Package ‘GRridge’

April 25, 2017

**Type** Package

**Title** Better prediction by use of co-data: Adaptive group-regularized ridge regression

**Version** 1.0.0

**Date** 2016-10-25

**Author** Mark A. van de Wiel <mark.vdwiel@vumc.nl>

**Maintainer** Mark A. van de Wiel <mark.vdwiel@vumc.nl>

**Depends** R (>= 3.3), penalized, Iso, survival, GSEABase, BiocGenerics, Biobase, annotate, methods, graph, stats

**Suggests** testthat

**Description** This package allows the use of multiple sources of co-data (e.g. external p-values, gene lists, annotation) to improve prediction of binary, continuous and survival response using (logistic, linear or Cox) group-regularized ridge regression. It also facilitates post-hoc variable selection and prediction diagnostics by cross-validation using ROC curves and AUC.

**biocViews** Classification, Regression, Survival, Bayesian, RNASeq, GenePrediction, GeneExpression, Pathways, GeneSetEnrichment, GO, KEGG, GraphAndNetwork

**License** GPL-3

**LazyLoad** yes

**NeedsCompilation** no

---

**R topics documented:**

<table>
<thead>
<tr>
<th>Topic</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>GRridge-package</td>
<td>2</td>
</tr>
<tr>
<td>auc</td>
<td>3</td>
</tr>
<tr>
<td>CreatePartition</td>
<td>4</td>
</tr>
<tr>
<td>dataFarkas</td>
<td>6</td>
</tr>
<tr>
<td>dataVerlaat</td>
<td>7</td>
</tr>
<tr>
<td>dataWurdinger</td>
<td>8</td>
</tr>
<tr>
<td>grridge</td>
<td>9</td>
</tr>
<tr>
<td>grridgeCV</td>
<td>12</td>
</tr>
<tr>
<td>hello</td>
<td>13</td>
</tr>
<tr>
<td>matchGeneSets</td>
<td>14</td>
</tr>
<tr>
<td>mergeGroups</td>
<td>15</td>
</tr>
</tbody>
</table>
GRridge-package

Description

This package implements adaptive group-regularized (logistic) ridge regression by use of co-data. It uses co-data to improve predictions of binary and continuous response from high-dimension (e.g. genomics) data. Here, co-data is auxiliary information on variables (e.g. genes), such as annotation or p-values from other studies. The package includes convenience functions to convert such co-data to the correct input format. In addition, it includes functions for evaluating the predictive performance.

Details

Package: GRridge
Type: Package
Version: 0.99.1
Date: 2015-05-12
License: GPL

Main functions in the GRridge package are:

- auc: Computes Area-under-the-ROC-curve
- CreatePartition: Creates a partition (groups) of variables
- dataFarkas: Large data set plus external information
- dataVerlaat: Data plus external information
- grridge: Group-regularized (logistic) ridge regression
- grridge.cv: Cross-validated predictions for a grridge (logistic) regression.
- matchGeneSets: Creates a grouping of variables (genes) from gene sets
- mergeGroups: Merge groups in a partition
- PartitionsSelection: Co-data selection in a Group-regularized ridge regression model
- predict.grridge: Predictions for new samples from a grridge object
- roc: Computes an ROC-curve for probabilistic classifiers

Author(s)

Mark A. van de Wiel (mark.vdwiel@vume.nl)

References

See Also

GRridge depends on: penalized. Examples: grridge

 auc

Area under the ROC curve

Description

Computes Area-under-the-ROC-curve

Usage

auc(rocout)

Arguments

rocout  
Matrix with two rows

Details

Operates on the output of roc. The rows of the input matrix represent the False Positive Rates (FPR) and corresponding True Positive Rates (TPR) at fixed thresholds.

Value

Numeric. Interpolated Area-under-the-ROC-curve.

Author(s)

Mark A. van de Wiel

See Also


Examples

# Load data objects
data(dataFarkas)

## In this example, we provide one partition only
## see "CreatePartition" for examples in creating multiple partitions
firstPartition <- CreatePartition(CpGannFarkas)

# grFarkas <- grridge(datcenFarkas,respFarkas, firstPartition,monotone=FALSE)

## Prediction of the grridge model to the training samples
#cutoffs <- rev(seq(0,1,by=0.1))
#fakenew <- datcenFarkas
#yhat <- predict.grridge(grFarkas,fakenew)

#rocridgeF <- roc(probs=as.numeric(yhat[,2]),true=respFarkas[1:30],cutoffs=cutoffs)
#auc(rocridgeF)
CreatePartition

Creates a partition (groups) of variables

Description

Creates a partition (groups) of variables from nominal (factor) or numeric input

Usage

CreatePartition(vec, varnamesdata=NULL, subset=NULL, grsize=NULL, decreasing=TRUE, uniform=FALSE, ngroup=10, mingroup=25)

