

Package ‘SmCCNet’

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Title Sparse Multiple Canonical Correlation Network Analysis Tool
(‘SmCCNet’)

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Description

A canonical correlation based framework (‘SmCCNet’) designed for the construction of phenotype-specific multi-omics networks. This framework adeptly integrates single or multiple omics data types along with a quantitative or binary phenotype of interest. It offers a streamlined setup process that can be tailored manually or configured automatically, ensuring a flexible and user-friendly experience. Methods are described in Shi et al. (2019) “Unsupervised discovery of phenotype-specific multi-omics networks” <doi:10.1093/bioinformatics/btz226>.

URL <https://github.com/KechrisLab/SmCCNet>,
<https://kechrislab.github.io/SmCCNet/>,
<https://liux4283.github.io/SmCCNet/>

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aggregateCVSingle	<i>Aggregate and Save Cross-validation Result for Single-omics Analysis</i>
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Description

Saves cross-validation results in a table with the user-defined directory and outputs penalty term with the highest testing canonical correlation, lowest prediction error, and lowest scaled prediction error.

Usage

```

aggregateCVSingle(
  CVDDir,
  SCCAMethod = "SmCCA",
  K = 5,
  NumSubsamp = 500,
  verbose = FALSE
)

```

Arguments

CVDDir	A directory where the result is stored.
SCCAMethod	The canonical correlation analysis method that is used in the model, used to name cross-validation table file, default is set to 'SmCCA'.
K	number of folds for cross-validation.
NumSubsamp	Number of subsampling used.
verbose	Logical; if TRUE, print progress messages during execution, otherwise run silently.

Value

A vector of length 3 with indices of the penalty term that (1) maximize the testing canonical correlation, (2) minimize the prediction error and (3) minimize the scaled prediction error.

classifierEval	<i>Evaluation of Binary Classifier with Different Evaluation Metrics</i>
----------------	--

Description

Evaluate binary classifier's performance with respect to user-selected metric (accuracy, auc score, precision, recall, f1 score) for binary phenotype.

Usage

```

classifierEval(
  obs,
  pred,
  EvalMethod = "accuracy",
  BinarizeThreshold = 0.5,
  print_score = TRUE
)

```

Arguments

obs	Observed phenotype, vector consists of 0, 1.
pred	Predicted probability of the phenotype, vector consists of any value between 0 and 1
EvalMethod	Binary classifier evaluation method, should be one of the following: 'accuracy' (default), 'auc', 'precision', 'recall', and 'f1'.
BinarizeThreshold	Cutoff threshold to binarize the predicted probability, default is set to 0.5.
print_score	Whether to print out the evaluation score, default is set to TRUE.

Value

An evaluation score corresponding to the selected metric.

Examples

```
# simulate observed binary phenotype
obs <- rbinom(100,1,0.5)
# simulate predicted probability
pred <- runif(100, 0,1)
# calculate the score
pred_score <- classifierEval(obs, pred, EvalMethod = 'f1', print_score = FALSE)
```

dataPreprocess

preprocess a omics dataset before running omics SmCCNet

Description

Data preprocess pipeline to: (1) filter by coefficient of variation (cv), (2) center or scale data and (3) adjust for clinical covariates.

Usage

```
dataPreprocess(
  X,
  covariates = NULL,
  is_cv = FALSE,
  cv_quantile = 0,
  center = TRUE,
  scale = TRUE
)
```

Arguments

<code>X</code>	dataframe with the size of n by p , where n is the sample size and p is the feature size.
<code>covariates</code>	dataframe with covariates to be adjusted for.
<code>is_cv</code>	Whether to use coefficient of variation filter (small cv filter out).
<code>cv_quantile</code>	CV filtering quantile.
<code>center</code>	Whether to center the dataset X .
<code>scale</code>	Whether to scale the dataset X .

Value

Processed omics data with the size of $n \times p$.

