Package 'melonnpan'

February 14, 2023

Title Model-based Genomically Informed High- dimensional Predictor of Microbial Community Metabolite Profiles	
Version 0.99.0	
Date 2019-05-21	
Description MelonnPan is a computational method for predicting metabolite compositions from crobiome sequencing data. It uses elastic net regularization to infer which sequencing features are predictive and combines these features to estimate the composite metabolome.	
$ \textbf{Depends} \ \ R \ (>= 3.6.0), \ plyr, \ dplyr, \ glmnet, \ for each, \ getopt, \ doParallel, \ vegan, \ data.table, \ ggplosocTests, \ optparse, \ tibble $	t2, As-
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CV.ENET

ArcSin

Arc Sine Square Root Transformation for Proportional Data

Description

This function applies arcsine square root transformation to proportional data.

Usage

```
ArcSin(x)
```

Arguments

Х

A numerical vector of proportions (must be between 0 and 1).

See Also

SqSin

Examples

```
ArcSin(runif(100,0,1))
```

CV.ENET

Fit a regularized linear model

Description

Fit a regularized linear model

Usage

```
CV.ENET(
  metab = metab,
  metag = metag,
  alpha = alpha,
  lambda.choice = lambda.choice,
  nfolds = nfolds,
  foldid = foldid,
  verbose = verbose,
  plot = plot,
  outputDirectory = outputDirectory
)
```

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Arguments

metab Training data of metabolite relative abundances. Should have the exact same

rows (subjects/samples) as metag.

metag Training data of microbial sequence features' relative abundances. Should have

the exact same rows (subjects/samples) as metab.

alpha Grid of alpha values between 0 and 1. Default is 'seq(0.05, 0.95, 0.05)'.

lambda.choice Choice of optimal lambda ('lambda.min' or 'lambda.lse'). Default is 'lambda.lse'.

nfolds Number of folds for internal cross-validation. Default is 10.

foldid A vector of values between 1 and nfold identifying what fold each observation

is in.

verbose Should progress bar be printed. Default is TRUE.

plot Should CV error as a function of lambda be plotted. Default is FALSE.

outputDirectory

Name of the desired output directory.

generateLambdaPlot

Plot CV Error As A Function of Lambda

Description

This function plots the CV error as a function of lambda from Elastic Net Training.

Usage

```
generateLambdaPlot(CV, x, alpha, outputDirectory)
```

Arguments

CV A glmnet object.

x Index of glmnet fit.

alpha Optimal alpha selected.

outputDirectory

Name of the desired output directory. Default is the current directory.

melonnpan.predict Model-based Genomically Informed High-dimensional Predictor of

Microbial Community Metabolite Profiles

Description

Predict metabolites from new microbiome samples.

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Usage

```
melonnpan.predict(
  metag,
  output,
  no.transform.metab = FALSE,
  no.transform.metag = FALSE,
  weight.matrix = NULL,
  train.metag = NULL,
  criticalpoint = 0.9793,
  corr.method = "pearson"
)
```

Arguments

metag Microbial sequence features' relative abundances (matrix) for which prediction

is desired. The sequence features' abundances are expected to be normalized.

output The output folder to write results.

no.transform.metab

Should back transformation be turned off for predicted metabolites? Default is FALSE. If FALSE, it is expected that the proportional data ranging from 0 to 1 was used for training.

no.transform.metag

Should rank-based inverse normal (RIN) transformation be turned off for 'metag'? Default is FALSE.

weight.matrix

The weight matrix to be used for prediction (optional). If not provided, by default, a pre-trained weight matrix based on UniRef90 gene families from the original MelonnPan paper (Mallick et al, 2019) will be used.

train.metag

Quality-controlled training metagenomes against which similarity is desired (optional). The sequence features' abundances are expected to be normalized. If not provided, a pre-processed UniRef90 gene family training table from the original MelonnPan paper (Mallick et al. 2019) will be used.

criticalpoint

A numeric value corresponding to the significance level to find the top PCs. If the significance level is 0.05, 0.01, 0.005, or 0.001, the criticalpoint should be set to be 0.9793, 2.0234, 2.4224, or 3.2724, accordingly. The default is 0.9793 (i.e. 0.05 significance level).

corr.method

Method to correlate new metagenomes and training PCs. Default is 'pearson'.

melonnpan.summarize

Summarize MelonnPan results

Description

This function returns prediction accuracy from a pair of measured and predicted metabolites tables.

