol_ranking_vector_IW(boosting_1,
    newdata = data_test1, iw=c(2,5,5,2), squared = FALSE)
  test_boosting1.1 <- errorevol_ranking_vector_IW(boosting_1,
    newdata = data_sub1, iw=c(2,5,5,2), squared = FALSE)

  # Plot the error evolution
  plot.errorevol(test_boosting1, test_boosting1.1)
```

```
## End(Not run)
```

---

errorevol *Shows the error evolution of the ensemble*

Description

Calculates the error evolution of an AdaBoost.M1, AdaBoost-SAMME or Bagging classifier for a data frame as the ensemble size grows

Usage

```
errorevol(object, newdata)
```

Arguments

object	This object must be the output of one of the functions bagging or boosting. This is assumed to be the result of some function that produces an object with two components named formula and trees, as those returned for instance by the bagging function.
newdata	Could be the same data frame used in object or a new one

Details

This can be useful to see how fast Bagging, boosting reduce the error of the ensemble. in addition, it can detect the presence of overfitting and, therefore, the convenience of pruning the ensemble using predict.bagging or predict.boosting.

Value

An object of class errorevol, which is a list with only one component:

error	a vector with the error evolution.

Author(s)

Esteban Alfaro-Cortes <Esteban.Alfaro@uclm.es>, Matias Gamez-Martinez <Matias.Gamez@uclm.es> and Noelia Garcia-Rubio <Noelia.Garcia@uclm.es>

References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Breiman, L. (1996): "Bagging predictors". Machine Learning, Vol 24, 2, pp.123–140.

Freund, Y. and Schapire, R.E. (1996): "Experiments with a new boosting algorithm". In Proceedings of the Thirteenth International Conference on Machine Learning, pp. 148–156, Morgan Kaufmann.

Zhu, J., Zou, H., Rosset, S. and Hastie, T. (2009): "Multi-class AdaBoost". Statistics and Its Interface, 2, pp. 349–360.

See Also

boosting, predict.boosting, bagging, predict.bagging

Examples

```
library(mlbench)
data(BreastCancer)
l <- length(BreastCancer[,1])
sub <- sample(1:l,2*l/3)
cntrl <- rpart.control(maxdepth = 3, minsplit = 0,  cp = -1)

BC.adaboost <- boosting(Class ~.,data=BreastCancer[sub,-1],mfinal=5, control=cntrl)
BC.adaboost.pred <- predict.boosting(BC.adaboost,newdata=BreastCancer[-sub,-1])

errorevol(BC.adaboost,newdata=BreastCancer[-sub,-1])->evol.test
errorevol(BC.adaboost,newdata=BreastCancer[sub,-1])->evol.train

plot.errorevol(evol.test,evol.train)
abline(h=min(evol.test[[1]]), col="red",lty=2,lwd=2)
abline(h=min(evol.train[[1]]), col="blue",lty=2,lwd=2)
```

---

errorevol_ranking_vector_IW

Calculate the error evolution and final predictions of an item-weighted ensemble for rankings

---

Description

This function calculates the error evolution and final predictions of an item-weigthed ensemble method for ranking data (Albano et al., 2023).

Usage