Examples

```
X1 <- as.data.frame(matrix(rnorm(600, 0, 1), nrow = 60))
covar <- as.data.frame(matrix(rnorm(120, 0, 1), nrow = 60))
processed_data <- dataPreprocess(X = X1, covariates = covar, is_cv = TRUE,
cv_quantile = 0.5, center = TRUE, scale = TRUE)
```

fastAutoSmCCNet

Automated SmCCNet to Streamline the SmCCNet Pipeline

Description

Automated SmCCNet automatically identifies the project problem (single-omics vs multi-omics), and type of analysis (CCA for quantitative phenotype vs. PLS for binary phenotype) based on the input data that is provided. This method automatically preprocesses data, chooses scaling factors, subsampling percentage, and optimal penalty terms, then runs through the complete SmCCNet pipeline without the requirement for users to provide additional information. This function will store all the subnetwork information to a user-defined directory, as well as return all the global network and evaluation information. Refer to the automated SmCCNet vignette for more information.

Usage

```
fastAutoSmCCNet(
  X,
  Y,
  AdjustedCovar = NULL,
  preprocess = FALSE,
  Kfold = 5,
  EvalMethod = "accuracy",
  subSampNum = 100,
  DataType,
  BetweenShrinkage = 2,
```

```

ScalingPen = c(0.1, 0.1),
CutHeight = 1 - 0.1^10,
min_size = 10,
max_size = 100,
summarization = "NetSHy",
saving_dir = tempdir(),
ncomp_pls = 3,
tuneLength = 5,
tuneRangeCCA = c(0.1, 0.5),
tuneRangePLS = c(0.5, 0.9),
seed = 123,
verbose = FALSE
)

```

Arguments

X	A list of matrices with same set and order of subjects (n).
Y	Phenotype variable of either numeric or binary, for binary variable, for binary Y, it should be binarized to 0,1 before running this function.
AdjustedCovar	A data frame of covariates of interest to be adjusted for through regressing-out approach, argument preprocess need to be set to TRUE if adjusting covariates are supplied.
preprocess	Whether the data preprocessing step should be conducted, default is set to FALSE. If regressing out covariates is needed, provide corresponding covariates to AdjustCovar argument.
Kfold	Number of folds for cross-validation, default is set to 5.
EvalMethod	The evaluation methods used to selected the optimal penalty parameter(s) when binary phenotype is given. The selections is among 'accuracy', 'auc', 'precision', 'recall', and 'f1', default is set to 'accuracy'.
subSampNum	Number of subsampling to run, the higher the better in terms of accuracy, but at a cost of computational time, we generally recommend 500-1000 to increase robustness for larger data, default is set to 100.
DataType	A vector indicating annotation of each dataset of X, example would be c('gene', 'miRNA').
BetweenShrinkage	A real number > 0 that helps shrink the importance of omics-omics correlation component, the larger this number is, the greater the shrinkage it is, default is set to 2.
ScalingPen	A numeric vector of length 2 used as the penalty terms for scaling factor determination method: default set to 0.1 for both datasets, and should be between 0 and 1.
CutHeight	A numeric value specifying the cut height for hierarchical clustering, should be between 0 and 1, default is set to $1 - 0.1^{10}$.
min_size	Minimally possible subnetwork size after network pruning, default set to 10.
max_size	Maximally possible subnetwork size after network pruning, default set to 100.

summarization	Summarization method used for network pruning and summarization, should be either 'NetSHy' or 'PCA'.
saving_dir	Directory where user would like to store the subnetwork results, default is set to the current working directory.
ncomp_pls	Number of components for PLS algorithm, only used when binary phenotype is given, default is set to 3.
tuneLength	The total number of candidate penalty term values for each omics data, default is set to 5.
tuneRangeCCA	A vector of length 2 that represents the range of candidate penalty term values for each omics data based on canonical correlation analysis, default is set to $c(0.1, 0.5)$.
tuneRangePLS	A vector of length 2 that represents the range of candidate penalty term values for each omics data based on partial least squared discriminant analysis, default is set to $c(0.5, 0.9)$.
seed	Random seed for result reproducibility, default is set to 123.
verbose	Logical; if TRUE, print progress messages during execution, otherwise run silently.

