Package ‘erboost’

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Title Nonparametric Multiple Expectile Regression via ER-Boost

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Depends R (>= 2.12.0), lattice, splines

Description Expectile regression is a nice tool for estimating the conditional expectiles of a response variable given a set of covariates. This package implements a regression tree based gradient boosting estimator for nonparametric multiple expectile regression, proposed by Yang, Y., Qian, W. and Zou, H. (2018) <doi:10.1080/00949655.2013.876024>. The code is based on the 'gbm' package originally developed by Greg Ridgeway.

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Repository CRAN

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erboost *ER-Boost Expectile Regression Modeling*

Description

Fits ER-Boost Expectile Regression models.

Usage

```
erboost(formula = formula(data),
    distribution = list(name="expectile",alpha=0.5),
    data = list(),
    weights,
    var.monotone = NULL,
    n.trees = 3000,
    interaction.depth = 3,
    n.minobsinnode = 10,
    shrinkage = 0.001,
    bag.fraction = 0.5,
    train.fraction = 1.0,
    cv.folds=0,
    keep.data = TRUE,
    verbose = TRUE)

erboost.fit(x,y,
        offset = NULL,
        misc = NULL,
        distribution = list(name="expectile",alpha=0.5),
        w = NULL,
        var.monotone = NULL,
        n.trees = 3000,
        interaction.depth = 3,
        n.minobsinnode = 10,
        shrinkage = 0.001,
        bag.fraction = 0.5,
        train.fraction = 1.0,
        keep.data = TRUE,
        verbose = TRUE,
        var.names = NULL,
        response.name = NULL)

erboost.more(object,
         n.new.trees = 3000,
         data = NULL,
         weights = NULL,
         offset = NULL,
         verbose = NULL)
```

Arguments

- `formula`: a symbolic description of the model to be fit. The formula may include an offset term (e.g. y~offset(n)+x). If `keep.data=FALSE` in the initial call to `erboost` then it is the user's responsibility to resupply the offset to `erboost.more`.
- `distribution`: a list with a component `name` specifying the distribution and any additional parameters needed. Expectile regression is available and `distribution` must a list of the form `list(name="expectile",alpha=0.25)` where `alpha` is the expectile to estimate. The current version's expectile regression methods do not handle non-constant weights and will stop.
- `data`: an optional data frame containing the variables in the model. By default the variables are taken from `environment(formula)`, typically the environment from which `erboost` is called. If `keep.data=TRUE` in the initial call to `erboost` then `erboost` stores a copy with the object. If `keep.data=FALSE` then subsequent calls to `erboost.more` must resupply the same dataset. It becomes the user's responsibility to resupply the same data at this point.
- `weights`: an optional vector of weights to be used in the fitting process. Must be positive but do not need to be normalized. If `keep.data=FALSE` in the initial call to `erboost` then it is the user's responsibility to resupply the weights to `erboost.more`.
- `var.monotone`: an optional vector, the same length as the number of predictors, indicating which variables have a monotone increasing (+1), decreasing (-1), or arbitrary (0) relationship with the outcome.
- `n.trees`: the total number of trees to fit. This is equivalent to the number of iterations and the number of basis functions in the additive expansion. The default number is 3000. **Users should not always use the default value, but choose the appropriate value of `n.trees` based on their data.** Please see "details" section below.
- `cv.folds`: Number of cross-validation folds to perform. If `cv.folds`>1 then `erboost`, in addition to the usual fit, will perform a cross-validation, calculate an estimate of generalization error returned in `cv.error`.
- `interaction.depth`: The maximum depth of variable interactions. 1 implies an additive model, 2 implies a model with up to 2-way interactions, etc. The default value is 3. **Users should not always use the default value, but choose the appropriate value of `interaction.depth` based on their data.** Please see "details" section below.
- `n.minobsinnode`: minimum number of observations in the trees terminal nodes. Note that this is the actual number of observations not the total weight.
- `shrinkage`: a shrinkage parameter applied to each tree in the expansion. Also known as the learning rate or step-size reduction.
- `bag.fraction`: the fraction of the training set observations randomly selected to propose the next tree in the expansion. This introduces randomnesses into the model fit. If `bag.fraction`<1 then running the same model twice will result in similar but different fits. `erboost` uses the R random number generator so `set.seed` can ensure that the model can be reconstructed. Preferably, the user can save the returned `erboost.object` using `save`.