```
errorevol_ranking_vector_IW(object, newdata, iw, squared = FALSE)
```

Arguments

`object`	an object of class 'bagging' or 'boosting' generated by the `Ensemble_ranking_IW` function.
`newdata`	a data frame that can be the same as the one used in the `object` or a new one. Continuous variables are allowed, while the dummy coding should be used for categorical variables. It must be the output of the `prep_data` function.
`iw`	a weighting vector or matrix. For coherence, `iw` should be the same vector/matrix used in `Ensemble_ranking_IW(...)`.
`squared`	logical value indicating whether squared weighting should be used in the final prediction. Default is `FALSE`. When set to `TRUE`, it corresponds to utilizing the AdaBoost.R.M3 algorithm defined by Albano et al. (2023).

Details

This function computes the error and final predictions for a boosting or bagging ranking model using item weighting.

Value

An object of class 'errorevol'. It has two components:

`error`	a vector with the error values at each ensemble iteration
`final_prediction`	a data frame of final predictions for each observation in `newdata`.

References

Albano, A., Sciandra, M., and Plaia, A. (2023): "A weighted distance-based approach with boosted decision trees for label ranking." *Expert Systems with Applications*.

Alfaro, E., Gamez, M., and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging." *Journal of Statistical Software*, Vol. 54, 2, pp. 1–35.

Breiman, L. (1998): "Arcing classifiers." *The Annals of Statistics*, Vol. 26, 3, pp. 801–849.

D'Ambrosio, A.[aut, cre], Amodio, S. [ctb], Mazzeo, G. [ctb], Albano, A. [ctb], Plaia, A. [ctb] (2023). ConsRank: Compute the Median Ranking(s) According to the Kemeny's Axiomatic Approach. R package version 2.1.3, https://cran.r-project.org/package=ConsRank.

Freund, Y., and Schapire, R.E. (1996): "Experiments with a new boosting algorithm." In *Proceedings of the Thirteenth International Conference on Machine Learning*, pp. 148–156, Morgan Kaufmann.

Plaia, A., Buscemi, S., Furnkranz, J., and Mencıa, E.L. (2021): "Comparing boosting and bagging for decision trees of rankings." *Journal of Classification*, pages 1–22.

Zhu, J., Zou, H., Rosset, S., and Hastie, T. (2009): "Multi-class AdaBoost." *Statistics and Its Interface*, 2, pp. 349–360.

Examples

```
## Not run:
  # Load simulated ranking data
  data(simulatedRankingData)
  x <- simulatedRankingData$x
  y <- simulatedRankingData$y

  # Prepare the data with item weights
  dati <- prep_data(y, x, iw = c(2, 5, 5, 2))

  # Divide the data into training and test sets
  set.seed(12345)
  samp <- sample(nrow(dati))
  l <- length(dati[, 1])
  sub <- sample(1:l, 2 * l / 3)
  data_sub1 <- dati[sub, ]
  data_test1 <- dati[-sub, ]

  # Apply ensemble ranking with AdaBoost.M1
  boosting_1 <- Ensemble_ranking_IW(
    Label ~ .,
    data = data_sub1,
    iw = c(2, 5, 5, 2),
    mfinal = 3,
    coeflearn = "Breiman",
    control = rpart.control(maxdepth = 4, cp = -1),
    algo = "boosting",
    bin = FALSE
  )

  # Evaluate the performance
  test_boosting1 <- errorevol_ranking_vector_IW(boosting_1,
    newdata = data_test1, iw=c(2,5,5,2), squared = FALSE)
  test_boosting1.1 <- errorevol_ranking_vector_IW(boosting_1,
    newdata = data_sub1, iw=c(2,5,5,2), squared = FALSE)

  # Plot the error evolution
  plot.errorevol(test_boosting1, test_boosting1.1)

## End(Not run)
```

`importanceplot` *Plots the variables relative importance*

Description

Plots the relative importance of each variable in the classification task. This measure takes into account the gain of the Gini index given by a variable in a tree and, in the boosting case, the weight of this tree.

Usage

```
importanceplot(object, ...)
```

Arguments

object	fitted model object of class boosting or bagging. This is assumed to be the result of some function that produces an object with a component named importance as that returned by the boosting and bagging functions.
...	further arguments passed to or from other methods.

Details

For this goal, the varImp function of the caret package is used to get the gain of the Gini index of the variables in each tree.

Value

A labeled plot is produced on the current graphics device (one being opened if needed).

Author(s)

Esteban Alfaro-Cortes <Esteban.Alfaro@uclm.es>, Matias Gamez-Martinez <Matias.Gamez@uclm.es> and Noelia Garcia-Rubio <Noelia.Garcia@uclm.es>

References

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Zhu, J., Zou, H., Rosset, S. and Hastie, T. (2009): "Multi-class AdaBoost". Statistics and Its Interface, 2, pp. 349–360.

See Also

boosting, bagging,

Examples

