

Introduction to RBM package

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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:

```
> source("http://bioconductor.org/biocLite.R")
> biocLite("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
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(myresult$permutation_p<=0.05)
```

```
[1] 54
```

```

> which(myresult$permutation_p<=0.05)

[1] 11 17 30 36 48 50 63 93 106 126 158 167 178 181 183 207 227 234 267
[20] 295 303 318 319 325 329 334 363 416 418 436 454 470 509 524 529 534 607 614
[39] 633 641 653 689 706 719 765 783 797 824 836 841 843 857 908 912

> sum(myresult$bootstrap_p<=0.05)

[1] 7

> which(myresult$bootstrap_p<=0.05)

[1] 66 191 248 385 463 466 691

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

[1] 9

> 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] 25

> which(myresult2$bootstrap_p<=0.05)

[1] 30 39 48 81 115 134 155 161 304 318 324 370 463 468 475 486 543 580 595
[20] 615 747 773 824 929 942

> 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] 55

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

[1] 55

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

[1] 53

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

[1]  36  37  65 101 129 139 150 240 270 288 291 294 299 376 389 391 410 414 424
[20] 434 435 480 498 517 531 535 545 555 562 606 608 637 673 675 704 706 719 752
[39] 769 774 787 809 820 849 864 913 917 919 939 940 941 965 968 969 973

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

[1]  34  36  37  42  65  73 101 129 139 144 240 255 270 275 288 291 295 299 317
[20] 375 376 387 410 424 434 435 493 498 517 531 535 555 606 608 618 637 675 704
[39] 706 719 752 769 774 804 809 820 849 864 913 917 919 939 941 965 973

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

[1]  37  65  73 101 139 188 240 255 270 288 291 295 299 356 379 389 391 410 424
[20] 434 435 493 517 531 535 555 562 606 608 619 673 675 704 706 719 752 769 774
[39] 787 796 804 809 820 864 874 913 917 919 939 941 965 969 973

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

[1] 16

```

```

> con2_adj_p <- p.adjust(myresult_F$permutation_p[, 2], "BH")
> sum(con2_adj_p<=0.05/3)

[1] 14

> con3_adj_p <- p.adjust(myresult_F$permutation_p[, 3], "BH")
> sum(con3_adj_p<=0.05/3)

[1] 10

> which(con2_adj_p<=0.05/3)

[1] 37 291 299 435 517 608 637 706 719 809 820 864 917 919

> which(con3_adj_p<=0.05/3)

[1] 73 291 299 424 434 517 608 719 809 913

> 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] 40

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

[1] 52

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

[1] 36

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

[1] 2 10 14 18 41 95 130 131 152 231 254 271 281 314 386 426 434 444 460
[20] 484 489 492 498 594 598 602 685 768 804 813 901 943 959 963 969 973 974 984
[39] 990 994

```

```

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

[1] 2 10 14 18 35 41 56 78 95 97 130 131 152 194 200 231 271 311 312
[20] 314 386 388 434 444 460 484 489 498 509 549 556 575 594 598 641 656 738 768
[39] 813 839 840 872 901 928 950 959 963 969 973 974 984 990

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

[1] 2 10 14 31 35 41 95 131 152 194 200 231 279 301 386 444 460 484 489
[20] 492 498 594 598 641 768 795 813 840 901 959 963 969 973 974 984 990

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

[1] 3

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

[1] 1

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

[1] 0

```

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] "C:/biocbld/bbs-3.2-bioc/tmpdir/Rtmpch0Abf/Rinst26646cca5ca7/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] 69

```

```

> sum(diff_results$bootstrap_p<=0.05)

```

```
[1] 53
```

```
> 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] 5
```

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

```
[1] 5
```

```
> 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]
83	cg00072216	0.04505377	0.04598964	0.04000674	0.03231534
103	cg00094319	0.73784280	0.73532960	0.75574900	0.73830220
106	cg00095674	0.07076291	0.05045181	0.03861991	0.03337576
848	cg00826384	0.05721674	0.05612171	0.06644259	0.06358381
851	cg00830029	0.58362500	0.59397870	0.64739610	0.67269640
	exmdata5[, 2]	exmdata6[, 2]	exmdata7[, 2]	exmdata8[, 2]	
83	0.04965089	0.04833366	0.03466159	0.04390894	
103	0.67349260	0.73510200	0.75715920	0.78981220	
106	0.04693030	0.06837343	0.04534005	0.03709488	
848	0.05230160	0.06119713	0.06542751	0.06240686	
851	0.50820240	0.34657470	0.66276570	0.64634510	
	diff_results\$ordfit_t[diff_list_perm]				
83	2.514109				
103	-2.268711				
106	3.100324				
848	-2.314412				
851	-2.841244				
	diff_results\$permutation_p[diff_list_perm]				
83	0				
103	0				
106	0				
848	0				
851	0				


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

	IlmnID	Beta	exmdata2[, 2]	exmdata3[, 2]	exmdata4[, 2]
95	cg00081975	0.03633894	0.04975194	0.06024723	0.05598723
106	cg00095674	0.07076291	0.05045181	0.03861991	0.03337576
259	cg00234961	0.04192170	0.04321576	0.05707140	0.05327565
911	cg00888479	0.07388961	0.07361080	0.10149800	0.09985076
928	cg00901493	0.03737166	0.03903724	0.04684618	0.04981432

	exmdata5[, 2]	exmdata6[, 2]	exmdata7[, 2]	exmdata8[, 2]
95	0.04561792	0.05115624	0.06068253	0.06168212
106	0.04693030	0.06837343	0.04534005	0.03709488
259	0.04030003	0.03996053	0.05086962	0.05445672
911	0.08633986	0.06765189	0.09070268	0.12417730
928	0.04490690	0.04204062	0.05050039	0.05268215

	diff_results\$ordfit_t[diff_list_boot]
95	-3.252063
106	3.100324
259	-4.052697
911	-3.621731
928	-2.716443

	diff_results\$bootstrap_p[diff_list_boot]
95	0
106	0
259	0
911	0
928	0