# Package ‘JOUSBoost’

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**Title**  Implements Under/Oversampling for Probability Estimation  
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## R topics documented:

<table>
<thead>
<tr>
<th>Topic</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>adaboost</td>
<td>2</td>
</tr>
<tr>
<td>circle_data</td>
<td>3</td>
</tr>
<tr>
<td>friedman_data</td>
<td>4</td>
</tr>
<tr>
<td>grid_probs</td>
<td>5</td>
</tr>
<tr>
<td>index_over</td>
<td>6</td>
</tr>
<tr>
<td>index_under</td>
<td>6</td>
</tr>
<tr>
<td>jous</td>
<td>7</td>
</tr>
<tr>
<td>JOUSBoost</td>
<td>9</td>
</tr>
<tr>
<td>predict.adaboost</td>
<td>10</td>
</tr>
<tr>
<td>predict.jous</td>
<td>11</td>
</tr>
<tr>
<td>print.adaboost</td>
<td>12</td>
</tr>
</tbody>
</table>
Description

An implementation of the AdaBoost algorithm from Freund and Shapire (1997) applied to decision tree classifiers.

Usage

adaboost(X, y, tree_depth = 3, n_rounds = 100, verbose = FALSE, control = NULL)

Arguments

- **X**: A matrix of continuous predictors.
- **y**: A vector of responses with entries in \( c(-1, 1) \).
- **tree_depth**: The depth of the base tree classifier to use.
- **n_rounds**: The number of rounds of boosting to use.
- **verbose**: Whether to print the number of iterations.
- **control**: A `rpart.control` list that controls properties of fitted decision trees.

Value

Returns an object of class `adaboost` containing the following values:

- **alphas**: Weights computed in the adaboost fit.
- **trees**: The trees constructed in each round of boosting. Storing trees allows one to make predictions on new data.
- **confusion_matrix**: A confusion matrix for the in-sample fits.

Note

Trees are grown using the CART algorithm implemented in the `rpart` package. In order to conserve memory, the only parts of the fitted tree objects that are retained are those essential to making predictions. In practice, the number of rounds of boosting to use is chosen by cross-validation.

References

Examples

```r
## Not run:
# Generate data from the circle model
set.seed(111)
dat = circle_data(n = 500)
train_index = sample(1:500, 400)

ada = adaboost(dat$X[train_index,], dat$y[train_index], tree_depth = 2,
n_rounds = 200, verbose = TRUE)
print(ada)
yhat_ada = predict(ada, dat$X[-train_index,])

# calculate misclassification rate
mean(dat$y[-train_index] != yhat_ada)
## End(Not run)
```

---

circle_data

Simulate data from the circle model.

Description

Simulate draws from a bernoulli distribution over c(-1,1). First, the predictors \(x\) are drawn i.i.d. uniformly over the square in the two dimensional plane centered at the origin with side length \(2 \times \text{outer}_r\), and then the response is drawn according to \(p(y = 1| x)\), which depends on \(r(x)\), the euclidean norm of \(x\). If \(r(x) \leq \text{inner}_r\), then \(p(y = 1| x) = 1\), if \(r(x) \geq \text{outer}_r\) then \(p(y = 1| x) = 1\), and \(p(y = 1| x) = (\text{outer}_r - r(x))/(\text{outer}_r - \text{inner}_r)\) when \(\text{inner}_r < r(x) < \text{outer}_r\). See Mease (2008).

Usage

circle_data(n = 500, inner_r = 8, outer_r = 28)

Arguments

- `n`: Number of points to simulate.
- `inner_r`: Inner radius of annulus.
- `outer_r`: Outer radius of annulus.