```
#Examples
#Iris example
library(rpart)
data(iris)
sub <- c(sample(1:50, 25), sample(51:100, 25), sample(101:150, 25))
```

```
iris.adaboost <- boosting(Species ~ ., data=iris[sub,], mfinal=3)
importanceplot(iris.adaboost)

#Examples with bagging
#iris.bagging <- bagging(Species ~ ., data=iris[sub,], mfinal=5)
#importanceplot(iris.bagging, horiz=TRUE, cex.names=.6)
```

`MarginOrderedPruning.Bagging` *MarginOrderedPruning.Bagging*

Description

Margin-based ordered aggregation for bagging pruning

Usage

```
MarginOrderedPruning.Bagging(baggingObject, trainingset, pruningset,
marginType = "unsupervised", doTrace = TRUE)
```

Arguments

`baggingObject`	fitted model object of class `bagging`
`trainingset`	the training set of the `bagging` object
`pruningset`	a set aside dataset for `bagging` pruning
`marginType`	if "unsupervised" (by default) the margin is the difference between the proportions of votes of the first and second most popular classes. Else the margin is calculated as the difference between the proportion of votes of the correct class and the most popular among the other classes
`doTrace`	If set to `TRUE`, give a more verbose output as `MarginOrderedPruning.Bagging` is running

Value

Returns a list with the following components:

`prunedBagging`	a pruned `bagging` object
`AccuracyOrderedEnsemblePruningSet`	Accuracy of each ordered ensemble on pruning set

Note

Questions about this function should be sent to Li Guo

Author(s)

Li Guo <guoli84@hotmail.com>

References

Guo, L. and Boukir, S. (2013): "Margin-based ordered aggregation for ensemble pruning". Pattern Recognition Letters, 34(6), 603-609.

See Also

bagging, predict.bagging

Examples

```
## mlbench package should be loaded
library(mlbench)
data(Satellite)
## Separate data into 3 parts: training set, pruning set and test set
ind <- sample(3, nrow(Satellite), replace = TRUE, prob=c(0.3, 0.2,0.5))

## create bagging with training set
#increase mfinal in your own execution of this example to see
#the real usefulness of this function
Satellite.bagging<-bagging(classes~.,data=Satellite[ind==1,],mfinal=3)
#Satellite.bagging.pred<-predict(Satellite.bagging,Satellite[ind==3,])

##pruning bagging
Satellite.bagging.pruning<-MarginOrderedPruning.Bagging(Satellite.bagging,
Satellite[ind==1,],Satellite[ind==2,])
#Satellite.bagging.pruning.pred<-predict(Satellite.bagging.pruning$prunedBagging,
#Satellite[ind==3,])

## create bagging with training and pruning set
#This example has been hidden to fulfill execution time <5s
#Satellite.bagging2<-bagging(classes~.,data=Satellite[ind!=3,],25)
#Satellite.bagging2.pred<-predict(Satellite.bagging2,Satellite[ind==3,])
```

---

margins *Calculates the margins*

Description

Calculates the margins of an AdaBoost.M1, AdaBoost-SAMME or Bagging classifier for a data frame

Usage

```
margins(object, newdata)
```

Arguments

object	This object must be the output of one of the functions bagging, boosting, predict.bagging or predict.boosting. This is assumed to be the result of some function that produces an object with two components named formula and class, as those returned for instance by the bagging function.
newdata	The same data frame used for building the object

Details

Intuitively, the margin for an observation is related to the certainty of its classification. It is calculated as the difference between the support of the correct class and the maximum support of an incorrect class

Value

An object of class margins, which is a list with only one component:

margins	a vector with the margins.

Author(s)

Esteban Alfaro-Cortes <Esteban.Alfaro@uclm.es>, Matias Gamez-Martinez <Matias.Gamez@uclm.es> and Noelia Garcia-Rubio <Noelia.Garcia@uclm.es>

References

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See Also

bagging, boosting, plot.margins, predict.boosting, predict.bagging

Examples

