

Gene set analyses with the gCMAP package

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This document exemplifies the structure and use of the classes and (some of) the methods offered by the gCMAP package. For information on performing queries via an R-only, custom web application and to access a tutorial with examples using real biological datasets available from public databases, please refer to the documentation of the gCMAPWeb companion package.

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1 Introduction

The **gCMAP** package offers unified access to a number of different algorithms to compare a sets of genes across expression profiling experiments. It extends the functionality of the **GSEABase** package, which provides functions to generate and combine GeneSets from various sources.

2 CMAPCollection, SignedGeneSet and CMAPResults classes

Them **gCMAP** package introduces three new classes:

- **SignedGeneSet**: Extends the **GeneSet** class, with an additional **geneSign** slot to distinguish up- and downregulated set members.
- **CMAPCollection**: Is derived from the **eSet** class for efficient storage of large numbers of gene sets and related annotations.
- **CMAPResults**: Provides a unified output class for different gene set enrichment analysis methods.

2.1 CMAPCollections

To evaluate large gene sets collections containing thousands of gene sets, the **gCMAP** package introduces a new class **CMAPCollections**, to store gene sets and their relationships with each other in the form of a (sparse) incidence matrix. A derivative of the **eSet** class, a **CMAPCollection** also stores gene and gene set annotations in its **featureData** and **phenoData** slots.

CMAPCollections can be created de novo, e.g. with the **newCMAPCollection** function, or by coercing existing **GeneSet**, **SignedGeneSet** or **GeneSetCollection** objects. Often, large data matrices e.g. containing differential expression data from many different experiments, are available. The **induceCMAPCollection** function can be used to define gene sets from any **eSet** object by applying a user-defined threshold.

The **gCMAPData NChannelSet** object stores the results of three perturbation experiments, stimulation of tissue culture cells with drug1, drug2 or drug3. For each experiment, log2 fold change, z-scores and p-values (from differential expression analysis with the **limma** package) are available.

```
> library(gCMAP)
> data( gCMAPData ) ## example NChannelSet
> sampleNames( gCMAPData )

[1] "drug1" "drug2" "drug3"

> channelNames( gCMAPData )

[1] "log_fc" "p"      "z"
```

To induce gene sets of interest, a data slot and thresholds must be chosen.

```
> ## select all genes with z-scores > 2 or < -2
> cmap <- induceCMAPCollection( gCMAPData, element="z", lower=-2, higher=2)
> cmap
```

```

CMapCollection (storageMode: lockedEnvironment)
assayData: 1000 features, 3 samples
  element names: members
protocolData: none
phenoData
  sampleNames: drug1 drug2 drug3
  varLabels: UID signed
  varMetadata: labelDescription
featureData: none
experimentData: use 'experimentData(object)'
Annotation:

```

```
> pData( cmap )
```

```

      UID signed
drug1  1  TRUE
drug2  2  TRUE
drug3  3  TRUE

```

The sign of the differential expression (e.g. the sign of the z-score or log2 fold change) is stored in the sparseMatrix stored as `assayData` in the `CMapCollection` . Up-regulated gene set members are indicated by +1, down-regulated members by -1.

```
> head( members( cmap ) )
```

```

6 x 3 sparse Matrix of class "dgCMatrix"
      drug1 drug2 drug3
gene.1    .    .    .
gene.2    .    .    .
gene.3    .    .    .
gene.4   -1    .    .
gene.5    .    .    .
gene.6    .   -1    .

