

Introduction to RBM package

Dongmei Li

May 1, 2024

Clinical and Translational Science Institute, University of Rochester School of Medicine and Dentistry, Rochester, NY 14642-0708

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1 Overview

This document provides an introduction to the RBM package. The RBM package executes the resampling-based empirical Bayes approach using either permutation or bootstrap tests based on moderated t-statistics through the following steps.

- Firstly, the RBM package computes the moderated t-statistics based on the observed data set for each feature using the `lmFit` and `eBayes` function.
- Secondly, the original data are permuted or bootstrapped in a way that matches the null hypothesis to generate permuted or bootstrapped resamples, and the reference distribution is constructed using the resampled moderated t-statistics calculated from permutation or bootstrap resamples.
- Finally, the p-values from permutation or bootstrap tests are calculated based on the proportion of the permuted or bootstrapped moderated t-statistics that are as extreme as, or more extreme than, the observed moderated t-statistics.

Additional detailed information regarding resampling-based empirical Bayes approach can be found elsewhere (Li et al., 2013).

2 Getting started

The RBM package can be installed and loaded through the following R code. Install the RBM package with:

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

Load the RBM package with:

```
> library(RBM)
```

3 RBM_T and RBM_F functions

There are two functions in the RBM package: `RBM_T` and `RBM_F`. Both functions require input data in the matrix format with rows denoting features and columns denoting samples. `RBM_T` is used for two-group comparisons such as study designs with a treatment group and a control group. `RBM_F` can be used for more complex study designs such as more than two groups or time-course studies. Both functions need a vector for group notation, i.e., "1" denotes the treatment group and "0" denotes the control group. For the `RBM_F` function, a contrast vector need to be provided by users to perform pairwise comparisons between groups. For example, if the design has three groups (0, 1, 2), the `aContrast` parameter will be a vector such as ("X1-X0", "X2-X1", "X2-X0") to denote all pairwise comparisons. Users just need to add an extra "X" before the group labels to do the contrasts.

- Examples using the `RBM_T` function: `normdata` simulates a standardized gene expression data and `unifdata` simulates a methylation microarray data. The p -values from the `RBM_T` function could be further adjusted using the `p.adjust` function in the `stats` package through the Benjamini-Hochberg method.

```
> library(RBM)
> normdata <- matrix(rnorm(1000*6, 0, 1),1000,6)
> mydesign <- c(0,0,0,1,1,1)
> myresult <- RBM_T(normdata,mydesign,100,0.05)
> summary(myresult)
```

	Length	Class	Mode
<code>ordfit_t</code>	1000	-none-	numeric
<code>ordfit_pvalue</code>	1000	-none-	numeric
<code>ordfit_beta0</code>	1000	-none-	numeric
<code>ordfit_beta1</code>	1000	-none-	numeric
<code>permutation_p</code>	1000	-none-	numeric
<code>bootstrap_p</code>	1000	-none-	numeric

```
> sum(myresult$permutation_p<=0.05)
```

```

[1] 47

> which(myresult$permutation_p<=0.05)

[1] 6 28 81 87 108 131 172 187 191 209 232 263 276 287 305 335 348 350 362
[20] 370 373 377 380 399 423 447 462 485 567 586 594 599 600 613 639 666 703 758
[39] 834 843 927 954 955 960 977 982 998

> sum(myresult$bootstrap_p<=0.05)

[1] 7

> which(myresult$bootstrap_p<=0.05)

[1] 131 192 215 492 650 720 923

> permutation_adj_p <- p.adjust(myresult$permutation_p, "BH")
> sum(permutation_adj_p<=0.05)

[1] 12

> bootstrap_adj_p <- p.adjust(myresult$bootstrap_p, "BH")
> sum(bootstrap_adj_p<=0.05)

[1] 0

> unifdata <- matrix(runif(1000*7,0.10, 0.95), 1000, 7)
> mydesign2 <- c(0,0,0, 1,1,1,1)
> myresult2 <- RBM_T(unifdata,mydesign2,100,0.05)
> sum(myresult2$permutatioin_p<=0.05)

[1] 0

> sum(myresult2$bootstrap_p<=0.05)

[1] 27

> which(myresult2$bootstrap_p<=0.05)

[1] 21 85 87 94 103 175 236 269 320 333 402 436 464 501 537 566 593 612 666
[20] 743 762 817 839 849 863 935 985

> bootstrap2_adj_p <- p.adjust(myresult2$bootstrap_p, "BH")
> sum(bootstrap2_adj_p<=0.05)

[1] 0

