

Package ‘BioMM’

October 16, 2020

Type Package

Title BioMM: Biological-informed Multi-stage Machine learning framework for phenotype prediction using omics data

Version 1.4.0

Date 2019-08-08

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Description The identification of reproducible biological patterns from high-dimensional omics data is a key factor in understanding the biology of complex disease or traits. Incorporating prior biological knowledge into machine learning is an important step in advancing such research. We have proposed a biologically informed multi-stage machine learning framework termed BioMM specifically for phenotype prediction based on omics-scale data where we can evaluate different machine learning models with prior biological meta information.

Imports stats, utils, grDevices, lattice, BiocParallel, glmnet, rms, nsprcomp, ranger, e1071, variancePartition, ggplot2, pROC, vioplot, CMplot

Depends R (>= 3.6)

Suggests BiocStyle, knitr, RUnit, BiocGenerics

VignetteBuilder knitr

biocViews Genetics, Classification, Regression, Pathways, GO, Software

Encoding UTF-8

LazyData true

License GPL-3

RoxygenNote 6.1.1

git_url <https://git.bioconductor.org/packages/BioMM>

git_branch RELEASE_3_11

git_last_commit 4635011

git_last_commit_date 2020-04-27

Date/Publication 2020-10-16

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baseGLMnet	<i>Prediction by generalized linear regression models</i>
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Description

Prediction by generalized regression models with lasso or elastic net regularization.

Usage

```
baseGLMnet(trainData, testData, predMode = c("classification",
      "probability", "regression"), paramlist = list(family = "binomial",
      alpha = 0.5, typeMeasure = "mse", typePred = "class"))
```

Arguments

trainData	The input training dataset. The first column is named the 'label'.
testData	The input test dataset. The first column is named the 'label'.
predMode	The prediction mode. Available options are c('classification', 'probability', 'regression').
paramlist	A set of model parameters defined in an R list object. The valid option: list(family, alpha, typeMeasure, typePred). <ol style="list-style-type: none"> 'family': Response type: 'gaussian', 'binomial', 'poisson', 'multinomial', 'cox', 'mgaussian'. (Default: 'binomial') 'alpha': The elastic net mixing parameter, with $0 \leq \alpha \leq 1$. 'typeMeasure': error metrics for internal cross-validation. 'mse' uses squared loss; 'deviance' uses actual deviance; 'mae' uses mean absolute error; 'class' gives misclassification error; 'auc' (for two-class logistic regression ONLY) gives area under the ROC curve.

4. 'typePred': The type of prediction: 'response' and 'class'. (Default: 'class' for binary classification)

Value

The predicted output for the test data.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
## select a subset of genome-wide methylation data at random
methylSub <- data.frame(label=dataY, methylData[,c(2:2001)])
trainIndex <- sample(nrow(methylSub), 30)
trainData = methylSub[trainIndex,]
testData = methylSub[-trainIndex,]
library(glmnet)
## classification
predY <- baseGLMnet(trainData, testData,
                    predMode='classification',
                    paramlist=list(family='binomial', alpha=0.5,
                                    typeMeasure='mse', typePred='class'))

testY <- testData[,1]
accuracy <- classifiACC(dataY=testY, predY=predY)
print(accuracy)
```

baseModel

Base supervised machine learning models for prediction

Description

Prediction using different supervised machine learning models.

Usage

```
baseModel(trainData, testData, classifier = c("randForest", "SVM",
      "glmnet"), predMode = c("classification", "probability", "regression"),
      paramlist)
```

Arguments

trainData	The input training dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
testData	The input test dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.

classifier	Machine learning classifiers. Available options are c('randForest', 'SVM', 'glmnet').
predMode	The prediction mode. Available options are c('classification', 'probability', 'regression'). 'probability' is currently only for 'randForest'.
paramlist	A set of model parameters defined in an R list object. See more details for each individual model.

Value

The predicted output for the test data.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
## select a subset of genome-wide methylation data at random
methylSub <- data.frame(label=dataY, methylData[,c(2:2001)])
trainIndex <- sample(nrow(methylSub), 30)
trainData = methylSub[trainIndex,]
testData = methylSub[-trainIndex,]
library(ranger)
set.seed(123)
predY <- baseModel(trainData, testData,
                   classifier='randForest',
                   predMode='classification',
                   paramlist=list(ntree=300, nthreads=20))
print(table(predY))
testY <- testData[,1]
accuracy <- classifiACC(dataY=testY, predY=predY)
print(accuracy)
```

baseRandForest

Prediction by random forest

Description

Prediction by random forest with different settings: 'probability', 'classification' and 'regression'.

