The RTopper package: perform run Gene Set Enrichment across genomic platforms

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1 Overview

Gene Set Enrichment (GSE) analysis has been widely use to assist the interpretation of gene expression data. We propose here to apply GSE for the integration of genomic data obtained from distinct analytical platform.

In the present implementation of the RTopper GSE analysis is performed using the geneSetTest function from the limma package [6]. This function enables testing the hypothesis that a specific set of genes (a Functional Gene Set, FGS) is more highly ranked on a given statistics.
particular this functions computes a p-value for each FGS by one or two-sided Wilcoxon rank-sum test. Alternative user-defined functions can also be used.

Furthermore multiple hypothesis testing correction is achieved by applying the Benjamini and Hochberg method [2] as implemented in the multtest R/Bioconductor package. Overall, this approach is conceptually analogous to Gene Set Enrichment Analysis (GSEA), as proposed by Mootha and colleagues [4, 8].

The integration can be achieved through two distinct approaches:

1. **GSE + INTEGRATION**: Separate GSE analysis on the individual genomic platforms followed by GSE results integration;

2. **INTEGRATION + GSE**: Integration of genomic data measurement using a logistic model followed by GSE analysis;

## 2 RTopper data structure

In this tutorial we demonstrate the functionality of RTopper package. To this end we will make use of simplified data generated within The Cancer Genome Atlas (TCGA) project, using Glioblastoma Multiforme (GBM) genomics data obtained from the same patients’ cohort using distinct platforms, including Differential Gene Expression (DGE), Copy Number Variation (CNV), and Differential Methylation (DM). This data is included with the RTopper package as the dataset **exampleData**, which consists of genomic measurements (the list *dat*) for 500 genes (in rows) and 95 patients (in columns) from 4 distinct platforms:

1. DGE obtained using Affymetrix;
2. DGE obtained using Agilent;
3. CNV data generated ad Harvard;
4. CNV data generated ad the MSKCC;

The phenotypic class for each patient is defined in the a data.frame **pheno** consisting of 95 rows (patients, **pheno$Sample**) and 2 columns, the first being patients identifiers, and the second variable giving the group indicator (**pheno$Class**).

To load the data set type `data(exampleData)`, and to view a description of this data type `?exampleData`. The structure of the data is shown below:

```r
> library(RTopper)
> data(exampleData)
> ls()
[1] "dat"   "pheno"

> class(dat)
[1] "list"

> names(dat)
[1] "dat.affy"   "dat.agilent"
[3] "dat.cnvHarvard" "dat.cnvMskcc"
```
In summary to perform the analysis with functions from RTopper the genomic data used as input must be in the following format:

1. **Genomic measurements**: a list of data.frames, in which each list item corresponds to a genomic platform, and comprises a data.frame with rows being genes and columns patients;

2. **Phenotype data**: a data.frame with 2 columns: patients and their phenotypes;

3. The number of columns of the Genomic measurements data.frames must match the number of rows of the Phenotype data;

4. The same set of genes must be measured in each platform and gene labels must be stored as rownames;

Below are shown the first 6 rows and 4 columns of each data.frame contained in dat, which share the same genes (shown for some of the possible combinations). Similarly column names in the dat data.frames correspond to rownames of pheno.
$dat.agilent

TCGA.02.0003 TCGA.02.0007 TCGA.02.0011
AACS  -1.0070000 -1.1164000 -0.913000
AARS  -1.2665000 -0.8981250  0.263500
AB11  -0.2765000  0.3356250  1.027250
ACHE  0.4403750  0.1234615  1.046692
ACTC1 4.3348000  2.2278000  3.330600

$dat.cnvHarvard

TCGA.02.0003 TCGA.02.0007 TCGA.02.0011
AACS  -0.08273213 -0.08917331 -0.02075644
AARS  -0.10233281 -0.20620608 -0.05157664
AB11  -0.86886659 -0.01214599  0.59307754
ACHE  0.31560002 -1.00166150 -0.14519639
ACTC1 -1.17495078 -0.26698279 -0.95662761
ACTN2 -0.11319016 -0.09657971  0.02582138

$dat.cnvMskcc

TCGA.02.0003 TCGA.02.0007 TCGA.02.0011
AACS  -0.0383875  0.09140000  0.00823333
AARS  0.0075600  0.02801667  0.10485000
AB11  -0.7006900  0.21270000  0.49947272
ACHE  0.8676000  0.23970000  0.07500000
ACTC1 -0.9779500 -0.11625000 -0.69295000
ACTN2 -0.1258571 -0.05394444  0.01020000

