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cvTools-package

Cross-validation tools for regression models

Description
Tools that allow developers to write functions for cross-validation with minimal programming effort and assist users with model selection.

Details

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**Author(s)**

Andreas Alfons

Maintainer: Andreas Alfons <andreas.alfons@econ.kuleuven.be>

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**Description**

Retrieve or set the names of cross-validation results, retrieve or set the identifiers of the models, or retrieve the number of cross-validation results or included models.

**Usage**

```r
cvNames(x)

cvNames(x) <- value

fits(x)

fits(x) <- value

ncv(x)

nfits(x)
```

**Arguments**

- **x**: an object inheriting from class "cv" or "cvSelect" that contains cross-validation results.
- **value**: a vector of replacement values.
Value

cvNames returns the names of the cross-validation results. The replacement function thereby returns them invisibly.

fits returns the identifiers of the models for objects inheriting from class "cvSelect" and NULL for objects inheriting from class "cv". The replacement function thereby returns those values invisibly.

ncv returns the number of cross-validation results.

nfits returns the number of models included in objects inheriting from class "cvSelect" and NULL for objects inheriting from class "cv".

Author(s)

Andreas Alfons

See Also

cvFit, cvSelect, cvTuning

Examples

library("robustbase")
data("coleman")
set.seed(1234) # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmspe, folds = folds,
                   fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmspe, folds = folds,
                    fit = "both", trim = 0.1)

# combine results into one object
cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts

# "cv" object
ncv(cvFitLts50)
nfits(cvFitLts50)
cvNames(cvFitLts50)
cvNames(cvFitLts50) <- c("improved", "initial")
fits(cvFitLts50)
aggregate.cv

Aggregate cross-validation results

Description

Compute summary statistics of results from repeated $K$-fold cross-validation.

Usage

```r
### S3 method for class 'cv'
aggregate(x, FUN = mean, select = NULL,
   ...)

### S3 method for class 'cvSelect'
aggregate(x, FUN = mean,
   select = NULL, ...)

### S3 method for class 'cvTuning'
aggregate(x, ...)
```

Arguments

- `x`
  an object inheriting from class "cv" or "cvSelect" that contains cross-validation results (note that the latter includes objects of class "cvTuning").
- `FUN`
  a function to compute the summary statistics.
- `select`
  a character, integer or logical vector indicating the columns of cross-validation results for which to compute the summary statistics.
- `...`
  for the "cvTuning" method, additional arguments to be passed to the "cvSelect" method. Otherwise additional arguments to be passed to FUN.

Value

The "cv" method returns a vector or matrix of aggregated cross-validation results, depending on whether FUN returns a single value or a vector.

For the other methods, a data frame containing the aggregated cross-validation results for each model is returned. In the case of the "cvTuning" method, the data frame contains the combinations of tuning parameters rather than a column describing the models.
Author(s)

Andreas Alfons

See Also

cvFit, cvSelect, cvTuning, aggregate

Examples

library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmse, folds = folds,
                  fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmse, folds = folds,
                  fit = "both", trim = 0.1)

# combine results into one object
cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts

# summary of the results with the 50% subsets
aggregate(cvFitLts50, summary)
# summary of the combined results
aggregate(cvFitsLts, summary)

## evaluate MM regression models tuned for
## 80%, 85%, 90% and 95% efficiency
tuning <- list(tuning.psi=c(3.14, 3.34, 3.88, 4.68))

# set up function call
call <- call("lmmrob", formula = Y ~ .)
# perform cross-validation
cvFitsLmmrob <- cvTuning(call, data = coleman,
        y = coleman$Y, tuning = tuning, cost = rtmse,
        folds = folds, costArgs = list(trim = 0.1))
cvFitsLmmrob
# summary of results
aggregate(cvFitsLmrob, summary)

## bwplot.cv

*Box-and-whisker plots of cross-validation results*

### Description

Produce box-and-whisker plots of results from repeated $K$-fold cross-validation.

### Usage

```r
## S3 method for class 'cv'
bwplot(x, data, select = NULL, ...)
```

```r
## S3 method for class 'cvSelect'
bwplot(x, data, subset = NULL,
       select = NULL, ...)```

### Arguments

- **x**: an object inheriting from class "cv" or "cvSelect" that contains cross-validation results.
- **data**: currently ignored.
- **subset**: a character, integer or logical vector indicating the subset of models for which to plot the cross-validation results.
- **select**: a character, integer or logical vector indicating the columns of cross-validation results to be plotted.
- **...**: additional arguments to be passed to the "formula" method of *bwplot*.

### Details

For objects with multiple columns of repeated cross-validation results, conditional box-and-whisker plots are produced.

### Value

An object of class "trellis" is returned invisibly. The *update* method can be used to update components of the object and the *print* method (usually called by default) will plot it on an appropriate plotting device.

### Author(s)

Andreas Alfons
See Also

cvFit, cvSelect, cvTuning, plot, densityplot, xyplot, dotplot

Examples

library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 50)

## compare LS, MM and LTS regression

# perform cross-validation for an LS regression model
fitLm <- lm(Y ~ ., data = coleman)
cvFitLm <- cvLm(fitLm, cost = rtmspe,
    folds = folds, trim = 0.1)

# perform cross-validation for an MM regression model
fitLmrob <- lmrob(Y ~ ., data = coleman, k.max = 500)
cvFitLmrob <- cvLmrob(fitLmrob, cost = rtmspe,
    folds = folds, trim = 0.1)

# perform cross-validation for an LTS regression model
fitLts <- ltsReg(Y ~ ., data = coleman)
cvFitLts <- cvLts(fitLts, cost = rtmspe,
    folds = folds, trim = 0.1)

# combine results into one object
cvFits <- cvSelect(LS = cvFitLm, MM = cvFitLmrob, LTS = cvFitLts)
cvFits

# plot results for the MM regression model
bwplot(cvFitLmrob)
# plot combined results
bwplot(cvFits)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmspe, folds = folds,
    fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmspe, folds = folds,
    fit = "both", trim = 0.1)
```r
# combine and plot results
cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts
bwplot(cvFitsLts)
```

<table>
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**Description**

Compute the prediction loss of a model.

**Usage**