```

Sometimes, e.g. when selecting gene sets based on p-values, no sign information is available and all set members will simply be indicated with +1. To distinguish sets without sign information from those only containing up-regulated members, the `signed` column of the `phenoData` slot indicates how the information should be interpreted.

```
> signed( cmap )
```

```

drug1 drug2 drug3
TRUE  TRUE  TRUE

```

As for other eSet-like objects, `CMapCollections` can be subset to extract specific genes or gene sets.

```
> dim( cmap )
```

```

Features  Samples
    1000         3

```

```
> cmap[,1] ## the first gene set
```

```

CMapCollection (storageMode: lockedEnvironment)
assayData: 1000 features, 1 samples
  element names: members
protocolData: none
phenoData
  sampleNames: drug1
  varLabels: UID signed
  varMetadata: labelDescription
featureData: none
experimentData: use 'experimentData(object)'
Annotation:

```

3 Comparing GeneSets

To compare the list of geneIds present in different `CMapCollections`, `GeneSets` or `GeneSetCollections`, the Fisher test can be used. In addition to the `GeneSets` of interest, we also need to provide information about the gene 'universe', the complete ensemble of genes that could potentially be included in any set, e.g. all genes for which probes are available on a microarray, etc. Here, we will use all identifiers present in the `gCMapData` dataset to define the gene identifier universe.

The following example compares the first gene set in our `CMapCollection` to all three included sets. (In this vignette, we will refer to 'query' and 'target' objects. Every query object is compared individually to all targets and the results are returned in a single object.)

```

> universe <- featureNames( gCMapData )
> results <- fisher_score(cmap[,1], cmap, universe)
> results

```

```

CMapResults object with the following data slots:
set, trend, pval, padj, effect, LOR, nSet, nFound, geneScores, UID, signed
for 3 gene sets.
1 test(s) obtained an adjusted p-value < 0.05

```

```

Results from Fisher exact tests.
P-values were adjusted using the 'p.adjust' function with method 'BH'.

```

	set	trend	pval	padj	effect	LOR	nSet	nFound	UID
1	drug1	over	2.132837e-210	6.398511e-210	30.96	Inf	190	190	1
2	drug2	over	2.415470e-01	3.623206e-01	1.17	0.3328643	83	20	2
3	drug3	over	6.880119e-01	6.880119e-01	0.40	0.1576603	42	9	3

```

signed
1 FALSE
2 FALSE
3 FALSE
... (only top 5 results shown, use 'cmapTable' function to see all) ...

```

The `fisher_score` method returns a `CMapResults` object, used by all analysis methods supported by the `gCMap` package.

3.1 CMapResults

Each `CMapResults` object contains three elements

- An `AnnotatedDataFrame` called 'table', storing the results of comparing one query to all of the targets. Additional columns can be used to store information about the target gene sets. The supported gene set enrichment analysis methods return various scores, effect sizes and p-values, documented in the `varMetadata` slot of the 'table'. They can be accessed with the `labels` method.
- A 'docs' `character` vector to record information about the analysis run as a whole.
- A list 'errors', where potential warnings and error messages can be stored.

To `cmapTable` method returns the full result table, including annotation columns (if present) and labels. Individual accessors have been to return the p-value columns (`pval` or `padj`), effect size (`effect`) or to transform the adjusted p-values to z-scores on a standard normal scale (`zscores`).

```
> cmapTable( results )

      set trend          pval          padj effect      LOR nSet nFound UID
1 drug1  over 2.132837e-210 6.398511e-210 30.96      Inf  190   190   1
2 drug2  over 2.415470e-01 3.623206e-01  1.17 0.3328643   83    20   2
3 drug3  over 6.880119e-01 6.880119e-01  0.40 0.1576603   42     9   3
signed
1 FALSE
2 FALSE
3 FALSE

> labels( results )

                                labelDescription
set                               SetName
trend                    Deviation from random expectation
pval                      Fisher's exact test p-value
padj                      Adjusted p-value (BH)
effect      z-score based on the standard normal distribution
LOR                                Log Odds Ratio
nSet      Number of genes annotated in the reference set
nFound    Number of genes found in query and target sets
geneScores Identifiers of genes found in query and target sets
UID                                UID
signed                                signed

> pval( results )

      drug1      drug2      drug3
2.132837e-210 2.415470e-01 6.880119e-01

> zscores( results )

      drug1      drug2      drug3
30.9201734  0.9109522  0.4015545
```