```
#Iris example
library(rpart)
data(iris)
sub <- c(sample(1:50, 25), sample(51:100, 25), sample(101:150, 25))
iris.adaboost <- boosting(Species ~ ., data=iris[sub,], mfinal=3)
margins(iris.adaboost,iris[sub,])->iris.margins # training set
plot.margins(iris.margins)

# test set
```

```
iris.predboosting<- predict.boosting(iris.adaboost, newdata=iris[-sub,])
margins(iris.predboosting,iris[-sub,])->iris.predmargins
plot.margins(iris.predmargins,iris.margins)

#Examples with bagging
iris.bagging <- bagging(Species ~ ., data=iris[sub,], mfinal=3)
margins(iris.bagging,iris[sub,])->iris.bagging.margins # training set

iris.predbagging<- predict.bagging(iris.bagging, newdata=iris[-sub,])
margins(iris.predbagging,iris[-sub,])->iris.bagging.predmargins # test set
par(bg="lightyellow")
plot.margins(iris.bagging.predmargins,iris.bagging.margins)
```

`plot.errorevol` *Plots the error evolution of the ensemble*

Description

Plots the previously calculated error evolution of an AdaBoost.M1, AdaBoost-SAMME or Bagging classifier for a data frame as the ensemble size grows

Usage

```
## S3 method for class 'errorevol'
plot(x, y = NULL, ...)
```

Arguments

`x`	An object of class `errorevol`. This is assumed to be the result of some function that produces an object with a component named `error` as that returned by the `errorevol` function.
`y`	This argument can be used to represent in the same plot the evolution of the test and train errors, `x` and `y`, respectively. Should be `NULL` (by default) or an object of class `errorevol`.
`...`	further arguments passed to or from other methods.

Details

This can be useful to see how fast `bagging` or `boosting` reduce the error of the ensemble. in addition, it can detect the presence of overfitting and, therefore, the convenience of pruning the ensemble using `predict.bagging` or `predict.boosting`.

Value

A labeled plot is produced on the current graphics device (one being opened if needed).

Author(s)

Esteban Alfaro-Cortes <Esteban.Alfaro@uclm.es>, Matias Gamez-Martinez <Matias.Gamez@uclm.es> and Noelia Garcia-Rubio <Noelia.Garcia@uclm.es>

References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Breiman, L. (1996): "Bagging predictors". Machine Learning, Vol 24, 2, pp.123–140.

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Zhu, J., Zou, H., Rosset, S. and Hastie, T. (2009): "Multi-class AdaBoost". Statistics and Its Interface, 2, pp. 349–360.

See Also

boosting, predict.boosting, bagging, predict.bagging, errorevol

Examples

```
data(iris)
train <- c(sample(1:50, 25), sample(51:100, 25), sample(101:150, 25))

cntrl<-rpart.control(maxdepth=1)
#increase mfinal in your own execution of this example to see
#the real usefulness of this function
iris.adaboost <- boosting(Species ~ ., data=iris[train,], mfinal=10, control=cntrl)

#Error evolution along the iterations in training set
errorevol(iris.adaboost,iris[train,])->evol.train
plot.errorevol(evol.train)

#comparing error evolution in training and test set
errorevol(iris.adaboost,iris[-train,])->evol.test
plot.errorevol(evol.test, evol.train)

# See the help of the functions error evolution and boosting
# for more examples of the use of the error evolution
```

plot.margins *Plots the margins of the ensemble*

Description

Plots the previously calculated margins of an AdaBoost.M1, AdaBoost-SAMME or Bagging classifier for a data frame

Usage

