

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:

```
> 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
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] 48

> which(myresult$permutation_p<=0.05)

[1] 31 45 68 89 91 104 110 111 113 183 197 228 249 265 266 280 282 293 312
[20] 322 326 344 360 432 442 530 549 597 635 646 655 703 762 765 798 803 811 837
[39] 843 869 871 878 909 910 927 928 956 960

> sum(myresult$bootstrap_p<=0.05)

[1] 10

> which(myresult$bootstrap_p<=0.05)

[1] 149 252 409 429 563 703 869 871 876 909

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

[1] 6

> 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] 20

> which(myresult2$bootstrap_p<=0.05)

[1] 31 218 244 281 349 366 378 392 406 534 562 628 701 747 783 835 856 939 951
[20] 964

> 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] 68

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

[1] 79

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

[1] 57

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

[1] 20 33 46 60 89 124 127 185 194 228 231 270 272 274 300 308 348 349 353
[20] 354 364 368 369 400 401 434 454 461 468 491 526 542 562 604 606 608 612 634
[39] 643 646 658 671 683 711 722 727 760 762 764 771 776 781 823 856 860 879 891
[58] 899 900 926 937 940 948 969 970 985 986 996

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

[1] 20 33 46 53 60 89 93 119 124 127 156 185 194 231 270 272 274 300 308
[20] 348 349 353 354 363 364 368 369 400 401 405 434 439 446 454 461 468 491 504
[39] 526 542 551 562 582 600 604 606 608 612 634 643 646 658 671 683 696 711 722
[58] 727 760 776 781 809 823 829 856 860 891 893 899 926 930 937 940 948 969 982
[77] 985 986 996

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

[1] 33 46 60 89 124 127 185 193 231 270 300 308 349 353 354 364 368 369 400
[20] 434 454 461 468 526 542 591 606 612 634 646 658 674 683 711 722 727 760 762
[39] 781 802 823 835 856 860 881 891 899 915 926 937 940 948 969 982 985 986 996
```

```

> con1_adj_p <- p.adjust(myresult_F$permutation_p[, 1], "BH")
> sum(con1_adj_p<=0.05/3)

[1] 10

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

[1] 21

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

[1] 5

> which(con2_adj_p<=0.05/3)

[1] 33 124 185 270 300 349 353 354 364 369 434 454 634 646 722 760 823 856 926
[20] 937 985

> which(con3_adj_p<=0.05/3)

[1] 354 722 760 937 940

> 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] 52

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

[1] 76

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

[1] 68

```

```

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

[1] 11 71 76 87 114 152 165 248 255 270 275 317 336 340 345
[16] 365 368 403 409 415 416 432 439 448 475 479 510 524 550 553
[31] 583 584 597 622 653 698 708 737 762 788 795 807 833 846 858
[46] 901 962 964 967 968 981 1000

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

[1] 1 11 27 29 71 76 87 114 142 146 149 152 165 197 232
[16] 236 248 255 265 270 274 275 317 336 345 357 368 384 394 396
[31] 403 409 415 416 439 448 457 467 475 479 510 519 524 550 553
[46] 570 583 584 597 609 643 648 653 698 708 711 737 762 788 792
[61] 833 846 858 867 879 901 937 962 964 967 968 979 981 983 998
[76] 1000

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

[1] 1 11 12 27 32 71 76 114 142 144 152 165 197 237 248
[16] 255 265 270 274 275 317 336 345 368 396 403 409 410 415 416
[31] 432 439 448 475 479 510 519 524 583 584 597 609 622 643 653
[46] 698 708 711 734 737 762 788 792 795 833 858 867 901 927 962
[61] 964 967 968 979 981 983 994 1000

> con21_adjp <- p.adjust(myresult2_F$bootstrap_p[, 1], "BH")
> sum(con21_adjp<=0.05/3)

[1] 5

> con22_adjp <- p.adjust(myresult2_F$bootstrap_p[, 2], "BH")
> sum(con22_adjp<=0.05/3)

[1] 10

> con23_adjp <- p.adjust(myresult2_F$bootstrap_p[, 3], "BH")
> sum(con23_adjp<=0.05/3)

[1] 14