Several gene set enrichment analyses support many-to-many comparisons, including `fisher_score`. In this case, we receive a list of multiple `CMAPEResults` objects, one for each element of the query. Each `CMAPEResults` object contains the results for all query gene sets ordered by p-value. To extract individual slots from all `CMAPEResult` objects in the list, e.g. with `sapply`, we must ensure that all results are returned in the same order, e.g. ordered by `sampleNames`.

```
> result.list <- fisher_score( cmap, cmap, universe )
> class( result.list )
```

```

[1] "list"
> length( result.list )
[1] 3
> class( result.list[[1]] )
[1] "CMAPResults"
attr("package")
[1] "gCMAP"

> ## all pairwise adjusted p-values
> sapply(result.list, function( x ) {
+     padj( x )[ sampleNames( cmap )]
+ })

              drug1      drug2      drug3
drug1 6.398511e-210  2.415470e-01 6.880119e-01
drug2 3.623206e-01  3.922263e-123 2.271885e-01
drug3 6.880119e-01  2.271885e-01 1.009276e-74

```

4 Differential expression analysis with gene sets

Frequently, we are interested in differential expression of gene sets across two or more conditions. The `gCMAP` package currently provides unified access to the sample-label permutation strategy implemented in the `GSEAlm` package, as well as multiple functions from the `limma` package: `camera`, `romer` and `mroast`. (For a detailed explanation of the different methods, please consult the help entries of the original packages directly.)

For all methods, pre-processed expression data can be supplied as a data matrix, an `ExpressionSet` or any other `eSet` derivative. To perform a differential expression analysis, the experimental design must be specified, either by providing a design matrix directly or, for `eSet` or `ExpressionSet` objects, as a character string matching a `phenoData` column name.

Let's generate an `matrix` with random expression values, three treated and three control samples:

```

> ## random score matrix
> y <- matrix(rnorm(1000*6),1000,6,
+           dimnames=list( featureNames( gCMAPData ), 1:6 ))
> predictor <- c( rep("Control", 3), rep("Case", 3))

```

along with a `CMAPCollection` containing four unsigned gene sets, the first of which is actually differentially up-regulated in the 'Case' group.

```

> m <- replicate(4, {
+   s <- rep(0,1000)
+   s[ sample(1:1000, 20)] <- 1
+   s[ sample(1:1000, 20)] <- -1
+   s
+ })
> dimnames(m) <- list(row.names( y ),
+                    paste("set", 1:4, sep=""))
> ## Set1 is up-regulated
> y[,c(4:6)] <- y[,c(4:6)] + m[,1]*2
> ## create CMAPCollection
> cmap <- CMAPCollection(m, signed=rep(TRUE,4))

```

The gCMAP package offers four different algorithms to test for differential expression between the 'control' and 'treatment' samples:

```
> gsealm_score(y, cmap, predictor=predictor, nPerm=100)
```

CMAPResults object with the following data slots:
 set, trend, pval, padj, effect, nSet, nFound, geneScores, signed
 for 4 gene sets.
 0 test(s) obtained an adjusted p-value < 0.05

GSEalm analysis with formula ~predictor using 100 sample label permutations.
 P-values were adjusted with the 'p-adjust' function using method 'BH'.

	set	trend	pval	padj	effect	nSet	nFound	signed
1	set1	anticorrelated	0.04950495	0.0990099	-18.1394626	40	40	TRUE
2	set4	correlated	0.04950495	0.0990099	2.8394696	39	39	TRUE
3	set3	anticorrelated	0.17821782	0.2376238	-1.0283187	40	40	TRUE
4	set2	correlated	0.41584158	0.4158416	0.5457554	40	40	TRUE

... (only top 5 results shown, use 'cmapTable' function to see all) ...

```
> mroast_score(y, cmap, predictor=predictor)
```

CMAPResults object with the following data slots:
 set, trend, pval, padj, nSet, geneScores, signed
 for 4 gene sets.
 0 test(s) obtained an adjusted p-value < 0.05

All results, including adjusted p-values, were obtained
 with the 'mroast' function from the 'limma' package..

	set	trend	pval	padj	nSet	signed
1	set3	Down	0.067	0.2660000	40	FALSE
2	set4	Up	0.419	0.7286667	39	FALSE
3	set1	Up	0.547	0.7286667	40	FALSE
4	set2	Down	0.786	0.7860000	40	FALSE

... (only top 5 results shown, use 'cmapTable' function to see all) ...

