

# 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] 21
```

```

> which(myresult$permutation_p<=0.05)

[1] 30 68 117 177 182 232 235 276 343 393 488 541 593 649 738 822 853 864 875
[20] 909 992

> sum(myresult$bootstrap_p<=0.05)

[1] 1

> which(myresult$bootstrap_p<=0.05)

[1] 308

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

[1] 1

> 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] 42

> which(myresult2$bootstrap_p<=0.05)

[1] 56 62 89 145 155 161 180 219 229 235 239 250 262 275 278 288 343 383 425
[20] 433 444 461 476 483 496 521 525 600 628 631 665 671 688 697 776 778 906 922
[39] 927 945 987 991

> 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] 47

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

[1] 61

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

[1] 67

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

[1]  29  56 107 165 186 199 250 265 270 275 302 326 378 379 382 403 411 429 463
[20] 476 480 487 497 552 594 599 604 605 612 632 637 719 744 765 784 806 809 834
[39] 837 851 858 861 884 926 935 940 967

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

[1]  16  19  48  56 107 114 165 186 199 242 250 259 265 270 275 292 318 326 357
[20] 379 382 390 403 411 424 429 463 470 476 480 487 497 511 515 552 594 599 604
[39] 605 612 632 637 698 718 719 744 765 784 809 837 850 851 858 861 884 926 940
[58] 967 989 993 998

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

[1]  16  48  99 100 107 165 186 199 242 250 259 265 270 275 302 315 318 326 357
[20] 362 379 382 411 424 428 429 450 463 470 471 476 480 487 497 511 520 552 581
[39] 594 599 604 605 612 632 637 640 718 719 720 744 765 784 809 834 837 850 851
[58] 858 900 901 926 935 940 967 989 993 998

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

```

```

[1] 2

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

[1] 10

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

[1] 13

> which(con2_adjp<=0.05/3)

[1] 186 199 429 497 552 604 605 765 837 967

> which(con3_adjp<=0.05/3)

[1] 199 250 429 463 497 552 604 605 718 744 765 837 858

> 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] 45

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

[1] 55

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

[1] 51

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

```

```
[1] 40 41 59 60 65 72 86 92 127 134 149 170 188 193 196 218 251 312 365
[20] 387 388 419 428 439 443 461 525 533 582 618 640 664 732 746 761 762 813 827
[39] 839 863 868 914 919 930 978
```

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

```
[1] 26 39 40 41 65 72 92 127 149 160 166 170 188 218 251 312 365 368 387
[20] 388 399 428 439 443 451 461 473 533 545 582 618 640 664 666 701 732 742 746
[39] 761 762 813 837 839 850 863 868 876 911 913 914 919 930 934 978 993
```

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

```
[1] 40 41 60 65 72 92 127 149 166 170 188 218 251 312 365 368 387 388 419
[20] 428 439 443 461 506 525 531 533 545 582 618 640 664 666 746 761 762 813 827
[39] 837 839 850 863 868 911 914 919 930 934 978 987 993
```

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

```
[1] 8
```

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

```
[1] 7
```

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

```
[1] 5
```

## 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] "E:/biocbld/bbs-3.3-bioc/tmpdir/RtmpmcR0eP/Rinst233463275a6b/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] 74
```

```
> sum(diff_results$bootstrap_p<=0.05)
```

```
[1] 57
```

```
> 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] 30
```