Value

This function returns the global adjacency matrix, omics data details, network clustering outcomes, and cross-validation results. Pruned subnetwork modules are saved in the directory specified by the user.

Examples

```
library(SmCCNet)
set.seed(123)
Y <- rnorm(50)
X1 <- matrix(rnorm(2500), nrow = 50, ncol = 50)
colnames(X1) <- paste0("Gene_", 1:50)
X1[, 1:10] <- X1[, 1:10] + matrix(rep(Y, 10), ncol = 10)
X2 <- matrix(rnorm(1000), nrow = 50, ncol = 20)
colnames(X2) <- paste0("miRNA_", 1:20)
X2[, 1:5] <- X2[, 1:5] + matrix(rep(Y, 5), ncol = 5)
Y_binary <- ifelse(Y > median(Y), 1, 0)
## single-omics CCA
result <- fastAutoSmCCNet(X = list(X1), Y = Y,
                        Kfold = 3, preprocess = FALSE,
                        subSampNum = 10,
                        DataType = c('Gene'),
                        saving_dir = tempdir(),
                        summarization = 'NetSHy',
                        CutHeight = 1 - 0.1^10,
                        min_size = 5)
## single-omics PLS
result <- fastAutoSmCCNet(X = list(X1),
                        Y = as.factor(Y_binary),
```

```
Kfold = 3, subSampNum = 10,
DataType = c('Gene'),
saving_dir = tempdir(),
EvalMethod = 'auc',
summarization = 'NetSHy',
CutHeight = 1 - 0.1^10,
min_size = 5, ncomp_pls = 3)
```

getAbar

Calculate similarity matrix based on canonical weights.

Description

Compute the similarity matrix based on the outer products of absolute canonical correlation weights, can be used for both single and multi-omics setting.

Usage

```
getAbar(Ws, FeatureLabel = NULL)
```

Arguments

Ws A canonical correlation weight vector or matrix. If Ws is a matrix, then each column corresponds to one weight vector.

FeatureLabel A vector of feature labels for each feature in the adjacency matrix

Value

A $p \times p$ symmetric non-negative matrix.

Examples

```
w <- matrix(rnorm(6), nrow = 3)
Ws <- apply(w, 2, function(x)return(x/sqrt(sum(x^2))))
abar <- getAbar(Ws, FeatureLabel = c('omics1', 'omics2', 'omics3'))
```

getCanCorMulti	<i>Canonical Correlation Value for SmCCA</i>
----------------	--

Description

Calculate canonical correlation value for SmCCA given canonical weight vectors and scaling factor

Usage

```
getCanCorMulti(X, CCcoef, CCWeight, Y)
```

Arguments

X	A list of data each with same number of subjects.
CCcoef	A vector of scaling factors indicating weights for each pairwise canonical correlation.
CCWeight	A list of canonical weight vectors corresponds to each data in X.
Y	A phenotype matrix, should have only one column.

Value

A numeric value of the total canonical correlation

Examples

```
library(SmCCNet)
data("ExampleData")
getCanCorMulti(list(X1,X2), CCcoef = c(1,1,1),
  CCWeight = list(rnorm(500,0,1), rnorm(100,0,1)), Y = Y)
```

getCanWeightsMulti	<i>Get Canonical Weight SmCCA Algorithm (No Subsampling)</i>
--------------------	--

Description

Run Sparse multiple Canonical Correlation Analysis (SmCCA) and return canonical weight vectors.