Both gsealm_score and mroast perform self-contained test. (Goeman and Buhlmann, 2007).
 (Please note that we only run 100 gsealm_score permutations to obtain a p-value in this example
 - in a real analysis, increasing this number, e.g. to 1000, is recommended.) In case a competitive
 hypothesis needs to be tested, the camera_score and romer_score methods (calling the romer and
 camera functions from the limma package, respectively) can be used instead.

```
> camera_score(y, cmap, predictor=predictor)
```

CMAPResults object with the following data slots:
 set, trend, pval, padj, effect, nSet, nFound, geneScores, signed
 for 4 gene sets.
 0 test(s) obtained an adjusted p-value < 0.05

Results were obtained with the 'camera' function from the 'limma' package.

	set	trend	pval	padj	effect	nSet	nFound	signed
1	set3	Down	0.1518880	0.6075520	-0.017673733	40	40	FALSE
2	set4	Up	0.5120371	0.7974286	-0.006552903	39	39	FALSE
3	set1	Up	0.6370618	0.7974286	0.003749492	40	40	FALSE

```

4 set2 Down 0.7974286 0.7974286 -0.007800256 40 40 FALSE
... (only top 5 results shown, use 'cmapTable' function to see all) ...

> romer_score(y, cmap, predictor=predictor)

CMAPResults object with the following data slots:
set, trend, pval, padj, nSet, nFound, geneScores, signed
for 12 gene sets.
1 test(s) obtained an adjusted p-value < 0.05
nResults obtained with the 'romer' function from the 'limma' package.
P-values were adjusted with the 'p-adjust' function using method 'BH'.

  set trend  pval  padj nSet nFound signed
1 set1 Mixed 0.0003 0.00360 40 40 FALSE
2 set3 Down 0.0218 0.13080 40 40 FALSE
3 set4 Up 0.2384 0.75660 39 39 FALSE
4 set2 Down 0.2522 0.75660 40 40 FALSE
5 set1 Up 0.3483 0.83592 40 40 FALSE
... (only top 5 results shown, use 'cmapTable' function to see all) ...

```

Currently, only `gsealm_score` takes the sign of the gene set members (indicating whether a gene had originally be identified as up- or down-regulated) into account.

5 Analysis of individual score profiles

In addition to analyzing complete experiments, other approaches to gene set enrichment testing evaluate whether a given statistic for the members of a gene set ranked highly relative to random sets.

The `wilcox_score` method calculates the Wilcox-rank sum statistic, assessing whether the ranked scores of a gene set are enriched at the top or bottom of the complete list of scores.

The `gsealm_jg_score` calculates the mean score for all gene set members and provides a p-value based on the standard normal distribution (Jiang and Gentleman, 2007).

The `connectivity_score` is calculated according to Lamb, J. et al. (2006) and corresponds to the scaled score described in this publication. (It does not provide a p-value.)