```r
mspe(y, yHat, includeSE = FALSE)
rmspe(y, yHat, includeSE = FALSE)
mape(y, yHat, includeSE = FALSE)
tmspe(y, yHat, trim = 0.25, includeSE = FALSE)
rtmspe(y, yHat, trim = 0.25, includeSE = FALSE)
```

**Arguments**

- `y`: a numeric vector or matrix giving the observed values.
- `yHat`: a numeric vector or matrix of the same dimensions as `y` giving the fitted values.
- `trim`: a numeric value giving the trimming proportion (the default is 0.25).
- `includeSE`: a logical indicating whether standard errors should be computed as well.

**Details**

`mspe` and `rmspe` compute the mean squared prediction error and the root mean squared prediction error, respectively. In addition, `mape` returns the mean absolute prediction error, which is somewhat more robust.

Robust prediction loss based on trimming is implemented in `tmspe` and `rtmspe`. To be more precise, `tmspe` computes the trimmed mean squared prediction error and `rtmspe` computes the root trimmed mean squared prediction error. A proportion of the largest squared differences of the observed and fitted values are thereby trimmed.

Standard errors can be requested via the `includeSE` argument. Note that standard errors for `tmspe` are based on a winsorized standard deviation. Furthermore, standard errors for `rmspe` and `rtmspe` are computed from the respective standard errors of `mspe` and `tmspe` via the delta method.
Value

If standard errors are not requested, a numeric value giving the prediction loss is returned.

Otherwise a list is returned, with the first component containing the prediction loss and the second component the corresponding standard error.

Author(s)

Andreas Alfons

References


See Also

cvFit, cvTuning

Examples

```r
# fit an MM-regression model
data("coleman")
fit <- lmrob(Y~., data=coleman)

# compute the prediction loss from the fitted values
# (hence the prediction loss is underestimated in this simple
# example since all observations are used to fit the model)
mspe(coleman$Y, predict(fit))
rmspe(coleman$Y, predict(fit))
mape(coleman$Y, predict(fit))
tmspe(coleman$Y, predict(fit), trim = 0.1)
rtmspe(coleman$Y, predict(fit), trim = 0.1)

# include standard error
mspe(coleman$Y, predict(fit), includeSE = TRUE)
rmspe(coleman$Y, predict(fit), includeSE = TRUE)
mape(coleman$Y, predict(fit), includeSE = TRUE)
tmspe(coleman$Y, predict(fit), trim = 0.1, includeSE = TRUE)
rtmspe(coleman$Y, predict(fit), trim = 0.1, includeSE = TRUE)
```
cvFit

Cross-validation for model evaluation

Description

Estimate the prediction error of a model via (repeated) \( K \)-fold cross-validation. It is thereby possible to supply an object returned by a model fitting function, a model fitting function itself, or an unevaluated function call to a model fitting function.

Usage

```r
CVdefaultS method:
cvFit(object, data = NULL, x = NULL,
y, cost = rmspe, K = 5, R = 1,
foldType = c("random", "consecutive", "interleaved"),
folds = NULL, names = NULL, predictArgs = list(),
costArgs = list(), envir = parent.frame(), seed = NULL,
...)

CVS method for class ’function’
cvFit(object, formula, data = NULL,
x = NULL, y, args = list(), cost = rmspe, K = 5, R = 1,
foldType = c("random", "consecutive", "interleaved"),
folds = NULL, names = NULL, predictArgs = list(),
costArgs = list(), envir = parent.frame(), seed = NULL,
...)

CVS method for class ’call’
cvFit(object, data = NULL, x = NULL, y,
cost = rmspe, K = 5, R = 1,
foldType = c("random", "consecutive", "interleaved"),
folds = NULL, names = NULL, predictArgs = list(),
costArgs = list(), envir = parent.frame(), seed = NULL,
...)
```

Arguments

- `object` the fitted model for which to estimate the prediction error, a function for fitting a model, or an unevaluated function call for fitting a model (see `call` for the latter). In the case of a fitted model, the object is required to contain a component `call` that stores the function call used to fit the model, which is typically the case for objects returned by model fitting functions.
- `formula` a formula describing the model.
- `data` a data frame containing the variables required for fitting the models. This is typically used if the model in the function call is described by a formula.
x  a numeric matrix containing the predictor variables. This is typically used if the
function call for fitting the models requires the predictor matrix and the response
to be supplied as separate arguments.

y  a numeric vector or matrix containing the response.

args  a list of additional arguments to be passed to the model fitting function.

cost  a cost function measuring prediction loss. It should expect the observed values
of the response to be passed as the first argument and the predicted values as the
second argument, and must return either a non-negative scalar value, or a list
with the first component containing the prediction error and the second com-
ponent containing the standard error. The default is to use the root mean squared
prediction error (see cost).

K  an integer giving the number of groups into which the data should be split (the
default is five). Keep in mind that this should be chosen such that all groups
are of approximately equal size. Setting K equal to n yields leave-one-out cross-
validation.

R  an integer giving the number of replications for repeated K-fold cross-validation.
This is ignored for for leave-one-out cross-validation and other non-random
splits of the data.

foldType  a character string specifying the type of folds to be generated. Possible values
are "random" (the default), "consecutive" or "interleaved".

folds  an object of class "cvFolds" giving the folds of the data for cross-validation (as
returned by cvFolds). If supplied, this is preferred over K and R.

names  an optional character vector giving names for the arguments containing the data
to be used in the function call (see “Details”).

predictArgs  a list of additional arguments to be passed to the predict method of the fitted
models.

costArgs  a list of additional arguments to be passed to the prediction loss function cost.

envir  the environment in which to evaluate the function call for fitting the models
(see eval).

seed  optional initial seed for the random number generator (see .Random.seed).

...  additional arguments to be passed down.

Details

(Repeated) K-fold cross-validation is performed in the following way. The data are first split into
K previously obtained blocks of approximately equal size. Each of the K data blocks is left out
once to fit the model, and predictions are computed for the observations in the left-out block with
the predict method of the fitted model. Thus a prediction is obtained for each observation.

The response variable and the obtained predictions for all observations are then passed to the predic-
tion loss function cost to estimate the prediction error. For repeated cross-validation, this process
is replicated and the estimated prediction errors from all replications as well as their average are
included in the returned object.

Furthermore, if the response is a vector but the predict method of the fitted models returns a
matrix, the prediction error is computed for each column. A typical use case for this behavior would
be if the `predict` method returns predictions from an initial model fit and stepwise improvements thereof.

If `formula` or `data` are supplied, all variables required for fitting the models are added as one argument to the function call, which is the typical behavior of model fitting functions with a `formula` interface. In this case, the accepted values for `names` depend on the method. For the function method, a character vector of length two should be supplied, with the first element specifying the argument name for the formula and the second element specifying the argument name for the data (the default is to use `c("formula", "data")`). Note that names for both arguments should be supplied even if only one is actually used. For the other methods, which do not have a `formula` argument, a character string specifying the argument name for the data should be supplied (the default is to use "data").

If `x` is supplied, on the other hand, the predictor matrix and the response are added as separate arguments to the function call. In this case, `names` should be a character vector of length two, with the first element specifying the argument name for the predictor matrix and the second element specifying the argument name for the response (the default is to use `c("x", "y")`). It should be noted that the `formula` or `data` arguments take precedence over `x`.

**Value**

An object of class "cv" with the following components:

- `n` an integer giving the number of observations.
- `K` an integer giving the number of folds.
- `R` an integer giving the number of replications.
- `cv` a numeric vector containing the respective estimated prediction errors. For repeated cross-validation, those are average values over all replications.
- `se` a numeric vector containing the respective estimated standard errors of the prediction loss.
- `reps` a numeric matrix in which each column contains the respective estimated prediction errors from all replications. This is only returned for repeated cross-validation.
- `seed` the seed of the random number generator before cross-validation was performed.
- `call` the matched function call.

**Author(s)**

Andreas Alfons

**See Also**

`cvTool`, `cvSelect`, `cvTuning`, `cvFolds`, `cost`

**Examples**