Usage

```
baseRandForest(trainData, testData, predMode = c("classification",
"probability", "regression"), paramlist = list(ntree = 2000, nthreads =
20))
```

Arguments

trainData	The input training dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
testData	The input test dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
predMode	The prediction mode. Available options are c('probability', 'classification', 'regression').
paramlist	A set of model parameters defined in an R list object. The valid option: list(ntree, nthreads). 'ntree' is the number of trees used. The default is 2000. 'nthreads' is the number of threads used for computation. The default is 20.

Value

The predicted output for the test data.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
## test a subset of genome-wide methylation data at random
methylSub <- data.frame(label=dataY, methylData[,c(2:2001)])
trainIndex <- sample(nrow(methylSub), 30)
trainData = methylSub[trainIndex,]
testData = methylSub[-trainIndex,]
library(ranger)
predY <- baseRandForest(trainData, testData,
                        predMode='classification',
                        paramlist=list(ntree=300, nthreads=20))
testY <- testData[,1]
accuracy <- classifiACC(dataY=testY, predY=predY)
print(accuracy)
```

baseSVM

Prediction by SVM

Description

Prediction by support vector machine (SVM) with two different settings: 'classification' and 'regression'.

Usage

```
baseSVM(trainData, testData, predMode = c("classification",
      "probability", "regression"), paramlist = list(tuneP = TRUE, kernel =
      "radial", gamma = 10^(-3:-1), cost = 10^(-2:2)))
```

Arguments

trainData	The input training dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
testData	The input test dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
predMode	The prediction mode. Available options are c('classification', 'probability', 'regression').
paramlist	A set of model parameters defined in an R list object. The valid option: list(kernel, gamma, cost, tuneP). <ol style="list-style-type: none"> 'tuneP': a logical value indicating if hyperparameter tuning should be conducted or not. The default is FALSE. 'kernel': options are c('linear', 'polynomial', 'radial', 'sigmoid'). The default is 'radial'. 'gamma': the parameter needed for all kernels except 'linear'. If tuneP is TRUE, more than one value is suggested. 'cost': is the cost of constraints violation. If tuneP is TRUE, more than one value is suggested.

Details

Hyperparameter tuning is recommended in many biological data mining applications. The best parameters can be determined via an internal cross validation.

Value

The predicted output for the test data.

Author(s)

Junfang Chen

See Also

[svm](#)

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
## select a subset of genome-wide methylation data at random
methylSub <- data.frame(label=dataY, methylData[,c(2:2001)])
trainIndex <- sample(nrow(methylSub), 30)
trainData = methylSub[trainIndex,]
testData = methylSub[-trainIndex,]
library(e1071)
predY <- baseSVM(trainData, testData,
                 predMode='classification',
                 paramlist=list(tuneP=FALSE, kernel='radial',
                               gamma=10^(-3:-1), cost=10^(-3:1)))
testY <- testData[,1]
```

```
accuracy <- classifiACC(dataY=testY, predY=predY)
print(accuracy)
```

 BioMM

BioMM end-to-end prediction

Description

End-to-end prediction by BioMM framework using either supervised or unsupervised learning at stage-1, then supervised learning at stage-2.

Usage

```
BioMM(trainData, testData, pathlistDB, featureAnno, restrictUp,
  restrictDown, minPathSize, supervisedStage1 = TRUE, typePCA,
  resample1 = "BS", resample2 = "CV", dataMode = "allTrain",
  repeatA1 = 100, repeatA2 = 1, repeatB1 = 20, repeatB2 = 1,
  nfolds = 10, FSmethod1, FSmethod2, cutP1, cutP2, fdr2,
  FScore = MulticoreParam(), classifier, predMode, paramlist,
  innerCore = MulticoreParam())
```