```
## S3 method for class 'margins'
plot(x, y = NULL, ...)
```

Arguments

x	An object of class margins. This is assumed to be the result of some function that produces an object with a component named margins as that returned by the margins function.
y	This argument can be used to represent in the same plot the margins in the test and train sets, x and y, respectively. Should be NULL (by default) or an object of class margins.
...	further arguments passed to or from other methods.

Details

Intuitively, the margin for an observation is related to the certainty of its classification. It is calculated as the difference between the support of the correct class and the maximum support of an incorrect class

Value

A labeled plot is produced on the current graphics device (one being opened if needed).

Author(s)

Esteban Alfaro-Cortes <Esteban.Alfaro@uclm.es>, Matias Gamez-Martinez <Matias.Gamez@uclm.es> and Noelia Garcia-Rubio <Noelia.Garcia@uclm.es>

References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Schapire, R.E., Freund, Y., Bartlett, P. and Lee, W.S. (1998): "Boosting the margin: A new explanation for the effectiveness of voting methods". The Annals of Statistics, vol 26, 5, pp. 1651–1686.

See Also

margins, boosting, predict.boosting, bagging, predict.bagging

Examples

```
library(mlbench)
data(BreastCancer)
l <- length(BreastCancer[,1])
sub <- sample(1:l,2*l/3)
cntrl <- rpart.control(maxdepth = 3, minsplit = 0,  cp = -1)

BC.adaboost <- boosting(Class ~.,data=BreastCancer[sub,-1],mfinal=5, control=cntrl)
BC.adaboost.pred <- predict.boosting(BC.adaboost,newdata=BreastCancer[-sub,-1])

BC.margins<-margins(BC.adaboost,BreastCancer[sub,-1]) # training set
BC.predmargins<-margins(BC.adaboost.pred,BreastCancer[-sub,-1]) # test set
plot.margins(BC.predmargins,BC.margins)
```

---

predict.bagging *Predicts from a fitted bagging object*

Description

Classifies a dataframe using a fitted bagging object.

Usage

```
## S3 method for class 'bagging'
predict(object, newdata, newmfinal=length(object$trees), ...)
```

Arguments

object	fitted model object of class bagging. This is assumed to be the result of some function that produces an object with the same named components as that returned by the bagging function.
newdata	data frame containing the values at which predictions are required. The predictors referred to in the right side of formula(object) must be present by name in newdata.
newmfinal	The number of trees of the bagging object to be used in the prediction. This argument allows the user to prune the ensemble. By default all the trees in the bagging object are used
...	further arguments passed to or from other methods.

Value

An object of class `predict.bagging`, which is a list with the following components:

`formula`	the formula used.
`votes`	a matrix describing, for each observation, the number of trees that assigned it to each class.
`prob`	a matrix describing, for each observation, the posterior probability or degree of support of each class. These probabilities are calculated using the proportion of votes in the final ensemble.
`class`	the class predicted by the ensemble classifier.
`confusion`	the confusion matrix which compares the real class with the predicted one.
`error`	returns the average error.

Author(s)

Esteban Alfaro-Cortes <Esteban.Alfaro@uclm.es>, Matias Gamez-Martinez <Matias.Gamez@uclm.es> and Noelia Garcia-Rubio <Noelia.Garcia@uclm.es>

References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

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Breiman, L. (1996): "Bagging predictors". Machine Learning, Vol 24, 2, pp. 123–140.

Breiman, L. (1998). "Arcing classifiers". The Annals of Statistics, Vol 26, 3, pp. 801–849.

See Also

`bagging`, `bagging.cv`

Examples

```
#library(rpart)
#data(iris)
#sub <- c(sample(1:50, 25), sample(51:100, 25), sample(101:150, 25))
#iris.bagging <- bagging(Species ~ ., data=iris[sub,], mfinal=5)
#iris.predbagging<- predict.bagging(iris.bagging, newdata=iris[-sub,])
#iris.predbagging