```r
library("robustbase")
data("coleman")
```
cvFolds

Cross-validation folds

Description

Split \( n \) observations into \( K \) groups to be used for (repeated) \( K \)-fold cross-validation. \( K \) should thereby be chosen such that all groups are of approximately equal size.

Usage

\[
\text{cvFolds}(n, K = 5, R = 1, \\
type = c("random", "consecutive", "interleaved"))
\]

Arguments

- \( n \) : an integer giving the number of observations to be split into groups.
- \( K \) : an integer giving the number of groups into which the observations should be split (the default is five). Setting \( K \) equal to \( n \) yields leave-one-out cross-validation.
- \( R \) : an integer giving the number of replications for repeated \( K \)-fold cross-validation. This is ignored for for leave-one-out cross-validation and other non-random splits of the data.
- \( \text{type} \) : a character string specifying the type of folds to be generated. Possible values are "random" (the default), "consecutive" or "interleaved".
Value

An object of class "cvFolds" with the following components:

- `n`: an integer giving the number of observations.
- `K`: an integer giving the number of folds.
- `R`: an integer giving the number of replications.
- `subsets`: an integer matrix in which each column contains a permutation of the indices.
- `which`: an integer vector giving the fold for each permuted observation.

Author(s)

Andreas Alfons

See Also

cvFit, cvSelect, cvTuning

Examples

```r
set.seed(1234) # set seed for reproducibility
cvfolds(20, K = 5, type = "random")
cvfolds(20, K = 5, type = "consecutive")
cvfolds(20, K = 5, type = "interleaved")
cvfolds(20, K = 5, R = 10)
```

---

**cvReshape**

Reshape cross-validation results into an object of class "cvSelect" with only one column of results.

Usage

```r
cvReshape(x, ...)
```

## S3 method for class 'cv'
cvReshape(x,
    selectBest = c("min", "hastie"), seFactor = 1, ...)

## S3 method for class 'cvSelect'
cvReshape(x,
    selectBest = c("min", "hastie"), seFactor = 1, ...)
Arguments

x an object inheriting from class "cv" or "cvSelect" that contains cross-validation results.

selectBest a character string specifying a criterion for selecting the best model. Possible values are "min" (the default) or "hastie". The former selects the model with the smallest prediction error. The latter is useful for nested models or for models with a tuning parameter controlling the complexity of the model (e.g., penalized regression). It selects the most parsimonious model whose prediction error is no larger than seFactor standard errors above the prediction error of the best overall model. Note that the models are thereby assumed to be ordered from the most parsimonious one to the most complex one. In particular a one-standard-error rule is frequently applied.

seFactor a numeric value giving a multiplication factor of the standard error for the selection of the best model. This is ignored if selectBest is "min".

... additional arguments to be passed down.

Value

An object of class "cvSelect" with the following components:

n an integer giving the number of observations.

K an integer giving the number of folds used in cross-validation.

R an integer giving the number of replications used in cross-validation.

best an integer giving the index of the model with the best prediction performance.

cv a data frame containing the estimated prediction errors for the models. For repeated cross-validation, those are average values over all replications.

se a data frame containing the estimated standard errors of the prediction loss for the models.

selectBest a character string specifying the criterion used for selecting the best model.

seFactor a numeric value giving the multiplication factor of the standard error used for the selection of the best model.

reps a data frame containing the estimated prediction errors for the models from all replications. This is only returned if repeated cross-validation was performed.

Author(s)

Andreas Alfons

References


See Also

cvFit, cvSelect, cvTuning
cvSelect

Examples

```r
library("robustbase")
data("coleman")

# perform cross-validation for an LTS regression model
fitLts <- ltsReg(Y ~ ., data = coleman)
cvFitLts <- cvLts(fitLts, cost = rtmspe, K = 5, R = 10,
    fit = "both", trim = 0.1, seed = 1234)
# compare original and reshaped object
cvFitLts
cvReshape(cvFitLts)
```

---

**cvSelect**

*Model selection based on cross-validation*

Description

Combine cross-validation results for various models into one object and select the model with the best prediction performance.

Usage

```r
cvSelect(..., .reshape = FALSE,
    .selectBest = c("min", "hastie"), .seFactor = 1)
```

Arguments

- `...`: objects inheriting from class "cv" or "cvSelect" that contain cross-validation results.
- `reshape`: a logical indicating whether objects with more than one column of cross-validation results should be reshaped to have only one column (see “Details”).
- `selectBest`: a character string specifying a criterion for selecting the best model. Possible values are "min" (the default) or "hastie". The former selects the model with the smallest prediction error. The latter is useful for nested models or for models with a tuning parameter controlling the complexity of the model (e.g., penalized regression). It selects the most parsimonious model whose prediction error is no larger than `.seFactor` standard errors above the prediction error of the best overall model. Note that the models are thereby assumed to be ordered from the most parsimonious one to the most complex one. In particular a one-standard-error rule is frequently applied.
- `seFactor`: a numeric value giving a multiplication factor of the standard error for the selection of the best model. This is ignored if `.selectBest` is "min".
Details

Keep in mind that objects inheriting from class "cv" or "cvSelect" may contain multiple columns of cross-validation results. This is the case if the response is univariate but the predict method of the fitted model returns a matrix.

The .reshape argument determines how to handle such objects. If .reshape is FALSE, all objects are required to have the same number of columns and the best model for each column is selected. A typical use case for this behavior would be if the investigated models contain cross-validation results for a raw and a reweighted fit. It might then be of interest to researchers to compare the best model for the raw estimators with the best model for the reweighted estimators.

If .reshape is TRUE, objects with more than one column of results are first transformed with cvReshape to have only one column. Then the best overall model is selected.

It should also be noted that the argument names of .reshape, .selectBest and .seFactor start with a dot to avoid conflicts with the argument names used for the objects containing cross-validation results.

Value

An object of class "cvSelect" with the following components:

- \( n \) an integer giving the number of observations.
- \( K \) an integer vector giving the number of folds used in cross-validation for the respective model.
- \( R \) an integer vector giving the number of replications used in cross-validation for the respective model.
- \( \text{best} \) an integer vector giving the indices of the models with the best prediction performance.
- \( \text{cv} \) a data frame containing the estimated prediction errors for the models. For models for which repeated cross-validation was performed, those are average values over all replications.
- \( \text{se} \) a data frame containing the estimated standard errors of the prediction loss for the models.
- \( \text{selectBest} \) a character string specifying the criterion used for selecting the best model.
- \( \text{seFactor} \) a numeric value giving the multiplication factor of the standard error used for the selection of the best model.
- \( \text{reps} \) a data frame containing the estimated prediction errors from all replications for those models for which repeated cross-validation was performed. This is only returned if repeated cross-validation was performed for at least one of the models.

Note

Even though the function allows to compare cross-validation results obtained with a different number of folds or a different number of replications, such comparisons should be made with care. Hence warnings are issued in those cases. For maximum comparability, the same data folds should be used in cross-validation for all models to be compared.
cvSelect

Author(s)

Andreas Alfons

References


See Also

cvFit, cvTuning

Examples

library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

# set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)

## compare LS, MM and LTS regression

# perform cross-validation for an LS regression model
fitlm <- lm(Y ~ ., data = coleman)
cvfitlm <- cvlm(fitlm, cost = rtmspe,
               folds = folds, trim = 0.1)

# perform cross-validation for an MM regression model
fitlmrob <- lmr(Y ~ ., data = coleman)
cvfitlmrob <- cvlmrob(fitlmrob, cost = rtmspe,
                       folds = folds, trim = 0.1)

# perform cross-validation for an LTS regression model
fitlts <- ltsReg(Y ~ ., data = coleman)
cvfitlts <- cvlts(fitlts, cost = rtmspe,
                 folds = folds, trim = 0.1)

# compare cross-validation results
cvSelect(LS = cvfitlm, MM = cvfitlmrob, LTS = cvfitlts)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitlts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvfitlts50 <- cvlts(fitlts50, cost = rtmspe, folds = folds,
                    fit = "both", trim = 0.1)

# 75% subsets