train.fraction	The first train.fraction * nrows(data) observations are used to fit the erboost and the remainder are used for computing out-of-sample estimates of the loss function.
keep.data	a logical variable indicating whether to keep the data and an index of the data stored with the object. Keeping the data and index makes subsequent calls to erboost.more faster at the cost of storing an extra copy of the dataset.
object	a erboost object created from an initial call to erboost.
n.new.trees	the number of additional trees to add to object. The default number is 3000.
verbose	If TRUE, erboost will print out progress and performance indicators. If this option is left unspecified for erboost.more then it uses verbose from object.
x, y	For erboost.fit: x is a data frame or data matrix containing the predictor variables and y is the vector of outcomes. The number of rows in x must be the same as the length of y.
offset	a vector of values for the offset
misc	For erboost.fit: misc is an R object that is simply passed on to the erboost engine.
w	For erboost.fit: w is a vector of weights of the same length as the y.
var.names	For erboost.fit: A vector of strings of length equal to the number of columns of x containing the names of the predictor variables.
response.name	For erboost.fit: A character string label for the response variable.

Details

Expectile regression (Newey & Powell 1987) is a nice tool for estimating the conditional expectiles of a response variable given a set of covariates. This package implements a regression tree based gradient boosting estimator for nonparametric multiple expectile regression. The code is a modified version of gbm library (https://cran.r-project.org/package=gbm) originally written by Greg Ridgeway.

Boosting is the process of iteratively adding basis functions in a greedy fashion so that each additional basis function further reduces the selected loss function. This implementation closely follows Friedman's Gradient Boosting Machine (Friedman, 2001).

In addition to many of the features documented in the Gradient Boosting Machine, erboost offers additional features including the out-of-bag estimator for the optimal number of iterations, the ability to store and manipulate the resulting erboost object.

Concerning tuning parameters, interaction.depth and n.trees are two of the most important tuning parameters in **erboost**. **Users should not always use the default values of those two parameters, instead they should choose the appropriate values of** interaction.depth **and** n.trees **according to their data.** For example, if n.trees, which is the maximal number of trees to fit, is set to be too small, then it is possible that the actual optimal number of trees (which is best.iter selected by the function erboost.perf in "example" section) for a particular data exceeds this number, resulting a sub-optimal model. **Therefore, users should always fit the model with a large enough** n.trees **such that** n.trees **is greater than the potential optimal number of trees. The same principle also applies on** interaction.depth.

erboost.fit provides the link between R and the C++ erboost engine. erboost is a front-end to erboost.fit that uses the familiar R modeling formulas. However, model.frame is very slow if there are many predictor variables. For power-users with many variables use `erboost.fit`. For general practice `erboost` is preferable.

Value

`erboost`, `erboost.fit`, and `erboost.more` return a `erboost.object`.

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References

Yang, Y. and Zou, H. (2015), "Nonparametric Multiple Expectile Regression via ER-Boost," *Journal of Statistical Computation and Simulation*, 84(1), 84-95.

G. Ridgeway (1999). "The state of boosting," *Computing Science and Statistics* 31:172-181.

https://cran.r-project.org/package=gbm

J.H. Friedman (2001). "Greedy Function Approximation: A Gradient Boosting Machine," *Annals of Statistics* 29(5):1189-1232.

J.H. Friedman (2002). "Stochastic Gradient Boosting," *Computational Statistics and Data Analysis* 38(4):367-378.

See Also

`erboost.object`, `erboost.perf`, `plot.erboost`, `predict.erboost`, `summary.erboost`,