> sum(rownames(dat[[1]])%in%rownames(dat[[2]]))
[1] 500

> sum(rownames(dat[[2]])%in%rownames(dat[[3]]))
[1] 500

2.1 Creation of Functional Gene Sets

Functional Gene Sets (FGS) are list of genes that share a specific biological function. Examples of FGS are genes that operate in the same signaling pathway (i.e. Notch signaling genes), or that share the same biological function (i.e. Cell adhesion genes). FGS can be retrieved from various database, or can be constructed ad hoc. A convenient source of FGS are the R-Bioconductor metaData packages, and S4 classes and methods for handling FGS are provided by the GSEABase package. Below is shown a simple way to extract FGS from the human genome metaData package org.Hs.eg.db. As a general rule the name of the metaData package, without the .db extension, can be used a function to see the content of the package, as shown below:

> library(org.Hs.eg.db)
> org.Hs.eg()
Quality control information for org.Hs.eg:

This package has the following mappings:

org.Hs.egACCNUM has 41992 mapped keys (of 60136 keys)
org.Hs.egACCNUM2EG has 835900 mapped keys (of 835900 keys)
org.Hs.egALIAS2EG has 120040 mapped keys (of 120040 keys)
org.Hs.egCHR has 59663 mapped keys (of 60136 keys)
org.Hs.egCHRLENGTHS has 455 mapped keys (of 455 keys)
org.Hs.egCHRLOC has 27198 mapped keys (of 60136 keys)
org.Hs.egCHRLOCEnd has 27198 mapped keys (of 60136 keys)
org.Hs.egENSEMBL has 25725 mapped keys (of 60136 keys)
org.Hs.egENSEMBL2EG has 28015 mapped keys (of 28015 keys)
org.Hs.egENSEMBLPROT has 7633 mapped keys (of 60136 keys)
org.Hs.egENSEMBLPROT2EG has 23645 mapped keys (of 23645 keys)
org.Hs.egENSEMBLTRANS has 8055 mapped keys (of 60136 keys)
org.Hs.egENSEMBLTRANS2EG has 36277 mapped keys (of 36277 keys)
org.Hs.egENZYMEO has 2230 mapped keys (of 60136 keys)
org.Hs.egENZYME2EG has 975 mapped keys (of 975 keys)
org.Hs.egGENENAME has 60136 mapped keys (of 60136 keys)
org.Hs.egGO has 18622 mapped keys (of 60136 keys)
org.Hs.egGO2ALLEGS has 21161 mapped keys (of 21161 keys)
org.Hs.egGO2EG has 16581 mapped keys (of 16581 keys)
org.Hs.egMAP has 39672 mapped keys (of 60136 keys)
org.Hs.egMAP2EG has 2290 mapped keys (of 2290 keys)
org.Hs.egOMIM has 15379 mapped keys (of 60136 keys)
org.Hs.egOMIM2EG has 20070 mapped keys (of 20070 keys)
org.Hs.egPATH has 5869 mapped keys (of 60136 keys)
org.Hs.egPATH2EG has 229 mapped keys (of 229 keys)
org.Hs.egPMID has 34115 mapped keys (of 60136 keys)
org.Hs.egPMID2EG has 514571 mapped keys (of 514571 keys)
org.Hs.egREFSEQ has 39484 mapped keys (of 60136 keys)
org.Hs.egREFSEQ2EG has 293128 mapped keys (of 293128 keys)
org.Hs.egSYMBOL has 60136 mapped keys (of 60136 keys)
org.Hs.egSYMBOL2EG has 60083 mapped keys (of 60083 keys)
org.Hs.egUCSCKG has 25217 mapped keys (of 60136 keys)
org.Hs.egUNIGENE has 26577 mapped keys (of 60136 keys)
org.Hs.egUNIGENE2EG has 29368 mapped keys (of 29368 keys)
org.Hs.egUNIPROT has 19241 mapped keys (of 60136 keys)

Additional Information about this package:

DB schema: HUMAN_DB
DB schema version: 2.1
Organism: Homo sapiens
Date for NCBI data: 2016-Sep26
Date for GO data: 2016-Sep21
Date for KEGG data: 2011-Mar15
Date for Golden Path data: 2016-Sep16
Date for Ensembl data: 2016-Jul19