```r
fitLts75 <- ltsReg(Y ~ ., data = colman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmspe, folds = folds,
                   fit = "both", trim = 0.1)

# combine and plot results
cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
```

---

**cvTool**  
*Low-level function for cross-validation*

**Description**

Basic function to estimate the prediction error of a model via (repeated) \( K \)-fold cross-validation. The model is thereby specified by an unevaluated function call to a model fitting function.

**Usage**

```r
cvTool(call, data = NULL, x = NULL, y, cost = rmspe,
       folds, names = NULL, predictArgs = list(),
       costArgs = list(), envir = parent.frame())
```

**Arguments**

- **call**: an unevaluated function call for fitting a model (see `call`).
- **data**: a data frame containing the variables required for fitting the models. This is typically used if the model in the function call is described by a `formula`.
- **x**: a numeric matrix containing the predictor variables. This is typically used if the function call for fitting the models requires the predictor matrix and the response to be supplied as separate arguments.
- **y**: a numeric vector or matrix containing the response.
- **cost**: a cost function measuring prediction loss. It should expect the observed values of the response to be passed as the first argument and the predicted values as the second argument, and must return either a non-negative scalar value, or a list with the first component containing the prediction error and the second component containing the standard error. The default is to use the root mean squared prediction error (see `cost`).
- **folds**: an object of class "cvFolds" giving the folds of the data for cross-validation (as returned by `cvFolds`).
- **names**: an optional character vector giving names for the arguments containing the data to be used in the function call (see “Details”).
- **predictArgs**: a list of additional arguments to be passed to the `predict` method of the fitted models.
- **costArgs**: a list of additional arguments to be passed to the prediction loss function `cost`.
- **envir**: the `environment` in which to evaluate the function call for fitting the models (see `eval`).
Details

(Repeated) $K$-fold cross-validation is performed in the following way. The data are first split into $K$ previously obtained blocks of approximately equal size (given by `folds`). Each of the $K$ data blocks is left out once to fit the model, and predictions are computed for the observations in the left-out block with the `predict` method of the fitted model. Thus a prediction is obtained for each observation.

The response variable and the obtained predictions for all observations are then passed to the prediction loss function `cost` to estimate the prediction error. For repeated cross-validation (as indicated by `folds`), this process is replicated and the estimated prediction errors from all replications are returned.

Furthermore, if the response is a vector but the `predict` method of the fitted models returns a matrix, the prediction error is computed for each column. A typical use case for this behavior would be if the `predict` method returns predictions from an initial model fit and stepwise improvements thereof.

If `data` is supplied, all variables required for fitting the models are added as one argument to the function call, which is the typical behavior of model fitting functions with a `formula` interface. In this case, a character string specifying the argument name can be passed via `names` (the default is to use "data").

If `x` is supplied, on the other hand, the predictor matrix and the response are added as separate arguments to the function call. In this case, `names` should be a character vector of length two, with the first element specifying the argument name for the predictor matrix and the second element specifying the argument name for the response (the default is to use c("x", "y")). It should be noted that `data` takes precedence over `x` if both are supplied.

Value

If only one replication is requested and the prediction loss function `cost` also returns the standard error, a list is returned, with the first component containing the estimated prediction errors and the second component the corresponding estimated standard errors.

Otherwise the return value is a numeric matrix in which each column contains the respective estimated prediction errors from all replications.

Author(s)

Andreas Alfons

See Also

`cvFit`, `cvTuning`, `cvFolds`, `cost`

Examples

```r
library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

# set up function call for an MM regression model
call <- call("lmrob", formula = Y ~ .)
```
cvTuning

Cross-validation for tuning parameter selection

Description
Select tuning parameters of a model by estimating the respective prediction errors via (repeated) $K$-fold cross-validation. It is thereby possible to supply a model fitting function or an unevaluated function call to a model fitting function.

Usage
cvTuning(object, ...) 

## S3 method for class 'function'

```r
cvTuning(object, formula,  
data = NULL, x = NULL, y, tuning = list(),  
args = list(), cost = rmse, K = 5, R = 1,  
foldType = c("random", "consecutive", "interleaved"),  
folds = NULL, names = NULL, predictArgs = list(),  
costArgs = list(), selectBest = c("min", "hastie"),  
seFactor = 1, envir = parent.frame(), seed = NULL, ...)
```

## S3 method for class 'call'