For illustration, we compare the first column of z-scores stored in the `gCMAPData NChannelSet` to the three gene sets induced from the same dataset in the first section of this vignette..

```

> profile <- assayDataElement(gCMAPData[,1], "z") ## extract first column
> head(profile)

      drug1
gene.1 -0.4600253
gene.2 -1.8756099
gene.3 -0.7766186
gene.4 -2.9651795
gene.5 -1.2265235
gene.6 -0.1037107

> sampleNames(cmap) ## three gene sets
[1] "set1" "set2" "set3" "set4"

> gsealm_jg_score(profile, cmap)

```

CMAResults object with the following data slots:
 set, trend, pval, padj, effect, nSet, nFound, geneScores, signed
 for 4 gene sets.
 0 test(s) obtained an adjusted p-value < 0.05

Parametric 'JG' score summary.
 P-values were adjusted with the 'p-adjust' function using method 'BH'.

	set	trend	pval	padj	effect	nSet	nFound	signed
1	set3	correlated	0.01322858	0.05291433	2.47755549	40	40	TRUE
2	set1	anticorrelated	0.50258109	0.70089216	-0.67043412	40	40	TRUE
3	set4	anticorrelated	0.52566912	0.70089216	-0.63463098	39	39	TRUE
4	set2	anticorrelated	0.93556014	0.93556014	-0.08085139	40	40	TRUE

... (only top 5 results shown, use 'cmapTable' function to see all) ...

As expected the first gene set, which was derived from the same experiment as the profile, receives highly significant p-values.

Alternatively, the Wilcox Rank sum test or the original Connectivity Score can be calculated. (Please note that the `connectivity_score` does not return a p-value and is hard to interpret for a single profile.)

```
> wilcox_score(profile, cmap)
```

CMAResults object with the following data slots:
 set, trend, pval, padj, effect, nSet, nFound, geneScores, signed
 for 4 gene sets.
 0 test(s) obtained an adjusted p-value < 0.05

Results from a two-tailed Wilcox-Rank Sum test
 p-values were adjusted using the 'p.adjust' function with method 'BH'.

	set	trend	pval	padj	effect	nSet	nFound	signed
1	set3	correlated	0.06368996	0.2547598	1.52451580	40	40	TRUE
2	set4	anticorrelated	0.22921011	0.4584202	-0.74145070	39	39	TRUE
3	set2	correlated	0.40517372	0.4718261	0.23997784	40	40	TRUE
4	set1	anticorrelated	0.47182609	0.4718261	-0.07068032	40	40	TRUE

... (only top 5 results shown, use 'cmapTable' function to see all) ...

```
> connectivity_score(profile, cmap)
```

CMAResults object with the following data slots:
 set, trend, effect, nSet, nFound, geneScores, signed
 for 4 gene sets.
 Scores were calculated and scaled according to Lamb, J. et al. (2006).

	set	trend	effect	nSet	nFound	signed
1	set3	up	1.0000000	40	40	TRUE
2	set4	down	-1.0000000	39	39	TRUE
3	set2	up	0.9169139	40	40	TRUE
4	set1	up	0.0000000	40	40	TRUE

... (only top 5 results shown, use 'cmapTable' function to see all) ...

6 Overview plots

When comparing a set of genes, a profile or a complete experiment to a large gene set collection, e.g. induced from the original Connectivity map data generated at the Broad institute (Lamb et al, Science, 2006), high level diagnostic plots can provide a first overview of the results.