Arguments

vec Factor, numeric vector or character vector.
subset Character vector. Names of variables (features) that correspond to the values in vec. Allows to make a partition on a subset of all variables. Requires varnamesdata.
varnamesdata Character vector. Names of the variables (features). Only relevant when vec is a character vector OR when subset is specified.
grsize Numeric. Size of the groups. Only relevant when vec is a numeric vector and uniform=TRUE.
decreasing Boolean. If TRUE then vec is sorted in decreasing order.
uniform Boolean. If TRUE the group sizes are as equal as possible.
ngroup Numeric. Number of the groups to create. Only relevant when vec is a numeric vector.
mingr Numeric. Minimum group size. Only relevant when vec is a numeric vector and uniform=FALSE.

Details

A convenience function to create partitions of variables from external information that is stored in vec. If vec is a factor then the levels of the factor define the groups. If vec is a character vector, then varnamesdata need to be specified (vec is supposed to be a subset of varnamesdata, e.g. a published gene list). In this case a partition of two groups is created: one with those variables of varnamesdata that also appear in vec and one which do not appear in vec. If vec is a numeric vector, then groups contain the variables corresponding to grsize consecutive values of the values in vec. Alternatively, the group size is determined automatically from ngroup. If uniform=FALSE, a group with rank $r$ is of approximate size $\text{mingr} \cdot (r^f)$, where $f>1$ is determined such that the total number of groups equals ngroup. Such unequal group sizes enable the use of fewer groups (and hence faster computations) while still maintaining a good ‘resolution’ for the extreme values in vec. About decreasing: if smaller values of components of vec mean ‘less relevant’ (e.g. test statistics, absolute regression coefficients) use decreasing=TRUE, else use decreasing=FALSE, e.g. for p-values. If subset is defined, then varnamesdata should be specified as well. The partition will then only be applied to variables in subset and in varnamesdata.

Value

A list the components of which contain the indices of the variables belonging to each of the groups.
**CreatePartition**

**Author(s)**

Mark A. van de Wiel

**See Also**

For gene sets (overlapping groups): `matchGeneSets`. Further example in real life dataset: `grridge`.

**Examples**

# SOME EXAMPLES ON SMALL NR OF VARIABLES

# EXAMPLE 1: partition based on known gene signature

genset <- sapply(1:100, function(x) paste("Gene",x))
signature <- sapply(seq(1,100,by=2), function(x) paste("Gene",x))
SignaturePartition <- CreatePartition(signature, varnamesdata=genset)

# EXAMPLE 2: partition based on factor variable

Genetype <- factor(sapply(rep(1:4,25), function(x) paste("Type",x)))
TypePartition <- CreatePartition(Genetype)

# EXAMPLE 3: partition based on continuous variable, e.g. p-value

pvals <- rbeta(100,1,4)
PvPartition <- CreatePartition(pvals, decreasing=FALSE, uniform=TRUE, ngroup=10)

# Alternatively, create a partition of 10 equally-sized groups, corresponding to increasing p-values.
PvPartition2 <- CreatePartition(pvals, decreasing=FALSE, uniform=FALSE, ngroup=5, mingr=10)

# EXAMPLE 4: partition based on subset of variables, e.g. p-values only available for 50 genes.

genset <- sapply(1:100, function(x) paste("Gene",x))
subsetgenes <- sort(sapply(sample(1:100,50), function(x) paste("Gene",x)))
pvals50 <- rbeta(50,1,6)
PvPartitionSubset <- CreatePartition(pvals50, varnamesdata = genset, subset = subsetgenes, decreasing=FALSE, uniform=TRUE, ngroup=5)

# EXAMPLE 5: COMBINING PARTITIONS

# Combines partitions into one list with named components.
# This can be use as input for the grridge() function.
# NOTE: if one aims to use one partition only, then this can be directly used in grridge().

MyPart <- list(signature=SignaturePartition, type = TypePartition,
               pval = PvPartition, pvals50=PvPartitionSubset)
dataFarkas

Contains three R-objects, including the data and the binary response

Description
The three objects are: 
datcenFarkas: methylation data for cervix samples (arcsine-transformed beta values); 
respFarkas: binary response; and 
CpGannFarkas: annotation of probes according to location.

Format
• datcenFarkas: data frame [1:40000,1:37]
• respfarkas: Factor w/ 2 levels "Normal","Precursor"
• CpGannFarkas: Factor w/ 6 levels "CpG-Island", "North-Shelf", "South-Shelf", "North- Shore", "South-Shore", "Distant"

Details
This data is used for illustration in the statistical paper below.