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Usage

```
melonnpan.summarize(
  metab = metab,
  pred = pred,
  method = method,
  correction = correction,
  cutoff = cutoff
)
```

Arguments

Measured metabolite relative abundances (normalized). Should have same feametab tures and samples as pred. pred

Predicted metabolite relative abundances (normalized). Should have same fea-

tures and samples as metab.

method Method to correlate measured and predicted metabolites. Default is 'spearman'.

Multiplicity adjustment method, same as 'p.adjust'. Default is 'fdr'. correction

cutoff Q-value threshold for significant prediction. Default is 0.05.

Normalized gene family abundances in the NLIBD dataset (Franzosa melonnpan.test.data et al., 2019).

Description

Normalized gene family abundance used for MelonnPan validation (Mallick et al., 2019).

Usage

```
data(melonnpan.test.data)
```

Format

A data frame of normalized gene familty abundances, as described in Mallick et al. (2019), with subjects in rows and UniRef90 IDs in columns.

References

Franzosa EA et al. (2019). Gut microbiome structure and metabolic activity in inflammatory bowel disease. Nature Microbiology 4(2):293-305.

Mallick H, Franzosa EA, McIver LJ, Banerjee S, Sirota-Madi A, Kostic AD, Clish CB, Vlamakis H, Xavier R, Huttenhower C (2019). Predictive metabolomic profiling of microbial communities using amplicon or metagenomic sequences. Nature Communications 10(1):3136-3146.

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melonnpan.train	Model-based Genomically Informed High-dimensional Predictor of Microbial Community Metabolite Profiles
	Microviai Community Metabotile Profiles

Description

Predict metabolites from microbial sequence features' abundances. Both measurements are expected to be normalized before using MelonnPan.

Usage

```
melonnpan.train(
  metab,
  metag,
  output,
  alpha = seq(0.05, 0.95, 0.05),
  lambda.choice = "lambda.1se",
  nfolds = 10,
  correction = "fdr",
  method = "spearman",
  cores = 4,
  seed = 1234,
  cutoff = 0.05,
  verbose = TRUE,
  no.transform.metab = FALSE,
  no.transform.metag = FALSE,
  discard.poor.predictions = FALSE,
  plot = FALSE,
  outputString = c("MelonnPan_Training_Summary", "MelonnPan_Trained_Weights",
    "MelonnPan_Trained_Metabolites")
)
```

Arguments

metab	Training data of metabolite relative abundances (normalized). Must have the exact same rows (subjects/samples) as metag.
metag	Training data of metagenomics sequence features' relative abundances (normalized). Must have the exact same rows (subjects/samples) as metab.
output	The output folder to write results.
alpha	Grid of alpha values between 0 and 1. Default is 'seq(0.05, 0.95, 0.05)'.
lambda.choice	Choice of optimal lambda ('lambda.min' or 'lambda.1se'). Default is 'lambda.1se'.
nfolds	Number of folds for internal cross-validation. Default is 10.
correction	Multiplicity adjustment method, same as 'p.adjust'. Default is 'fdr'.
method	Method to correlate measured and predicted metabolites ('spearman' or 'pearson'). Default is 'spearman'.
cores	Number of cores to use for parallel processing. Default is 4.
seed	Specify the arbitrary seed value for reproducibility. Default is 1234.
cutoff	Q-value threshold for significant prediction. Default is 0.05.

verbose Should detalied message be printed. Default is TRUE.

no.transform.metab

Should arcsine square root transformation (AST) be turned off for 'metab'? Default is FALSE. If FALSE, 'metab' must be proportional data ranging from 0 to 1.

no.transform.metag

Should rank-based inverse normal (RIN) transformation be turned off for 'metag'? Default is FALSE.

discard.poor.predictions

Should predictions with model size = 1 be discarded? Default is FALSE.

plot Should CV error as a function of lambda be plotted. Default is FALSE.

 $output String \qquad Names \ of \ the \ three \ output \ files. \ Default \ is \ 'Melonn Pan_Training_Summary',$

'MelonnPan_Trained_Weights', and 'MelonnPan_Trained_Metabolites'.

melonnpan.trained.model

Weights from a pre-trained MelonnPan model in the PRISM dataset (Franzosa et al., 2019).

Description

Weight matrix (or model coefficients) based on MelonnPan training in the PRISM dataset (Franzosa et al., 2019).