```r
cvTuning(object, data = NULL, x = NULL,  
y, tuning = list(), cost = rmse, K = 5, R = 1,  
foldType = c("random", "consecutive", "interleaved"),  
folds = NULL, names = NULL, predictArgs = list(),  
costArgs = list(), selectBest = c("min", "hastie"),  
seFactor = 1, envir = parent.frame(), seed = NULL, ...)
```

Arguments
- **object**
  a function or an unevaluated function call for fitting a model (see call for the latter).
- **formula**
  a formula describing the model.
- **data**
  a data frame containing the variables required for fitting the models. This is typically used if the model in the function call is described by a formula.
- **x**
  a numeric matrix containing the predictor variables. This is typically used if the function call for fitting the models requires the predictor matrix and the response to be supplied as separate arguments.
cvTuning

y
a numeric vector or matrix containing the response.

tuning
a list of arguments giving the tuning parameter values to be evaluated. The
names of the list components should thereby correspond to the argument names
of the tuning parameters. For each tuning parameter, a vector of values can be
supplied. Cross-validation is then applied over the grid of all possible combina-
tions of tuning parameter values.

args
a list of additional arguments to be passed to the model fitting function.

cost
a cost function measuring prediction loss. It should expect the observed values
of the response to be passed as the first argument and the predicted values as the
second argument, and must return either a non-negative scalar value, or a list
with the first component containing the prediction error and the second compo-
nent containing the standard error. The default is to use the root mean squared
prediction error (see cost).

K
an integer giving the number of groups into which the data should be split (the
default is five). Keep in mind that this should be chosen such that all groups
are of approximately equal size. Setting K equal to n yields leave-one-out cross-
validation.

R
an integer giving the number of replications for repeated K-fold cross-validation.
This is ignored for for leave-one-out cross-validation and other non-random
splits of the data.

foldType
a character string specifying the type of folds to be generated. Possible values
are "random" (the default), "consecutive" or "interleaved".

folds
an object of class "cvFolds" giving the folds of the data for cross-validation (as
returned by cvFolds). If supplied, this is preferred over K and R.

names
an optional character vector giving names for the arguments containing the data
to be used in the function call (see “Details”).

predictArgs
a list of additional arguments to be passed to the predict method of the fitted
models.

costArgs
a list of additional arguments to be passed to the prediction loss function cost.

selectBest
a character string specifying a criterion for selecting the best model. Possible
values are "min" (the default) or "hastie". The former selects the model with
the smallest prediction error. The latter is useful for models with a tuning pa-
rameter controlling the complexity of the model (e.g., penalized regression). It
selects the most parsimonious model whose prediction error is no larger than
seFactor standard errors above the prediction error of the best overall model.
Note that the models are thereby assumed to be ordered from the most parsi-
mious one to the most complex one. In particular a one-standard-error rule is
frequently applied.

seFactor
a numeric value giving a multiplication factor of the standard error for the selec-
tion of the best model. This is ignored if selectBest is "min".

envir
the environment in which to evaluate the function call for fitting the models
(see eval).

seed
optional initial seed for the random number generator (see .Random.seed).

...additional arguments to be passed down.
Details

(Repeated) \(K\)-fold cross-validation is performed in the following way. The data are first split into \(K\) previously obtained blocks of approximately equal size. Each of the \(K\) data blocks is left out once to fit the model, and predictions are computed for the observations in the left-out block with the \texttt{predict} method of the fitted model. Thus a prediction is obtained for each observation.

The response variable and the obtained predictions for all observations are then passed to the prediction loss function \texttt{cost} to estimate the prediction error. For repeated cross-validation, this process is replicated and the estimated prediction errors from all replications as well as their average are included in the returned object.

Furthermore, if the response is a vector but the \texttt{predict} method of the fitted models returns a matrix, the prediction error is computed for each column. A typical use case for this behavior would be if the \texttt{predict} method returns predictions from an initial model fit and stepwise improvements thereof.

If \texttt{formula} or \texttt{data} are supplied, all variables required for fitting the models are added as one argument to the function call, which is the typical behavior of model fitting functions with a \texttt{formula} interface. In this case, the accepted values for \texttt{names} depend on the method. For the function method, a character vector of length two should supplied, with the first element specifying the argument name for the formula and the second element specifying the argument name for the data (the default is to use \texttt{c("formula", "data")}). Note that names for both arguments should be supplied even if only one is actually used. For the \texttt{call} method, which does not have a \texttt{formula} argument, a character string specifying the argument name for the data should be supplied (the default is to use \texttt{"data"}).

If \texttt{x} is supplied, on the other hand, the predictor matrix and the response are added as separate arguments to the function call. In this case, \texttt{names} should be a character vector of length two, with the first element specifying the argument name for the predictor matrix and the second element specifying the argument name for the response (the default is to use \texttt{c("x", "y")}). It should be noted that the \texttt{formula} or \texttt{data} arguments take precedence over \texttt{x}.

Value

If \texttt{tuning} is an empty list, \texttt{cvFit} is called to return an object of class "cv".

Otherwise an object of class "cvTuning" (which inherits from class "cvSelect") with the following components is returned:

\texttt{n} an integer giving the number of observations.
\texttt{K} an integer giving the number of folds.
\texttt{R} an integer giving the number of replications.
\texttt{tuning} a data frame containing the grid of tuning parameter values for which the prediction error was estimated.
\texttt{best} an integer vector giving the indices of the optimal combinations of tuning parameters.
\texttt{cv} a data frame containing the estimated prediction errors for all combinations of tuning parameter values. For repeated cross-validation, those are average values over all replications.
se a data frame containing the estimated standard errors of the prediction loss for all combinations of tuning parameter values.

selectBest a character string specifying the criterion used for selecting the best model.

seFactor a numeric value giving the multiplication factor of the standard error used for the selection of the best model.

reps a data frame containing the estimated prediction errors from all replications for all combinations of tuning parameter values. This is only returned for repeated cross-validation.

seed the seed of the random number generator before cross-validation was performed.

call the matched function call.

Note
The same cross-validation folds are used for all combinations of tuning parameter values for maximum comparability.

Author(s)
Andreas Alfons

References

See Also
cvTool, cvFit, cvSelect, cvFolds, cost

Examples

```r
library("robustbase")
data("coleman")

## evaluate MM regression models tuned for 85% and 95% efficiency
tuning <- list(tuning.psi = c(3.443689, 4.685061))

## via model fitting function
# perform cross-validation
# note that the response is extracted from 'data' in
# this example and does not have to be supplied
cvTuning(lmrob, formula = Y ~ ., data = coleman, tuning = tuning,
       cost = rtmse, K = 5, R = 10, costArgs = list(trim = 0.1),
       seed = 1234)

## via function call
# set up function call
call <- call("lmrob", formula = Y ~ .)
# perform cross-validation
cvTuning(call, data = coleman, y = coleman$Y, tuning = tuning,
       cost = rtmse, K = 5, R = 10, costArgs = list(trim = 0.1),
       seed = 1234)
```
densityplot.cv

Kernel density plots of cross-validation results

Description

Produce kernel density plots of results from repeated $K$-fold cross-validation.

Usage

```r
## S3 method for class 'cv'
densityplot(x, data, select = NULL, ...)

