Package 'zenith'

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Type Package

Title Gene set analysis following differential expression using linear (mixed) modeling with dream

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Description Zenith performs gene set analysis on the result of differential expression using linear (mixed) modeling with dream by considering the correlation between gene expression traits. This package implements the camera method from the limma package proposed by Wu and Smyth (2012). Zenith is a simple extension of camera to be compatible with linear mixed models implemented in variancePartition::dream().

VignetteBuilder knitr

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BugReports https://github.com/DiseaseNeuroGenomics/zenith/issues

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Author Gabriel Hoffman [aut, cre] (ORCID:
<https://orcid.org/0000-0002-0957-0224>)

Maintainer Gabriel Hoffman <gabriel.hoffman@mssm.edu>

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`.rankSumTestWithCorrelation`
Two Sample Wilcoxon-Mann-Whitney Rank Sum Test Allowing For Correlation

---

Description

Same as `limma::.rankSumTestWithCorrelation`, but returns effect size.

Usage

```
.rankSumTestWithCorrelation(index, statistics, correlation = 0, df = Inf)
```

Arguments

`index`	any index vector such that `statistics[index]` contains the values of the statistic for the test group.
`statistics`	numeric vector giving values of the test statistic.
`correlation`	numeric scalar, average correlation between cases in the test group. Cases in the second group are assumed independent of each other and other the first group.
`df`	degrees of freedom which the correlation has been estimated.

Details

See `limma::.rankSumTestWithCorrelation`

Value

data.frame storing results of hypothesis test

`corInGeneSet` *Evaluate mean correlation between residuals in gene set*

Description

Evaluate mean correlation between residuals in gene set based on results from dream

Usage

```
corInGeneSet(fit, idx, squareCorr = FALSE)
```

Arguments

`fit`	result of differential expression with dream
`idx`	indeces or rownames to extract
`squareCorr`	compute the mean squared correlation instead

Value

list storing correlation and variance inflation factor

`get_GeneOntology` *Load Gene Ontology genesets*

Description

Load Gene Ontology genesets

Usage

```
get_GeneOntology(
  onto = c("BP", "MF", "CC"),
  to = "ENSEMBL",
  includeOffspring = TRUE,
  org = "hsa"
)
```

Arguments

onto	array of categories to load
to	convert gene names to this type using EnrichmentBrowser::idMap(). See EnrichmentBrowser::idTypes(org="hsa") for valid types
includeOffspring	if TRUE, follow the GO hierarchy down and include all genes in offspring sets for a given gene set
org	organism. human ('hsa'), mouse ('mmu'), etc

Details

This function loads the GO gene sets using the packages EnrichmentBrowser and GO.db It can take a mintute to load because converting gene name type is slow.

Value

Gene sets stored as GeneSetCollection

Examples

```
# load GO Biological Process
# gs = get_GeneOntology('BP')

# load all gene sets
# gs = get_GeneOntology()
```

---

get_MSigDB *Load MSigDB genesets*

Description

Load MSigDB genesets

Usage

```
get_MSigDB(
  cat,
  to = c("ENSEMBL", "SYMBOL", "ENTREZ"),
  organism = c("HS", "MM")
)
```

Arguments

cat	array of categories to load.
to	return genes names as 'ENSEMBL' or 'SYMBOL'
organism	organism: human ('HS') or mouse ('MS')

Details

This function loads the MSigDB gene sets using the packages and `msigdbr`. It can take a mintute to load because converting gene name type is slow.

Value

Gene sets stored as GeneSetCollection

Examples

```
# load Hallmark gene sets
gs = get_MSigDB('H')

# load all gene sets
# gs = get_MSigDB()
```

---

plotZenithResults *Heatmap of zenith results using ggplot2*

Description

Heatmap of zenith results showing genesets that have the top and bottom t-statistics from each assay.

Usage

```
plotZenithResults(
  df,
  ntop = 5,
  nbottom = 5,
  label.angle = 45,
  zmax = NULL,
  transpose = FALSE,
  sortByGeneset = TRUE
)
```

Arguments

`df`	result `data.frame` from zenith_gsa
`ntop`	number of gene sets with highest t-statistic to show
`nbottom`	number of gene sets with lowest t-statistic to show
`label.angle`	angle of x-axis label
`zmax`	maxium of the color scales. If not specified, used range of the observed t-statistics
`transpose`	transpose the axes of the plot
`sortByGeneset`	use hierarchical clustering to sort gene sets. Default is TRUE