Examples

```
N <- 200
X1 <- runif(N)
X2 <- 2*runif(N)
X3 <- ordered(sample(letters[1:4],N,replace=TRUE),levels=letters[4:1])
X4 <- factor(sample(letters[1:6],N,replace=TRUE))
X5 <- factor(sample(letters[1:3],N,replace=TRUE))
X6 <- 3*runif(N)
mu <- c(-1,0,1,2)[as.numeric(X3)]

SNR <- 10 # signal-to-noise ratio
Y <- X1**1.5 + 2 * (X2**.5) + mu
sigma <- sqrt(var(Y)/SNR)
Y <- Y + rnorm(N,0,sigma)

# introduce some missing values
X1[sample(1:N,size=50)] <- NA
X4[sample(1:N,size=30)] <- NA

data <- data.frame(Y=Y,X1=X1,X2=X2,X3=X3,X4=X4,X5=X5,X6=X6)

# fit initial model
```

```
erboost1 <- erboost(Y~X1+X2+X3+X4+X5+X6,         # formula
    data=data,                   # dataset
    var.monotone=c(0,0,0,0,0,0), # -1: monotone decrease,
                                 # +1: monotone increase,
                                 #  0: no monotone restrictions
    distribution=list(name="expectile",alpha=0.5),
                                 # expectile
    n.trees=3000,                # number of trees
    shrinkage=0.005,             # shrinkage or learning rate,
                                 # 0.001 to 0.1 usually work
    interaction.depth=3,         # 1: additive model, 2: two-way interactions, etc.
    bag.fraction = 0.5,          # subsampling fraction, 0.5 is probably best
    train.fraction = 0.5,        # fraction of data for training,
                                 # first train.fraction*N used for training
    n.minobsinnode = 10,         # minimum total weight needed in each node
    cv.folds = 5,                # do 5-fold cross-validation
    keep.data=TRUE,              # keep a copy of the dataset with the object
    verbose=TRUE)                # print out progress


# check performance using a 50% heldout test set
best.iter <- erboost.perf(erboost1,method="test")
print(best.iter)

# check performance using 5-fold cross-validation
best.iter <- erboost.perf(erboost1,method="cv")
print(best.iter)

# plot the performance
# plot variable influence
summary(erboost1,n.trees=1)         # based on the first tree
summary(erboost1,n.trees=best.iter) # based on the estimated best number of trees

# make some new data
N <- 20
X1 <- runif(N)
X2 <- 2*runif(N)
X3 <- ordered(sample(letters[1:4],N,replace=TRUE))
X4 <- factor(sample(letters[1:6],N,replace=TRUE))
X5 <- factor(sample(letters[1:3],N,replace=TRUE))
X6 <- 3*runif(N)
mu <- c(-1,0,1,2)[as.numeric(X3)]

Y <- X1**1.5 + 2 * (X2**.5) + mu + rnorm(N,0,sigma)

data2 <- data.frame(Y=Y,X1=X1,X2=X2,X3=X3,X4=X4,X5=X5,X6=X6)

# predict on the new data using "best" number of trees
# f.predict generally will be on the canonical scale
f.predict <- predict.erboost(erboost1,data2,best.iter)

# least squares error
print(sum((data2$Y-f.predict)^2))
```

```
# create marginal plots
# plot variable X1 after "best" iterations
plot.erboost(erboost1,1,best.iter)
# contour plot of variables 1 and 3 after "best" iterations
plot.erboost(erboost1,c(1,3),best.iter)

# do another 20 iterations
erboost2 <- erboost.more(erboost1,20,
                 verbose=FALSE) # stop printing detailed progress
```

`erboost.object` *ER-Boost Expectile Regression Model Object*

Description

These are objects representing fitted `erboost`s.

Value

- `initF` the "intercept" term, the initial predicted value to which trees make adjustments
- `fit` a vector containing the fitted values on the scale of regression function
- `train.error` a vector of length equal to the number of fitted trees containing the value of the loss function for each boosting iteration evaluated on the training data
- `valid.error` a vector of length equal to the number of fitted trees containing the value of the loss function for each boosting iteration evaluated on the validation data
- `cv.error` if `cv.folds`<2 this component is NULL. Otherwise, this component is a vector of length equal to the number of fitted trees containing a cross-validated estimate of the loss function for each boosting iteration
- `oobag.improve` a vector of length equal to the number of fitted trees containing an out-of-bag estimate of the marginal reduction in the expected value of the loss function. The out-of-bag estimate uses only the training data and is useful for estimating the optimal number of boosting iterations. See `erboost.perf`
- `trees` a list containing the tree structures.
- `c.splits` a list of all the categorical splits in the collection of trees. If the `trees[[i]]` component of a `erboost` object describes a categorical split then the splitting value will refer to a component of `c.splits`. That component of `c.splits` will be a vector of length equal to the number of levels in the categorical split variable. -1 indicates left, +1 indicates right, and 0 indicates that the level was not present in the training data

Structure

The following components must be included in a legitimate `erboost` object.