## S3 method for class 'cvSelect'
densityplot(x, data, subset = NULL,
select = NULL, ...)
```

Arguments

- `x`: an object inheriting from class "cv" or "cvSelect" that contains cross-validation results.
- `data`: currently ignored.
- `subset`: a character, integer or logical vector indicating the subset of models for which to plot the cross-validation results.
- `select`: a character, integer or logical vector indicating the columns of cross-validation results to be plotted.
- `...`: additional arguments to be passed to the "formula" method of `densityplot`.

Details

For objects with multiple columns of repeated cross-validation results, conditional kernel density plots are produced.

Value

An object of class "trellis" is returned invisibly. The `update` method can be used to update components of the object and the `print` method (usually called by default) will plot it on an appropriate plotting device.

Author(s)

Andreas Alfons
See Also

cvFit, cvSelect, cvTuning, plot, bwplot, xyplot, dotplot

Examples

library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 50)

## compare LS, MM and LTS regression

# perform cross-validation for an LS regression model
fitlm <- lm(Y ~ ., data = coleman)
cvFitlm <- cvLm(fitlm, cost = rtmspe,
               folds = folds, trim = 0.1)

# perform cross-validation for an MM regression model
fitLmrob <- lmrob(Y ~ ., data = coleman, k.max = 500)
cvFitLmrob <- cvLmrob(fitLmrob, cost = rtmspe,
                      folds = folds, trim = 0.1)

# perform cross-validation for an LTS regression model
fitLts <- ltsReg(Y ~ ., data = coleman)
cvFitLts <- cvLts(fitLts, cost = rtmspe,
                  folds = folds, trim = 0.1)

# combine results into one object
cvfs <- cvSelect(LS = cvFitlm, MM = cvFitLmrob, LTS = cvFitLts)
cvfs

# plot results for the MM regression model
densityplot(cvFitLmrob)
# plot combined results
densityplot(cvfits)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmspe, folds = folds,
                    fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmspe, folds = folds,
                    fit = "both", trim = 0.1)
# combine and plot results
cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts
densityplot(cvFitsLts)

---

**dotplot.cv**

*Dot plots of cross-validation results*

**Description**

Produce dot plots of (average) results from (repeated) \( K \)-fold cross-validation.

**Usage**

```r
## S3 method for class 'cv'
dotplot(x, data, select = NULL, seFactor = NA, ...)

## S3 method for class 'cvSelect'
dotplot(x, data, subset = NULL, select = NULL, seFactor = x$seFactor, ...)
```

**Arguments**

- `x`: an object inheriting from class "cvSelect" that contains cross-validation results.
- `data`: currently ignored.
- `subset`: a character, integer or logical vector indicating the subset of models for which to plot the cross-validation results.
- `select`: a character, integer or logical vector indicating the columns of cross-validation results to be plotted.
- `seFactor`: a numeric value giving the multiplication factor of the standard error for displaying error bars. Error bars can be suppressed by setting this to NA.
- `...`: additional arguments to be passed to the "formula" method of `dotplot`.

**Details**

For objects with multiple columns of repeated cross-validation results, conditional dot plots are produced.

**Value**

An object of class "trellis" is returned invisibly. The `update` method can be used to update components of the object and the `print` method (usually called by default) will plot it on an appropriate plotting device.
Author(s)
Andreas Alfons

See Also
cvFit, cvSelect, cvTuning, plot, xyplot, bwplot, densityplot

Examples
library("robustbase")
data("coleman")
set.seed(1234) # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)

## compare LS, MM and LTS regression

# perform cross-validation for an LS regression model
fitLm <- lm(Y ~ ., data = coleman)
cvFitLm <- cvLm(fitLm, cost = rtmse,
               folds = folds, trim = 0.1)

# perform cross-validation for an MM regression model
fitLmrob <- lmrob(Y ~ ., data = coleman, k.max = 500)
cvFitLmrob <- cvLmrob(fitLmrob, cost = rtmse,
                      folds = folds, trim = 0.1)

# perform cross-validation for an LTS regression model
fitLts <- ltsReg(Y ~ ., data = coleman)
cvFitLts <- cvLts(fitLts, cost = rtmse,
               folds = folds, trim = 0.1)

# combine and plot results
cvFits <- cvSelect(LS = cvFitLm, MM = cvFitLmrob, LTS = cvFitLts)
cvFits
dotpplot(cvFits)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmse, folds = folds,
                    fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmse, folds = folds,
                    fit = "both", trim = 0.1)
# combine and plot results

cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts

dotplot(cvFitsLts)

plot.cv  

*Plot cross-validation results*

**Description**

Plot results from (repeated) $K$-fold cross-validation.

**Usage**

```r
## S3 method for class 'cv'
plot(x,
     method = c("bwplot", "densityplot", "xyplot", "dotplot"),
     ...
)

## S3 method for class 'cvSelect'
plot(x,
     method = c("bwplot", "densityplot", "xyplot", "dotplot"),
     ...
)
```

**Arguments**

- `x`  
  an object inheriting from class "cv" or "cvSelect" that contains cross-validation results.

- `method`  
  a character string specifying the type of plot. For the "cv" method, possible values are "bwplot" to create a box-and-whisker plot via `bwplot` (the default), or "densityplot" to create a kernel density plot via `densityplot`. Note that those plots are only meaningful for results from repeated cross-validation. For the "cvSelect" method, there are two additional possibilities: "xyplot" to plot the (average) results for each model via `xyplot`, or "dotplot" to create a similar dot plot via `dotplot`. The default is to use "bwplot" for results from repeated cross-validation and "xyplot" otherwise. In any case, partial string matching allows supply abbreviations of the accepted values.

- `...`  
  additional arguments to be passed down.

**Details**

For objects with multiple columns of cross-validation results, conditional plots are produced.

**Value**

An object of class "trellis" is returned invisibly. The `update` method can be used to update components of the object and the `print` method (usually called by default) will plot it on an appropriate plotting device.
Author(s)

Andreas Alfons

See Also

cvFit, cvSelect, cvTuning, bwpplot, densityplot, xyplot, dotplot

Examples

```r
library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

# set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 50)

## compare LS, MM and LTS regression

# perform cross-validation for an LS regression model
fitlm <- lm(Y ~ ., data = coleman)
cvFitlm <- cvlm(fitlm, cost = rtmse,
               folds = folds, trim = 0.1)

# perform cross-validation for an MM regression model
fitlmrob <- lmrob(Y ~ ., data = coleman, k.max = 500)
cvFitlmrob <- cvlmrob(fitlmrob, cost = rtmse,
                     folds = folds, trim = 0.1)

# perform cross-validation for an LTS regression model
fitlts <- ltsReg(Y ~ ., data = coleman)
cvfItlts <- cvlts(fitlts, cost = rtmse,
               folds = folds, trim = 0.1)

# combine results into one object
cvfits <- cvselect(LS = cvFitlm, MM = cvFitlmrob, LTS = cvFitlts)
cvfits

# plot results for the MM regression model
plot(cvFitlmrob, method = "bw")
plot(cvFitlmrob, method = "density")

# plot combined results
plot(cvfits, method = "bw")
plot(cvfits, method = "density")
plot(cvfits, method = "xy")
plot(cvfits, method = "dot")