Value
Three R objects, i.e. a matrix contains methylation data, a vector contains binary responses and an annotation matrix.

Source

References

Examples
data(dataFarkas)
Description
The five objects are: datcenVerlaat: methylation data for cervix samples (arcsine-transformed beta values); respVerlaat: binary response; diffmeanFarkas: effect size external study, Cases minus Controls; pvalFarkas: p-values from external study; and CpGann: annotation of probes according to location

Usage

data(dataVerlaat)

Format
The formats are:
datcenVerlaat: data frame [1:9691,1:44];
respVerlaat: numeric [1:44], 0 = Normal, 1 = Precursor;
diffmeanFarkas: numeric [1:44];
pvalFarkas: numeric [1:44];
CpGann: Factor w/ 6 levels "CpG-Island", "North-Shelf", "South-Shelf", "North-1ore", "South-Shore", "Distant"

Details
This data is used for illustration in the statistical paper below.

Value
Five R objects (see description)

References

Examples

data(dataVerlaat)
The four objects are:

- `datWurdinger_BC`: A matrix containing preprocessed mRNA sequencing data (quasi-gaussian scale, normalized). Columns are samples (81 samples with Breast Cancer and Colorectal Cancer) and rows are features (18410 features).
- `respWurdinger`: A factor containing responses for samples with Breast cancer (n=40) and colorectal cancer (n=41).
- `annotationWurdinger`: A list containing ensembleID, geneSymbol, entrezID and chromosome location.
- `coDataWurdinger`: A list containing co-data sets from external sources, namely (i) a list of genes that are expressed in platelets; (ii) immunologic signature pathway and; (iii) transcription factor based pathway and a list of cancer somatic genes.

This data is used for illustration in the application paper below.

### Details

This data is used for illustration in the application paper below.

### Value

Four R objects (see Description)

### Source


### Examples

```r
data(dataWurdinger)

# Transform the data set to the square root scale
dataSqrtWurdinger <- sqrt(datWurdinger_BC)

# Standardize the transformed data
datStdWurdinger <- t(apply(dataSqrtWurdinger, 1, function(x) (x-mean(x))/sd(x)))

# A list of gene names in the primary RNAseq data
genesWurdinger <- annotationWurdinger$geneSymbol
```
grridge

Group-regularized (logistic) ridge regression

Description

This function implements adaptive group-regularized (logistic) ridge regression by use of co-data. It uses co-data to improve predictions of binary and continuous response from high-dimension (e.g. genomics) data. Here, co-data is auxiliary information on variables (e.g. genes), such as annotation or p-values from other studies.

Usage

grridge(highdimdata, response, partitions, unpenal = ~1, offset=NULL, method="exactstable", niter=10, monotone=NULL, optl=NULL, innfold=NULL, fixedfoldsinn=TRUE, selectionForward=FALSE, maxsel=100, selectionEN=FALSE, stepsel=1, cvlmargin=1, savepredobj="all", dataunpen=NULL, ord = 1:length(partitions), comparelasso=FALSE, optllasso=NULL, cvllasso=TRUE, compareEN=FALSE, compareunpenal=FALSE, trace=FALSE, modus=1)

Arguments

highdimdata Matrix or numerical data frame. Contains the primary data of the study. Columns are samples, rows are variables (features).

response Factor, numeric, binary or survival. Response values. The number of response values should equal ncol(highdimdata).

partitions List of lists. Each list component contains a partition of the variables, which is again a list. See details.

unpenal Formula. Includes unpenalized variables. Set to unpenal = ~0 if an intercept is not desired.

offset Numeric (vector). Optional offset, either one constant or sample-specific, in which case length(offset)=ncol(highdimdata).

method Character. Equal to "exactstable": the stable iterative, systems-based method, "stable": the iterative non-systems-based method, "exact": the non-iterative, systems-based method, "adaptridge": adaptive ridge (not recommended).

niter Integer. Maximum number of re-penalization iterations.

monotone Vector of booleans. If the jth component of monotone equals TRUE, then the group-penalties are forced to be monotone. If monotone=NULL monotony is not imposed for any partition.

optl Numeric. Value of the global regularization parameter (lambda). If specified, it skips optimization by cross-validation.

innfold Integer. The fold for cross-validating the global regularization parameter lambda and for computing cross-validated likelihoods. Defaults too LOOCV.

fixedfoldsinn Boolean. Use fixed folds for inner cross-validation?

selectionForward Boolean. If selectionForward=TRUE post-hoc forward variable selection is performed.
**selectionEN** | Boolean. If selectionEN=TRUE then post-hoc variable selection by weighted elastic net is performed.

