# How To Use LncPath

Junwei Han, Zeguo Sun

November 6, 2024

## Contents



## 1 Overview

This vignette illustrates how to easily use the LncPath package. The package can prioritize pathways coordinately regulated by lncRNAs based on a network diffusion strategy. We firstly constructed a lncRNA-mRNA relationship network by integrating the co-expression pairs between lncRNAs and mRNAs with the protein-protein interaction pairs. The lncRNAs user inputted will be mapped into the lncRNA-mRNA relationship network to evaluate the extent of each gene influenced by the lncRNAs based on a network diffusion strategy. We then built a ranked gene list based on the extent of influence. Finally, we mapped the genes of each pathway into the rank gene list and calculated the pathway enrichment score(ES) using a weighted Kolmogorov-Smirnov statistic. The permutation analysis was performed to selecting significant pathways.

## 2 Finding the differentially expressed genes from a expression profile

This section introduces how to find signigicantly differentially expressed genes from an expression profile. We provided two ways to find differentially expressed genes from an expression profile, student's t-test and fold change. For each strategy, a threshold is defined for selecting significant differentially expressed genes.

```
> #obtain the expression profile data
> Profile <- getExampleData("Profile")
> Profile[1:10, 1:10]
```

```
                     A10U         A14Y       A14Y.1         A16R       A14Y.2
MIR143HG      4.817622e-05 2.714833e-05 3.938226e-05 1.583580e-05 4.759946e-06
NPY6R         2.776750e-05 4.436461e-05 1.471648e-05 7.396511e-06 7.028282e-07
AL078621.4    4.745406e-05 5.929525e-05 4.890773e-05 6.076707e-05 1.558605e-05
RP4-791K14.2  1.298476e-05 4.597001e-06 8.998136e-06 4.714152e-06 5.665172e-07
RP11-399O19.5 3.404506e-05 1.921294e-05 3.255811e-05 1.910943e-05 3.607389e-06
RP11-357C3.3  4.899702e-05 4.459881e-05 5.840064e-05 2.664671e-05 1.246263e-05
AL589743.1    1.281410e-07 2.004831e-07 8.481405e-08 5.464789e-08 1.655219e-08
RP11-175K6.1  1.720569e-06 1.892652e-06 1.807399e-06 2.654562e-06 4.858749e-07
PGM5-AS1      1.953075e-04 2.153569e-04 1.682733e-04 3.074801e-04 7.435103e-05
CTC-228N24.3  8.655112e-06 1.044819e-05 1.108406e-05 9.040964e-06 3.394420e-06
                    A14Y.3       A10U.1       A10U.2       A10U.3         A13Y
MIR143HG      3.587065e-06 4.103880e-05 3.444775e-05 2.057273e-06 1.200087e-06
NPY6R         2.470614e-06 2.180325e-05 5.335282e-06 1.468536e-07 0.000000e+00
AL078621.4    2.598227e-05 2.196803e-05 1.136785e-04 1.174064e-07 1.741630e-07
RP4-791K14.2  1.222805e-06 7.377760e-06 3.551054e-06 1.007499e-07 1.760444e-07
RP11-399O19.5 6.122954e-06 3.500004e-05 2.828171e-05 1.354029e-06 1.137123e-06
RP11-357C3.3  1.738906e-05 5.062899e-05 3.225693e-05 1.828165e-05 1.404827e-05
AL589743.1    2.047051e-07 2.418385e-08 4.843106e-07 2.112712e-05 6.100757e-06
RP11-175K6.1  8.300081e-07 6.021785e-07 2.264556e-06 2.618080e-07 2.890107e-07
PGM5-AS1      1.005791e-04 8.785996e-05 4.693726e-04 2.389673e-07 0.000000e+00
CTC-228N24.3  5.648797e-06 7.110228e-06 7.912642e-06 4.127547e-06 5.448670e-06
```

```
> #obtain the labels of the samples of the expression profile, the label vector is a vector of 0/1s,
> # 0 represents the case sample and 1 represents the control sample
> Labels <- getExampleData("Labels")
> Labels[1:10]

 [1] 0 0 0 0 0 0 0 0 1 1

> ##find differentially expressed genes, using t-Test defautly
> options(stringsAsFactors = FALSE)
> SigGenes <- findSigGenes(Profile, Labels, Method = "tTest", FdrCut = 0.01)
> head(SigGenes)

$Up
[1] "RP11-166D19.1" "LINC00476"     "LRFN5"         "MORF4L2"
[5] "MEIS1"

$Low
[1] "SFT2D1"  "SRSF9"   "MRGBP"   "MTHFD1L" "TICRR"   "ATP13A1"
```