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See Also

erboost

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erboost.perf *erboost performance*

Description

Estimates the optimal number of boosting iterations for a erboost object and optionally plots various performance measures

Usage

```
erboost.perf(object,
         plot.it = TRUE,
         oobag.curve = FALSE,
         overlay = TRUE,
         method)
```

Arguments

object	a erboost.object created from an initial call to erboost.
plot.it	an indicator of whether or not to plot the performance measures. Setting plot.it=TRUE creates two plots. The first plot plots object$train.error (in black) and object$valid.error (in red) versus the iteration number. The scale of the error measurement, shown on the left vertical axis, depends on the distribution argument used in the initial call to erboost.
oobag.curve	indicates whether to plot the out-of-bag performance measures in a second plot.
overlay	if TRUE and oobag.curve=TRUE then a right y-axis is added to the training and test error plot and the estimated cumulative improvement in the loss function is plotted versus the iteration number.
method	indicate the method used to estimate the optimal number of boosting iterations. method="OOB" computes the out-of-bag estimate and method="test" uses the test (or validation) dataset to compute an out-of-sample estimate. method="cv" extracts the optimal number of iterations using cross-validation if erboost was called with cv.folds>1

Value

erboost.perf returns the estimated optimal number of iterations. The method of computation depends on the method argument.

Author(s)

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References

Yang, Y. and Zou, H. (2015), "Nonparametric Multiple Expectile Regression via ER-Boost," *Journal of Statistical Computation and Simulation*, 84(1), 84-95.

G. Ridgeway (1999). "The state of boosting," *Computing Science and Statistics* 31:172-181.

https://cran.r-project.org/package=gbm

See Also

erboost, erboost.object

`plot.erboost` *Marginal plots of fitted erboost objects*

Description

Plots the marginal effect of the selected variables by "integrating" out the other variables.

Usage

```
## S3 method for class 'erboost'
plot(x,
     i.var = 1,
     n.trees = x$n.trees,
     continuous.resolution = 100,
     return.grid = FALSE,
     ...)
```

Arguments

`x` a erboost.object fitted using a call to erboost

`i.var` a vector of indices or the names of the variables to plot. If using indices, the variables are indexed in the same order that they appear in the initial `erboost` formula. If `length(i.var)` is between 1 and 3 then `plot.erboost` produces the plots. Otherwise, `plot.erboost` returns only the grid of evaluation points and their average predictions

`n.trees` the number of trees used to generate the plot. Only the first `n.trees` trees will be used

`continuous.resolution` The number of equally space points at which to evaluate continuous predictors

return.grid	if TRUE then plot.erboost produces no graphics and only returns the grid of evaluation points and their average predictions. This is useful for customizing the graphics for special variable types or for dimensions greater than 3
...	other arguments passed to the plot function

Details

plot.erboost produces low dimensional projections of the erboost.object by integrating out the variables not included in the i.var argument. The function selects a grid of points and uses the weighted tree traversal method described in Friedman (2001) to do the integration. Based on the variable types included in the projection, plot.erboost selects an appropriate display choosing amongst line plots, contour plots, and lattice plots. If the default graphics are not sufficient the user may set return.grid=TRUE, store the result of the function, and develop another graphic display more appropriate to the particular example.

Value

Nothing unless return.grid is true then plot.erboost produces no graphics and only returns the grid of evaluation points and their average predictions.

Author(s)

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References

Yang, Y. and Zou, H. (2015), “Nonparametric Multiple Expectile Regression via ER-Boost,” *Journal of Statistical Computation and Simulation*, 84(1), 84-95.

G. Ridgeway (1999). “The state of boosting,” *Computing Science and Statistics* 31:172-181.

https://cran.r-project.org/package=gbm

J.H. Friedman (2001). "Greedy Function Approximation: A Gradient Boosting Machine," Annals of Statistics 29(4).

See Also

erboost, erboost.object, plot

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predict.erboost *Predict method for erboost Model Fits*

Description

Predicted values based on an ER-Boost Expectile regression model object

Usage

```
## S3 method for class 'erboost'
predict(object,
        newdata,
        n.trees,
        single.tree=FALSE,
        ...)
```

Arguments

`object`	Object of class inheriting from (`erboost.object`)
`newdata`	Data frame of observations for which to make predictions
`n.trees`	Number of trees used in the prediction. `n.trees` may be a vector in which case predictions are returned for each iteration specified
`single.tree`	If `single.tree=TRUE` then `predict.erboost` returns only the predictions from tree(s) `n.trees`
`...`	further arguments passed to or from other methods

Details

`predict.erboost` produces predicted values for each observation in `newdata` using the the first `n.trees` iterations of the boosting sequence. If `n.trees` is a vector than the result is a matrix with each column representing the predictions from erboost models with `n.trees[1]` iterations, `n.trees[2]` iterations, and so on.