**maxsel** | Integer. The maximum number of selected variables.

**stepsel** | Integer. Step-size for variable selection.

**cvlmarg** | Numeric. Maximum margin (in percentage) that the cross-validated likelihood of the model with selected variables may deviate from the optimum one.

**savepredobj** | Character. If savepredobj="last", only the last penalized prediction object is saved; if savepredobj="all" all are saved; if savepredobj="none", none are saved.

**dataunpen** | Data frame. Optional data for unpenalized variables.

**ord** | Integer vector. The order in which the partitions in partitions are used.

**comparelasso** | Boolean. If comparelasso=TRUE the results of lasso regression are included.

**optllasso** | Numeric. Value of the global regularization parameter (lambda) in the lasso. If specified, optimization by cross-validation is skipped.

**cvllasso** | Boolean. If cvllasso=TRUE it returns the cross-validated likelihood for lasso when comparelasso=TRUE.

**compareEN** | Boolean. If compareEN=TRUE, the results of feature selection based on L1-penalization is included.

**compareunpenal** | Boolean. If compareunpenal=TRUE the results of regression with unpenalized covariates only are included. Only relevant when dataunpenal is specified.

**trace** | Boolean. If trace=TRUE the results of the cross-validation for parameter (lambda) tuning are shown.

**modus** | Integer. Please use modus=1. Only use modus=2 when backward compatibility with versions <= 1.6 is desired.

**Details**

About partitions: this is a list of partitions or one partition represented as a simple list. Each partition is a (named) list that contains the indices (row numbers) of the variables in the concerning group. Such a partition is usually created by CreatePartition.

About savepredobj: use savepredobj="all" if you want to compare performances of the various predictors (e.g. ordinary ridge, group-regularized ridge, group-regularized ridge + selection) using grridgeCV. About monotone: We recommend to set the jth component of monotone to TRUE when the jth partition is based on external p-values, test statistics or regression coefficients. This increases stability of the predictions. About selectionForward and selectionEN: the first refers to forward selection, the latter to elastic net (EN) selection. If both are TRUE, the EN selection will select the same number of variables as forward selection, which can select fewer than maxsel variables. If selectionForward=FALSE and selectionEN=TRUE, EN selection will select exactly maxsel variables. EN selection is recommended. Note that EN is only used for selection; the final predictive model is a group-ridge model fitted only on the selected variables using the penalties estimated by GRridge. About cvlmarg: We recommended to use values between 0 and 2. A larger value will generally result in fewer selected variables by forward selection. About innfold: for large data sets considerable computing time may be saved when setting innfold=10 instead of default leave-one-out-cross-validation (LOOCV). About method: "exactstable" is recommended. If the number of variables is not very large, say <2000, the faster non-iterative "exact" method can be used as an alternative.
**grridge**

**Value**

A list object containing:

- `true`: True values of the response
- `cvls`: Cross-validated likelihoods from the iterations
- `lambdamults`: List of lists object containing the penalty multipliers per group per partition
- `optl`: Global penalty parameter lambda
- `lambdamultvec`: Vector with penalty multipliers per variable
- `predobj`: List of prediction objects
- `betas`: Estimated regression coefficients
- `whichsel`: Indices of selected variables
- `cvlssel`: Trace of cross-validated likelihoods for the number of selected variables
- `reslasso`: Results of the lasso. NULL when `comparelasso=FALSE`
- `resEN`: Results of the Elastic Net selection. NULL when `compareEN=FALSE`
- `model`: Model used for fitting: logistic, linear or survival
- `arguments`: Arguments used to call the function

**Author(s)**

Mark A. van de Wiel

**References**


**See Also**

Creating partitions: `CreatePartition`; Cross-validation for assessing predictive performance: `grridgeCV`.

**Examples**

```r
## NOTE:
## 1. EXAMPLE DEVIATES SOMEWHAT FROM THE EXAMPLE IN THE MANUSCRIPT IN ORDER TO SHOW SOME
##    OTHER FUNCTIONALITIES.
## 2. HERE WE SHOW A SIMPLE EXAMPLE FROM THE FARKAS DATA SET
##    MORE EXTENSIVE EXAMPLES OF FUNCTIONALITIES IN THE GRRIGDE PACKAGE ARE PROVIDED IN
##    VIGNETTE DOCUMENTATION FILE

## 1ST EXAMPLE: Farkas DATA, USING ANNOTATION: DISTANCE TO CpG

# load data objects:
# datacenFarkas: methylation data for cervix samples (arcsine-transformed beta values)
# respFarkas: binary response (Normal and Precursor)
# CpGannFarkas: annotation of probes according to location
# ((CpG-Island, North-Shelf, South-Shelf, North-Shore, South-Shore, Distant)
data(dataFarkas)
```
## Create list of partition(s), here only one partition included

```r
partitionFarkas <- list(cpg=CreatePartition(CpGannFarkas))
```