Value

Heatmap showing enrichment for gene sets and cell types

Examples

```
# Load packages
library(edgeR)
library(variancePartition)
library(tweeDEseqCountData)

# Load RNA-seq data from LCL's
data(pickrell)
geneCounts = exprs(pickrell.eset)
df_metadata = pData(pickrell.eset)

# Filter genes
# Note this is low coverage data, so just use as code example
dsgn = model.matrix(~ gender, df_metadata)
keep = filterByExpr(geneCounts, dsgn, min.count=5)

# Compute library size normalization
dge = DGEList(counts = geneCounts[keep,])
dge = calcNormFactors(dge)

# Estimate precision weights using voom
vobj = voomWithDreamWeights(dge, ~ gender, df_metadata)

# Apply dream analysis
fit = dream(vobj, ~ gender,df_metadata)
fit = eBayes(fit)

# Load Hallmark genes from MSigDB
# use gene 'SYMBOL', or 'ENSEMBL' id
# use get_GeneOntology() to load Gene Ontology
gs = get_MSigDB("H", to="ENSEMBL")

# Run zenith analysis
res.gsa = zenith_gsa(fit, gs, 'gendermale', progressbar=FALSE )

# Show top gene sets
head(res.gsa, 2)

# for each cell type select 3 genesets with largest t-statistic
# and 1 geneset with the lowest
# Grey boxes indicate the gene set could not be evaluted because
#    to few genes were represented
plotZenithResults(res.gsa)
```

`zenith` *Gene set analysis following differential expression with dream*

Description

Perform gene set analysis on the result of differential expression using linear (mixed) modeling with `variancePartition::dream` by considering the correlation between gene expression traits. This package is a slight modification of `limma::camera` to 1) be compatible with dream, and 2) allow identification of gene sets with log fold changes with mixed sign.

Usage

```
zenith(
  fit,
  coef,
  index,
  use.ranks = FALSE,
  allow.neg.cor = FALSE,
  progressbar = TRUE,
  inter.gene.cor = 0.01
)
```

Arguments

`fit`	result of differential expression with dream
`coef`	coefficient to test using `topTable(fit, coef)`
`index`	an index vector or a list of index vectors. Can be any vector such that `fit[index,]` selects the rows corresponding to the test set. The list can be made using `ids2indices`.
`use.ranks`	do a rank-based test (`TRUE`) or a parametric test ('FALSE')?
`allow.neg.cor`	should reduced variance inflation factors be allowed for negative correlations?
`progressbar`	if TRUE, show progress bar
`inter.gene.cor`	if NA, estimate correlation from data. Otherwise, use specified value

Details

`zenith` gives the same results as `camera(..., inter.gene.cor=NA)` which estimates the correlation with each gene set.

For differential expression with dream using linear (mixed) models see Hoffman and Roussos (2020). For the original camera gene set test see Wu and Smyth (2012).

Value

- NGenes: number of genes in this set
- Correlation: mean correlation between expression of genes in this set
- delta: difference in mean t-statistic for genes in this set compared to genes not in this set
- se: standard error of delta
- p.less: p-value for hypothesis test of H0: delta < 0
- p.greater: p-value for hypothesis test of H0: delta > 0
- PValue: p-value for hypothesis test H0: delta != 0
- Direction: direction of effect based on sign(delta)
- FDR: false discovery rate based on Benjamini-Hochberg method in p.adjust

References

Hoffman, G. E., & Roussos, P. (2021). Dream: powerful differential expression analysis for repeated measures designs. Bioinformatics, 37(2), 192-201.

Wu, Di, and Gordon K. Smyth. "Camera: a competitive gene set test accounting for inter-gene correlation." Nucleic acids research 40.17 (2012): e133-e133.

Examples

```
library(variancePartition)

# simulate meta-data
info <- data.frame(Age=c(20, 31, 52, 35, 43, 45),Group=c(0,0,0,1,1,1))

# simulate expression data
y <- matrix(rnorm(1000*6),1000,6)
rownames(y) = paste0("gene", 1:1000)
colnames(y) = rownames(info)

# First set of 20 genes are genuinely differentially expressed
index1 <- 1:20
y[index1,4:6] <- y[index1,4:6]+1

# Second set of 20 genes are not DE
index2 <- 21:40

# perform differential expression analysis with dream
fit = dream(y, ~ Age + Group, info)
fit = eBayes(fit)

# perform gene set analysis testing Age
res = zenith(fit, "Age", list(set1=index1,set2=index2) )

head(res)
```

zenithPR_gsa *Gene set analysis using pre-computed test statistic*

Description

Perform gene set analysis on the result of a pre-computed test statistic. Test whether statistics in a gene set are larger/smaller than statistics not in the set.

Usage

```
zenithPR_gsa(
  statistics,
  ids,
  geneSets,
  use.ranks = FALSE,
  n_genes_min = 10,
  progressbar = TRUE,
  inter.gene.cor = 0.01,
  coef.name = "zenithPR"
)
```

Arguments

statistics	pre-computed test statistics
ids	name of gene for each entry in statistics
geneSets	GeneSetCollection
use.ranks	do a rank-based test TRUE or a parametric test FALSE? default: FALSE
n_genes_min	minumum number of genes in a geneset
progressbar	if TRUE, show progress bar
inter.gene.cor	correlation of test statistics with in gene set
coef.name	name of column to store test statistic

Details

This is the same as zenith_gsa(), but uses pre-computed test statistics. Note that zenithPR_gsa() may give slightly different results for small samples sizes, if zenithPR_gsa() is fed t-statistics instead of z-statistics.