```

- Examples using the `RBM_F` function: `normdata_F` simulates a standardized gene expression data and `unifdata_F` simulates a methylation microarray data. In both examples, we were interested in pairwise comparisons.

```

> normdata_F <- matrix(rnorm(1000*9,0,2), 1000, 9)
> mydesign_F <- c(0, 0, 0, 1, 1, 1, 2, 2, 2)
> aContrast <- c("X1-X0", "X2-X1", "X2-X0")
> myresult_F <- RBM_F(normdata_F, mydesign_F, aContrast, 100, 0.05)
> summary(myresult_F)

              Length Class  Mode
ordfit_t      3000  -none- numeric
ordfit_pvalue 3000  -none- numeric
ordfit_beta1  3000  -none- numeric
permutation_p 3000  -none- numeric
bootstrap_p   3000  -none- numeric

> sum(myresult_F$permutation_p[, 1]<=0.05)

[1] 52

> sum(myresult_F$permutation_p[, 2]<=0.05)

[1] 41

> sum(myresult_F$permutation_p[, 3]<=0.05)

[1] 49

> which(myresult_F$permutation_p[, 1]<=0.05)

[1] 29 46 57 62 63 76 86 139 142 167 171 172 183 219 332 364 417 437 460
[20] 475 491 503 514 539 548 577 617 620 622 655 667 705 708 715 734 762 806 811
[39] 821 822 824 829 839 840 874 875 882 885 922 932 964 976

> which(myresult_F$permutation_p[, 2]<=0.05)

[1] 29 51 62 63 76 86 90 139 142 172 183 219 313 332 363 402 470 482 491
[20] 503 514 539 577 617 620 633 655 659 667 705 762 806 810 822 824 829 840 875
[39] 882 948 964

> which(myresult_F$permutation_p[, 3]<=0.05)

[1] 29 62 63 76 84 86 90 139 142 171 172 183 219 313 332 364 402 437 470
[20] 503 507 514 532 539 549 577 617 620 622 633 655 667 705 715 762 806 810 811
[39] 822 824 829 840 874 875 882 885 922 964 976

```

```

> con1_adjp <- p.adjust(myresult_F$permutation_p[, 1], "BH")
> sum(con1_adjp<=0.05/3)

[1] 9

> con2_adjp <- p.adjust(myresult_F$permutation_p[, 2], "BH")
> sum(con2_adjp<=0.05/3)

[1] 8

> con3_adjp <- p.adjust(myresult_F$permutation_p[, 3], "BH")
> sum(con3_adjp<=0.05/3)

[1] 7

> which(con2_adjp<=0.05/3)

[1] 29 76 86 514 667 705 762 875

> which(con3_adjp<=0.05/3)

[1] 86 142 514 620 667 762 875

> unifdata_F <- matrix(runif(1000*18, 0.15, 0.98), 1000, 18)
> mydesign2_F <- c(rep(0, 6), rep(1, 6), rep(2, 6))
> aContrast <- c("X1-X0", "X2-X1", "X2-X0")
> myresult2_F <- RBM_F(unifdata_F, mydesign2_F, aContrast, 100, 0.05)
> summary(myresult2_F)

              Length Class  Mode
ordfit_t      3000   -none- numeric
ordfit_pvalue 3000   -none- numeric
ordfit_beta1  3000   -none- numeric
permutation_p 3000   -none- numeric
bootstrap_p   3000   -none- numeric

> sum(myresult2_F$bootstrap_p[, 1]<=0.05)

[1] 61

> sum(myresult2_F$bootstrap_p[, 2]<=0.05)

[1] 59

> sum(myresult2_F$bootstrap_p[, 3]<=0.05)

[1] 54

```

```

> which(myresult2_F$bootstrap_p[, 1]<=0.05)

[1] 28 35 41 73 125 129 156 197 203 205 218 221 238 272 276 289 305 310 335
[20] 360 397 416 436 447 449 460 461 489 495 501 510 536 557 628 635 637 650 657
[39] 662 700 704 714 740 752 755 757 789 792 799 819 832 837 861 876 882 883 903
[58] 915 976 978 988

> which(myresult2_F$bootstrap_p[, 2]<=0.05)

[1] 28 41 43 55 73 80 125 129 156 177 197 203 205 208 218 221 233 238 272
[20] 276 289 305 335 397 416 436 447 449 460 461 474 489 501 510 535 536 539 575
[39] 615 628 635 637 657 658 662 700 702 755 757 819 837 861 876 882 883 896 903
[58] 915 978

> which(myresult2_F$bootstrap_p[, 3]<=0.05)

[1] 28 35 41 125 129 156 177 197 203 208 218 221 233 266 272 276 284 289 305
[20] 335 358 360 436 449 460 489 501 510 536 557 628 635 637 650 657 700 702 704
[39] 714 740 755 757 789 792 819 832 837 876 882 883 903 915 978 988

> con21_adj_p <- p.adjust(myresult2_F$bootstrap_p[, 1], "BH")
> sum(con21_adj_p<=0.05/3)

[1] 9

> con22_adj_p <- p.adjust(myresult2_F$bootstrap_p[, 2], "BH")
> sum(con22_adj_p<=0.05/3)

[1] 4

> con23_adj_p <- p.adjust(myresult2_F$bootstrap_p[, 3], "BH")
> sum(con23_adj_p<=0.05/3)

[1] 3