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

```
> sum(boot_adj_p<=0.05)
```

```
[1] 0
```

```
> 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]
16	cg00014085	0.05906804	0.04518973	0.04211710	0.03665208
19	cg00016968	0.80628480	NA	0.81440820	0.83623180
83	cg00072216	0.04505377	0.04598964	0.04000674	0.03231534
95	cg00081975	0.03633894	0.04975194	0.06024723	0.05598723
103	cg00094319	0.73784280	0.73532960	0.75574900	0.73830220
106	cg00095674	0.07076291	0.05045181	0.03861991	0.03337576
131	cg00121904	0.15449580	0.17949750	0.23608110	0.24354150
146	cg00134539	0.61101320	0.53321780	0.45999340	0.46787420
237	cg00215066	0.94926640	0.95311870	0.94634910	0.94561120
245	cg00224508	0.04479948	0.04972043	0.04152814	0.04189373
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
349	cg00332745	0.04703361	0.04634372	0.03676908	0.04518837
437	cg00424946	0.04122172	0.04325330	0.03339863	0.02876798
520	cg00502442	0.03163993	0.03581662	0.02785063	0.02549502
627	cg00612467	0.04777553	0.03783457	0.05380982	0.05582291
632	cg00615377	0.11265030	0.16140570	0.19404450	0.17468600
743	cg00717862	0.07999436	0.07873347	0.06089359	0.06171374
764	cg00730260	0.90471270	0.90542290	0.91002680	0.91258610



772	cg00743372	0.03922780	0.02919634	0.02187972	0.02568053
804	cg00777121	0.04540701	0.05430304	0.04154242	0.04221162
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
911	cg00888479	0.07388961	0.07361080	0.10149800	0.09985076
928	cg00901493	0.03737166	0.03903724	0.04684618	0.04981432
931	cg00901704	0.05734342	0.04812868	0.04478214	0.03878488
939	cg00906183	0.03949030	0.04365079	0.03720015	0.03575748
979	cg00945507	0.13432250	0.23854600	0.34749760	0.28903340
	exmdata5[, 2]	exmdata6[, 2]	exmdata7[, 2]	exmdata8[, 2]	
16	0.04222944	0.05324246	0.03728026	0.04062589	
19	0.80831380	0.73306440	0.82968340	0.84917800	
83	0.04965089	0.04833366	0.03466159	0.04390894	
95	0.04561792	0.05115624	0.06068253	0.06168212	
103	0.67349260	0.73510200	0.75715920	0.78981220	
106	0.04693030	0.06837343	0.04534005	0.03709488	
131	0.17352980	0.12564280	0.18193170	0.20847670	
146	0.67191510	0.63137380	0.47929610	0.45428300	
237	0.94837410	0.94665570	0.94089070	0.94600090	
245	0.04208405	0.05284988	0.03775905	0.03955271	
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	
349	0.04975075	0.05253778	0.04444665	0.03717721	
437	0.03353116	0.03719167	0.03096761	0.03234779	
520	0.03111720	0.03189393	0.02415307	0.02941176	
627	0.04740551	0.05332965	0.05775211	0.05579710	
632	0.12573100	0.14483660	0.16338240	0.20130510	
743	0.07594936	0.09062161	0.06475791	0.07271878	
764	0.90575890	0.88760470	0.90756300	0.90946790	
772	0.02796053	0.03512214	0.02575992	0.02093909	
804	0.04911277	0.04872797	0.04261405	0.04474881	
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	
911	0.08633986	0.06765189	0.09070268	0.12417730	
928	0.04490690	0.04204062	0.05050039	0.05268215	
931	0.04497277	0.05751033	0.03089829	0.04423603	
939	0.03856975	0.06024309	0.03594439	0.03502819	
979	0.11848510	0.16653850	0.30718420	0.26624740	
	diff_results\$ordfit_t[diff_list_perm]				
16		2.325659			
19		-2.446404			
83		2.514109			

95	-3.252063
103	-2.268711
106	3.100324
131	-3.451679
146	5.394750
237	1.419654
245	1.962457
259	-4.052697
280	4.170347
285	-3.093997
349	2.165826
437	2.102892
520	1.873471
627	-2.239498
632	-3.661161
743	3.444684
764	-1.808081
772	2.416991
804	1.995220
848	-2.314412
851	-2.841244
887	-3.217939
911	-3.621731
928	-2.716443
931	2.464709
939	1.762879
979	-4.750997

	diff_results\$permutation_p[diff_list_perm]
16	0
19	0
83	0
95	0
103	0
106	0
131	0
146	0
237	0
245	0
259	0
280	0
285	0
349	0
437	0
520	0
627	0

632	0
743	0
764	0
772	0
804	0
848	0
851	0
887	0
911	0
928	0
931	0
939	0
979	0

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

```
[1] IlmnID
[2] Beta
[3] exmdata2[, 2]
[4] exmdata3[, 2]
[5] exmdata4[, 2]
[6] exmdata5[, 2]
[7] exmdata6[, 2]
[8] exmdata7[, 2]
[9] exmdata8[, 2]
[10] diff_results$ordfit_t[diff_list_boot]
[11] diff_results$bootstrap_p[diff_list_boot]
<0 rows> (or 0-length row.names)
```