Usage

```
getCanWeightsMulti(
  X,
  Trait = NULL,
  Lambda,
  CCcoef = NULL,
  NoTrait = TRUE,
  trace = FALSE,
  TraitWeight = FALSE
)
```

Arguments

X	A list of omics data each with n subjects.
Trait	An n by 1 trait (phenotype) data for the same samples.
Lambda	Lasso penalty vector with length equals to the number of omics data (X). Lambda needs to be between 0 and 1.
CCcoef	Optional scaling factors for the SmCCA pairwise canonical correlations. If CCcoef = NULL (default), then the objective function is the total sum of all pairwise canonical correlations. It follows the column order of <code>combn(T+1, 2)</code> , where T is the total number of omics data.
NoTrait	Whether or not trait (phenotype) information is provided, default is set to TRUE.
trace	Whether to display CCA algorithm trace, default is set to FALSE.
TraitWeight	Whether to return canonical weight for trait (phenotype), default is set to FALSE.

Value

A canonical weight vector with size of p by 1.

Examples

```
x1 <- matrix(rnorm(1000), nrow = 50)
x2 <- matrix(rnorm(1000), nrow = 50)
y <- matrix(rnorm(50), nrow = 50)
X <- list(x1,x2)
result <- getCanWeightsMulti(X, Trait = y, Lambda = c(0.5,0.5), NoTrait = FALSE)
result <- getCanWeightsMulti(X, Trait = NULL, Lambda = c(0.5,0.5), NoTrait = TRUE)
cccoef <- c(1,10,10)
result <- getCanWeightsMulti(X, Trait = y, CCcoef = cccoeff,
                             Lambda = c(0.5,0.5), NoTrait = FALSE)
```

getOmicsModules

Extract Omics Modules based on Similarity Matrix.

Description

Apply hierarchical tree cutting to the similarity matrix and extract multi/single-omics network modules.

Usage

```
getOmicsModules(Abar, CutHeight = 1 - 0.1^10, PlotTree = TRUE)
```

Arguments

Abar	A similarity matrix for all features (all omics data types).
CutHeight	Height threshold for the hierarchical tree cutting. Default is $1 - 0.1^{10}$.
PlotTree	Logical. Whether to create a hierarchical tree plot, default is set to TRUE.

Value

A list of multi/single-omics modules.

Examples

```
set.seed(123)
w <- rnorm(5)
w <- w/sqrt(sum(w^2))
feature_name <- paste0('feature_', 1:5)
abar <- getAbar(w, FeatureLabel = feature_name)
modules <- getOmicsModules(abar, CutHeight = 0.5)
```

getRobustWeightsMulti *Run Sparse multiple Canonical Correlation Analysis and Obtain Canonical Weights (with Subsampling)*

Description

SmCCNet algorithm with multi-omics data and quantitative phenotype. Calculate the canonical weights for SmCCA.

Usage

```
getRobustWeightsMulti(
  X,
  Trait,
  Lambda,
  s = NULL,
  NoTrait = FALSE,
  SubsamplingNum = 1000,
  CCcoef = NULL,
  trace = FALSE,
  TraitWeight = FALSE
)
```

Arguments

X	A list of omics data each with n subjects.
Trait	An $n \times 1$ trait (phenotype) data matrix for the same n subjects.
Lambda	Lasso penalty vector with length equals to the number of omics data (X). Lambda needs to be between 0 and 1.
s	A vector with length equals to the number of omics data (X), specifying the percentage of omics feature being subsampled at each subsampling iteration.
NoTrait	Logical, default is FALSE. Whether trait information is provided.
SubsamplingNum	Number of feature subsamples. Default is 1000. Larger number leads to more accurate results, but at a higher computational cost.

CCcoef	Optional scaling factors for the SmCCA pairwise canonical correlations. If CCcoef = NULL (default), then the objective function is the total sum of all pairwise canonical correlations. This coefficient vector follows the column order of $\text{combn}(T+1, 2)$ assuming there are T omics data and a phenotype data.
trace	Whether to display the CCA algorithm trace, default is set to FALSE.
TraitWeight	Whether to return canonical weight for trait (phenotype), default is set to FALSE.

