

# Package ‘BioMM’

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**Type** Package

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

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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, precrec, nsprcomp, ranger, e1071, ggplot2, vioplot, CMplot, imager, topGO, xlsx

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**R topics documented:**

baseGLMnet	2
baseModel	3
baseRandForest	5
baseSVM	6
BioMM	7
BioMMstage2pred	11
cirPlot4pathway	13
classifiACC	13
getDataByFilter	14
getMetrics	16
omics2pathlist	17
plotRankedFeature	18
plotVarExplained	20
predByBS	21
predByCV	22
predByFS	24
reconBySupervised	26
reconByUnsupervised	28
<b>Index</b>	<b>30</b>

baseGLMnet

*Prediction by generalized linear regression models***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).

1. 'family': Response type: 'gaussian', 'binomial', 'poisson', 'multinomial', 'cox', 'mgaussian'. (Default: 'binomial')
2. 'alpha': The elastic net mixing parameter, with  $0 \leq \alpha \leq 1$ .
3. '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), 16)
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**

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

**Value**

Based on a given machine learning, the predicted score/output will be estimated 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), 16)
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	<i>Prediction by random forest</i>
----------------	------------------------------------

---

## 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), 12)
```

```

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"> <li>1. 'tuneP': a logical value indicating if hyperparameter tuning should be conducted or not. The default is FALSE.</li> <li>2. 'kernel': options are c('linear', 'polynomial', 'radial', 'sigmoid'). The default is 'radial'.</li> <li>3. 'gamma': the parameter needed for all kernels except 'linear'. If tuneP is TRUE, more than one value is suggested.</li> <li>4. 'cost': is the cost of constraints violation. If tuneP is TRUE, more than one value is suggested.</li> </ol> |

**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), 12)
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**

The BioMM framework uses two-stage machine learning models that can allow us to integrate prior biological knowledge for end-to-end phenotype prediction.

**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,
  nfold = 10,
  FMethod1,
  FMethod2,
  cutP1,
  cutP2,
  fdr2,
  FScore = MulticoreParam(),
  classifier,
  predMode,
  paramlist,
  innerCore = MulticoreParam()
)

```

**Arguments**

<code>trainData</code>	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.
<code>testData</code>	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.
<code>pathlistDB</code>	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').
<code>featureAnno</code>	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)
<code>restrictUp</code>	The upper-bound of the number of probes or genes in each biological stratified block.
<code>restrictDown</code>	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.
nfold	The number of folds is defined for cross validation. The default is 10.
FMethod1	Feature selection methods at stage-1. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox').
FMethod2	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). If "FMethod1" is NULL, Then no cutoff is applied.
cutP2	The cutoff used for p value thresholding at stage-2. Commonly used cutoffs are c(0.5, 0.1, 0.05, 0.01, etc). If "FMethod2" is NULL, Then no cutoff is applied.
fdr2	Multiple testing correction method at stage-2. Available options are c(NULL, 'fdr', 'BH', 'holm', etc). See also <a href="#">p.adjust</a> . The default is NULL. This option is useful particularly when large sets of pathways are investigated.
FScore	The number of cores used for feature selection.
classifier	Machine learning classifiers at both stages. Available options are c('randForest', 'SVM', 'glmnet').
predMode	The prediction mode at both stages. Available options are c('probability', 'classification', 'regression').
paramlist	A list of model parameters at both stages. The set of parameters are different for each classifier. Please see the detailed parameters are implemented for each individual classifier, e.g., 'baseRandForest()', 'baseSVM()', and 'baseGLMnet()'.
innerCore	The number of cores used for computation. It needs to be reconciled with "FS-core" depending on the number of cores available.

## 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 predicted score for the training data and test set predicted score 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)
testData <- NULL
## Annotation file
probeAnnoFile <- system.file('extdata', 'cpgAnno.rds', package='BioMM')
probeAnno <- readRDS(file=probeAnnoFile)
golist <- readRDS(system.file("extdata", "goDB.rds", package="BioMM"))
pathlistDB <- golist[1:100]
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=200, restrictDown=10, 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)
## if (is.null(testData)) {
##   predY <- result
```

```

##   trainDataY <- methylData[,1]
##   metricCV <- getMetrics(dataY = trainDataY, predY)
##   message("Cross-validation prediction performance:")
##   print(metricCV)
## } else if (!is.null(testData)){
##   trainDataY <- methylData[,1]
##   testDataY <- testData[,1]
##   cvYscore <- result[[1]]
##   testYscore <- result[[2]]
##   metricCV <- getMetrics(dataY = trainDataY, cvYscore)
##   metricTest <- getMetrics(dataY = testDataY, testYscore)
##   message("Cross-validation performance:")
##   print(metricCV)
##   message("Test set prediction performance:")
##   print(metricTest)
## }