Arguments

trainData	The input training dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
testData	The input test dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
pathlistDB	A list of pathways with pathway IDs and their corresponding genes ('entrezID' is used). This is only used for pathway-based stratification (only stratify is 'pathway').
featureAnno	The annotation data stored in a data.frame for probe mapping. It must have at least two columns named 'ID' and 'entrezID'. If it's NULL, then the input probe is from the transcriptomic data. (Default: NULL)
restrictUp	The upper-bound of the number of probes or genes in each biological stratified block.
restrictDown	The lower-bound of the number of probes or genes in each biological stratified block.
minPathSize	The minimal defined pathway size after mapping your own data to GO database. This is only used for pathway-based stratification (only stratify is 'pathway').
supervisedStage1	A logical value. If TRUE, then supervised learning models are applied; if FALSE, unsupervised learning.
typePCA	the type of PCA. Available options are c('regular', 'sparse').
resample1	The resampling methods at stage-1. Valid options are 'CV' and 'BS'. 'CV' for cross validation and 'BS' for bootstrapping resampling. The default is 'BS'.
resample2	The resampling methods at stage-2. Valid options are 'CV' and 'BS'. 'CV' for cross validation and 'BS' for bootstrapping resampling. The default is 'CV'.

dataMode	The input training data mode for model training. It is used only if 'testData' is present. It can be a subset of the whole training data or the entire training data. 'subTrain' is the given for subsetting and 'allTrain' for the entire training dataset.
repeatA1	The number of repeats N is used during resampling procedure. Repeated cross validation or multiple bootstrapping is performed if $N \geq 2$. One can choose 10 repeats for 'CV' and 100 repeats for 'BS'.
repeatA2	The number of repeats N is used during resampling prediction. The default is 1 for 'CV'.
repeatB1	The number of repeats N is used for generating stage-2 test data prediction scores. The default is 20.
repeatB2	The number of repeats N is used for test data prediction. The default is 1.
nfolds	The number of folds is defined for cross validation. The default is 10.
FSmethod1	Feature selection methods at stage-1. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox').
FSmethod2	Feature selection methods at stage-2. Features that are positively associated with the outcome will be used.
cutP1	The cutoff used for p value thresholding at stage-1. Commonly used cutoffs are c(0.5, 0.1, 0.05, 0.01, etc).
cutP2	The cutoff used for p value thresholding at stage-2.
fdr2	Multiple testing correction method at stage-2. Available options are c(NULL, 'fdr', 'BH', 'holm', etc). See also p.adjust . The default is NULL.
FScore	The number of cores used for feature selection.
classifier	Machine learning classifiers at both stages.
predMode	The prediction mode at both stages. Available options are c('probability', 'classification', 'regression').
paramlist	A list of model parameters at both stages.
innerCore	The number of cores used for computation.

Details

Stage-2 training data can be learned either using bootstrapping or cross validation resampling methods in the supervised learning setting. Stage-2 test data is learned via independent test set prediction.

Value

The CV or BS prediction performance for the training data and test set prediction performance if testData is given.

References

- Chen, J., & Schwarz, E. (2017). BioMM: Biologically-informed Multi-stage Machine learning for identification of epigenetic fingerprints. *arXiv preprint arXiv:1712.00336*.
- Perlich, C., & Swirszcz, G. (2011). On cross-validation and stacking: Building seemingly predictive models on random data. *ACM SIGKDD Explorations Newsletter*, 12(2), 11-15.

See Also

[reconBySupervised](#); [reconByUnsupervised](#); [BioMMstage2pred](#)

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
## Annotation file
probeAnnoFile <- system.file('extdata', 'cpgAnno.rds', package='BioMM')
probeAnno <- readRDS(file=probeAnnoFile)
supervisedStage1=TRUE
classifier <- 'randForest'
predMode <- 'classification'
paramlist <- list(ntree=300, nthreads=30)
library(BiocParallel)
library(ranger)
param1 <- MulticoreParam(workers = 2)
param2 <- MulticoreParam(workers = 20)
## Not Run
## result <- BioMM(trainData=methylData, testData=NULL,
##                 pathlistDB, featureAnno=probeAnno,
##                 restrictUp=10, restrictDown=200, minPathSize=10,
##                 supervisedStage1, typePCA='regular',
##                 resample1='BS', resample2='CV', dataMode="allTrain",
##                 repeatA1=20, repeatA2=1, repeatB1=20, repeatB2=1,
##                 nfolDs=10, FSmethod1=NULL, FSmethod2=NULL,
##                 cutP1=0.1, cutP2=0.1, fdr2=NULL, FScore=param1,
##                 classifier, predMode, paramlist, innerCore=param2)
```

BioMMstage2pred

Prediction performance for stage-2 data using supervised machine learning

Description

Prediction performance for reconstructed stage-2 data using supervised machine learning with feature selection methods.

Usage