## rpart and mlbench libraries should be loaded
library(rpart)
library(mlbench)
data(BreastCancer)
l <- length(BreastCancer[,1])
sub <- sample(1:l,2*l/3)
BC.bagging <- bagging(Class ~.,data=BreastCancer[,-1],mfinal=5,
control=rpart.control(maxdepth=3))
```

```
BC.bagging.pred <- predict.bagging(BC.bagging,newdata=BreastCancer[-sub,-1])
BC.bagging.pred$prob
BC.bagging.pred$confusion
BC.bagging.pred$error
```

`predict.boosting` *Predicts from a fitted boosting object*

Description

Classifies a dataframe using a fitted boosting object.

Usage

```
## S3 method for class 'boosting'
predict(object, newdata, newmfinal=length(object$trees), ...)
```

Arguments

`object`	fitted model object of class `boosting`. This is assumed to be the result of some function that produces an object with the same named components as that returned by the `boosting` function.
`newdata`	data frame containing the values at which predictions are required. The predictors referred to in the right side of `formula(object)` must be present by name in newdata.
`newmfinal`	The number of trees of the boosting object to be used in the prediction. This argument allows the user to prune the ensemble. By default all the trees in `object` are used
`...`	further arguments passed to or from other methods.

Value

An object of class predict.boosting, which is a list with the following components:

`formula`	the formula used.
`votes`	a matrix describing, for each observation, the number of trees that assigned it to each class, weighting each tree by its `alpha` coefficient.
`prob`	a matrix describing, for each observation, the posterior probability or degree of support of each class. These probabilities are calculated using the proportion of votes in the final ensemble.
`class`	the class predicted by the ensemble classifier.
`confusion`	the confusion matrix which compares the real class with the predicted one.
`error`	returns the average error.

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References

Alfaro, E., Gamez, M. and Garcia, N. (2013): "adabag: An R Package for Classification with Boosting and Bagging". Journal of Statistical Software, Vol 54, 2, pp. 1–35.

Alfaro, E., Garcia, N., Gamez, M. and Elizondo, D. (2008): "Bankruptcy forecasting: An empirical comparison of AdaBoost and neural networks". Decision Support Systems, 45, pp. 110–122.

Breiman, L. (1998): "Arcing classifiers". The Annals of Statistics, Vol 26, 3, pp. 801–849.

Freund, Y. and Schapire, R.E. (1996): "Experiments with a new boosting algorithm". En Proceedings of the Thirteenth International Conference on Machine Learning, pp. 148–156, Morgan Kaufmann.

Zhu, J., Zou, H., Rosset, S. and Hastie, T. (2009): "Multi-class AdaBoost". Statistics and Its Interface, 2, pp. 349–360.

See Also

boosting, boosting.cv

Examples

```
## rpart library should be loaded
#This example has been hidden to fulfill execution time <5s
#library(rpart)
#data(iris)
#sub <- c(sample(1:50, 25), sample(51:100, 25), sample(101:150, 25))
#iris.adaboost <- boosting(Species ~ ., data=iris[sub,], mfinal=10)
#iris.predboosting<- predict.boosting(iris.adaboost, newdata=iris[-sub,])
#iris.predboosting$prob

## rpart and mlbench libraries should be loaded
## Comparing the test error of rpart and adaboost.M1
library(rpart)
library(mlbench)
data(BreastCancer)
l <- length(BreastCancer[,1])
sub <- sample(1:l,2*l/3)

BC.rpart <- rpart(Class~.,data=BreastCancer[sub,-1], maxdepth=3)
BC.rpart.pred <- predict(BC.rpart,newdata=BreastCancer[-sub,-1],type="class")
tb <-table(BC.rpart.pred,BreastCancer$Class[-sub])
error.rpart <- 1-(sum(diag(tb))/sum(tb))
tb
error.rpart

BC.adaboost <- boosting(Class ~.,data=BreastCancer[,-1],mfinal=10, coeflearn="Freund",
boos=FALSE , control=rpart.control(maxdepth=3))
```