# 3 Identifying pathways coordinately regulated by user interested lncRNAs

This section introduces how to identify pathways coordinately regulated by user interested lncRNAs. A vector of lncRNAs should be inputted, and they will be mapped into the lncRNA-mRNA relationship network as seed nodes to perform a network diffusion strategy. Here we constructed a huge lncRNA-mRNA network constructed by ingergrating a lncRNA-mRNA co-expression network and the protein-protein interaction network. Considering the huge network may be time consuming, we provided a litte example network for little trial. A weighted Kolmogorov-Smirnov statistic is used to prioritize

the pathways regulated by the user inputted lncRNAs. Now three pathway databases are surpported: KEGG, Reactome and Biocarta. The pathways with the number of genes between the user defined limit will be kept for further analysis to avoid potential bias. The permutation analysis was performed to filter significant pathways and the times of permutations can be set by the user.

```
> #get lncRNA-mRNA interaction network
> NetLncPath <- getNet();
> dim(NetLncPath);

[1] 295698      2

> print(head(NetLncPath), row.names = FALSE)

      V1     V2
 PLEKHF2  SCYL3
 PLEKHF2  STT3B
 PLEKHF2  RAD21
 PLEKHF2 GOLPH3
 PLEKHF2 UBE2D3
 PLEKHF2   NME3

> #get example lncRNA sets
> SigLncs <- getExampleData("SigLncs")
> print(head(SigLncs), row.names = FALSE)

[1] "ENSG00000262117" "ENSG00000236824" "ENSG00000240498" "ENSG00000235123"
[5] "ENSG00000234741" "ENSG00000130600"

> #get the example lncRNA-mRNA interaction network
> ExampleNet <- getExampleData("ExampleNet")
> print(head(ExampleNet), row.names = FALSE)

     V1      V2
  SPRY2 C6orf48
 GNB2L1   RPS18
 GNB2L1    TPT1
 GNB2L1  IMPDH2
 GNB2L1   RPS19
 GNB2L1  POLR1D

> #evaluate the rate of pathways regulated by lncRNA sets
> Result <- lncPath(SigLncs, ExampleNet,  Weighted = TRUE, PathwayDataSet = "KEGG", nperm = 100,
+ minPathSize = 0, maxPathSize = 500)

Now start the random walking...
[1] "ENSG00000234741" "ENSG00000251562" "ENSG00000214548" "ENSG00000236824"
[5] "ENSG00000229807" "ENSG00000130600" "ENSG00000228630" "ENSG00000281560"
[9] "ENSG00000235123"
9 of 14 were mapped to the huge net with 267 Nodes.
Now, calculating running scores of each pathway...Now, do the purtabationsions...

> ## Generate a table of the summary of each pathway
> PathwaySummaryTable <- lncPath2Table(Result)
> print(head(PathwaySummaryTable), row.names = FALSE)
```

```
                                    Gene Set Name Gene Set Size
                          KEGG_PURINE_METABOLISM             3
                       KEGG_PYRIMIDINE_METABOLISM             2
                                    KEGG_RIBOSOME            11
 KEGG_ALANINE_ASPARTATE_AND_GLUTAMATE_METABOLISM             1
                      KEGG_GLUTATHIONE_METABOLISM             1
                         KEGG_NITROGEN_METABOLISM             1
 Enrichment Scores Normalized Enrichment Scores P Value False Discovery Rate
          -0.62222           -0.838196386522472    0.94                 0.94
          -0.65217           -0.878542215612421    0.91                 0.94
           0.57517                            1    0.32                 0.94
          -0.70213           -0.945843638695355    <NA>                 <NA>
          -0.91489            -1.23245394244085    <NA>                 <NA>
          -0.70213           -0.945843638695355    <NA>                 <NA>
```