For instance the \texttt{org.Hs.egGO2ALLEGS} environment contains the mapping of all ENTREZ Gene identifiers to the \textbf{Gene Ontology Terms} \cite{1}, while \texttt{org.Hs.egPATH2EG} maps the identifiers to \textbf{KEGG} pathways \cite{3}. The corresponding lists of FGS can be retrieve from the corresponding environments using the the R command \texttt{as.list()}, as shown below for KEGG and GO:

\begin{verbatim}
> kegg <- as.list(org.Hs.egPATH2EG)
> go   <- as.list(org.Hs.egGO2ALLEGS)
> length(kegg)
[1] 229
> length(go)
[1] 21161
> str(kegg[1:5])
List of 5
$ 04610: chr [1:69] "2" "462" "623" "624" ...
$ 00232: chr [1:7] "9" "10" "1544" "1548" ...
$ 00983: chr [1:52] "9" "10" "978" "1066" ...
$ 01100: chr [1:1130] "9" "10" "15" "18" ...
$ 00380: chr [1:42] "15" "26" "38" "39" ...
> names(kegg)[1:5]
[1] "04610" "00232" "00983" "01100" "00380"
> str(go[1:5])
List of 5
$ GO:00000002: Named chr [1:31] "142" "291" "1763" "3980" ...
..- attr(*, "names")= chr [1:31] "IMP" "TAS" "IDA" "IMP" ...
$ GO:00000003: Named chr [1:1536] "18" "49" "49" "49" ...
..- attr(*, "names")= chr [1:1536] "IEA" "IEA" "IMP" "ISS" ...
$ GO:00000011: Named chr "64145"
..- attr(*, "names")= chr "IBA"
$ GO:00000012: Named chr [1:10] "3981" "7014" "7141" "7515" ...
..- attr(*, "names")= chr [1:10] "IDA" "NAS" "IDA" "IEA" ...
$ GO:00000018: Named chr [1:66] "604" "641" "940" "958" ...
..- attr(*, "names")= chr [1:66] "IEA" "IMP" "IEA" "IEA" ...
> names(go)[1:5]
[1] "GO:00000002" "GO:00000003" "GO:00000011" 
[4] "GO:00000012" "GO:00000018"
\end{verbatim}

In the \texttt{kegg} list genes are identified by their ENTREZ Gene identifiers, while in the \texttt{dat} genes are identified by their Gene Symbol. Below is an example of the code that can be used to perform the identifiers conversion, using only a subset of KEGG and GO FGS:
> kegg <- lapply(kegg[sample(1:length(kegg),5)],function(x) unique(unlist(mget(x,org.Hs.egSYMBOL))))
> go <- lapply(go[sample(1:length(go),5)],function(x) unique(unlist(mget(x,org.Hs.egSYMBOL))))
> str(kegg)

List of 5
$ 05414: chr [1:90] "ACTB" "ACTC1" "ACTG1" "ADCY1" ...
$ 05310: chr [1:30] "CD40" "CD40LG" "FCER1A" "MS4A2" ...
$ 04666: chr [1:94] "AKT1" "AKT2" "AMPH" "ARF6" ...
$ 01100: chr [1:1130] "NAT1" "NAT2" "AANAT" "ABAT" ...
$ 04916: chr [1:101] "ADCY1" "ADCY2" "ADCY3" "ADCY5" ...

> str(go)

List of 5
$ GO:0032610: chr [1:7] "CASP1" "ISL1" "P2RX7" "S100A13" ...
$ GO:0000379: chr [1:3] "TSEN34" "TSEN2" "TSEN54"
$ GO:0043337: chr "CRLS1"
$ GO:0000469: chr [1:25] "RPSA" "EXOSC9" "RPS21" "NOP14" ...
$ GO:0006525: chr [1:19] "ARG1" "ARG2" "ART4" "ASL" ...

Finally, it is also possible to annotate FGS, mapping pathways identifiers to pathway names, as shown below for KEGG, using the KEGG.db.

> library(KEGG.db)
> KEGG()

Quality control information for KEGG:

This package has the following mappings:

KEGGENZYMEID2GO has 4178 mapped keys (of 4178 keys)
KEGGEXTID2PATHID has 75100 mapped keys (of 75100 keys)
KEGGGO2ENZYMEID has 5224 mapped keys (of 5224 keys)
KEGGPATHID2EXTID has 3152 mapped keys (of 3152 keys)
KEGGPATHID2NAME has 478 mapped keys (of 478 keys)
KEGGPATHNAME2ID has 478 mapped keys (of 478 keys)

Additional Information about this package:

DB schema: KEGG_DB
DB schema version: 2.1
Date for KEGG data: 2011-Mar15

> names(kegg) <- paste(names(kegg),unlist(mget(names(kegg),KEGGPATHID2NAME)),sep=".")