Value

Returns a list with the following components:

- `y`: Vector of simulated response in c(-1,1).
- `X`: An nx2 matrix of simulated predictors.
- `p`: The true conditional probability \(p(y = 1| x)\).
References


Examples

# Generate data from the circle model
set.seed(111)
dat = circle_data(n = 500, inner_r = 1, outer_r = 5)

## Not run:
# Visualization of conditional probability p(y=1|x)
inner_r = 0.5
outer_r = 1.5
x = seq(-outer_r, outer_r, by=0.02)
radius = sqrt(out(x^2, x^2, "+"))
prob = ifelse(radius >= outer_r, 0, ifelse(radius <= inner_r, 1,
(outer_r-radius)/(outer_r-inner_r)))
image(x, x, prob, main="Probability Density: Circle Example')

## End(Not run)

friedman_data

Simulate data from the Friedman model

Description

Simulate draws from a bernoulli distribution over c(-1,1), where the log-odds is defined according to:

\[ \log \frac{p(y=1|x)}{p(y=-1|x)} = \gamma \left( 1 - x_1 + x_2 - \ldots + x_6 \right) \left( x_1 + x_2 + \ldots + x_6 \right) \]

and \( x \) is distributed as N(0, I_6). See Friedman (2000).

Usage

friedman_data(n = 500, d = 10, gamma = 10)

Arguments

- **n**: Number of points to simulate.
- **d**: The dimension of the predictor variable \( x \).
- **gamma**: A parameter controlling the Bayes error, with higher values of gamma corresponding to lower error rates.
grid_probs

Value

Returns a list with the following components:

- **y**: Vector of simulated response in $\mathbb{c}(-1,1)$.
- **X**: An $nxd$ matrix of simulated predictors.
- **p**: The true conditional probability $p(y = 1|x)$.

References


Examples

```r
set.seed(111)
dat = friedman_data(n = 500, gamma = 0.5)
```

grid_probs

Function to compute predicted quantiles

Description

Find predicted quantiles given classification results at different quantiles.

Usage

```r
grid_probs(X, q, delta, median_loc)
```

Arguments

- **X**: Matrix of class predictions, where each column gives the predictions for a given quantile in $q$.
- **q**: The quantiles for which the columns of $X$ are predictions.
- **delta**: The number of quantiles used.
- **median_loc**: Location of median quantile (0-based indexing).
**index_over**

Return indices to be used for jittered data in oversampling

**Description**

Return indices to be used for jittered data in oversampling

**Usage**

```
index_over(ix_pos, ix_neg, q)
```

**Arguments**

- `ix_pos`: Indices for positive examples in data.
- `ix_neg`: Indices for negative examples in data.
- `q`: Quantiles for which to construct tilted datasets.

**Value**

returns a list, each of element of which gives indices to be used on a particular cut (note: will be of length delta - 1)

**index_under**

Return indices to be used in original data for undersampling

**Description**

(note: sampling is done without replacement)

**Usage**

```
index_under(ix_pos, ix_neg, q, delta)
```

**Arguments**

- `ix_pos`: Indices for positive examples in data.
- `ix_neg`: Indices for negative examples in data.
- `q`: Quantiles for which to construct tilted datasets.
- `delta`: Number of quantiles.

**Value**

returns a list, each of element of which gives indices to be used on a particular cut (note: will be of length delta - 1)
Description

Perform probability estimation using jittering with over or undersampling.

Usage

\[
\text{jous}(X, y, \text{class}_\text{func}, \text{pred}_\text{func}, \text{type} = \text{c}(\text{"under", } \text{"over"}), \text{delta} = 10, \\
\text{nu} = 1, X_\text{pred} = \text{NULL}, \text{keep}_\text{models} = \text{FALSE}, \text{verbose} = \text{FALSE}, \\
\text{parallel} = \text{FALSE}, \text{packages} = \text{NULL})
\]