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets
```
# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmspe, folds = folds,
  fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmspe, folds = folds,
  fit = "both", trim = 0.1)

# combine results into one object
cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts

# plot combined results
plot(cvFitsLts, method = "bw")
plot(cvFitsLts, method = "density")
plot(cvFitsLts, method = "xy")
plot(cvFitsLts, method = "dot")

---

**repCV**

Cross-validation for linear models

**Description**

Estimate the prediction error of a linear model via (repeated) \( K \)-fold cross-validation. Cross-validation functions are available for least squares fits computed with `lm` as well as for the following robust alternatives: MM-type models computed with `lmrob` and least trimmed squares fits computed with `ltsReg`.

**Usage**

```r
repCV(object, ...)  
```

## S3 method for class 'lm'

```r
repCV(object, cost = rmspe, K = 5, R = 1,  
  foldType = c("random", "consecutive", "interleaved"),  
  folds = NULL, seed = NULL, ...)  
```

## S3 method for class 'lmrob'

```r
repCV(object, cost = rtmspe, K = 5, R = 1,  
  foldType = c("random", "consecutive", "interleaved"),  
  folds = NULL, seed = NULL, ...)  
```

## S3 method for class 'lts'

```r
repCV(object, cost = rtmspe, K = 5, R = 1,  
  foldType = c("random", "consecutive", "interleaved"),  
```
folds = NULL, fit = c("reweighted", "raw", "both"),
seed = NULL, ...)

cvLm(object, cost = rmspe, K = 5, R = 1,
foldType = c("random", "consecutive", "interleaved"),
folds = NULL, seed = NULL, ...
)

cvLmrob(object, cost = rtmspe, K = 5, R = 1,
foldType = c("random", "consecutive", "interleaved"),
folds = NULL, seed = NULL, ...
)

cvLts(object, cost = rtmspe, K = 5, R = 1,
foldType = c("random", "consecutive", "interleaved"),
folds = NULL, fit = c("reweighted", "raw", "both"),
seed = NULL, ...)

Arguments

object an object returned from a model fitting function. Methods are implemented for
objects of class "lm" computed with lm, objects of class "lmrob" computed
with lmrob, and object of class "lts" computed with ltsReg.

cost a cost function measuring prediction loss. It should expect the observed values
of the response to be passed as the first argument and the predicted values as the
second argument, and must return either a non-negative scalar value, or a list
with the first component containing the prediction error and the second compo-
nent containing the standard error. The default is to use the root mean squared
prediction error for the "lm" method and the root trimmed mean squared pre-
diction error for the "lmrob" and "lts" methods (see cost).

K an integer giving the number of groups into which the data should be split (the
default is five). Keep in mind that this should be chosen such that all groups
are of approximately equal size. Setting K equal to n yields leave-one-out cross-
validation.

R an integer giving the number of replications for repeated K-fold cross-validation.
This is ignored for for leave-one-out cross-validation and other non-random
splits of the data.

foldType a character string specifying the type of folds to be generated. Possible values
are "random" (the default), "consecutive" or "interleaved".

tests an object of class "cvFolds" giving the folds of the data for cross-validation (as
returned by cvFolds). If supplied, this is preferred over K and R.

fit a character string specifying for which fit to estimate the prediction error. Possi-
ble values are "reweighted" (the default) for the prediction error of the reweighted
fit, "raw" for the prediction error of the raw fit, or "both" for the prediction error
of both fits.

seed optional initial seed for the random number generator (see .Random.seed).

... additional arguments to be passed to the prediction loss function cost.
Details

(Repeated) $K$-fold cross-validation is performed in the following way. The data are first split into $K$ previously obtained blocks of approximately equal size. Each of the $K$ data blocks is left out once to fit the model, and predictions are computed for the observations in the left-out block with the predict method of the fitted model. Thus a prediction is obtained for each observation.

The response variable and the obtained predictions for all observations are then passed to the prediction loss function cost to estimate the prediction error. For repeated cross-validation, this process is replicated and the estimated prediction errors from all replications as well as their average are included in the returned object.

Value

An object of class "cv" with the following components:

- **n**: an integer giving the number of observations.
- **K**: an integer giving the number of folds.
- **R**: an integer giving the number of replications.
- **cv**: a numeric vector containing the estimated prediction errors. For the "lm" and "lmrob" methods, this is a single numeric value. For the "lts" method, this contains one value for each of the requested fits. In the case of repeated cross-validation, those are average values over all replications.
- **se**: a numeric vector containing the estimated standard errors of the prediction loss. For the "lm" and "lmrob" methods, this is a single numeric value. For the "lts" method, this contains one value for each of the requested fits.
- **reps**: a numeric matrix containing the estimated prediction errors from all replications. For the "lm" and "lmrob" methods, this is a matrix with one column. For the "lts" method, this contains one column for each of the requested fits. However, this is only returned for repeated cross-validation.
- **seed**: the seed of the random number generator before cross-validation was performed.
- **call**: the matched function call.

Note

The repCV methods are simple wrapper functions that extract the data from the fitted model and call cvFit to perform cross-validation. In addition, cvLm, cvLmrob and cvLts are aliases for the respective methods.

Author(s)

Andreas Alfons

See Also

cvFit, cvFolds, cost, lm, lmrob, ltsReg
Examples

```r
library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

# set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)

# perform cross-validation for an LS regression model
fitLm <- lm(Y ~ ., data = coleman)
repCV(fitLm, cost = rtmse, folds = folds, trim = 0.1)

# perform cross-validation for an MM regression model
fitLmrob <- lmrob(Y ~ ., data = coleman)
repCV(fitLmrob, cost = rtmse, folds = folds, trim = 0.1)

# perform cross-validation for an LTS regression model
fitLts <- ltsReg(Y ~ ., data = coleman)
repCV(fitLts, cost = rtmse, folds = folds, trim = 0.1)
repCV(fitLts, cost = rtmse, folds = folds,
      fit = "both", trim = 0.1)
```

---

subset.cv

Subsetting cross-validation results

Description

Extract subsets of results from (repeated) $K$-fold cross-validation.

Usage

```r
## S3 method for class 'cv'
subset(x, select = NULL, ...)