> names(kegg)
[1] "05414.Dilated cardiomyopathy"
[2] "05310.Asthma"
[3] "04666.Fc gamma R-mediated phagocytosis"
Similarly GO Terms can be retrieved from the GO.db (please refer to the vignettes of the corresponding packages for details).

```r
> library(GO.db)
> GO()
```

Quality control information for GO:

This package has the following mappings:

- **GOBGPANCESTOR** has 29022 mapped keys (of 29022 keys)
- **GOBPCHILDREN** has 17075 mapped keys (of 29022 keys)
- **GOBPOFFSPRING** has 17075 mapped keys (of 29022 keys)
- **GOBPPARENTS** has 29022 mapped keys (of 29022 keys)
- **GOCCANCESTOR** has 4014 mapped keys (of 4014 keys)
- **GOCCCHILDREN** has 1389 mapped keys (of 4014 keys)
- **GOCCOFFSPRING** has 1389 mapped keys (of 4014 keys)
- **GOCCPARENTS** has 4014 mapped keys (of 4014 keys)
- **GOMFANCESTOR** has 10297 mapped keys (of 10297 keys)
- **GOMFCHILDREN** has 2064 mapped keys (of 10297 keys)
- **GOMFFSPRING** has 2064 mapped keys (of 10297 keys)
- **GOMFPARENTS** has 10297 mapped keys (of 10297 keys)
- **GOOBSOLETE** has 2056 mapped keys (of 2056 keys)
- **GOTERM** has 43334 mapped keys (of 43334 keys)

Additional Information about this package:

- **DB schema**: GO_DB
- **DB schema version**: 2.1
- **Date for GO data**: 2016-Sep21

```r
> names(go) <- paste(names(go),Term(names(go)),sep=".")
> names(go)
```

[1] "GO:0032610.interleukin-1 alpha production"
[2] "GO:0000379.tRNA-type intron splice site recognition and cleavage"
[4] "GO:0000469.cleavage involved in rRNA processing"
[5] "GO:00006525arginine metabolic process"

Finally we can be combine the two FGS collections into a named list for further used in GSE analysis (see below).

```r
> fgsList <- list(go=go,kegg=kegg)
```
3 Data analysis with RTopper

To compute gene-to-phenotype association scores the first step required is the conversion of the data into a list, where each list item corresponds to a gene, and comprises a data.frame with the rows being patients, and columns being measurements for each data type, along with the class phenotype (the response). Importantly each element of the list with the data should have the same genes and patients.

The `convertToDr` function is used to make such conversion. Below is a short description of the arguments to this function:

- `dataIntersection`: a list of data.frames containing the same set of patients(columns) and genes (rows)
- `response`: a data.frame indicating patients' phenotypic class;
- `nPlatforms`: the number of platforms;

This can be achieved as follows using our examples data:

```r
> dataDr <- convertToDr(dat, pheno, 4)
> class(dataDr)
[1] "list"
> length(dataDr)
[1] 500
> names(dataDr)[1:5]
[1] "AACS" "AARS" "ABI1" "ACHE" "ACTC1"
> str(dataDr[1:2])

List of 2
$ AACS:<'data.frame': 95 obs. of 5 variables:
 ..$ dat.affy : num [1:95] 7.75 7.69 7.54 7.3 7.01 ...
 ..$ dat.agilent: num [1:95] -1.007 -1.116 -0.913 -1.061 -1.775 ...
 ..$ dat.cnvHarvard: num [1:95] -0.0827 -0.0892 -0.1811 -0.0625 ...
 ..$ dat.cnvMskcc : num [1:95] -0.03839 -0.0914 0.00823 0.03456 0.0573 ...
 ..$ response : int [1:95] 0 0 1 1 0 0 0 0 0 0 ...

$ AARS:<'data.frame': 95 obs. of 5 variables:
 ..$ dat.affy : num [1:95] 9.38 9.3 10.2 9.54 9.37 ...
 ..$ dat.agilent: num [1:95] -1.266 -0.898 0.264 -0.599 -1.437 ...
 ..$ dat.cnvHarvard: num [1:95] -0.1023 -0.2062 -0.0923 -0.1199 ...
 ..$ dat.cnvMskcc : num [1:95] 0.00756 0.02802 0.10485 0.0841 0.12262 ...
 ..$ response : int [1:95] 0 0 1 1 0 0 0 0 0 0 ...
```

It is now possible to compute gene-to-phenotype association scores, using as input the gene-centered list produced by `convertToDr`. Therefore the `computeDrStat` function assumes that each gene-centered data.frame contains a column (the last one) called `response`, as created by the `convertToDr`. Below is a short description of the arguments to this function:
• **data**: a list of data.frames, one for each gene analyzed, containing the genomic measurements from all platforms (by column) for all the patients (by row), along with the phenotypic response;