For illustration purposes, we generate a random profile of z-scores for 1000 genes as well as CMAPCollection with a random set of 1000 gene sets. One of them, set1, is actually differentially regulated.

```
> ## create random score profile
> set.seed(123)
> z <- rnorm(1000)
> names(z) <- paste("g", 1:1000, sep="")
> ## generate random incidence matrix of gene sets
> n <- replicate(1000, {
+   s <- rep(0,1000)
+   s[ sample(1:1000, 20)] <- 1
+   s[ sample(1:1000, 20)] <- -1
+   s
+ })
> dimnames(n) <- list(names(z), paste("set",
+                                     1:1000,
+                                     sep=""))
> ## Set1 is up-regulated
> z <- z + n[,1]*2
> ## create CMAPCollection
> cmap.2 <- CMAPCollection(n, signed=rep(TRUE,1000))

> ## gene-set enrichment test
> res <- gsealm_jg_score(z, cmap.2)
> class(res)

[1] "CMAPResults"
attr(,"package")
[1] "gCMAP"

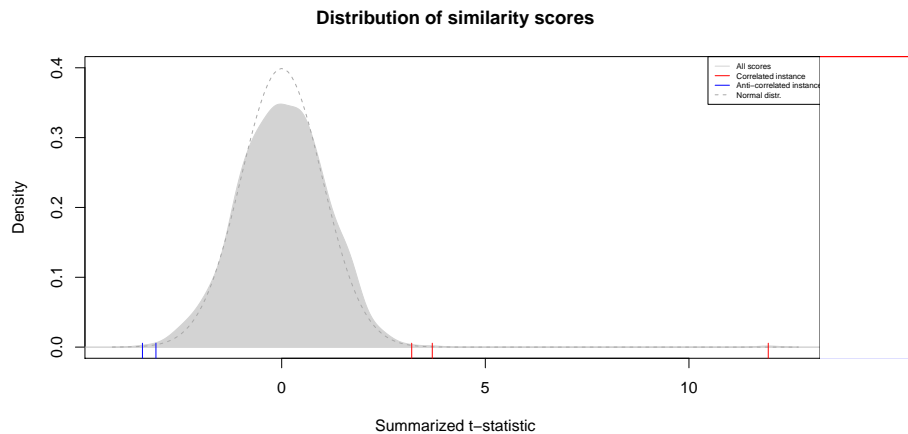
> res

CMAPResults object with the following data slots:
set, trend, pval, padj, effect, nSet, nFound, geneScores, signed
for 1000 gene sets.
1 test(s) obtained an adjusted p-value < 0.05

Parametric 'JG' score summary.
P-values were adjusted with the 'p-adjust' function using method 'BH'.

      set      trend      pval      padj      effect nSet nFound signed
1  set1    correlated 6.698361e-33 6.698361e-30 11.947406   40    40   TRUE
2 set941    correlated 2.174263e-04 1.087131e-01  3.697858   40    40   TRUE
3 set648 anticorrelated 6.287339e-04 2.095780e-01 -3.418906   40    40   TRUE
4 set664    correlated 1.411126e-03 3.527814e-01  3.192366   40    40   TRUE
5 set732 anticorrelated 2.015862e-03 4.031725e-01 -3.087885   40    40   TRUE
... (only top 5 results shown, use 'cmapTable' function to see all) ...

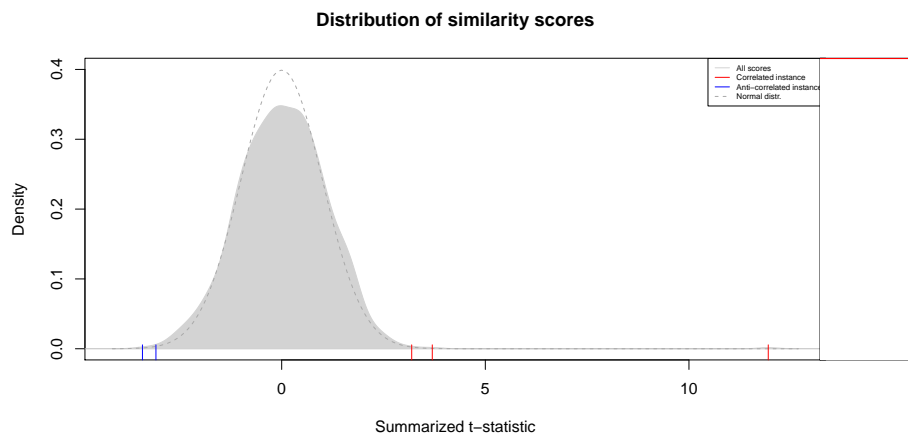
> plot(res)
```



A call to the `plot` method on a `CMAResults` object yields two graphical overviews: on the left, a density of all 1000 reported effect sizes, in this case JG-scores, is shown. In the absence of correlation between genes, this distribution follows a normal distribution. (While this is true for this set of randomly generated scores, the distribution of JG scores observed in practice is actually broader than expected, testament to the non-random patterns of gene expression.)