Value

A canonical correlation weight matrix with $p = \sum_i p_i$ rows, where p_i is the number of features for the i th omics. Each column is the canonical correlation weights based on subsampled features. The number of columns is SubsamplingNum.

Examples

```
## For illustration, we only subsample 5 times.
set.seed(123)
X1 <- matrix(rnorm(600,0,1), nrow = 60)
X2 <- matrix(rnorm(600,0,1), nrow = 60)
Y <- matrix(rnorm(60,0,1), nrow = 60)
# Unweighted SmCCA
result <- getRobustWeightsMulti(X = list(X1, X2), Trait = Y, NoTrait = FALSE,
Lambda = c(0.5, 0.5), s = c(0.7, 0.7), SubsamplingNum = 20)
```

```
getRobustWeightsMultiBinary
```

Run Sparse multiple Canonical Correlation Analysis and Obtain Canonical Weights (with Subsampling)

Description

SmCCNet algorithm with multi-omics data and binary phenotype. This is a stepwise approach (1) use SmCCA to identify relationship between omics (exclude phenotype), (2) within highly connected omics features selected in step 1, identify relationship between these selected omics features and phenotype of interest with sparse PLS. First, it computes PLSDA by assuming outcome is continuous to extract multiple latent factors, then uses latent factors to fit logistic regression, and weight latent factor by regression parameters. Refer to multi-omics vignette for more detail.

Usage

```
getRobustWeightsMultiBinary(
  X,
  Y,
  Between_Discriminate_Ratio = c(1, 1),
  SubsamplingPercent = NULL,
```

```

    CCcoef = NULL,
    LambdaBetween,
    LambdaPheno = NULL,
    SubsamplingNum = 1000,
    ncomp_pls = 3,
    EvalClassifier = FALSE,
    testData = NULL,
    verbose = FALSE
)

```

Arguments

X A list of omics data each with n subjects.

Y A vector of binary variable, user needs to set the level of this variable to 0 and 1.

Between_Discriminate_Ratio A vector with length 2 specifying the relative importance of between-omics relationship and omics-phenotype relationship.

SubsamplingPercent A vector with length equal to the number of omics data (X).

CCcoef A vector of scaling factors only for between-omics relationship.

LambdaBetween A vector of sparsity penalty value for each omics data.

LambdaPheno A penalty term when running the sparse PLS with phenotype.

SubsamplingNum Number of feature subsamples.

ncomp_pls Number of latent components for PLS.

EvalClassifier If TRUE, return latent factors for classification.

testData A list of testing omics data matrix.

verbose Logical; if TRUE, print progress/error messages, otherwise run silently.

Value

Canonical weight matrix or latent projections depending on EvalClassifier.

getRobustWeightsSingle

Single-omics SmCCA with Quantitative Phenotype

Description

Compute aggregated (SmCCA) canonical weights for single omics data with quantitative phenotype (subampling enabled).

Usage

```
getRobustWeightsSingle(
  X1,
  Trait,
  Lambda1,
  s1 = 0.7,
  SubsamplingNum = 1000,
  trace = FALSE
)
```

Arguments

X1	An $n \times p_1$ data matrix (e.g. mRNA) with p_1 features and n subjects.
Trait	An $n \times 1$ trait (phenotype) data matrix for the same n subjects.
Lambda1	LASSO penalty parameter for X1. Lambda1 needs to be between 0 and 1.
s1	Proportion of features in X1 to be included, default at $s1 = 0.7$. s1 needs to be between 0 and 1, default is set to 0.7.
SubsamplingNum	Number of feature subsamples. Default is 1000. Larger number leads to more accurate results, but at a higher computational cost.
trace	Whether to display the CCA algorithm trace, default is set to FALSE.

Value

A canonical correlation weight matrix with p_1 rows. Each column is the canonical correlation weights based on subsampled X1 features. The number of columns is SubsamplingNum.