## Group-regularized ridge applied to data datcenFarkas, response respFarkas and partition partitionFarkas.
## Saves the prediction objects from ordinary and group-regularized ridge.
## Includes unpenalized intercept by default.

```r
grFarkas <- grridge(datcenFarkas, respFarkas, optl=5.680087, partitionFarkas, monotone=FALSE)
```

## 2ND EXAMPLE: Verlaat DATA, USING P-VALUES AND SIGN OF EFFECT FROM FARKAS DATA
## see vignette documentation file!

---

### grridgeCV

**Returns the cross-validated predictions**

#### Description

Returns the cross-validated predictions for a `grridge` logistic, linear or Cox regression.

#### Usage

```r
grridgeCV(grr, highdimdata, response, outerfold = length(response), fixedfolds = TRUE, recalibrate=FALSE)
```

#### Arguments

- `grr` List. Output of GRridge function.
- `highdimdata` Matrix or numerical data frame. Contains the primary data of the study. Columns are samples, rows are variables (features).
- `response` Factor, numeric, binary or survival. Response values. The number of response values should equal `ncol(highdimdata)`.
- `outerfold` Integer. Fold used for cross-validation loop.
- `fixedfolds` Boolean. Use fixed folds for cross-validation?
- `recalibrate` Boolean. Should the prediction model be recalibrated on the test samples? Only implemented for logistic and linear regression with only penalized covariates.

#### Details

This convenience function returns cross-validated predictions from `grridge`, including those from ordinary (logistic) ridge regression. It can be used to compute ROC-curves. About `recalibrate`: this option allows to compare recalibrated models, but only if the test sample size is large enough.

See `predict.grridge`
Value

For linear and logistic regression: A matrix containing the predictions. The first column contains the sample indices, the second the prediction by ordinary ridge, the third the predictions by group-regularized ridge, the fourth (optional) the predictions by group-regularized ridge plus selection. Finally, it may contain predictions by lasso and/or a regression model with unpenalized covariates only. For Cox regression: a list with three components. First, a matrix with the linear predictions, in the same format as above. Second, a list of survival probability matrices (one for each prediction model), the rows of which indicate the individuals and the columns indicate the observed times. Third, a vector with the observed times.

Author(s)

Mark A. van de Wiel

References


See Also

For logistic regression: ROC-curves: roc. AUC: auc. GRridge: link{grridge}.

Examples

# load data objects
data(dataFarkas)

data(dataFarkas)
# In this example, we provide one partition only
# see "CreatePartition" for examples in creating multiple partitions
firstPartition <- CreatePartition(CpGannFarkas)

# the optimum lambda2 is provided in this example
# worth to try:
# grFarkas <- grridge(datcenFarkas, respFarkas, firstPartition, monotone=FALSE)
# grFarkas$optl
gFarkas <- grridge(datcenFarkas, respFarkas, optl=5.680087,
firstPartition, monotone=FALSE)

###
# grFarkasCV <- grridgeCV(grFarkas, datcenFarkas, respFarkas, outerfold=10)

---

Hello, World!

Description

Prints 'Hello, world!'.
matchGeneSets

Usage

hello()

Value

An empty object.

Examples

hello()

matchGeneSets

Creates a grouping of variables (genes) from gene sets

Description

Creates a grouping of variables (genes) from gene sets by matching the IDs of the genes with the IDs of the members of the gene sets

Usage

matchGeneSets(GeneIds, GeneSets, minlen = 25, remain = TRUE)

Arguments

GeneIds

Character vector. Vector of gene IDs. Can be any ID (gene symbol, entrezID, etc) as long as it matches with IDs used in GeneSets.

GeneSets

Named list of character vectors. Each component of the list represents a named gene set. Each vector a list of member genes.

minlen

Integer. Minimum number of members of a gene set.

remain

Boolean. If remain=TRUE, all genes that are not in any list will be grouped in one remainder group.

Details

About minlen: to avoid overfitting in the grridge function, we recommend to not use groups with less than 25 members, unless monotone=TRUE is used in the grridge function, in which case 10 members may suffice as a lower bound. About remain: it is often beneficial to down-weight genes that are not part of any gene set, so we recommend to use remain=TRUE

Value

A list the components of which contain the indices of the variables belonging to each of the groups.