```
BioMMstage2pred(trainData, testData, resample = "CV", dataMode,
  repeatA = 1, repeatB = 1, nfolDs, FSmethod, cutP, fdr,
  FScore = MulticoreParam(), classifier, predMode, paramlist,
  innerCore = MulticoreParam())
```

Arguments

trainData The input training dataset (stage-2 data). The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.

testData The input test dataset (stage-2 data). The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.

resample	The resampling methods. Valid options are 'CV' and 'BS'. 'CV' for cross validation and 'BS' for bootstrapping resampling. The default is 'CV'.
dataMode	The mode of data used. 'subTrain' or 'allTrain'.
repeatA	The number of repeats N is used during resampling prediction. The default is 1.
repeatB	The number of repeats N is used for test data prediction. The default is 1.
nfolds	The number of folds is defined for cross validation.
FMethod	Feature selection methods. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox', or 'top10pCor').
cutP	The cutoff used for p value thresholding. Commonly used cutoffs are c(0.5, 0.1, 0.05, 0.01, etc). The default is 0.05.
fdr	Multiple testing correction method. Available options are c(NULL, 'fdr', 'BH', 'holm', etc). See also p.adjust . The default is NULL.
FScore	The number of cores used for feature selection if parallel computing needed.
classifier	Machine learning classifiers.
predMode	The prediction mode. Available options are c('probability', 'classification', 'regression').
paramlist	A set of model parameters defined in an R list object.
innerCore	The number of cores used for computation.

Details

Stage-2 prediction is performed typically using positively correlated features. Since negative associations likely reflect random effects in the underlying data

Value

The CV or BS prediction performance for stage-2 training data and test set prediction performance for stage-2 test data if the test set is given.

Author(s)

Junfang Chen

References

Perlich, C., & Swirszcz, G. (2011). On cross-validation and stacking: Building seemingly predictive models on random data. *ACM SIGKDD Explorations Newsletter*, 12(2), 11-15.

cirPlot4pathway

Circular plot for a set of pathways

Description

Plot the individual CpGs within a given set of pathways. The significance of the CpGs are illustrated by the negative log P value.

Usage

```
cirPlot4pathway(datalist, topPathID, core = MulticoreParam(),  
  fileName = NULL)
```

Arguments

datalist	The input data list containing ordered collections of matrices.
topPathID	A predefined pathway IDs.
core	The number of cores used for computation. (Default: 10)
fileName	The plot file name. (Default: 'cpgTopGOplot.png')

Details

Top 10 or 20 pathways are usually suggested to be visualized.

Value

An output image file.

See Also

[omics2pathlist](#).

classifiACC

Compute the classification accuracy

Description

Compute the classification accuracy for the binary classification problem.

Usage

```
classifiACC(dataY, predY)
```

Arguments

dataY	The observed outcome.
predY	The predicted outcome.

Value

The classification accuracy in terms of percentage.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
methylSub <- data.frame(label=dataY, methylData[,c(2:1001)])
library(ranger)
library(BiocParallel)
param1 <- MulticoreParam(workers = 1)
param2 <- MulticoreParam(workers = 10)
predY <- predByCV(methylSub, repeats=1, nfolds=10,
                 FSmethod=NULL, cutP=0.1,
                 fdr=NULL, FScore=param1,
                 classifier='randForest',
                 predMode='classification',
                 paramlist=list(ntree=300, nthreads=1),
                 innerCore=param2)
accuracy <- classifiACC(dataY=dataY, predY=predY)
print(accuracy)
```

getDataByFilter

Return the data by feature filtering

Description

Identify and select a subset of outcome-associated or predictive features in the training data based on filtering methods. Return the same set of selected features for the test data if it is available.

Usage

```
getDataByFilter(trainData, testData, FSmethod, cutP = 0.1, fdr = NULL,
               FScore = MulticoreParam())
```

Arguments

trainData	The input training dataset. The first column is the label.
testData	The input test dataset. The first column is the label.
FSmethod	Feature selection methods. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox', or 'top10pCor'). 'positive' is the positively outcome-associated features using the Pearson correlation method. 'posWilcox' is the positively outcome-associated features using Pearson correlation method together with 'wilcox.test' method. 'top10pCor' is the top 10 outcome-associated features. This is helpful when no features can be picked during stringent feature selection procedure.
cutP	The cutoff used for p value thresholding. It can be any value between 0 and 1. Commonly used cutoffs are c(0.5, 0.1, 0.05, 0.01, etc.). The default is 0.1.
fdr	Multiple testing correction method. Available options are c(NULL, 'fdr', 'BH', 'holm' etc). See also p.adjust . The default is NULL.
FScore	The number of cores used for some feature selection methods. The default is 10.