Arguments

- **X**: A matrix of continuous predictors.
- **y**: A vector of responses with entries in \([-1, 1]\).
- **class_func**: Function to perform classification. This function definition must be exactly of the form \(\text{class}_\text{func}(X, y)\) where \(X\) is a matrix and \(y\) is a vector with entries in \([-1, 1]\), and it must return an object on which \(\text{pred}_\text{func}\) can create predictions. See examples.
- **pred_func**: Function to create predictions. This function definition must be exactly of the form \(\text{pred}_\text{func}(\text{fit}_\text{obj}, X)\) where \(\text{fit}_\text{obj}\) is an object returned by \(\text{class}_\text{func}\) and \(X\) is a matrix of new data values, and it must return a vector with entries in \([-1, 1]\). See examples.
- **type**: Type of sampling: "over" for oversampling, or "under" for undersampling.
- **delta**: An integer (greater than 3) to control the number of quantiles to estimate.
- **nu**: The amount of noise to apply to predictors when oversampling data. The noise level is controlled by \(\text{nu} \times \text{sd}(X[, j])\) for each predictor - the default of \(\text{nu} = 1\) works well. Such "jittering" of the predictors is essential when applying \(\text{jous}\) to boosting type methods.
- **X_pred**: A matrix of predictors for which to form probability estimates.
- **keep_models**: Whether to store all of the models used to create the probability estimates. If \(\text{type} = \text{FALSE}\), the user will need to re-run \(\text{jous}\) when creating probability estimates for test data.
- **verbose**: If \(\text{TRUE}\), print the function’s progress to the terminal.
- **parallel**: If \(\text{TRUE}\), use parallel \text{foreach} to fit models. Must register parallel before hand, such as \text{doParallel}. See examples below.
- **packages**: If \(\text{parallel} = \text{TRUE}\), a vector of strings containing the names of any packages used in \(\text{class}_\text{func}\) or \(\text{pred}_\text{func}\). See examples below.
Value

Returns a list containing information about the parameters used in the jous function call, as well as the following additional components:

- **q**: The vector of target quantiles estimated by jous. Note that the estimated probabilities will be located at the midpoints of the values in q.
- **phat_train**: The in-sample probability estimates \( p(y = 1|x) \).
- **phat_test**: Probability estimates for the optional test data in X_test.
- **models**: If keep_models=TRUE, a list of models fitted to the resampled data sets.
- **confusion_matrix**: A confusion matrix for the in-sample fits.

Note

The jous function runs the classifier class_func a total of delta times on the data, which can be computationally expensive. Also, jous cannot yet be applied to categorical predictors - in the oversampling case, it is not clear how to “jitter” a categorical variable.

References


Examples

```r
## Not run:
# Generate data from Friedman model #
set.seed(111)
dat = friedman_data(n = 500, gamma = 0.5)
train_index = sample(1:500, 400)

# Apply jous to adaboost classifier
class_func = function(X, y) adaboost(X, y, tree_depth = 2, n_rounds = 200)
pred_func = function(fit_obj, X_test) predict(fit_obj, X_test)

jous_fit = jous(dat$X[train_index,], dat$y[train_index], class_func,
pred_func, keep_models = TRUE)

# get probability
phat_jous = predict(jous_fit, dat$X[-train_index, ], type = "prob")

# compare with probability from AdaBoost
ada = adaboost(dat$X[train_index,], dat$y[train_index], 
tree_depth = 2, n_rounds = 200)
phat_ada = predict(ada, dat$X[train_index, ], type = "prob")

mean((phat_jous - dat$p[-train_index])^2)
mean((phat_ada - dat$p[-train_index])^2)
```

## Example using parallel option
library(doParallel)
cl <- makeCluster(4)
registerDoParallel(cl)

# n.b. the packages='rpart' is not really needed here since it gets
# exported automatically by JOUSBoost, but for illustration
jous_fit = jous(dat$X[train_index,], dat$y[train_index], class_func,
    pred_func, keep_models = TRUE, parallel = TRUE,
    packages = 'rpart')
phat = predict(jous_fit, dat$X[-train_index,], type = 'prob')
stopCluster(cl)

## Example using SVM

library(kernlab)
class_func = function(X, y) ksvm(X, as.factor(y), kernel = 'rbfdot')
pred_func = function(obj, X) as.numeric(as.character(predict(obj, X)))
jous_obj = jous(dat$X[train_index,], dat$y[train_index], class_func = class_func,
    pred_func = pred_func, keep_models = TRUE)
jous_pred = predict(jous_obj, dat$X[-train_index,], type = 'prob')

## End(Not run)

---

**JOUSBoost**

**JOUSBoost: A package for probability estimation**

**Description**

JOUSBoost implements under/oversampling with jittering for probability estimation. Its intent is to be used to improve probability estimates that come from boosting algorithms (such as AdaBoost), but is modular enough to be used with virtually any classification algorithm from machine learning.