Author(s)

Mark A. van de Wiel

See Also

grridge, CreatePartition
Examples

# Load data objects
data(dataWurdinger)

# Transform the data set to the square root scale
dataSqrtWurdinger <- sqrt(datWurdinger_BC)

# Standardize the transformed data
datStdWurdinger <- t(apply(dataSqrtWurdinger, 1, function(x) ((x - mean(x))/sd(x))))

# A list of gene names in the primary RNAseq data
genesWurdinger <- annotationWurdinger$geneSymbol

# We show an example of GRridge classification model by using overlapping groups,
# i.e. pathway-based grouping. Transcription factor based pathway was extracted from
# the MSigDB (Section C3: motif gene sets; subsection: transcription factor targets;
# file's name: "c3.tft.v5.0.symbols.gmt"). The gene sets are based on
# TRANSFAC version 7.5 database (http://www.gene-regulation.com/).

# Some features may belong to more than one group. The argument minlen=25 implies
# the minimum number of features in a gene set. If remain=TRUE, gene sets with less
# than 25 members are grouped to the "remainder" group. "genesWurdinger" is an object
# containing gene names from the mRNA sequencing data set.
# See help(matchGeneSets) for more detail information.
# Also see Vignette for more detail examples

## The "TFsym" is available on https://github.com/markvdwiel/GRridgeCodata
# gseTF <- matchGeneSets(genesWurdinger, TFsym, minlen=25, remain=TRUE)

mergeGroups

**Merge groups in a partition**

Description

Pathway-based partition often contains a considerable number of gene sets (or groups). This function merges groups resulted by `matchGeneSets`. The first principal component in each group is calculated. Hierarchical clustering analysis is then performed on the first principal components from all groups. Important Note: re-grouping is only done in the non-reminder group.

Usage

```r
mergeGroups(highdimdata, initGroups=initGroups, maxGroups=maxGroups,
            methodDistance="manhattan", methodClust="complete")
```

Arguments

- `highdimdata`: Matrix or numerical data frame. Contains the primary data of the study. Columns are samples, rows are features.
- `initGroups`: A list of initial given groups resulted from `matchGeneSets`.
- `maxGroups`: Numeric. The new desired number of groups.
mergeGroups

methodDistance  The distance method used for clustering. See dist for further options. Default: manhattan distance.

methodClust     The agglomeration method used for Grouping. See hclust for further options. Default: complete.

Value

A list object containing:

newGroups       A list the components of which contain the indices of the features belonging to each of the group. This object is the same as the object created by matchGeneSets and CreatePartition

newGroupMembers A list of members in the new merged groups.

Author(s)

Putri W. Novianti

See Also


Examples

# Load data objects
data(dataWurdinger)

dataSqrtWurdinger <- sqrt(datWurdinger_BC)

datStdWurdinger <- t(apply(dataSqrtWurdinger,1,function(x){(x-mean(x))/sd(x)}))

genesWurdinger <- annotationWurdinger$geneSymbol

## Creating partitions based on pathways information (e.g. GSEA object)
## Some variables may belong to more than one groups (gene sets).
## The argument minlen=25 implies the minimum number of members in a gene set
## If remain=TRUE, gene sets with less than 25 members are grouped to the "remainder" group.
## The "TFsym" is available on https://github.com/markvdwiel/GRridgeCodata
# gseTF <- matchGeneSets(genesWurdinger,TFsym,minlen=25,remain=TRUE)
## Regrouping gene sets by hierarchical clustering analysis.

The number of gene sets from the GSEA database is relatively too high to be used in the GRridge model. Here, the initial gene sets are re-grouped into maxGroups=5, using information from the primary data set.

```r
gseTF_newGroups <- mergeGroups(highdimdata=datStdWurdinger, initGroups =gseTF, maxGroups=5);
```

## Extracting indices of new groups

This following object (gseTF2) can be used further as an input in the "partitions" argument in the "grridge" function.

```r
gseTF2 <- gseTF_newGroups$newGroups
```

## Members of the new groups

```r
newGroupMembers <- gseTF_newGroups$newGroupMembers
```

---

### Description

This function implements a procedure to optimize the use of co-data in a GRridge model. Although there is no harm to include as much as co-data in a GRridge model, ordering and selecting co-data can optimized the performance of a GRridge model. This procedure is similar with forward feature selection in a classical regression model.

### Usage

```r
PartitionsSelection(highdimdata, response, partitions,
                    monotoneFunctions, optl=NULL, innfold=NULL)
```

### Arguments

- **highdimdata**: Matrix or numerical data frame. Contains the primary data of the study. Columns are samples, rows are features.
- **response**: Factor, numeric, binary or survival. Response values. The number of response values should equal `ncol(highdimdata)`.
- **partitions**: List of lists. Each list component contains a partition of the variables, which is again a list.
- **monotoneFunctions**: Vector. Monotone functions from each partition. This argument is necesarily specified. If the jth component of monotone equals TRUE, then the group-penalities are forced to be monotone. If monotone=NULL monotony is not imposed for any partition.
- **optl**: Global penalty parameter lambda
- **innfold**: Integer. The fold for cross-validating the global regularization parameter lambda and for computing cross-validated likelihoods. Defaults LOOCV.