Details

Parallel computing is helpful if your input data is high dimensional. For 'cutP', a soft thresholding of 0.1 may be favorable than more stringent p value cutoff because the features with small effect size can be taken into consideration for downstream analysis. However, for high dimensional (e.g. $p > 10,000$) data, many false positive features may exist, thus, rigorous p value thresholding should be applied. The choice of feature selection method depends on the characteristics of the input data.

Value

Both training and test data (if provided) with pre-selected features are returned if feature selection method is applied. If no feature can be selected during feature selection procedure, then the output is NULL.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
trainIndex <- sample(nrow(methylData), 20)
trainData = methylData[trainIndex,]
testData = methylData[-trainIndex,]
## Feature selection
library(BiocParallel)
param <- MulticoreParam(workers = 10)
## Select outcome-associated features based on the Wilcoxon test (P<0.1)
datalist <- getDataByFilter(trainData, testData, FSmethod="wilcox.test",
                           cutP=0.1, fdr=NULL, FScore=param)
trainDataSub <- datalist[[1]]
testDataSub <- datalist[[2]]
print(dim(trainData))
print(dim(trainDataSub))
```

getMetrics

Compute the evaluation metrics

Description

Compute the evaluation metrics in the classification setting: area under curve (AUC), classification accuracy (ACC) and the pseudo R square (R2).

Usage

```
getMetrics(dataY, predY)
```

Arguments

dataY	The observed outcome.
predY	The predicted outcome.

Details

If all samples are predicted into one class, then R2 is 0.

Value

A set of metrics for model evaluation: AUC, ACC and R2.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
methylSub <- data.frame(label=dataY, methylData[,c(2:1001)])
library(ranger)
library(pROC)
library(rms)
library(BiocParallel)
param1 <- MulticoreParam(workers = 1)
param2 <- MulticoreParam(workers = 10)
predY <- predByCV(methylSub, repeats=1, nfolds=10,
                 FSmethod=NULL, cutP=0.1,
                 fdr=NULL, FScore=param1,
                 classifier='randForest',
                 predMode='classification',
                 paramlist=list(ntree=300, nthreads=20),
                 innerCore=param2)
accuracy <- getMetrics(dataY=dataY, predY=predY)
print(accuracy)
```

omics2pathlist

Map individual probes into pathway

Description

Map a set of individual probes from different omics (i.e. SNPs, gene expression probes, CpGs etc.) into pathway such as Gene Ontology (GO) categories and KEGG.

Usage

```
omics2pathlist(data, pathlistDB, featureAnno = NULL, restrictUp = 200,
               restrictDown = 10, minPathSize = 5)
```

plotRankedFeature *Plot top outcome-associated features*

Description

Plot top ranked outcome-associated features from stage-2 data. The ranking criteria are based on metrics such as Nagelkerke pseudo R-square.

Usage

```
plotRankedFeature(data, posF = TRUE, topF = 10, blocklist,
  rankMetric = c("AUC", "ACC", "R2", "size"), colorMetric = c("AUC",
  "ACC", "R2", "size"), core = MulticoreParam(), fileName = NULL)
```

Arguments

data	The input stage-2 data (either data.frame or matrix). Rows are the samples, columns are pathway names, except that the first column is the label (the outcome).
posF	A logical value indicating if only positively outcome-associated features should be used. (Default: TRUE)
topF	The top ranked number of features at stage-2 (topF >= 2). (Default: 10)
blocklist	A list of matrices with block IDs as the associated list member names. The block IDs identical to the stage-2 feature names. For each matrix, rows are the samples and columns are the probe names, except that the first column is named 'label'. See also omics2pathlist .
rankMetric	A string representing the metrics used for ranking. Valid options are c('AUC', 'ACC', 'R2', 'size'). 'size' is the block size.
colorMetric	A string representing the metric used to color the plot. Valid options are c('AUC', 'ACC', 'R2', 'size'). 'size' is the block size.
core	The number of cores used for computation. (Default: 10)
fileName	The plot file name. (Default: 'plottopF.png')

Details

If the argument posF is TRUE, and no positively outcome-associated features are present in stage-2 data, then an error is reported. In addition, if topF is bigger than the number of positively outcome-associated features, an error is returned.

Value

An output image file and the summary statistics of the top pathways.

References

Perlich, C., & Swirszcz, G. (2011). On cross-validation and stacking: Building seemingly predictive models on random data. *ACM SIGKDD Explorations Newsletter*, 12(2), 11-15.