• **columns**: a numeric vector indicating column indexes corresponding the genomic measurements to be used for computing the gene-to-phenotype association scores; the default is `columns = c(1:(ncol(data) - 1))`, assuming the phenotypic response to be the last column;

• **method**: the method used to compute the association score;

• **integrate**: logical, whether an integrated gene-to-phenotype score should be computed, or separate scores for each platform/data sets specified by `columns`;

In the current implementation of the `RTopper` there are three methods for computing gene-to-phenotype association scores:

1. **dev**: this approach computes the score as the difference of deviances (as described in Tyekucheva et al, manuscript under review [9]);

2. **aic**: this approach computes the score as the Akaike information criterion for model selection;

3. **bic**: this approach computes the score as the penalized likelihood ratio;

### 3.1 Integrated Gene-to-Phenotype score computation

This approach first integrates genomic data across platform, and subsequently perform GSE to identify the FGS most strongly associated with the integrated score. Below is an example of application to compute the gene-to-phenotype association scores for 4 data type simultaneously:

```r
> bicStatInt <- computeDrStat(dataDr, columns = c(1:4), method="bic", integrate = TRUE)
> names(bicStatInt)
[1] "integrated"
> str(bicStatInt)
List of 1
..- attr(*, "names")= chr [1:500] "AACS" "AARS" "ABI1" "ACHE" ...
```

### 3.2 Separate Gene-to-Phenotype score computation

This approach first computes gene-to-phenotype score separately for each platform, uses the scores to perform separate GSE analysis in each platform for identifying the FGS most strongly associated with the score, and finally integrates the results from GSE analysis, Below is an example of this approach:

```r
> bicStatSep <- computeDrStat(dataDr, columns = c(1:4), method="bic", integrate = FALSE)
> names(bicStatSep)
[1] "dat.affy"    "dat.agilent"
[3] "dat.cnvHarvard" "dat.cnvMskcc"
```
> str(bicStatSep)

List of 4
$ dat.affy : Named num [1:500] 0.545 -4.269 -2.334 -4.471 -3.625 ...
  ..- attr(*, "names")= chr [1:500] "AACS" "AARS" "ABI1" "ACHE" ...
$ dat.agilent : Named num [1:500] -3.57 -4.5 -3.66 -4.52 -1.05 ...
  ..- attr(*, "names")= chr [1:500] "AACS" "AARS" "ABI1" "ACHE" ...
  ..- attr(*, "names")= chr [1:500] "AACS" "AARS" "ABI1" "ACHE" ...
$ dat.cnvMskcc : Named num [1:500] -4.53 -4.48 2.1 -2.55 -4.25 ...
  ..- attr(*, "names")= chr [1:500] "AACS" "AARS" "ABI1" "ACHE" ...

3.3 Gene Set Enrichment using integrated and separate score

After the gene-to-phenotype scores have been obtained it is possible to perform a GSE analysis. To this end we will use the `runBatchGSE` function, as shown below. This function enables to perform GSE analysis over multiple collections of FGS, and over multiple ranking statistics. In the current implementation of the `runBatchGSE` the default is performing the enrichment analysis using the `geneSetTest` function from the `limma` package, and most of the arguments passed to `runBatchGSE` are indeed passed to `geneSetTest` (see the relative help for the details).

As an alternative the user can also define his own function to test for FGS enrichment, passing the selection of genes within the FGS and the ranking ranking statistics in the same way as done for `geneSetTest`. In this tutorial we apply `geneSetTest` in order to perform a Wilcoxon rank-sum test, using the absolute value of the gene-to-phenotype scores as the ranking statistics.

> args(runBatchGSE)

function (dataList, fgsList, ...)
NULL

Below a short description of the arguments that can be passed to this function:

- **dataList**: a list containing gene-to-phenotype scores to be used as ranking statistics in the GSE analysis;
- **fgsList**: a list of FGS collection, in which each element is a list of character vectors, one for each gene set;
- ...: any other argument to be passed to lower level functions, including the lower level enrichment function to be used (like the `geneSetTest` function from the `limma` package, which is used as the default);
- **absolute**: logical specifying whether the absolute values of the ranking statistics should be used in the test (the default being TRUE);
- **gseFunc**: a function to perform GSE analysis, when not specified (the default) the `geneSetTest` from the `limma` package is used. When a function is specified, the membership of the analyzed genes to a FGS, and the ranking statistics must be defined in the same way this is done for `geneSetTest`, and the new function must return an integer (usually a p-value) (see the help for `geneSetTest` in the `limma` package).
Below are few examples to perform Wilcoxon rank-sum test over multiple FGS collections, and over multiple ranking statistics, using the runBatchGSE. To this end we will use the KEGG and GO collections created above, and the separate and integrated gene-to-phenotype scores computed using the computeDrStat. The output of this function is a named list of lists, containing an element for each ranking statistics considered in the input. Each one of these elements, in turn, is another list, containing the GSE results for each collection sets. In the examples below we will therefore obtain a list of length one in the case of the integrated gene-to-phenotype score, and a list of length four (on element for each genomic platform) in the case of the separate scores. For all the rankings we will obtain GSE result for both the collections of FGS.