# 4 Gain insight into the details of each pathway

## 4.1 Plot the running erichment score of a pathway

The function `plotRunningES` can plot global cumulative running enrichment scores of each gene of a certain pathway.

```
> #get an example result data
> Result <- getExampleData("Result")

> #plot the running score of the KEGG RIBOSOME pathway
> plotRunningES(Result, Name = "KEGG_RIBOSOME")
```

Figure 1 shows the running scores of each gene in the KEGG RIBOSOME pathway.

## 4.2 Check the detail of genes of each pathway.

The function `geneSetDetail` can show the detail of each gene in a certain pathway.

```
> #get an example result data
> Result <- getExampleData("Result")
> #get the details of genes in the KEGG_RIBOSOME pathway
> Detail <- geneSetDetail(Result, Name = "KEGG_RIBOSOME")
> head(Detail)

  #  GENE LIST LOC    S2N    RES CORE_ENRICHMENT
1 1 RPS19       18 0.0401 0.0392             YES
2 2 RPL37       36 0.0349 0.0732             YES
3 3 RPS17       45 0.0298  0.103             YES
4 4 RPS11       48 0.0295  0.132             YES
5 5 RPL29       49 0.0295  0.161             YES
6 6  RPL7       50 0.0294  0.191             YES
```

## 4.3 Draw the heat map of genes in a certain pathway.

The function `drawAHeatMap` can draw a heatmap of the genes in a certain pathway based on the expression profile user specified.