See Also

[omics2pathlist](#).

plotVarExplained *Plot data summary statistics*

Description

Plot data summary statistics in terms of the proportion of variance explained.

Usage

```
plotVarExplained(data, posF = TRUE, core = MulticoreParam(),
  horizontal = FALSE, fileName = NULL)
```

Arguments

data	The input dataset (either data.frame or matrix). Rows are the samples, columns are the probes/genes, except that the first column is the label (the outcome).
posF	A logical value indicating if only positively outcome-associated features should be used. (Default: TRUE)
core	The number of cores used for computation. (Default: 1)
horizontal	A logical value indicating if the plot should be horizontal or not. The default is FALSE.
fileName	The file name specified for the plot. If it is not NULL, then the plot will be generated. The plot will project the data on the first two components. (Default: 'R2explained.png')

Value

An output image file with '.png' format.

References

Yu, Guangchuang, et al. 'clusterProfiler: an R package for comparing biological themes among gene clusters.' *Omics: a journal of integrative biology* 16.5 (2012): 284-287.

Perlich, C., & Swirszcz, G. (2011). On cross-validation and stacking: Building seemingly predictive models on random data. *ACM SIGKDD Explorations Newsletter*, 12(2), 11-15.

predByBS *Bootstrap resampling prediction via supervised machine learning with feature selection*

Description

Prediction via supervised machine learning using bootstrap resampling along with feature selection methods.

Usage

```
predByBS(trainData, testData, dataMode, repeats, FSmethod, cutP, fdr,
  FScore = MulticoreParam(), classifier, predMode, paramlist,
  innerCore = MulticoreParam())
```

Arguments

trainData	The input training dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
testData	The input test dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
dataMode	The input training data mode for model training. It is used only if 'testData' is present. It can be a subset of the whole training data or the entire training data. 'subTrain' is the given for subsetting and 'allTrain' for the entire training dataset.
repeats	The number of repeats used for bootstrapping.
FMethod	Feature selection methods. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox', or 'top10pCor').
cutP	The cutoff used for p value thresholding. Commonly used cutoffs are c(0.5, 0.1, 0.05, 0.01, etc). The default is 0.05.
fdr	Multiple testing correction method. Available options are c(NULL, 'fdr', 'BH', 'holm', etc). See also p.adjust . The default is NULL.
FScore	The number of cores used for feature selection if parallel computing needed.
classifier	Machine learning classifiers.
predMode	The prediction mode. Available options are c('probability', 'classification', 'regression').
paramlist	A set of model parameters defined in an R list object.
innerCore	The number of cores used for computation.

Value

The predicted output for the test data.

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
## select a subset of genome-wide methylation data at random
methylSub <- data.frame(label=dataY, methylData[,c(2:2001)])
trainIndex <- sample(nrow(methylSub), 30)
trainData = methylSub[trainIndex,]
testData = methylSub[-trainIndex,]
library(ranger)
library(BiocParallel)
param1 <- MulticoreParam(workers = 1)
param2 <- MulticoreParam(workers = 20)
predY <- predByBS(trainData, testData,
                  dataMode='allTrain', repeats=50,
                  FMethod=NULL, cutP=0.1,
                  fdr=NULL, FScore=param1,
                  classifier='randForest',
                  predMode='classification',
                  paramlist=list(ntree=300, nthreads=10),
                  innerCore=param2)
```

```
testY <- testData[,1]
accuracy <- classifiACC(dataY=testY, predY=predY)
print(accuracy)
```

predByCV	<i>Cross validation prediction by supervised machine learning and feature selection</i>
----------	---

Description

Prediction by supervised machine learning models using cross validation along with feature selection methods.

Usage