The predictions from `erboost` do not include the offset term. The user may add the value of the offset to the predicted value if desired.

If `object` was fit using `erboost.fit` there will be no `Terms` component. Therefore, the user has greater responsibility to make sure that `newdata` is of the same format (order and number of variables) as the one originally used to fit the model.

Value

Returns a vector of predictions. By default the predictions are on the scale of f(x).

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See Also

`erboost`, `erboost.object`

relative.influence *Methods for estimating relative influence*

Description

Helper functions for computing the relative influence of each variable in the erboost object.

Usage

```
relative.influence(object, n.trees)
permutation.test.erboost(object, n.trees)
erboost.loss(y,f,w,offset,dist,baseline)
```

Arguments

`object`	a `erboost` object created from an initial call to `erboost`.
`n.trees`	the number of trees to use for computations.
`y`, `f`, `w`, `offset`, `dist`, `baseline`	For `erboost.loss`: These components are the outcome, predicted value, observation weight, offset, distribution, and comparison loss function, respectively.

Details

This is not intended for end-user use. These functions offer the different methods for computing the relative influence in `summary.erboost`. `erboost.loss` is a helper function for `permutation.test.erboost`.

Value

Returns an unprocessed vector of estimated relative influences.

Author(s)

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References

Yang, Y. and Zou, H. (2015), "Nonparametric Multiple Expectile Regression via ER-Boost," *Journal of Statistical Computation and Simulation*, 84(1), 84-95.

G. Ridgeway (1999). "The state of boosting," *Computing Science and Statistics* 31:172-181.

https://cran.r-project.org/package=gbm

J.H. Friedman (2001). "Greedy Function Approximation: A Gradient Boosting Machine," Annals of Statistics 29(5):1189-1232.

See Also

`summary.erboost`

`summary.erboost` *Summary of a erboost object*

Description

Computes the relative influence of each variable in the erboost object.

Usage

```
## S3 method for class 'erboost'
summary(object,
        cBars=length(object$var.names),
        n.trees=object$n.trees,
        plotit=TRUE,
        order=TRUE,
        method=relative.influence,
        normalize=TRUE,
        ...)
```

Arguments

`object`	a `erboost` object created from an initial call to `erboost`.
`cBars`	the number of bars to plot. If `order=TRUE` the only the variables with the `cBars` largest relative influence will appear in the barplot. If `order=FALSE` then the first `cBars` variables will appear in the plot. In either case, the function will return the relative influence of all of the variables.
`n.trees`	the number of trees used to generate the plot. Only the first `n.trees` trees will be used.
`plotit`	an indicator as to whether the plot is generated.
`order`	an indicator as to whether the plotted and/or returned relative influences are sorted.
`method`	The function used to compute the relative influence. `relative.influence` is the default and is the same as that described in Friedman (2001). The other current (and experimental) choice is `permutation.test.erboost`. This method randomly permutes each predictor variable at a time and computes the associated reduction in predictive performance. This is similar to the variable importance measures Breiman uses for random forests, but `erboost` currently computes using the entire training dataset (not the out-of-bag observations.
`normalize`	if `FALSE` then `summary.erboost` returns the unnormalized influence.
`...`	other arguments passed to the plot function.

Details

This returns the reduction attributeable to each varaible in sum of squared error in predicting the gradient on each iteration. It describes the relative influence of each variable in reducing the loss function. See the references below for exact details on the computation.

Value

Returns a data frame where the first component is the variable name and the second is the computed relative influence, normalized to sum to 100.

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References

Yang, Y. and Zou, H. (2015), “Nonparametric Multiple Expectile Regression via ER-Boost,” *Journal of Statistical Computation and Simulation*, 84(1), 84-95.

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https://cran.r-project.org/package=gbm

J.H. Friedman (2001). "Greedy Function Approximation: A Gradient Boosting Machine," Annals of Statistics 29(5):1189-1232.

See Also

erboost

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