On the right, a heatmap of the rank-ordered scores is displayed, with low and high scores displayed as blue and red stripes, respectively. By default, scores between -3 and 3 are hidden. To display scores above 3 or below -3, a color gradient from white to red or from white to blue is applied, respectively. (Both the choice of colors and thresholds of the color gradients can be configured, please see the `CMAResults` help page for details.)

```
> sets.down <- effect( res ) < -3
> plot(res)
```



7 Retrieving gene-level information

Once significantly enriched gene sets have been identified, we may want to take a closer look at the behavior of individual genes. Are expression changes associated with many gene set members or do specific genes respond particularly strongly ?

All methods implemented in the `gCMAP` package, with the exception of `fisher_score`, return gene-level scores when the optional `'keep.scores'` parameter is set to `'TRUE'`. To demonstrate, we repeat the `gsealm_score` call from above.

```
> res <- gsealm_score(y, cmap, predictor=predictor, nPerm=100, keep.scores=TRUE)
> res
```

```
CMAPResults object with the following data slots:
set, trend, pval, padj, effect, nSet, nFound, geneScores, signed
for 4 gene sets.
0 test(s) obtained an adjusted p-value < 0.05
```

```
GSEalm analysis with formula ~predictor using 100 sample label permutations.
P-values were adjusted with the 'p-adjust' function using method 'BH'.
```

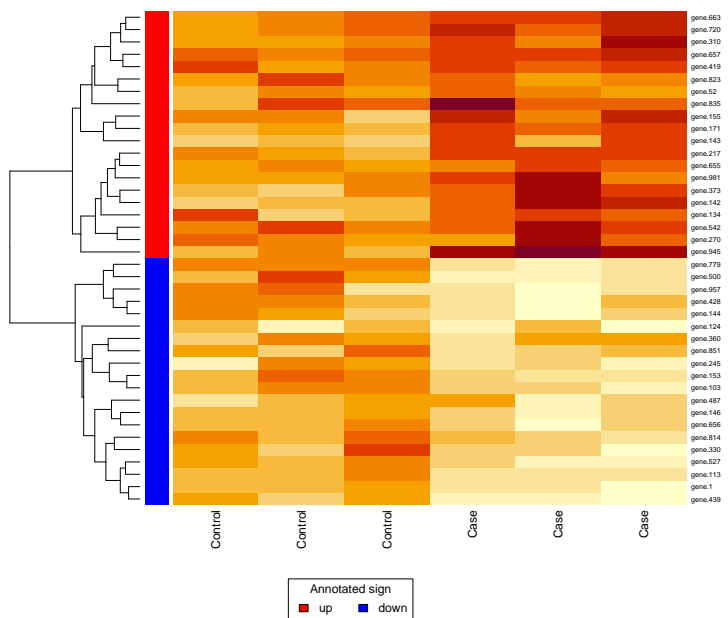
```
      set      trend      pval      padj      effect nSet nFound signed
1 set1 anticorrelated 0.06930693 0.1386139 -18.1394626  40    40   TRUE
2 set4      correlated 0.06930693 0.1386139  2.8394696  39    39   TRUE
3 set3 anticorrelated 0.27722772 0.3696370 -1.0283187  40    40   TRUE
4 set2      correlated 0.45544554 0.4554455  0.5457554  40    40   TRUE
  geneScores
1 40 x 6 matrix
2 39 x 6 matrix
3 40 x 6 matrix
4 40 x 6 matrix
... (only top 5 results shown, use 'cmapTable' function to see all) ...
> set1.expr <- geneScores(res)[["set1"]]
> head(set1.expr)
```