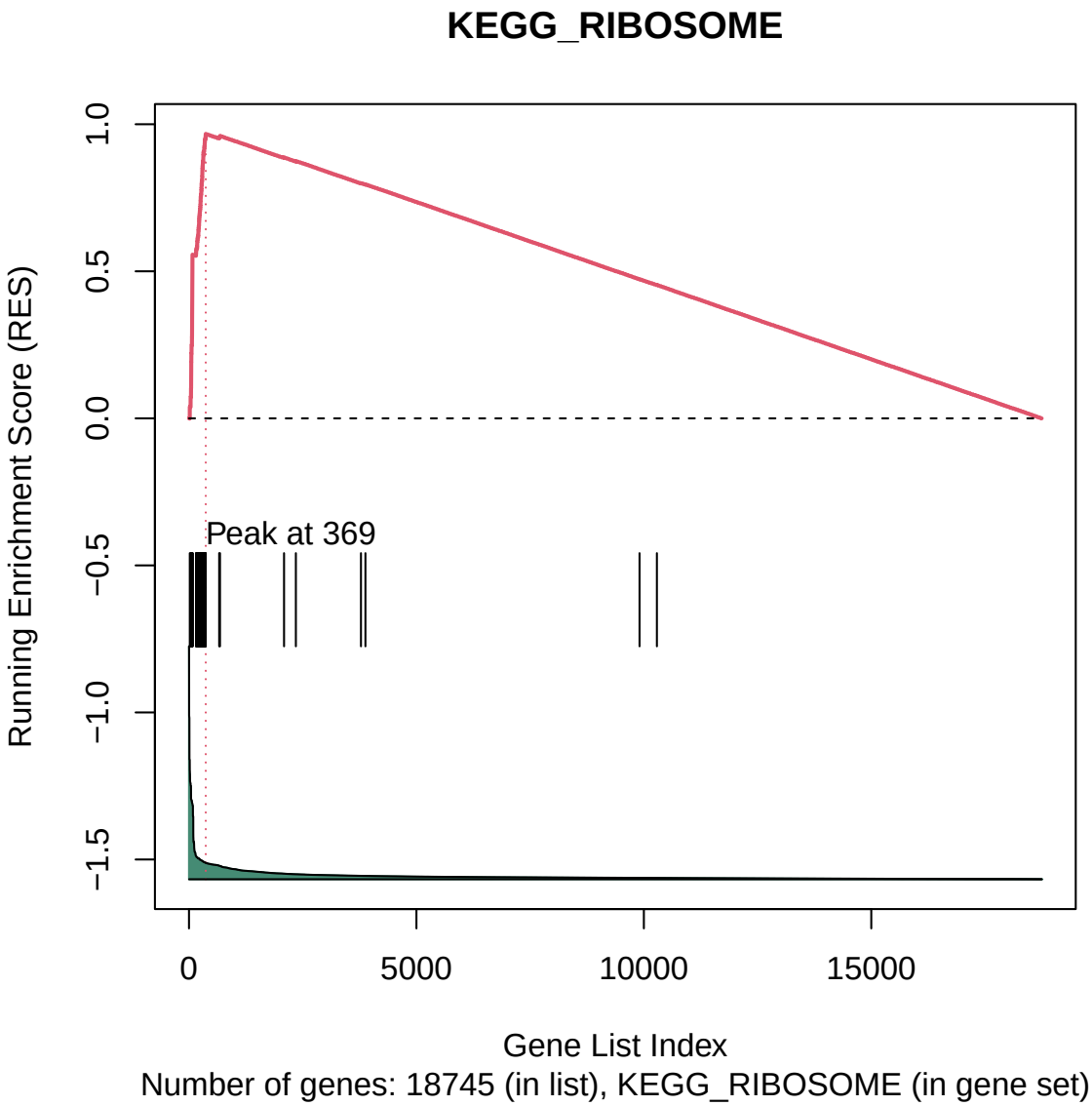


Figure 1: The running scores of each gene in the KEGG RIBOSOME pathway.

```
> #get an example result data
> Result <- getExampleData("Result")
> #get example data
> Profile <- getExampleData("Profile")
> Labels <- getExampleData("Labels")

> #Draw the heatmap of genes in KEGG_RIBOSOME pathway
> drawAHeatMap(Result, Name = "KEGG_RIBOSOME", PCExpr = Profile, Labels = Labels)

NULL
```

Figure 2 shows the heatmap of genes in KEGG RIBOSOME pathway based on the example expression profile.