**Details**

For more theoretical background, consult Mease (2007).

**References**

predict.adaboost  Create predictions from AdaBoost fit

Description

Makes a prediction on new data for a given fitted adaboost model.

Usage

```r
## S3 method for class 'adaboost'
predict(object, X, type = c("response", "prob"),
        n_tree = NULL, ...)
```

Arguments

- **object**: An object of class adaboost returned by the adaboost function.
- **X**: A design matrix of predictors.
- **type**: The type of prediction to return. If type="response", a class label of -1 or 1 is returned. If type="prob", the probability \( p(y = 1|x) \) is returned.
- **n_tree**: The number of trees to use in the prediction (by default, all them).
- **...**:...

Value

Returns a vector of class predictions if type="response", or a vector of class probabilities \( p(y = 1|x) \) if type="prob".

Note

Probabilities are estimated according to the formula:

\[
p(y = 1|x) = \frac{1}{1 + exp(-2 * f(x))}
\]

where \( f(x) \) is the score function produced by AdaBoost. See Friedman (2000).

References


Examples

```r
## Not run:
# Generate data from the circle model
set.seed(111)
dat = circle_data(n = 500)
train_index = sample(1:500, 400)
```
predict.jous

Create predictions

Description

Makes a prediction on new data for a given fitted jous model.

Usage

## S3 method for class 'jous'
predict(object, X, type = c("response", "prob"), ...)

Arguments

object An object of class jous returned by the jous function.
X A design matrix of predictors.
type The type of prediction to return. If type="response", a class label of -1 or 1 is returned. If type="prob", the probability p(y = 1|x) is returned.

Value

Returns a vector of class predictions if type="response", or a vector of class probabilities p(y = 1|x) if type="prob".

Examples

## Not run:
# Generate data from Friedman model #
set.seed(111)
dat = friedman_data(n = 500, gamma = 0.5)
train_index = sample(1:500, 400)

# Apply jous to adaboost classifier
class_func = function(X, y) adaboost(X, y, tree_depth = 2, n_rounds = 100)
pred_func = function(fit_obj, X_test) predict(fit_obj, X_test)
jous_fit = jous(dat$X[train_index,], dat$y[train_index], class_func, pred_func, keep_models=TRUE)
# get class prediction
yhat = predict(jous_fit, dat$X[-train_index, ])
# get probability estimate
phat = predict(jous_fit, dat$X[-train_index, ], type="prob")
## End(Not run)

print.adaboost

### Description
Print a summary of adaboost fit.

### Usage
## S3 method for class 'adaboost'
print(x, ...)

### Arguments
- **x**: An adaboost object fit using the adaboost function.
- ... ...

### Value
Printed summary of the fit, including information about the tree depth and number of boosting rounds used.

print.jous

### Description
Print a summary of jous fit.

### Usage
## S3 method for class 'jous'
print(x, ...)

### Arguments
- **x**: A jous object.
- ... ...

sonar

Value

Printed summary of the fit

<table>
<thead>
<tr>
<th>sonar</th>
<th>Dataset of sonar measurements of rocks and mines</th>
</tr>
</thead>
</table>

Description

A dataset containing sonar measurements used to discriminate rocks from mines.

Usage

data(sonar)

Format

A data frame with 208 observations on 61 variables. The variables V1-V60 represent the energy within a certain frequency band, and are to be used as predictors. The variable y is a class label, 1 for 'rock' and -1 for 'mine'.

Source

http://archive.ics.uci.edu/ml/

References

Index

* datasets
  sonar, 13

adaboost, 2

circle_data, 3

friedman_data, 4

grid_probs, 5

index_over, 6

index_under, 6

jous, 7

JOUSBoost, 9

JOUSBoost-package (JOUSBoost), 9

predict.adaboost, 10

predict.jous, 11

print.adaboost, 12

print.jous, 12

sonar, 13