### 3.4 INTEGRATION + GSE

The integrated gene-to-phenotype scores we have computed can be used to perform a GSE analysis. Below are reported few examples, using the default options, as well as passing several specific arguments to geneSetTest (see the relative help for details).

#### 3.4.1 One-sided Wilcoxon rank-sum test using absolute ranking statistics

This can be accomplished by calling the runBatchGSE with default values, or by specifying each argument, as shown below:

```r
> gseABS.int <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList)
> gseABS.int <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
  + absolute=TRUE, type="f", alternative="mixed")
```

#### 3.4.2 One-sided Wilcoxon rank-sum test using signed ranking statistics

When the signed ranking statistics has a sign, it is possible to perform a one-sided test assessing both tails separately, as well as a two-sided test. This can be accomplished by passing the corresponding arguments to runBatchGSE, as shown below:

```r
> gseUP.int <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
  + absolute=FALSE, type="t", alternative="up")
> gseDW.int <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
  + absolute=FALSE, type="t", alternative="down")
> gseBOTH.int <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
  + absolute=FALSE, type="t", alternative="either")
```

#### 3.4.3 Performing a simulation-based GSE test

It is also possible to perform an enrichment analysis comparing each FGS to randomly selected gene lists of the same size of the FGS. In this case the p-value is computed by simulation as the proportion of times the mean of the statistics in the FGS is smaller (or larger) than in the nsim random simulated sets of genes.

```r
> gseABSsim.int <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
  + absolute=TRUE, type="f", alternative="mixed",
```
> gseUPsim.int <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
+ absolute=FALSE, type="t", alternative="up",
+ ranks.only=FALSE, nsim=1000)

Results from this analysis are named lists of lists, as shown below:

> str(gseUP.int)
List of 1
 
$ integrated:List of 2
 ..$ go : Named num [1:5] NA NA NA 0.514 NA
 ....- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site recognition and cleavage" "GO:0043337.CDP-diacylglycerol-phosphatidylglycerol phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" "GO:0006525.arginine metabolic process"
 ..$ kegg: Named num [1:5] 0.456 NA 0.666 0.739 0.312

> gseABSsim.int

$integrated

$integrated$go

GO:0032610.interleukin-1 alpha production
NA
GO:0000379.tRNA-type intron splice site recognition and cleavage
NA
GO:0043337.CDP-diacylglycerol-phosphatidylglycerol phosphatidyltransferase activity
NA
GO:0000469.cleavage involved in rRNA processing
0.4605395
GO:0006525.arginine metabolic process
NA

$integrated$kegg

05414.Dilated cardiomyopathy
0.6063936
05310.Asthma
NA
04666.Fc gamma R-mediated phagocytosis
0.3886114
01100.Metabolic pathways
0.2597403
04916.Melanogenesis
0.7772228

3.4.4 Passing alternative enrichment functions to runBatchGSE

Below is show how to define and pass alternative enrichment functions to runBatchGSE. We will first show how to use the limma wilcoxGST function, which is a synonym for geneSetTest using ranks.only=TRUE and type="t".
library(limma)

gseUP.int.2 <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
   absolute=FALSE, gseFunc=wilcoxGST, alternative="up")

As shown below this approach will return the same results obtained with geneSetTest passing appropriate arguments.

> str(gseUP.int.2)

List of 1
  $ integrated:List of 2
   ..$ go : Named num [1:5] NA NA NA 0.514 NA
   .. ..- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site... phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" ...
   ..$ kegg: Named num [1:5] 0.456 NA 0.666 0.739 0.312
   .. ..- attr(*, "names")= chr [1:5] "05414.Dilated cardiomyopathy" "05310.Asthma" "04666.Fc gamma R-mediated phagocytosis" "01100.Metabolic pathways" ...

> all(gseUP.int.2$go==gseUP.int$go)

[1] TRUE

We can finally also pass any new user-defined enrichment function, provided that the arguments are passed in the same way as with geneSetTest, as shown below using the Fisher’s exact test, and a threshold for defining the list of differentially expressed genes.