### Value

A list containing (i) the indeces of the selected and ordered partitions and (ii) the optimum lambda penalty from the ridge regression.
PartitionsSelection

Author(s)

Putri W. Novianti

See Also


Examples

```r
# # Load data objects
# data(dataWurdinger)
#
# # Transform the data set to the square root scale
# dataSqrtWurdinger <- sqrt(dataWurdinger)
#
# # Standardize the transformed data
# dataStdWurdinger <- t(apply(dataSqrtWurdinger,1,function(x){(x-mean(x))/sd(x)}))
#
# # A list of gene names in the primary RNAseq data
# genesWurdinger <- annotationWurdinger$geneSymbol
#
# # co-data 1: a partition based on immunologic signature pathway
# The initial gene sets (groups) are merged into five new groups, using the "mergeGroups" function
# immunPathway <- coDataWurdinger$immunologicPathway
# parImmun <- immunPathway$newClust
#
# # co-data 2: a partition based on chromosomal location
# ChromosomeWur0 <- as.vector(annotationWurdinger$chromosome)
# ChromosomeWur <- ChromosomeWur0
# idC <- which(ChromosomeWur0=="MT" | ChromosomeWur0=="notBiomart" | ChromosomeWur0=="Un")
# ChromosomeWur[idC] <- "notMapped"
# parChromosome <- CreatePartition(as.factor(ChromosomeWur))
#
# # co-data 3: a partition based on a list of platelets expressed genes
# plateletsExprGenes <- coDataWurdinger$plateletgenes
# # Group genes in the primary data based on the list
# # The genes are grouped into
# # either "NormalGenes" or "Non-overlapGenes"
# is <- intersect(plateletsExprGenes,genesWurdinger)
# im <- match(is, genesWurdinger)
# plateletsGenes <- replicate(length(genesWurdinger),"Non-overlapGenes")
# plateletsGenes[im] <- "NormalGenes"
# plateletsGenes <- as.factor(plateletsGenes)
# parPlateletGenes <- CreatePartition(plateletsGenes)
#
# # co-data 4: a partition based on chromosomal location.
# A list of chromosomal location based on \texttt{biomaRt} data bases.
# ChromosomeWur0 <- as.vector(annotationWurdinger$chromosome)
# ChromosomeWur <- ChromosomeWur0
# idC <- which(ChromosomeWur0=="MT" | ChromosomeWur0=="notBiomart" | ChromosomeWur0=="Un")
# ChromosomeWur[idC] <- "notMapped"
# table(ChromosomeWur)
# parChromosome <- CreatePartition(as.factor(ChromosomeWur))
```

predict.grridge <- list(immunPathway=parImmun,
    transcriptionFactor=parTranscriptFactor,
    plateletsGenes=parPlateletGenes,
    chromosome=parChromosome)
#
# #A list of monotone functions from the corresponding partitions
# monotoneWurdinger <- c(FALSE,FALSE,FALSE,FALSE)
#
# # Start ordering and selecting partitions
# optPartitions <- PartitionsSelection(datStdWurdinger, respWurdinger,
# # partitions=partitionsWurdinger,
# # monotoneFunctions=monotoneWurdinger)

---

**predict.grridge**

*Predictions for new samples*

**Description**

Returns predictions for new samples from a grridge object

**Usage**

```
## S3 method for class 'grridge'
predict(object, datanew, printpred = FALSE, dataunpennew=NULL,
    responsetest=NULL, recalibrate=FALSE, ...)
```

**Arguments**

- `object` A model object resulted from the grridge function.
- `datanew` Vector or data frame. Contains the new data. For a data frame: columns are samples, rows are variables (features).
- `printpred` Boolean. Should the predictions be printed on the screen?
- `dataunpennew` Vector or data frame. Optional new data for unpenalized variables. NOTE: columns are covariates, rows are samples.
- `responsetest` Factor, numeric, binary or survival. Response values of test samples. The number of response values should equal ncol(datanew). Only relevant if recalibrate=TRUE.
- `recalibrate` Boolean. Should the prediction model be recalibrated on the test samples? Only implemented for logistic and linear regression with only penalized covariates.
- `...` There is no further argument is used.

**Details**

This function returns predictions of the response using the grridge output. It should be applied to samples NOT used for fitting of the models. About recalibrate: we noticed that recalibration of the linear predictor using a simple regression (with intercept and slope) can improve predictive performance, e.g. in terms of brier score or mean square error (not in terms of AUC, which is rank-based). We recommend to use it for large enough test sets (say >= 25 samples), in particular when one suspects that the test set could have somewhat different properties than the training set.
Value

A matrix containing the predictions from all models available in grridge.

