miRNA tap example use

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1 Introduction

miRNAmap package is designed to facilitate implementation of workflows requiring miRNA prediction. Aggregation of commonly used prediction algorithm outputs in a way that improves on performance of every single one of them on their own when compared against experimentally derived targets. microRNA (miRNA) is a 18-22nt long single strand that binds with RISC (RNA induced silencing complex) and targets mRNAs effectively reducing their translation rates.

Targets are aggregated from 5 most commonly cited prediction algorithms: DIANA (Maragkakis et al., 2011), Miranda (Enright et al., 2003), PicTar (Lall et al., 2006), TargetScan (Friedman et al., 2009), and miRDB (Wong and Wang, 2015).

Programmatic access to sources of data is crucial when streamlining the workflow of our analysis, this way we can run similar analysis for multiple input miRNAs or any other parameters. Not only does it allow us to obtain predictions from multiple sources straight into R but also through aggregation of sources it improves the quality of predictions.

Finally, although direct predictions from all sources are only available for *Homo sapiens* and *Mus musculus*, this package includes an algorithm that allows to translate target genes to other species (currently only *Rattus norvegicus*) using homology information where direct targets are not available.

2 Installation

This section briefly describes the necessary steps to get miRNAmap running on your system. We assume that the user has the R program (see the R project at http://www.r-project.org) already installed and is familiar with it. You will need to have R 3.2.0 or later to be able to install and run miRNAmap. The miRNAmap package is available from the Bioconductor repository at http://www.bioconductor.org To be able to install the package one needs first to install the core Bioconductor packages. If you have already installed Bioconductor packages on your system then you can skip the two lines below.

```r
> if (!requireNamespace("BiocManager", quietly=TRUE))
+ install.packages("BiocManager")
> BiocManager::install()
```

Once the core Bioconductor packages are installed, we can install the miRNAmap and accompanying database miRNAmap.db package by

```r
> if (!requireNamespace("BiocManager", quietly=TRUE))
+ install.packages("BiocManager")
> BiocManager::install("miRNAmap")
> BiocManager::install("miRNAmap.db")
```
3 Workflow

This section explains how miRNAtap package can be integrated in the workflow aimed at predicting which processes can be regulated by a given microRNA.

In this example workflow we’ll use miRNAtap as well as another Bioconductor package topGO together with Gene Ontology (GO) annotations. In case we don’t have topGO or GO annotations on our machine we need to install them first:

```r
> if (!requireNamespace("BiocManager", quietly=TRUE))
  + install.packages("BiocManager")
> BiocManager::install("topGO")
> BiocManager::install("org.Hs.eg.db")
```

Then, let’s load the required libraries

```r
> library(miRNAtap)
> library(topGO)
> library(org.Hs.eg.db)
```

Now we can start the analysis. First, we will obtain predicted targets for human miRNA miR-10b

```r
> mir = 'miR-10b'
> predictions = getPredictedTargets(mir, species = 'hsa',
  + method = 'geom', min_src = 2)
```

Let’s inspect the top of the prediction list.

```r
> head(predictions)

source_1 source_2 source_3 source_4 source_5 rank_product rank_final
627     103    10.0     1.0   NA    1        1.416281        1
79741   NA     NA     8.0     2   NA    2.000000        2
6095     5     2.5    73.5   NA    5        2.058173        3
348980   NA     2.5   20.0   NA   NA    3.535534        4
51365   NA    53.0     3.0   12   27    3.766392        5
7022     88    17.5     5.0  149    3    4.058725        6
```

We are using geometric mean aggregation method as it proves to perform best when tested against experimental data from MirBase (Griffiths-Jones et al., 2008).

We can compare it to the top of the list of the output of minimumum method:

```r
> predictions_min = getPredictedTargets(mir, species = 'hsa',
  + method = 'min', min_src = 2)
> head(predictions_min)
```
Where predictions for rat genes are not available we can obtain predictions for mouse genes and translate them into rat genes through homology. The operation happens automatically if we specify species as rno (for Rattus norvegicus).

```r
predictions_rat = getPredictedTargets(mir, species = 'rno',
   method = 'geom', min_src = 2)
```

Now we can use the ranked results as input to GO enrichment analysis. For that we will use our initial prediction for human mir-10b.

```r
rankedGenes = predictions[, 'rank_product']
selection = function(x) TRUE
# we do not want to impose a cut off, instead we are using rank information
allGO2genes = annFUN.org(whichOnto='BP', feasibleGenes = NULL,
   mapping="org.Hs.eg.db", ID = "entrez")
GOdata = new('topGOdata', ontology = 'BP', allGenes = rankedGenes,
   annot = annFUN.GO2genes, GO2genes = allGO2genes,
   geneSel = selection, nodeSize=10)
```