> gseFunc <- function (selected, statistics, threshold) {
+   diffExpGenes <- statistics > threshold
+   tab <- table(diffExpGenes, selected)
+   pVal <- fisher.test(tab)[["p.value"]]
+ }

> gseUP.int.3 <- runBatchGSE(dataList=bicStatInt, fgsList=fgsList,
   absolute=FALSE, gseFunc=gseFunc, threshold=7.5)

As shown below this approach will test for over-representation of the a specific gene set within the genes defined as differentially expressed (in our example the genes showing an integrated association score larger than 7.5). Results are somewhat comparable to what obtained using the Wilcoxon rank-sum test.

> str(gseUP.int.3)

List of 1
  $ integrated:List of 2
   ..$ go : Named num [1:5] NA NA NA 1 NA
   .. ..- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site... phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" ...
   ..$ kegg: Named num [1:5] 1 NA 1 0.222 1
   .. ..- attr(*, "names")= chr [1:5] "05414.Dilated cardiomyopathy" "05310.Asthma" "04666.Fc gamma R-mediated phagocytosis" "01100.Metabolic pathways" ...

> data.frame(fisher=gseUP.int.3$integrated$kegg,wilcoxon=gseUP.int$integrated$kegg)

<table>
<thead>
<tr>
<th>fisher</th>
<th>wilcoxon</th>
</tr>
</thead>
<tbody>
<tr>
<td>05414.Dilated cardiomyopathy</td>
<td>1.0000000</td>
</tr>
<tr>
<td>05310.Asthma</td>
<td>NA</td>
</tr>
<tr>
<td>04666.Fc gamma R-mediated phagocytosis</td>
<td>1.0000000</td>
</tr>
<tr>
<td>01100.Metabolic pathways</td>
<td>0.2217196</td>
</tr>
<tr>
<td>04916.Melanogenesis</td>
<td>1.0000000</td>
</tr>
</tbody>
</table>
3.5 GSE + INTEGRATION

The individual gene-to-phenotype scores computed for each platform can be similarly used to perform separate GSE analyses for each considered genomic platform, applying the same code and functions used to perform GSE analysis in the INTEGRATION + GSE approach above.

```r
> gseABS.sep <- runBatchGSE(dataList=bicStatSep, fgsList=fgsList)
```

This step of GSE analysis on separate platform is then followed by GSE results integration, which is achieved using the `combineGSE` function, which summarizes the individual p-values from the tests. To this end different methods are available, including the computation of the geometric or arithmetic means, the use of the median, the selection of the minimum or the maximum p-value, and the random selection (respectively `geometricMean`, `mean`, `median`, `min`, `max`, and `random`). Few examples are shown below:

```r
> gseABS.geoMean.sep <- combineGSE(gseABS.sep, method="geometricMean")
> gseABS.max.sep <- combineGSE(gseABS.sep, method="max")
```

Also in this case the results from the combination are named lists of lists, as shown below:

```r
> names(gseABS.sep)
[1] "dat.affy"     "dat.agilent"
[3] "dat.cnvHarvard" "dat.cnvMskcc"
```

```r
> str(gseABS.sep)
List of 4

$ dat.affy :List of 2
  ..$ go : Named num [1:5] NA NA NA 0.901 NA
     .. ..- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site... phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" "GO:0000468.posttranslational cleavage of pre-rRNA" "GO:0000470.cleavage involved in rRNA processing"
  ..$ kegg: Named num [1:5] 0.292 NA 0.177 0.344 0.294

$ dat.agilent :List of 2
  ..$ go : Named num [1:5] NA NA NA 0.86 NA
     .. ..- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site... phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" "GO:0000468.posttranslational cleavage of pre-rRNA" "GO:0000470.cleavage involved in rRNA processing"
  ..$ kegg: Named num [1:5] 0.5805 NA 0.5931 0.6151 0.0549

$ dat.cnvHarvard:List of 2
  ..$ go : Named num [1:5] NA NA NA 0.0952 NA
     .. ..- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site... phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" "GO:0000468.posttranslational cleavage of pre-rRNA" "GO:0000470.cleavage involved in rRNA processing"
  ..$ kegg: Named num [1:5] 0.336 NA 0.154 0.112 0.59

$ dat.cnvMskcc :List of 2
```
..$ go: Named num [1:5] NA NA NA 0.686 NA
  ..- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site recognition and cleavage" "GO:0043337.CDP-diacylglycerol-phosphatidylglycerol phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" "GO:0006525.arginine metabolic process"

..$ kegg: Named num [1:5] 0.0699 NA 0.2272 0.0306 0.6718

> str(gseABS.geoMean.sep)