```

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 gemone-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] "/private/tmp/Rtmp3eMrek/Rinst127206d39123b/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] 73

> 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] 10

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

[1] 8

> 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]
19 cg00016968 0.80628480          NA    0.81440820    0.83623180
103 cg00094319 0.73784280    0.73532960    0.75574900    0.73830220
131 cg00121904 0.15449580    0.17949750    0.23608110    0.24354150
245 cg00224508 0.04479948    0.04972043    0.04152814    0.04189373
627 cg00612467 0.04777553    0.03783457    0.05380982    0.05582291
764 cg00730260 0.90471270    0.90542290    0.91002680    0.91258610
848 cg00826384 0.05721674    0.05612171    0.06644259    0.06358381
851 cg00830029 0.58362500    0.59397870    0.64739610    0.67269640
887 cg00862290 0.43640520    0.54047160    0.60786800    0.56325950
979 cg00945507 0.13432250    0.23854600    0.34749760    0.28903340
      exmdata5[, 2] exmdata6[, 2] exmdata7[, 2] exmdata8[, 2]
19      0.80831380      0.73306440      0.82968340      0.84917800

```


103	0.67349260	0.73510200	0.75715920	0.78981220
131	0.17352980	0.12564280	0.18193170	0.20847670
245	0.04208405	0.05284988	0.03775905	0.03955271
627	0.04740551	0.05332965	0.05775211	0.05579710
764	0.90575890	0.88760470	0.90756300	0.90946790
848	0.05230160	0.06119713	0.06542751	0.06240686
851	0.50820240	0.34657470	0.66276570	0.64634510
887	0.50259740	0.40111730	0.56646700	0.54552980
979	0.11848510	0.16653850	0.30718420	0.26624740

diff_results\$ordfit_t[diff_list_perm]

19	-2.446404
103	-2.268711
131	-3.451679
245	1.962457
627	-2.239498
764	-1.808081
848	-2.314412
851	-2.841244
887	-3.217939
979	-4.750997

diff_results\$permutation_p[diff_list_perm]

19	0
103	0
131	0
245	0
627	0
764	0
848	0
851	0
887	0
979	0

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

	IlmnID	Beta	exmdata2[, 2]	exmdata3[, 2]	exmdata4[, 2]
95	cg00081975	0.03633894	0.04975194	0.06024723	0.05598723
200	cg00183916	0.03525946	0.03984548	0.02765822	0.02789838
259	cg00234961	0.04192170	0.04321576	0.05707140	0.05327565
280	cg00260778	0.64319890	0.60488960	0.56735060	0.53150910
285	cg00263760	0.09050395	0.10197760	0.14801710	0.12242400
743	cg00717862	0.07999436	0.07873347	0.06089359	0.06171374
882	cg00858899	0.11427700	0.11919540	0.07690343	0.08321229
911	cg00888479	0.07388961	0.07361080	0.10149800	0.09985076
	exmdata5[, 2]	exmdata6[, 2]	exmdata7[, 2]	exmdata8[, 2]	
95	0.04561792	0.05115624	0.06068253	0.06168212	

200	0.03034811	0.04302129	0.02753873	0.03067437
259	0.04030003	0.03996053	0.05086962	0.05445672
280	0.61920530	0.61925200	0.46753250	0.55632410
285	0.11693600	0.10650430	0.12281160	0.12310430
743	0.07594936	0.09062161	0.06475791	0.07271878
882	0.08961409	0.10730660	0.09203980	0.08726349
911	0.08633986	0.06765189	0.09070268	0.12417730
diff_results\$ordfit_t[diff_list_boot]				
95			-3.252063	
200			2.272449	
259			-4.052697	
280			4.170347	
285			-3.093997	
743			3.444684	
882			3.179415	
911			-3.621731	
diff_results\$bootstrap_p[diff_list_boot]				
95			0	
200			0	
259			0	
280			0	
285			0	
743			0	
882			0	
911			0	