```
predByCV(data, repeats, nfolds, FSmetho, cutP, fdr,
  FScore = MulticoreParam(), classifier, predMode, paramlist,
  innerCore = MulticoreParam())
```

Arguments

data	The input dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
repeats	The number of repeats used for cross validation. Repeated cross validation is performed if $N \geq 2$.
nfolds	The number of folds is defined for cross validation.
FSmetho	Feature selection methods. Available options are <code>c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox', or 'top10pCor')</code> .
cutP	The cutoff used for p value thresholding. Commonly used cutoffs are <code>c(0.5, 0.1, 0.05, 0.01, etc)</code> . The default is 0.05.
fdr	Multiple testing correction method. Available options are <code>c(NULL, 'fdr', 'BH', 'holm', etc)</code> . See also p.adjust . The default is NULL.
FScore	The number of cores used for feature selection if parallel computing needed.
classifier	Machine learning classifiers.
predMode	The prediction mode. Available options are <code>c('probability', 'classification', 'regression')</code> .
paramlist	A set of model parameters defined in an R list object.
innerCore	The number of cores used for computation.

Value

The predicted cross validation output.

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
## select a subset of genome-wide methylation data at random
methylSub <- data.frame(label=dataY, methylData[,c(2:2001)])
library(ranger)
library(BiocParallel)
param1 <- MulticoreParam(workers = 1)
param2 <- MulticoreParam(workers = 20)
predY <- predByCV(methylSub, repeats=1, nfolds=10,
                 FSmethod=NULL, cutP=0.1,
                 fdr=NULL, FScore=param1,
                 classifier='randForest',
                 predMode='classification',
                 paramlist=list(ntree=300, nthreads=1),
                 innerCore=param2)
dataY <- methylData[,1]
accuracy <- classifiACC(dataY=dataY, predY=predY)
print(accuracy)
```

predByFS

Prediction by supervised machine learning along with feature selection

Description

Prediction by supervised machine learning along with feature selection.

Usage

```
predByFS(trainData, testData, FSmethod, cutP, fdr,
         FScore = MulticoreParam(), classifier, predMode, paramlist)
```

Arguments

trainData	The input training dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
testData	The input test dataset. The first column is the label or the output. For binary classes, 0 and 1 are used to indicate the class member.
FSmethod	Feature selection methods. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox', or 'top10pCor').
cutP	The cutoff used for p value thresholding. Commonly used cutoffs are c(0.5, 0.1, 0.05, etc.). The default is 0.05.
fdr	Multiple testing correction method. Available options are c(NULL, 'fdr', 'BH', 'holm', etc.). See also p.adjust . The default is NULL.
FScore	The number of cores used for feature selection.
classifier	Machine learning classifiers. Available options are c('randForest', 'SVM', 'glmnet').

predMode	The prediction mode. Available options are c('probability', 'classification', 'regression').
paramlist	A set of model parameters defined in an R list object.

Details

If no feature selected or just one selected feature, then top 10

Value

The predicted output for the test data.

Author(s)

Junfang Chen

See Also

[getDataByFilter](#)

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
dataY <- methylData[,1]
## select a subset of genome-wide methylation data at random
methylSub <- data.frame(label=dataY, methylData[,c(2:501)])
trainIndex <- sample(nrow(methylSub), 30)
trainData = methylSub[trainIndex,]
testData = methylSub[-trainIndex,]
library(ranger)
library(BiocParallel)
param <- MulticoreParam(workers = 10)
predY <- predByFS(trainData, testData,
                  FSmethod='cor.test', cutP=0.1,
                  fdr=NULL, FScore=param,
                  classifier='randForest',
                  predMode='classification',
                  paramlist=list(ntree=300, nthreads=20))
testY <- testData[,1]
accuracy <- classifiACC(dataY=testY, predY=predY)
print(accuracy)
```

reconBySupervised *Reconstruct stage-2 data by supervised machine learning prediction*

Description

Reconstruct stage-2 data by supervised machine learning prediction.

Usage