List of 1
$ combinedScore:List of 2
  ..$ go: Named num [1:5] NA NA NA 0.474 NA
    ..- attr(*, "names")= chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site recognition and cleavage" "GO:0043337.CDP-diacylglycerol-phosphatidylglycerol phosphatidyltransferase activity" "GO:0000469.cleavage involved in rRNA processing" "GO:0006525.arginine metabolic process"
  ..$ kegg: Named num [1:5] 0.251 NA 0.246 0.164 0.283

> gseABS.geoMean.sep

$combinedScore
$combinedScore$go
  GO:0032610.interleukin-1 alpha production NA
  GO:0000379.tRNA-type intron splice site recognition and cleavage NA
  GO:0043337.CDP-diacylglycerol-phosphatidylglycerol phosphatidyltransferase activity NA
  GO:0000469.cleavage involved in rRNA processing 0.4743575
  GO:0006525.arginine metabolic process NA

$combinedScore$kegg
  05414.Dilated cardiomyopathy 0.2512723
  05310.Asthma NA
  04666.Fc gamma R-mediated phagocytosis 0.2461273
  01100.Metabolic pathways 0.1642053
  04916.Melanogenesis 0.2828949

3.6 Multiple testing correction

Finally the adjustPvalGSE enables to adjust the p-values computed by the runBatchGSE. This functions is an interface to the mt.rawp2adjp function from the multtest package.

> gseABS.int.BH <- adjustPvalGSE(gseABS.int)
> gseABS.int.holm <- adjustPvalGSE(gseABS.int, proc = "Holm")

Also in this case the results after the adjustment are named lists of lists, as shown below:
> names(gseABS.int.BH)
[1] "integrated"

> names(gseABS.int.holm)
[1] "integrated"

> str(gseABS.int.BH)
List of 1
$ integrated:List of 2
 ..$ go : num [1:5, 1:2] NA NA NA 0.492 NA ... 
 .. ..- attr(*, "dimnames")=List of 2 
 .. .. ..$ : chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site recognition" 
 .. .. ..$ : chr [1:2] "rawp" "BH" 
 ..$ kegg: num [1:5, 1:2] 0.553 NA 0.339 0.171 0.695 ... 
 .. ..- attr(*, "dimnames")=List of 2 
 .. .. ..$ : chr [1:5] "05414.Dilated cardiomyopathy" "05310.Asthma" "04666.Fc gamma R-mediated phagocytosis" 
 .. .. ..$ : chr [1:2] "rawp" "BH"

> str(gseABS.int.holm)
List of 1
$ integrated:List of 2
 ..$ go : num [1:5, 1:2] NA NA NA 0.492 NA ... 
 .. ..- attr(*, "dimnames")=List of 2 
 .. .. ..$ : chr [1:5] "GO:0032610.interleukin-1 alpha production" "GO:0000379.tRNA-type intron splice site recognition" 
 .. .. ..$ : chr [1:2] "rawp" "Holm" 
 ..$ kegg: num [1:5, 1:2] 0.553 NA 0.339 0.171 0.695 ... 
 .. ..- attr(*, "dimnames")=List of 2 
 .. .. ..$ : chr [1:5] "05414.Dilated cardiomyopathy" "05310.Asthma" "04666.Fc gamma R-mediated phagocytosis" 
 .. .. ..$ : chr [1:2] "rawp" "Holm"

4 System Information

Session information:

> sessionInfo()

R version 3.3.1 (2016-06-21)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 16.04.1 LTS

locale:
[1] LC_CTYPE=en_US.UTF-8
[2] LC_NUMERIC=C
[3] LC_TIME=en_US.UTF-8
[4] LC_COLLATE=C
[5] LC_MONETARY=en_US.UTF-8
[6] LC_MESSAGES=en_US.UTF-8

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attached base packages:

- stats4
- parallel
- stats
- graphics

other attached packages:

- limma_3.30.0
- GO.db_3.4.0
- KEGG.db_3.2.3
- org.Hs.eg.db_3.4.0
- AnnotationDbi_1.36.0
- IRanges_2.8.0
- S4Vectors_0.12.0
- RTopper_1.20.0
- Biobase_2.34.0
- BiocGenerics_0.20.0

loaded via a namespace (and not attached):

- lattice_0.20-34
- MASS_7.3-45
- grid_3.3.1
- DBI_0.5-1
- RSQLite_1.0.0
- Matrix_1.2-7.1
- splines_3.3.1
- tools_3.3.1
- survival_2.39-5
- multtest_2.30.0
5 References

References