Examples

```
## For illustration, we only subsample 5 times.
set.seed(123)

# Single Omics SmCCA
W1 <- getRobustWeightsSingle(X1, Trait = Y, Lambda1 = 0.05,
  s1 = 0.7,
  SubsamplingNum = 5, trace = FALSE)
```

```
getRobustWeightsSingleBinary
```

Single-omics SmCCA with Binary Phenotype

Description

Compute aggregated (SmCCA) canonical weights for single omics data with quantitative phenotype (subampling enabled).

Usage

```
getRobustWeightsSingleBinary(
  X1,
  Trait,
  Lambda1,
  s1 = 0.7,
  SubsamplingNum = 1000,
  K = 3
)
```

Arguments

X1	An $n \times p_1$ data matrix (e.g. mRNA) with p_1 features and n subjects.
Trait	An $n \times 1$ trait (phenotype) data matrix for the same n subjects.
Lambda1	LASSO penalty parameter for X1. Lambda1 needs to be between 0 and 1.
s1	Proportion of mRNA features to be included, default at $s1 = 0.7$. s1 needs to be between 0 and 1, default is set to 0.7.
SubsamplingNum	Number of feature subsamples. Default is 1000. Larger number leads to more accurate results, but at a higher computational cost.
K	Number of hidden components for PLSDA, default is set to 3.

Value

A partial least squared weight matrix with p_1 rows. Each column is the canonical correlation weights based on subsampled X1 features. The number of columns is SubsamplingNum.

Examples

```
X <- matrix(rnorm(600,0,1), nrow = 60)
Y <- rbinom(60,1,0.5)
Ws <- getRobustWeightsSingleBinary(X1 = X, Trait = as.matrix(Y), Lambda1 = 0.8,
0.7, SubsamplingNum = 10)
```

networkPruning

Prunes Subnetwork and Return Final Pruned Subnetwork Module

Description

Prunes subnetworks with network pruning algorithm (see multi-omics vignette for detail), and save the final pruned subnetwork to the user-defined directory. The final subnetwork is an .Rdata file with a name 'size_m_net_ind.Rdata', where m is the final pruned network size, and ind is the index of the subnetwork module after hierarchical clustering.

Usage

```
networkPruning(
  Abar,
  CorrMatrix,
  data,
  Pheno,
  type,
  ModuleIdx,
  min_mod_size = 10,
  max_mod_size,
  damping = 0.9,
  method = "NetSHy",
  saving_dir = tempdir(),
  verbose = FALSE
)
```

Arguments

Abar	Adjacency matrix of subnetwork with size m^* by m^* after hierarchical clustering.
CorrMatrix	The correlation matrix of features in Abar, it should be m^* by m^* as well.
data	The omics data for the subnetwork.
Pheno	The trait (phenotype) data used for network pruning.
type	A vector with length equal to total number of features in the adjacency matrix indicating the type of data for each feature. For instance, for a subnetwork with 2 genes and a protein, the type argument should be set to <code>c('gene', 'gene', 'protein')</code> , see multi-omics vignette for more information.
ModuleIdx	The index of the network module that summarization score is intended to be stored, this is used for naming the subnetwork file in user-defined directory.
min_mod_size	The minimally possible subnetwork size for the pruned network module, should be an integer from 1 to the largest possible size of the subnetwork, default is set to 10.
max_mod_size	the maximally possible subnetwork size for the pruned network module, should be an integer from 1 to the largest possible size of the subnetwork, and it needs to be greater than the value specified in min_mod_size.
damping	damping parameter for the PageRank algorithm, default is set to 0.9, see igraph package for more detail.
method	Selection between 'NetSHy' and 'PCA', specifying the network summarization method used for network pruning, default is set to NetSHy.
saving_dir	User-defined directory to store pruned subnetwork.
verbose	Logical; if TRUE, print progress messages during execution, otherwise run silently.