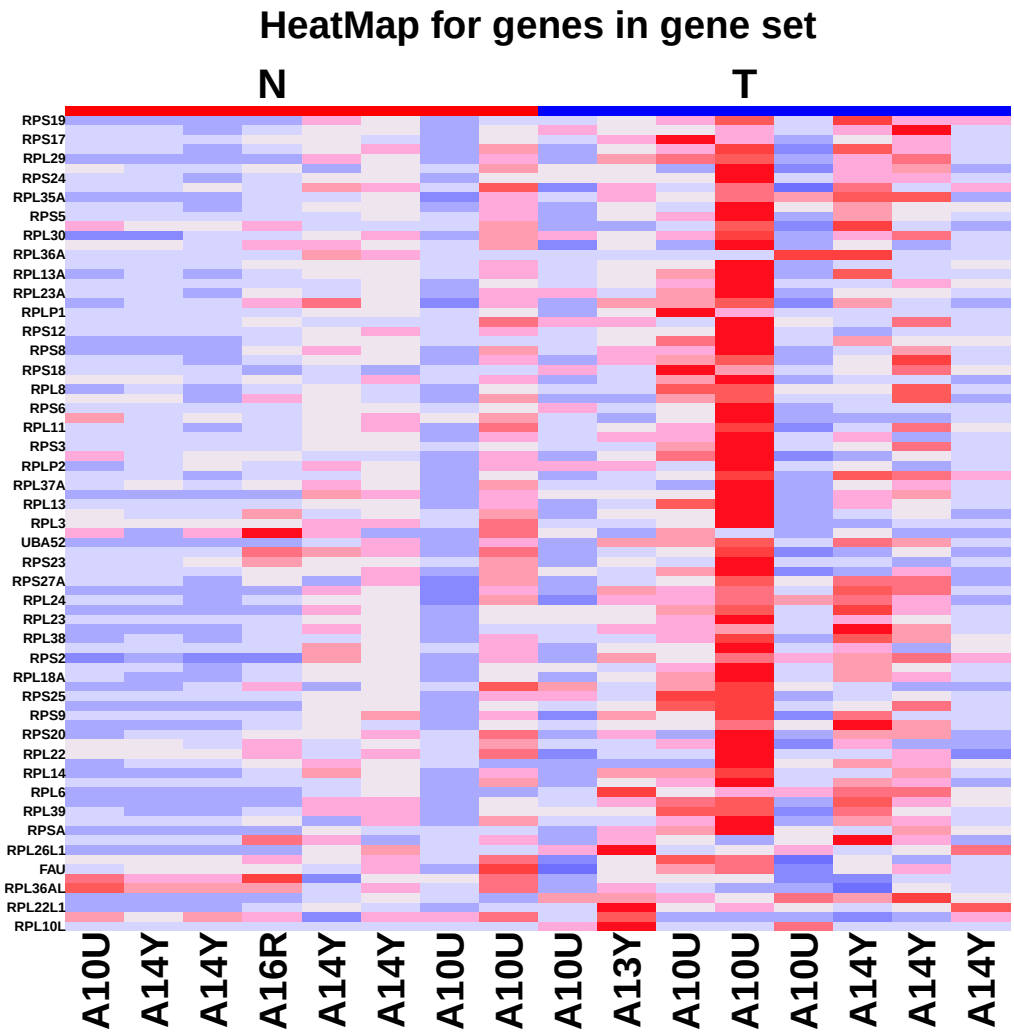


Figure 2: The heatmap of genes in KEGG RIBOSOME pathway based on the example expression profile.

# 5 Session Info

The script runs within the following session:

```
R version 4.4.2 (2024-10-31)
Platform: x86_64-pc-linux-gnu
Running under: Ubuntu 24.04.1 LTS

Matrix products: default
BLAS:   /usr/lib/x86_64-linux-gnu/openblas-pthread/libblas.so.3
LAPACK: /usr/lib/x86_64-linux-gnu/openblas-pthread/libopenblasp-r0.3.26.so;  LAPACK version 3.12.0

locale:
 [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
 [3] LC_TIME=en_US.UTF-8        LC_COLLATE=C
 [5] LC_MONETARY=en_US.UTF-8    LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_US.UTF-8       LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C

time zone: Etc/UTC
tzcode source: system (glibc)

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
[1] LncPath_1.1  igraph_2.1.1

loaded via a namespace (and not attached):
 [1] xfun_0.49        Matrix_1.7-1     lattice_0.22-6   magrittr_2.0.3
 [5] maketools_1.3.1  glue_1.8.0       knitr_1.48       pkgconfig_2.0.3
 [9] buildtools_1.0.0 lifecycle_1.0.4  cli_3.6.3        grid_4.4.2
[13] compiler_4.4.2   sys_3.4.3        tools_4.4.2      rlang_1.1.4
```

# References


[Subramanian *et al.*, 2005] Subramanian, A., Tamayo, P., Mootha, V.K., Mukherjee, S., Ebert, B.L., Gillette, M.A., Paulovich, A., Pomeroy, S.L., Golub, T.R., Lander, E.S. et al. (2005) Gene set enrichment analysis: a knowledgebased approach for interpreting genome-wide expression profiles. Proc Natl Acad Sci U S A, 102, 15545-15550.

[Liao Q *et al.*, 2011] Liao Q, Liu C, Yuan X, Kang S, Miao R, Xiao H, Zhao G, Luo H, Bu D, Zhao H, et al: Large-scale prediction of long non-coding RNA functions in a coding-non-coding gene co-expression network. Nucleic Acids Res 2011, 39:3864-3878.

[Guo X *et al.*, 2013] Guo X, Gao L, Liao Q, Xiao H, Ma X, Yang X, Luo H, Zhao G, Bu D, Jiao F, et al: Long non-coding RNAs function annotation: a global prediction method based on bi-colored networks. Nucleic Acids Res 2013, 41:e35.