## S3 method for class 'cvSelect'
subset(x, subset = NULL,
       select = NULL, ...)
```

Arguments

- **x**: an object inheriting from class "cv" or "cvSelect" that contains cross-validation results.
- **subset**: a character, integer or logical vector indicating the subset of models for which to keep the cross-validation results.
- **select**: a character, integer or logical vector indicating the columns of cross-validation results to be extracted.
- **...**: currently ignored.
Value
An object similar to x containing just the selected results.

Author(s)
Andreas Alfons

See Also
cvFit, cvSelect, cvTuning, subset

Examples

```r
library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmse, folds = folds,
                 fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmse, folds = folds,
                 fit = "both", trim = 0.1)

# combine results into one object
cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts

# extract reweighted LTS results with 50% subsets
subset(cvFitLts50, select = "reweighted")
subset(cvFitsLts, subset = c(TRUE, FALSE), select = "reweighted")
```

summary.cv

Summarize cross-validation results

Description
Produce a summary of results from (repeated) \( K \)-fold cross-validation.
Usage

```r
## S3 method for class 'cv'
summary(object, ...)
```

```r
## S3 method for class 'cvSelect'
summary(object, ...)
```

```r
## S3 method for class 'cvTuning'
summary(object, ...)
```

Arguments

- `object`: an object inheriting from class "cv" or "cvSelect" that contains cross-validation results (note that the latter includes objects of class "cvTuning").
- `...`: currently ignored.

Value

An object of class "summary.cv", "summary.cvSelect" or "summary.cvTuning", depending on the class of `object`.

Author(s)

Andreas Alfons

See Also

cvfit, cvSelect, cvTuning, summary

Examples

```r
library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)

## compare raw and reweighted LTS estimators for
## 50% and 75% subsets

# 50% subsets
fitLts50 <- ltsReg(Y ~ ., data = coleman, alpha = 0.5)
cvFitLts50 <- cvLts(fitLts50, cost = rtmspe, folds = folds,
                   fit = "both", trim = 0.1)

# 75% subsets
fitLts75 <- ltsReg(Y ~ ., data = coleman, alpha = 0.75)
cvFitLts75 <- cvLts(fitLts75, cost = rtmspe, folds = folds,
                   ...)
```r
fit = "both", trim = 0.1)

# combine results into one object
cvFitsLts <- cvSelect("0.5" = cvFitLts50, "0.75" = cvFitLts75)
cvFitsLts

# summary of the results with the 50% subsets
summary(cvFitsLts50)
# summary of the combined results
summary(cvFitsLts)

## evaluate MM regression models tuned for
## 80%, 85%, 90% and 95% efficiency
tuning <- list(tuning.psi = c(3.14, 3.44, 3.88, 4.68))

# set up function call
call <- call("lrmrob", formula = Y ~ .)
# perform cross-validation
cvFitsLrmrob <- cvTuning(call, data = coleman,
  y = coleman$Y, tuning = tuning, cost = rtmspe,
  folds = folds, costArgs = list(trim = 0.1))
cvFitsLrmrob

# summary of results
summary(cvFitsLrmrob)
```

---

**xyplot.cv**  
*X-Y plots of cross-validation results*

**Description**

Plot the (average) results from (repeated) $K$-fold cross-validation on the $y$-axis against the respective models on the $x$-axis.

**Usage**

```r
## S3 method for class 'cv'
xyplot(x, data, select = NULL,
  seFactor = NA, ...)

## S3 method for class 'cvSelect'
xyplot(x, data, subset = NULL,
  select = NULL, seFactor = x$seFactor, ...)

## S3 method for class 'cvTuning'
xyplot(x, data, subset = NULL,
  select = NULL, seFactor = x$seFactor, ...)
```
Arguments

x     an object inheriting from class "cvSelect" that contains cross-validation results (note that this includes objects of class "cvTuning").
data   currently ignored.
subset a character, integer or logical vector indicating the subset of models for which to plot the cross-validation results.
select a character, integer or logical vector indicating the columns of cross-validation results to be plotted.
seFactor a numeric value giving the multiplication factor of the standard error for displaying error bars. Error bars can be suppressed by setting this to NA.
... additional arguments to be passed to the "formula" method of xyplot.

Details

For objects with multiple columns of repeated cross-validation results, conditional plots are produced.

In most situations, the default behavior is to represent the cross-validation results for each model by a vertical line segment (i.e., to call the default method of xyplot with type = "h"). However, the behavior is different for objects of class "cvTuning" with only one numeric tuning parameter. In that situation, the cross-validation results are plotted against the values of the tuning parameter as a connected line (i.e., by using type = "b").

The default behavior can of course be overridden by supplying the type argument (a full list of accepted values can be found in the help file of panel.xyplot).

Value

An object of class "trellis" is returned invisibly. The update method can be used to update components of the object and the print method (usually called by default) will plot it on an appropriate plotting device.

Author(s)

Andreas Alfons

See Also

cvFit, cvSelect, cvTuning, plot, dotplot, bwplot, densityplot

Examples

library("robustbase")
data("coleman")
set.seed(1234)  # set seed for reproducibility

## set up folds for cross-validation
folds <- cvFolds(nrow(coleman), K = 5, R = 10)
## compare LS, MM and LTS regression

# perform cross-validation for an LS regression model
fitlm <- lm(Y ~ ., data = coleman)
cvFitlm <- cvlm(fitlm, cost = rtmspe,
               folds = folds, trim = 0.1)

# perform cross-validation for an MM regression model
fitlmrob <- lmrob(Y ~ ., data = coleman, k.max = 500)
cvFitlmrob <- cvlmrob(fitlmrob, cost = rtmspe,
                      folds = folds, trim = 0.1)

# perform cross-validation for an LTS regression model
fitlts <- ltsreg(Y ~ ., data = coleman)
cvFitlts <- cvlts(fitlts, cost = rtmspe,
                 folds = folds, trim = 0.1)

# combine and plot results
cvfits <- cvselect( LS = cvFitlm, MM = cvFitlmrob, LTS = cvFitlts)
cvfits
xyplot(cvfits)

## compare raw and reweighted LTS estimators for 50% and 75% subsets

# 50% subsets
fitlts50 <- ltsreg(Y ~ ., data = coleman, alpha = 0.5)
cvFitlts50 <- cvlts(fitlts50, cost = rtmspe, folds = folds,
                    fit = "both", trim = 0.1)

# 75% subsets
fitlts75 <- ltsreg(Y ~ ., data = coleman, alpha = 0.75)
cvFitlts75 <- cvlts(fitlts75, cost = rtmspe, folds = folds,
                    fit = "both", trim = 0.1)

# combine and plot results
cvfitslts <- cvselect("0.5" = cvFitlts50, "0.75" = cvFitlts75)
cvfitslts
xyplot(cvfitslts)

## evaluate MM regression models tuned for 80%, 85%, 90% and 95% efficiency

tuning <- list(tuning.psi=c(3.14, 3.44, 3.88, 4.68))

# perform cross-validation
cvFitslmrob <- cvtuning(fitlmrob$call, data = coleman,
                         y = coleman$y, tuning = tuning, cost = rtmspe,
                         folds = folds, costargs = list(trim = 0.1))
cvFitslmrob
# plot results
xyplot(cvFitsLmrob)
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