Value

A file stored in the user-defined directory, which contains the following: (1) correlation_sub: correlation matrix for the subnetwork. (2) M: adjacency matrix for the subnetwork. (3) omics_correlation_data: individual molecular feature correlation with phenotype. (4) pc_correlation: first 3 PCs correlation with phenotype. (5) pc_loading: principal component loadings. (6) pca_x1_score: principal component score and phenotype data. (7) mod_size: number of molecular features in the subnetwork. (8) sub_type: type of feature for each molecular features.

Examples

```
library(SmCCNet)
set.seed(123)
w <- rnorm(20)
w <- w/sqrt(sum(w^2))
X1 <- matrix(rnorm(1000,0,1),nrow = 50)
Y <- matrix(rnorm(50,0,1),nrow = 50)
labels <- paste0('feature_', 1:20)
colnames(X1) <- labels
abarc <- getAbar(w, FeatureLabel = labels)
modules <- getOmicsModules(abarc, CutHeight = 0.1)
x <- X1
corr <- stats::cor(x)
type <- c(rep(1,20))
# display only example
networkPruning(abarc, corr, data = x, Pheno = Y, type = type,
  ModuleIdx = 1, min_mod_size = 3, max_mod_size = 10, method = 'NetSHy', saving_dir = tempdir()
)
```

scalingFactorInput *Scaling Factor Input Prompt*

Description

Input the vector of the annotation of each type of dataset in the data list X (e.g., c('gene', 'protein')), and return prompt ask the user to supply the scaling factor for SmCCNet algorithm to prioritize the correlation structures of interest. All scaling factor values supplied should be numeric and nonnegative.

Usage

```
scalingFactorInput(DataType = NULL)
```

Arguments

DataType A character vector that contains the annotation of each type of omics dataset in X.

Value

A numeric vector of scaling factors.

Examples

```
if(interactive()){scalingFactorInput(c('gene', 'mirna', 'phenotype'))}
```

summarizeNetSHy

NetSHy Summarization Score

Description

Implement NetSHy network summarization via a hybrid approach (Vu et al.,) to summarize network by considering the network topology with Laplacian matrix.

Usage

```
summarizeNetSHy(X, A, npc = 1)
```

Arguments

X	An $n \times m$ data matrix with m features and n subjects.
A	Corresponding adjacency matrix of size p by p .
npc	Number of principal components used to summarize the network, default is set to 1.

Value

A list consists of (1) subject-level network summarization score, (2) principal component importance information: standard deviation, percent of variance explained, and cumulative proportion of variance explained, and (3) principal component feature-level loadings.

References

Vu, Thao, Elizabeth M. Litkowski, Weixuan Liu, Katherine A. Pratte, Leslie Lange, Russell P. Bowler, Farnoush Banaei-Kashani, and Katerina J. Kechris. "NetSHy: network summarization via a hybrid approach leveraging topological properties." *Bioinformatics* 39, no. 1 (2023): btac818.

Examples

```
# simulate omics data
OmicsData <- matrix(rnorm(200,0,1), nrow = 10, ncol = 20)
# simulate omics adjacency matrix
set.seed(123)
w <- rnorm(20)
w <- w/sqrt(sum(w^2))
featurelabel <- paste0('omics',1:20)
```

```
abbar <- getAbar(w, FeatureLabel = featurelabel)
# extract NetSHy summarization score
netshy_score <- summarizeNetSHy(OmicsData, abbar)
```

X1 *A synthetic mRNA expression dataset.*

Description

A matrix containing simulated mRNA expression levels for 358 subjects (rows) and 500 features (columns).

Usage

X1

Format

An object of class `matrix` (inherits from `array`) with 358 rows and 500 columns.

X2 *A synthetic miRNA expression dataset.*

Description

A matrix containing simulated miRNA expression levels for 358 subjects (rows) and 100 features (columns).

Usage

X2

Format

An object of class `matrix` (inherits from `array`) with 358 rows and 100 columns.

Y

A synthetic phenotype dataset.

Description

A matrix containing simulated quantitative phenotype measures for 358 subjects (rows).

Usage

Y

Format

An object of class `matrix` (inherits from `array`) with 358 rows and 1 columns.

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