	1	2	3	4	5	6
gene.1	-0.4676850	-0.9164483	0.04133489	-1.649489	-2.1038079	-3.5465618
gene.52	-0.7017887	0.7063692	0.20367207	1.048797	0.6993498	0.1803723
gene.103	-0.5893912	0.9316614	0.95587988	-1.288340	-1.4181353	-2.8523997
gene.113	-0.7683347	-0.8633709	0.58939571	-1.668827	-2.2778195	-2.0796107
gene.124	-0.8306497	-2.7617287	-0.56187130	-2.488218	-0.3598665	-3.2238847
gene.134	1.7222775	-1.3034488	-0.62093701	1.112516	1.9062430	1.6451637

Expression scores for each gene set are now available in the `geneScores` `cmapResults` column, which can be accessed through a method with the same name. Each matrix of expression scores is accompanied by an additional `'sign'` attribute to remind us whether gene set members were annotated as up- or down-regulated.

For example, we can now visualize the expression scores of `set1` member genes in a heatmap. As expected, genes annotated as `'up-regulated'` (red sidebar) show higher expression in Cases than Controls and the reverse is true for genes annotated as `'down-regulated'` (blue sidebar).

```
> heatmap(set1.expr, scale="none", Colv=NA, labCol=predictor,
+         RowSideColors=ifelse( attr(set1.expr, "sign") == "up", "red", "blue"),
+         margin=c(7,5))
> legend(0.35,0,legend=c("up", "down"),
+       fill=c("red", "blue"),
+       title="Annotated sign", horiz=TRUE, xpd=TRUE)
```



Each row in the `CMAPResults` objects features an subset of the original query `ExpressionSet`. As genes can be part of many different genes sets, querying large gene set collections may result in storing duplicate data rows over and over again, considerably increasing the memory footprint of the `CMAPResults` object.

Alternatively, we can extract the scores from the original data source. For example, we can obtain a nested list of scores for all sets and data columns by passing the `CMAPCollection` (`cmap`) and the score matrix (`y`) to the `featureScores` method. The element for 'set1' corresponds to the score matrix we obtained above.

```
> res <- featureScores(cmap, y)
> class(res)
[1] "list"
> names(res)
[1] "set1" "set2" "set3" "set4"
> identical( res[["set1"]], set1.expr )
[1] TRUE
> sessionInfo()
R version 3.6.0 (2019-04-26)
Platform: x86_64-apple-darwin15.6.0 (64-bit)
Running under: OS X El Capitan 10.11.6
```

Matrix products: default

BLAS: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRblas.0.dylib

LAPACK: /Library/Frameworks/R.framework/Versions/3.6/Resources/lib/libRlapack.dylib

locale:

```
[1] C/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
```

attached base packages:

```
[1] stats4      parallel  stats      graphics  grDevices  utils      datasets
[8] methods     base
```

other attached packages:

```
[1] bigmemory_4.5.33      DESeq_1.36.0          lattice_0.20-38
[4] locfit_1.5-9.1        gCMAP_1.28.0          limma_3.40.0
[7] GSEABase_1.46.0       graph_1.62.0          annotate_1.62.0
[10] XML_3.98-1.19         AnnotationDbi_1.46.0  IRanges_2.18.0
[13] S4Vectors_0.22.0      Biobase_2.44.0        BiocGenerics_0.30.0
```

loaded via a namespace (and not attached):

```
[1] Rcpp_1.0.1            compiler_3.6.0        RColorBrewer_1.1-2
[4] bigmemoryExtras_1.32.0 bitops_1.0-6          tools_3.6.0
[7] digest_0.6.18         bit_1.1-14           RSQlite_2.1.1
[10] memoise_1.1.0         Matrix_1.2-17        DBI_1.0.0
[13] Category_2.50.0       GSEAlm_1.44.0        genefilter_1.66.0
[16] bit64_0.9-7           grid_3.6.0           bigmemory.sri_0.1.3
[19] RBGL_1.60.0           survival_2.44-1.1     geneplotter_1.62.0
[22] blob_1.1.1            splines_3.6.0        xtable_1.8-4
[25] RCurl_1.95-4.12
```