```

---

BioMMstage2pred	<i>Prediction performance for stage-2 data using supervised machine learning</i>
-----------------	--

---

## 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**

<code>trainData</code>	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.
<code>testData</code>	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.
<code>resample</code>	The resampling methods. Valid options are 'CV' and 'BS'. 'CV' for cross validation and 'BS' for bootstrapping resampling. The default is 'CV'.
<code>dataMode</code>	The mode of data used. 'subTrain' or 'allTrain'.
<code>repeatA</code>	The number of repeats N is used during resampling prediction. The default is 1.
<code>repeatB</code>	The number of repeats N is used for test data prediction. The default is 1.
<code>nfolds</code>	The number of folds is defined for cross validation.
<code>FMethod</code>	Feature selection methods. Available options are c(NULL, 'positive', 'wilcox.test', 'cor.test', 'chisq.test', 'posWilcox', or 'top10pCor').
<code>cutP</code>	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.
<code>fdr</code>	Multiple testing correction method. Available options are c(NULL, 'fdr', 'BH', 'holm', etc). See also <a href="#">p.adjust</a> . The default is NULL.
<code>FScore</code>	The number of cores used for feature selection if parallel computing needed.
<code>classifier</code>	Machine learning classifiers.
<code>predMode</code>	The prediction mode. Available options are c('probability', 'classification', 'regression').
<code>paramlist</code>	A set of model parameters defined in an R list object.
<code>innerCore</code>	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 predicted score for stage-2 training data and test set predicted score 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	<i>Circular plot for a set of pathways</i>
-----------------	--

---

**Description**

The individual CpGs or genes within a given set of pathways are displayed as the dots in the resulting plot. The significance of the CpGs or genes 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	Add a character to the output file name. (Default: 'Circular-Manhattan.pval.jpeg')

**Details**

Top 10 or 20 pathways are usually suggested to be visualized. The significant features (if any) are highlighted using filled diamond. The significance line is set as 0.05 marked as dashed red line.

**Value**

An output image file.

**See Also**

[omics2pathlist](#).

---

classifiACC	<i>Compute the classification accuracy</i>
-------------	--

---

**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, n folds=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.
FMethod	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 <a href="#">p.adjust</a> . The default is NULL.
FScore	The number of cores used for some feature selection methods. If it's NULL, then no parallel computing is applied.

### 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 machine learning evaluation metrics*


---

## Description

Compute the evaluation metrics in the classification setting: area under curve (AUC), the area under the Precision-Recall curve, 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, AUCPR, 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(precrec)
library(rms)

```



```

library(BiocParallel)
param1 <- MulticoreParam(workers = 1)
param2 <- MulticoreParam(workers = 10)
predY <- predByCV(methylSub, repeats=1, nolds=10,
                  FSmeth=NULL, cutP=0.1,
                  fdr=NULL, FScore=param1,
                  classifier='randForest',
                  predMode='classification',
                  paramlist=list(ntree=300, nthreads=20),
                  innerCore=param2)
metrics <- getMetrics(dataY=dataY, predY=predY)
print(metrics)

```

---

omics2pathlist	<i>Map individual probes into pathway</i>
----------------	---

---

## 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
)

```

## 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. If it's transcriptomic data, gene ID is the 'entrezID'.
pathlistDB	A list of pathways with pathway IDs and their corresponding genes ('entrezID' is used).
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 transcriptomic data.
restrictUp	The upper-bound of the number of genes in each pathway. The default is 200.
restrictDown	The lower-bound of the number of genes in each pathway. The default is 10.
minPathSize	The minimal required number of probes in each pathway after mapping the input data to pathlistDB.

## Details

If gene expression data is the input, then featureAnno is NULL, since the gene IDs are already defined as column names of the data. Since online database is updated from time to time, it is advised to make sure that the study database (e.g. pathlistDB) is frozen at particular time for reproducing the results. The number of genes in each pathway can be restricted for downstream analysis because too small pathways are sparsely distributed, and too large pathways are often computationally intensive, and likely nonspecific.

## Value

A list of matrices with pathway IDs as the associated list member names. For each matrix, rows are the samples and columns are the probe names, except that the first column is named 'label'.