Value

- NGenes: number of genes in this set
- Correlation: mean correlation between expression of genes in this set
- delta: difference in mean t-statistic for genes in this set compared to genes not in this set
- se: standard error of delta

- p.less: p-value for hypothesis test of H0: delta < 0
- p.greater: p-value for hypothesis test of H0: delta > 0
- PValue: p-value for hypothesis test H0: delta != 0
- Direction: direction of effect based on sign(delta)
- FDR: false discovery rate based on Benjamini-Hochberg method in p.adjust
- coef.name: name for pre-computed test statistics. Default: zenithPR

See Also

zenith_gsa(), limma::cameraPR()

Examples

```
# Load packages
library(edgeR)
library(variancePartition)
library(tweeDEseqCountData)

# Load RNA-seq data from LCL's
data(pickrell)
geneCounts = exprs(pickrell.eset)
df_metadata = pData(pickrell.eset)

# Filter genes
# Note this is low coverage data, so just use as code example
dsgn = model.matrix(~ gender, df_metadata)
keep = filterByExpr(geneCounts, dsgn, min.count=5)

# Compute library size normalization
dge = DGEList(counts = geneCounts[keep,])
dge = calcNormFactors(dge)

# Estimate precision weights using voom
vobj = voomWithDreamWeights(dge, ~ gender, df_metadata)

# Apply dream analysis
fit = dream(vobj, ~ gender, df_metadata)
fit = eBayes(fit)

# Load Hallmark genes from MSigDB
# use gene 'SYMBOL', or 'ENSEMBL' id
# use get_GeneOntology() to load Gene Ontology
gs = get_MSigDB("H", to="ENSEMBL")

# Run zenithPR analysis with a test statistic for each gene
tab = topTable(fit, coef='gendermale', number=Inf)

res.gsa = zenithPR_gsa(tab$t, rownames(tab), gs)
```

zenith_gsa *Perform gene set analysis using zenith*

Description

Perform a competitive gene set analysis accounting for correlation between genes.

Usage

```
zenith_gsa(
  fit,
  geneSets,
  coefs,
  use.ranks = FALSE,
  n_genes_min = 10,
  inter.gene.cor = 0.01,
  progressbar = TRUE,
  ...
)

## S4 method for signature 'MArrayLM,GeneSetCollection'
zenith_gsa(
  fit,
  geneSets,
  coefs,
  use.ranks = FALSE,
  n_genes_min = 10,
  inter.gene.cor = 0.01,
  progressbar = TRUE,
  ...
)
```

Arguments

fit	results from dream()
geneSets	GeneSetCollection
coefs	list of coefficients to test using topTable(fit, coef=coefs[[i]])
use.ranks	do a rank-based test TRUE or a parametric test FALSE? default: FALSE
n_genes_min	minumum number of genes in a geneset
inter.gene.cor	if NA, estimate correlation from data. Otherwise, use specified value
progressbar	if TRUE, show progress bar
...	other arguments

Details

This code adapts the widely used `camera()` analysis (Wu and Smyth, 2012) in the `limma` package (Ritchie, et al. 2015) to the case of linear (mixed) models used by `variancePartition::dream()`.

Value

`data.frame` of results for each gene set and cell type

References

Wu, Di, and Gordon K. Smyth. "Camera: a competitive gene set test accounting for inter-gene correlation." Nucleic acids research 40.17 (2012): e133-e133.

Ritchie, M. E., Phipson, B., Wu, D. I., Hu, Y., Law, C. W., Shi, W., & Smyth, G. K. (2015). limma powers differential expression analyses for RNA-sequencing and microarray studies. Nucleic acids research, 43(7), e47-e47.

See Also

`limma::camera`

Examples

```
# Load packages
library(edgeR)
library(variancePartition)
library(tweeDEseqCountData)

# Load RNA-seq data from LCL's
data(pickrell)
geneCounts = exprs(pickrell.eset)
df_metadata = pData(pickrell.eset)

# Filter genes
# Note this is low coverage data, so just use as code example
dsgn = model.matrix(~ gender, df_metadata)
keep = filterByExpr(geneCounts, dsgn, min.count=5)

# Compute library size normalization
dge = DGEList(counts = geneCounts[keep,])
dge = calcNormFactors(dge)

# Estimate precision weights using voom
vobj = voomWithDreamWeights(dge, ~ gender, df_metadata)

# Apply dream analysis
fit = dream(vobj, ~ gender, df_metadata)
fit = eBayes(fit)

# Load Hallmark genes from MSigDB
# use gene 'SYMBOL', or 'ENSEMBL' id
# use get_GeneOntology() to load Gene Ontology
```

```
gs = get_MSigDB("H", to="ENSEMBL")

# Run zenith analysis
res.gsa = zenith_gsa(fit, gs, 'gendermale', progressbar=FALSE )

# Show top gene sets
head(res.gsa, 2)

# for each cell type select 3 genesets with largest t-statistic
# and 1 geneset with the lowest
# Grey boxes indicate the gene set could not be evaluted because
#    to few genes were represented
plotZenithResults(res.gsa)
```

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