```
#Using the pruning option
BC.adaboost.pred <- predict.boosting(BC.adaboost,newdata=BreastCancer[-sub,-1], newmfinal=10)
BC.adaboost.pred$confusion
BC.adaboost.pred$error
```

---

prep_data *Prepare Ranking Data for Item-Weighted Ensemble Algorithm*

Description

The prep_data function prepares item-weighted ranking data for further analysis. It takes a ranking matrix, predictors matrix, and weighting vector or matrix, and returns a data frame suitable for item-weighted ensemble algorithms for rankings.

Usage

```
prep_data(y, x, iw)
```

Arguments

y	an N by M matrix or data frame representing the ranking responses, where N is the number of individuals and M is the number of items. Each row corresponds to a ranking, ties are allowed.
x	an N by K matrix or data frame containing the K predictors associated with each individual ranking. Continuous variables are allowed, while the dummy coding should be used for categorical variables.
iw	a vector or matrix representing the item weights or dissimilarities for the ranking data. For a vector, it should be a row vector of length M. For a matrix, it should be a symmetric M by M matrix representing item dissimilarities.

Details

The prep_data function performs the following steps: Check the dimensions of the weighting vector or matrix to ensure compatibility with the ranking data. Adjust the ranking matrix *y* using the "min" method for ties. Convert the ranked matrix into a data frame. Generate the universe of rankings using the **ConsRank::**univranks function. Match the ranking matrix *y* with the whole universe of rankings to obtain a label for each ranking. Combine the Label column with the predictor matrix. Remove rows with missing values. The function then returns the prepared data frame for ensemble ranking. It also create the internal objects: item, perm_tab_complete_up, perm, mat.dist that are employed in the Ensemble_ranking_IW function.

Value

An N by (K+1) data frame containing the prepared item-weighted ranking data. The first column "Label" contains the transformed ranking responses, and the remaining columns contain the predictors.

References

Albano, A., Sciandra, M., and Plaia, A. (2023): "A Weighted Distance-Based Approach with Boosted Decision Trees for Label Ranking." *Expert Systems with Applications*.

D'Ambrosio, A.[aut, cre], Amodio, S. [ctb], Mazzeo, G. [ctb], Albano, A. [ctb], Plaia, A. [ctb] (2023). "ConsRank: Compute the Median Ranking(s) According to the Kemeny's Axiomatic Approach. R package version 2.1.3", https://cran.r-project.org/package=ConsRank.

Plaia, A., Buscemi, S., Furnkranz, J., and Mencıa, E.L. (2021): "Comparing Boosting and Bagging for Decision Trees of Rankings." *Journal of Classification*, pages 1–22.

Examples

```
 # Prepare item-weighted ranking data
y <- matrix(c(1, 2, 3, 4, 2, 3, 1, 4, 4, 1, 3, 2, 2, 3, 1, 4), nrow = 4, ncol = 4, byrow = TRUE)
x <- matrix(c(0.5, 0.8, 1.2, 0.7, 1.1, 0.9, 0.6, 1.3, 0.4, 1.5, 0.7, 0.9), nrow = 4, ncol = 3)
 iw <- c(2, 5, 5, 2)
 dati <- prep_data(y, x, iw)
```

---

simulatedRankingData *Simulated ranking data*

Description

The simulatedRankingData dataset is a list that includes the following components:

The ranking matrix, y, contains the ranking matrix. It consists of 500 rows and 4 columns, indicating the ranking positions. Each element in the matrix represents the rank assigned to an individual for a particular item.

The predictor matrix x in the dataset consists of 20 continuous explanatory variables. These variables are used for predicting the rankings.

Usage

```
data(simulatedRankingData)
```

References

Albano, A., Sciandra, M., and Plaia, A. (2023): "A weighted distance-based approach with boosted decision trees for label ranking." *Expert Systems with Applications*.

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