```

4 Ovarian cancer methylation example using the RBM_T function

Two-group comparisons are the most common contrast in biological and biomedical field. The ovarian cancer methylation example is used to illustrate the application of RBM_T in identifying differentially methylated loci. The ovarian cancer methylation example is taken from the genome-wide DNA methylation profiling of United Kingdom Ovarian Cancer Population Study (UKOPS). This study used Illumina Infinium 27k Human DNA methylation Beadchip v1.2 to obtain DNA methylation profiles on over 27,000 CpGs in whole blood cells from 266 ovarian cancer women and 274 age-matched healthy controls. The data are downloaded from the NCBI GEO website with access number GSE19711. For illustration purpose, we chose the first 1000 loci in 8 randomly selected women with 4 ovarian cancer cases (pre-treatment) and 4 healthy controls. The following codes show the process of generating significant differential DNA methylation loci using the RBM_T function and presenting the results for further validation and investigations.

```

> system.file("data", package = "RBM")

[1] "/tmp/RtmpLXoC6n/Rinstfc4dc34b50e1a/RBM/data"

> data(ovarian_cancer_methylation)
> summary(ovarian_cancer_methylation)

      IlmnID      Beta      exmdata2[, 2]      exmdata3[, 2]
cg00000292: 1  Min.   :0.01058  Min.   :0.01187  Min.   :0.009103
cg00002426: 1  1st Qu.:0.04111  1st Qu.:0.04407  1st Qu.:0.041543
cg00003994: 1  Median :0.08284  Median :0.09531  Median :0.087042
cg00005847: 1  Mean    :0.27397  Mean    :0.28872  Mean    :0.283729
cg00006414: 1  3rd Qu.:0.52135  3rd Qu.:0.59032  3rd Qu.:0.558575
cg00007981: 1  Max.    :0.97069  Max.    :0.96937  Max.    :0.970155
(Other)    :994      NA's    :4
exmdata4[, 2]  exmdata5[, 2]  exmdata6[, 2]  exmdata7[, 2]
Min.   :0.01019  Min.   :0.01108  Min.   :0.01937  Min.   :0.01278
1st Qu.:0.04092  1st Qu.:0.04059  1st Qu.:0.05060  1st Qu.:0.04260
Median :0.09042  Median :0.08527  Median :0.09502  Median :0.09362
Mean    :0.28508  Mean    :0.28482  Mean    :0.27348  Mean    :0.27563
3rd Qu.:0.57502  3rd Qu.:0.57300  3rd Qu.:0.52099  3rd Qu.:0.52240
Max.    :0.96658  Max.    :0.97516  Max.    :0.96681  Max.    :0.95974
      NA's      :1
exmdata8[, 2]
Min.   :0.01357
1st Qu.:0.04387
Median :0.09282
Mean    :0.28679
3rd Qu.:0.57217
Max.    :0.96268

> ovarian_cancer_data <- ovarian_cancer_methylation[, -1]
> label <- c(1, 1, 0, 0, 1, 1, 0, 0)
> diff_results <- RBM_T(aData=ovarian_cancer_data, vec_trt=label, repetition=100, alpha=0.05)
> summary(diff_results)

      Length Class  Mode
ordfit_t      1000  -none- numeric
ordfit_pvalue 1000  -none- numeric
ordfit_beta0  1000  -none- numeric
ordfit_beta1  1000  -none- numeric
permutation_p 1000  -none- numeric
bootstrap_p   1000  -none- numeric

> sum(diff_results$ordfit_pvalue<=0.05)

[1] 45

```

```

> sum(diff_results$permutation_p<=0.05)

[1] 57

> sum(diff_results$bootstrap_p<=0.05)

[1] 72

> ordfit_adj_p <- p.adjust(diff_results$ordfit_pvalue, "BH")
> sum(ordfit_adj_p<=0.05)

[1] 0

> perm_adj_p <- p.adjust(diff_results$permutation_p, "BH")
> sum(perm_adj_p<=0.05)

[1] 3

> boot_adj_p <- p.adjust(diff_results$bootstrap_p, "BH")
> sum(boot_adj_p<=0.05)

[1] 10

> diff_list_perm <- which(perm_adj_p<=0.05)
> diff_list_boot <- which(boot_adj_p<=0.05)
> sig_results_perm <- cbind(ovarian_cancer_methylation[diff_list_perm, ], diff_results$ordfit_t)
> print(sig_results_perm)

      IlmnID      Beta exmdata2[, 2] exmdata3[, 2] exmdata4[, 2]
245 cg00224508 0.04479948 0.04972043 0.04152814 0.04189373
280 cg00260778 0.64319890 0.60488960 0.56735060 0.53150910
764 cg00730260 0.90471270 0.90542290 0.91002680 0.91258610
      exmdata5[, 2] exmdata6[, 2] exmdata7[, 2] exmdata8[, 2]
245 0.04208405 0.05284988 0.03775905 0.03955271
280 0.61920530 0.61925200 0.46753250 0.55632410
764 0.90575890 0.88760470 0.90756300 0.90946790
      diff_results$ordfit_t[diff_list_perm]
245 1.962457
280 4.170347
764 -1.808081
      diff_results$permutation_p[diff_list_perm]
245 0
280 0
764 0

> sig_results_boot <- cbind(ovarian_cancer_methylation[diff_list_boot, ], diff_results$ordfit_t)
> print(sig_results_boot)

```