```
reconBySupervised(trainDataList, testDataList, resample = "BS", dataMode,
  repeatA, repeatB, n folds, FSmetho d, cutP, fdr,
  FScore = Multico reParam(), classifier, predMode, paramlist,
  innerCore = Multico reParam(), outFileA = NULL, outFileB = NULL)
```

Arguments

trainDataList	The input training data list containing ordered collections of matrices.
testDataList	The input test data list containing ordered collections of matrices.
resample	The resampling methods. Valid options are 'CV' and 'BS'. 'CV' for cross validation and 'BS' for bootstrapping resampling. The default is 'BS'.
dataMode	The mode of data used. 'subTrain' or 'allTrain'.
repeatA	The number of repeats N is used during resampling procedure. Repeated cross validation or multiple bootstrapping is performed if $N \geq 2$. One can choose 10 repeats for 'CV' and 100 repeats for 'BS'.
repeatB	The number of repeats N is used for generating test data prediction scores.
n folds	The number of folds is defined for cross validation.
FSmetho d	Feature selection methods. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox', or 'top10pCor').
cutP	The cutoff used for p value thresholding. Commonly used cutoffs are c(0.5, 0.1, 0.05, 0.01, etc). The default is 0.05.
fdr	Multiple testing correction method. Available options are c(NULL, 'fdr', 'BH', 'holm', etc). See also p.adjust . The default is NULL.
FScore	The number of cores used for feature selection, if parallel computing needed.
classifier	Machine learning classifiers.
predMode	The prediction mode. Available options are c('probability', 'classification', 'regression').
paramlist	A set of model parameters defined in an R list object.
innerCore	The number of cores used for computation.
outFileA	The file name of stage-2 training data with the '.rds' file extension. If it's provided, then the result will be saved in this file. The default is NULL.
outFileB	The file name of stage-2 training data with the '.rds' file extension. If it's provided, then the result will be saved in this file. The default is NULL.

Details

Stage-2 training data can be learned either using bootstrapping or cross validation resampling methods. Stage-2 test data is learned via independent test set prediction.

Value

The predicted stage-2 training data and also stage-2 test data, if 'testDataList' provided. If outFileA and outFileB are provided, then the results will be stored in the files.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
## Annotation file
probeAnnoFile <- system.file('extdata', 'cpgAnno.rds', package='BioMM')
featureAnno <- readRDS(file=probeAnnoFile)
## Mapping CpGs into Pathways
featureAnno <- readRDS(system.file("extdata", "cpgAnno.rds", package="BioMM"))
pathlistDB <- readRDS(system.file("extdata", "goDB.rds", package="BioMM"))
head(featureAnno)
dataList <- omics2pathlist(data=methylData, pathlistDB, featureAnno,
                          restrictUp=100, restrictDown=10, minPathSize=10)

length(dataList)
library(ranger)
library(BiocParallel)
param1 <- MulticoreParam(workers = 1)
param2 <- MulticoreParam(workers = 20)
## Not Run, this will take a bit long
## stage2data <- reconBySupervised(trainDataList=dataList, testDataList=NULL,
##                                resample='CV', dataMode='allTrain',
##                                repeatA=50, repeatB=20, nfolds=10,
##                                FSmethod=NULL, cutP=0.1,
##                                fdr=NULL, FScore=param1,
##                                classifier='randForest',
##                                predMode='classification',
##                                paramlist=list(ntree=500, nthreads=20),
##                                innerCore=param2, outFileA=NULL, outFileB=NULL)
## print(dim(stage2data))
## print(head(stage2data[,1:5]))
```

reconByUnsupervised *Reconstruct stage-2 data by PCA*

Description

Stage-2 data reconstruction by regular or sparse constrained principal component analysis (PCA).

Usage

```
reconByUnsupervised(trainDataList, testDataList, typeMode = "regular",
                    topPC = 1, innerCore = MulticoreParam(), outFileA = NULL,
                    outFileB = NULL)
```

Arguments

trainDataList	The input training data list containing ordered collections of matrices.
testDataList	The input test data list containing ordered collections of matrices.
typeMode	The type of PCA prediction mode. Available options are c('regular', 'sparse'). (Default: regular)
topPC	The number of top PCs selected. The default is 1, i.e. the first PC.

innerCore	The number of cores used for computation.
outFileA	The file name of stage-2 training data with the '.rds' file extension. If it's provided, then the result will be saved in this file. The default is NULL.
outFileB	The file name of stage-2 training data with the '.rds' file extension. If it's provided, then the result will be saved in this file. The default is NULL.

Value

The predicted stage-2 training data and also stage-2 test data if 'testDataList' provided. If outFileA and outFileB are provided then the results will be stored in the files.

Author(s)

Junfang Chen

Examples

```
## Load data
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
## Annotation file
probeAnnoFile <- system.file('extdata', 'cpgAnno.rds', package='BioMM')
## Mapping CpGs into Pathways
featureAnno <- readRDS(file=probeAnnoFile)
## Mapping CpGs into Pathways
featureAnno <- readRDS(system.file("extdata", "cpgAnno.rds", package="BioMM"))
pathlistDB <- readRDS(system.file("extdata", "goDB.rds", package="BioMM"))
head(featureAnno)
dataList <- omics2pathlist(data=methylData, pathlistDB, featureAnno,
                          restrictUp=100, restrictDown=10, minPathSize=10)
length(dataList)
library(BiocParallel)
param <- MulticoreParam(workers = 10)
stage2data <- reconByUnsupervised(trainDataList=dataList, testDataList=NULL,
                                  typeMode='regular', topPC=1,
                                  innerCore=param, outFileA=NULL, outFileB=NULL)
print(dim(stage2data))
print(head(stage2data[,1:5]))
```


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