Author(s)

Mark A. van de Wiel

References


See Also

Cross-validated predictions: grridgeCV. Examples: grridge.

Examples

data(dataFarkas)

firstPartition <- CreatePartition(CpGannFarkas)

sdsF <- apply(datcenFarkas,1,sd)

secondPartition <- CreatePartition(sdsF,decreasing=FALSE, uniform=TRUE, grsize=5000)

# Concatenate two partitions
partitionsFarkas <- list(cpg=firstPartition, sds=secondPartition)

# A list of monotone functions from the corresponding partition
monotoneFarkas <- c(FALSE,TRUE)

grFarkas <- grridge(datcenFarkas,respFarkas,optl=5.680087,
partitionsFarkas,monotone=monotoneFarkas)

# Prediction of the grridge model to the training samples
cutoffs <- rev(seq(0,1,by=0.1))

fakenew <- datcenFarkas

yhat <- predict.grridge(grFarkas,fakenew)

---

roc

Produces ROC curve for probabilistic classifiers (e.g. logistic regression)

Description

Computes an ROC-curve for probabilistic classifiers.

Usage

roc(probs, true, cutoffs)
Arguments

- **probs**: Numeric vector, with values between 0 and 1.
- **true**: Binary vector.
- **cutoffs**: Numeric vector, with increasing values between 0 and 1.

Details

The vector `probs` contains predicted probabilities for the response to equal 1, as produced by a probabilistic classifier like logistic regression. The `cutoffs` can simply represent a grid of values between 0 and 1.

Value

A matrix with two rows which contain corresponding False Positive and True Positive Rates for all cutoffs.

Author(s)

Mark A. van de Wiel

See Also

For area-under-the ROC-curve: `auc`. Examples: `grridge`.

Examples

```r
# Load data objects
data(dataFarkas)

firstPartition <- CreatePartition(CpGannFarkas)
sdsF <- apply(datcenFarkas,1,sd)
secondPartition <- CreatePartition(sdsF,decreasing=FALSE, uniform=TRUE, grsize=5000)

# Concatenate two partitions
partitionsFarkas <- list(cpg=firstPartition, sds=secondPartition)

# A list of monotone functions from the corresponding partition
monotoneFarkas <- c(FALSE,TRUE)

#grFarkas <- grridge(datcenFarkas,respFarkas,optl=5.680087,partitionsFarkas,monotone=monotoneFarkas)
#grFarkascv <- grridgeCV(grFarkas,datcenFarkas,respFarkas,outerfold=10)

#cutoffs <- rev(seq(0,1,by=0.01))
#rocgrridgeF <- roc(probs=grFarkascv[,3],true=grFarkascv[,1],cutoffs=cutoffs)
#rocridgeF <- roc(probs=grFarkascv[,2],true=grFarkascv[,1],cutoffs=cutoffs)
#plot(rocridgeF[1,],rocridgeF[2,],type="l",lty=1,ann=FALSE,col="grey")
#points(rocgrridgeF[1,],rocgrridgeF[2,],type="l",lty=1,col="black")
#legend(0.75,0.1, legend=c("ridge", "GRridge"),
#       lty=c(1,1), lwd=c(1,1),col=c("grey","black"))
```
Index

*Topic **datasets**
  - dataFarkas, 6
  - dataVerlaat, 7
  - dataWurdinger, 8

*Topic **package**
  - GRridge-package, 2

annotationWurdinger (dataWurdinger), 8
auc, 3, 13, 21
coDataWurdinger (dataWurdinger), 8
CpGann (dataVerlaat), 7
CpGannFarkas (dataFarkas), 6
CreatePartition, 3, 4, 10, 11, 14, 16, 18
dataFarkas, 6
dataVerlaat, 7
dataWurdinger, 8
datcenFarkas (dataFarkas), 6
datcenVerlaat (dataVerlaat), 7
datWurdinger_BC (dataWurdinger), 8
diffmeanFarkas (dataVerlaat), 7
dist, 16

GRridge (GRridge-package), 2
grridge, 3, 5, 9, 12, 14, 18–21
GRridge-package, 2
grridgeCV, 10, 11, 12, 20

hclust, 16
hello, 13

matchGeneSets, 5, 14, 15, 16
mergeGroups, 15

PartitionsSelection, 17
predict (predict.grridge), 19
predict.grridge, 12, 19
pvalFarkas (dataVerlaat), 7

respFarkas (dataFarkas), 6
respVerlaat (dataVerlaat), 7
respWurdinger (dataWurdinger), 8
roc, 3, 13, 20