## Examples

```
## Load data from DNA methylation
methylfile <- system.file('extdata', 'methylData.rds', package='BioMM')
methylData <- readRDS(methylfile)
## Annotation files for Mapping CpGs into pathways
pathlistDBfile <- system.file('extdata', 'goDB.rds', package='BioMM')
featureAnnoFile <- system.file('extdata', 'cpgAnno.rds', package='BioMM')
pathlistDB <- readRDS(file=pathlistDBfile)
featureAnno <- readRDS(file=featureAnnoFile)
## To reduce runtime
pathlistDB <- pathlistDB[1:20]
## Mapping CpGs into pathway list
dataList <- omics2pathlist(data=methylData,
                          pathlistDB, featureAnno,
                          restrictUp=100, restrictDown=20,
                          minPathSize=10)

length(dataList)
```

---

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,
  binarize = FALSE,
```

```

rankMetric = c("AUC", "R2", "Zscore", "negPlogit", "negPwilcox", "size"),
colorMetric = c("AUC", "R2", "Zscore", "negPlogit", "negPwilcox", "size"),
core = MulticoreParam(),
pathTitle = "GO pathways",
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 <a href="#">omics2pathlist</a> .
binarize	A logical value indicating if the individual features under investigation should be binarized. The default is FALSE, which provides the estimated class probabilities for each pathway-level feature. If TRUE, then the binary output is given for each feature.
rankMetric	A string representing the metrics used for ranking. Valid options are c("AUC", "R2", "Zscore", "negPlogit", "negPwilcox"). "negPlogit" denotes the negative log P value from the logistic regression and "negPwilcox" means the negative log P value based on the Wilcoxon test. "size" is the block size.
colorMetric	A string representing the metric used to color the plot. Valid options are c("AUC", "R2", "Zscore", "negPlogit", "negPwilcox"). "negPlogit" denotes the negative log P value from the logistic regression and "negPwilcox" means the negative log P value based on wilcoxon test. "size" is the block size.
core	The number of cores used for computation. (Default: 10)
pathTitle	A string indicating the name of pathway under investigation.
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,
  binarize = FALSE,
  core = MulticoreParam(),
  pathTitle = "GO pathways",
  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)
binarize	A logical value indicating if the individual features under investigation should be binarized. The default is FALSE, which provides the estimated class probabilities for each pathway-level feature. If TRUE, then the binary output is given for each feature.
core	The number of cores used for computation. (Default: 1)
pathTitle	A string indicating the name of pathway under investigation. This will be displayed as the name of y-axis.
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	<i>Bootstrap resampling prediction via supervised machine learning with feature selection</i>
----------	---

---

## 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.
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, 0.01, etc). The default is 0.05.
fdr	Multiple testing correction method. Available options are c(NULL, 'fdr', 'BH', 'holm', etc). See also <a href="#">p.adjust</a> . 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), 16)
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,
                 FSmeth=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)
```

**Description**

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

**Usage**

```
predByCV(
  data,
  repeats,
  nfolds,
  FSmethod,
  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.
FSmethod	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 <a href="#">p.adjust</a> . 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, nolds=10,
                 FSmetho=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,
  FSmetho,
  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 <a href="#">p.adjust</a> . 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), 16)
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,
  nfolds,
  FSmethod,
  cutP,
  fdr,
  FScore = MulticoreParam(),
  classifier,
  predMode,
  paramlist,
  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.
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.

nfolde	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 <a href="#">p.adjust</a> . 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, nfold=10,
##                               FSmeth=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]))
```

# Index

baseGLMnet, [2](#)  
baseModel, [3](#)  
baseRandForest, [5](#)  
baseSVM, [6](#)  
BioMM, [7](#)  
BioMMstage2pred, [10](#), [11](#)  
  
cirPlot4pathway, [13](#)  
classifiACC, [13](#)  
  
getDataByFilter, [14](#), [25](#)  
getMetrics, [16](#)  
  
omics2pathlist, [13](#), [17](#), [19](#), [20](#)  
  
p.adjust, [9](#), [12](#), [15](#), [22](#), [23](#), [25](#), [27](#)  
plotRankedFeature, [18](#)  
plotVarExplained, [20](#)  
predByBS, [21](#)  
predByCV, [22](#)  
predByFS, [24](#)  
  
reconBySupervised, [10](#), [26](#)  
reconByUnsupervised, [10](#), [28](#)  
  
svm, [7](#)