In order to make use of the rank information we will use Kolomonogorov Smirnov (K-S) test instead of Fisher exact test which is based only on counts.

```r
results.ks = runTest(GOdata, algorithm = "classic", statistic = "ks")
```

Description:
Ontology: BP
'classic' algorithm with the 'ks' test
576 GO terms scored: 7 terms with p < 0.01
Annotation data:
Annotated genes: 355
Significant genes: 355
Min. no. of genes annotated to a GO: 10
Nontrivial nodes: 576

We can view the most enriched GO terms (and potentially feed them to further steps in our workflow)

```r
allRes = GenTable(GOdata, KS = results.ks, orderBy = "KS", topNodes = 20)
allRes[,c('GO.ID', 'Term', 'KS')]
```
GO.ID Term KS
1 GO:0050789 regulation of biological process 0.00071
2 GO:0050794 regulation of cellular process 0.00106
3 GO:0044087 regulation of cellular component biogene... 0.00310
4 GO:0065007 biological regulation 0.00364
5 GO:0042692 muscle cell differentiation 0.00384
6 GO:0001934 positive regulation of protein phosphory... 0.00739
7 GO:0044089 positive regulation of cellular componen... 0.00891
8 GO:0051146 striated muscle cell differentiation 0.01009
9 GO:0031323 regulation of cellular metabolic process 0.01041
10 GO:0006351 DNA-templated transcription 0.01463
11 GO:0032774 RNA biosynthetic process 0.01463
12 GO:0010562 positive regulation of phosphorus metabo... 0.01527
13 GO:0045937 positive regulation of phosphate metabol... 0.01527
14 GO:0010468 regulation of gene expression 0.01553
15 GO:0010556 regulation of macromolecule biosynthetic... 0.01789
16 GO:0060255 regulation of macromolecule metabolic pr... 0.01946
17 GO:0006355 regulation of RNA-templated transcription... 0.02018
18 GO:2001141 regulation of RNA biosynthetic process 0.02018
19 GO:0001932 regulation of protein phosphorylation 0.02189
20 GO:0019219 regulation of nucleobase-containing comp... 0.02250

For more details about GO analysis refer to topGO package vignette (Alexa and Rahnenfuhrer, 2010).
Finally, we can use our predictions in a similar way for pathway enrichment analysis based on KEGG (Kanehisa and Goto, 2000), for example using Bioconductor’s KEGGprofile (Zhao, 2012).

4 Session Information

- R version 4.3.1 (2023-06-16), x86_64-pc-linux-gnu
- Time zone: America/New_York
- TZcode source: system (glibc)
- Running under: Ubuntu 22.04.3 LTS
- Matrix products: default
- BLAS: /home/biocbuild/bbs-3.18-bioc/R/lib/libRblas.so
• LAPACK:
  /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.10.0

• Base packages: base, datasets, grDevices, graphics, methods, stats, stats4, utils

• Other packages: AnnotationDbi 1.64.0, Biobase 2.62.0, BiocGenerics 0.48.0, GO.db 3.18.0, IRanges 2.36.0, S4Vectors 0.40.0, SparseM 1.81, graph 1.80.0, miRNAatap 1.36.0, miRNAatap.db 0.99.10, org.Hs.eg.db 3.18.0, topGO 2.54.0

• Loaded via a namespace (and not attached): Biostrings 2.70.0, DBI 1.1.3, GenomeInfoDb 1.38.0, GenomeInfoDbData 1.2.11, KEGGREST 1.42.0, R6 2.5.1, RCurl 1.98-1.12, RSQLite 2.3.1, Rcpp 1.0.11, XVector 0.42.0, bit 4.0.5, bit64 4.0.5, bitops 1.0-7, blob 1.2.4, cachem 1.0.8, chron 2.3-61, cli 3.6.1, compiler 4.3.1, crayon 1.5.2, fastmap 1.1.1, glue 1.6.2, grid 4.3.1, gsubfn 0.7, htr 1.4.7, lattice 0.22-5, lifecycle 1.0.3, magrittr 2.0.3, matrixStats 1.0.0, memoise 2.0.1, pkgconfig 2.0.3, plyr 1.8.9, png 0.1-8, proto 1.0.0, rlang 0.4-11, stringi 1.7.12, stringr 1.5.0, tools 4.3.1, vctrs 0.6.4, zlibbioc 1.48.0

References