Usage

data(melonnpan.trained.model)

Format

A data frame of model coefficients from a pre-trained MelonnPan model, as described in Mallick et al. (2019), with 814 UniRef90 IDs (excluding the intercept) and 80 well-predicted metabolites (unique, labeled).

References

Franzosa EA et al. (2019). Gut microbiome structure and metabolic activity in inflammatory bowel disease. Nature Microbiology 4(2):293-305.

Mallick H, Franzosa EA, McIver LJ, Banerjee S, Sirota-Madi A, Kostic AD, Clish CB, Vlamakis H, Xavier R, Huttenhower C (2019). Predictive metabolomic profiling of microbial communities using amplicon or metagenomic sequences. Nature Communications 10(1):3136-3146.

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```
melonnpan.training.data
```

Normalized gene family abundances in the PRISM dataset (Franzosa et al., 2019).

Description

Normalized gene family abundance used for MelonnPan training (Mallick et al., 2019).

Usage

```
data(melonnpan.training.data)
```

Format

A data frame of normalized gene familty abundances, as described in Mallick et al. (2019), with subjects in rows and UniRef90 IDs in columns.

References

Franzosa EA et al. (2019). Gut microbiome structure and metabolic activity in inflammatory bowel disease. Nature Microbiology 4(2):293-305.

Mallick H, Franzosa EA, McIver LJ, Banerjee S, Sirota-Madi A, Kostic AD, Clish CB, Vlamakis H, Xavier R, Huttenhower C (2019). Predictive metabolomic profiling of microbial communities using amplicon or metagenomic sequences. Nature Communications 10(1):3136-3146.

melonnpan.visualize

Visualization of Significant Results.

Description

This function produces scatter plots for significantly predicted compounds.

This function produces scatter plots for significantly predicted compounds.

Usage

```
melonnpan.visualize(
  metab,
  pred,
  cohenCorrelationCutoff,
  Output_file,
  ncol = 2,
  nrow = 2
)

melonnpan.visualize(
  metab,
  pred,
  cohenCorrelationCutoff,
```

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```
Output_file,
ncol = 2,
nrow = 2
```

Arguments

metab Measured normalized metabolite relative abundances. Should have same fea-

tures and samples as pred.

pred Predicted normalized metabolite relative abundances. Should have same fea-

tures and samples as metab.

cohenCorrelationCutoff

Correlation threshold for significant prediction. Default is 0.3.

Output_file Path to the file to write the output.

ncol Number of columns in batch scatter plot. Default is 2. nrow Number of rows in batch scatter plot. Default is 2.

readTable

Read data using a wrapper of data.table

Description

This function reads the input data using the data.table package but returns a matrix with row names (unlike fread).

Usage

```
readTable(Input)
```

Arguments

Input Full path of the input data.

rntransform

Rank-based inverse normal tranformation

Description

This function rank normal transforms a vector of data. The procedure is built off of that provided in the GenABEL pacakge.

Usage

```
rntransform(y, split_ties = FALSE)
```

Arguments

y a numeric vector which will be rank normal transformed

 ${\tt split_ties} \qquad {\tt a \ binary \ string \ of \ FALSE \ (default) \ or \ TRUE \ indicating \ if \ tied \ values, \ of \ the \ same}$

rank, should be randomly split giving them unique ranks.

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Value

returns a numeric vector, with the same length as y, of rank normal transformed values

Examples

```
## simulate a negative binomial distribution of values
nb_data = rnbinom(500, mu = 40, size = 100)
## rank normal transform those values
rnt_data = rntransform( nb_data , split_ties = TRUE )
```

SqSin

Back Transformation of Predicted Values from A Statistical Model with ArcSine Square Root Transformed Compositional Response Variable

Description

This function applies back transformation to the predicted values of a statistical model with arcsine square root transformed compositional response variable.

Usage

```
SqSin(x, adjust = TRUE)
```

Arguments

A numerical vector of arcsine square root transformed compositions or proportions.
 adjust Should values less than 0 be mapped to 0 and values greater than pi/2 be mapped to 1? Defaults to TRUE.

See Also

ArcSin

Examples

```
# This is a simple demonstration
y <- ArcSin(runif(100,0,1))
x <- rnorm(100,0,1)
z <- predict(lm(y ~ x))
SqSin(z)</pre>
```

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