

# DMRcate for bisulfite sequencing

Peters TJ

July 28, 2025

## Summary

Worked example to find DMRs from whole genome bisulfite sequencing data.

```
if (!require("BiocManager"))  
  install.packages("BiocManager")  
BiocManager::install("DMRcate")
```

Load DMRcate into the workspace:

```
library(DMRcate)
```

Bisulfite sequencing assays are fundamentally different to arrays, because methylation is represented as a pair of methylated and unmethylated reads per sample, instead of a single beta value. Although we could simply take the logit-transformed fraction of methylated reads per CpG, this removes the effect of varying read depth across the genome. For example, a sampling depth of 30 methylated reads and 10 unmethylated reads is a much more precise estimate of the methylation level of a given CpG site than 3 methylated and 1 unmethylated. Hence, we take advantage of the fact that the overall effect can be expressed as an interaction between the coefficient of interest and a two-level factor representing methylated and unmethylated reads [1].

The example shown here will be performed on a BSseq object containing bisulfite sequencing of regulatory T cells from various tissues as part of the **tissueTreg** package[2], imported using ExperimentHub. First, we will import the data:

```
library(ExperimentHub)  
eh <- ExperimentHub()  
bis_1072 <- eh[["EH1072"]]  
bis_1072  
  
## An object of type 'BSseq' with  
## 21867550 methylation loci
```

```
## 15 samples
## has been smoothed with
## BSmooth (ns = 70, h = 1000, maxGap = 100000000)
## All assays are in-memory

colnames(bis_1072)

## [1] "Fat-Treg-R1"      "Fat-Treg-R2"      "Fat-Treg-R3"      "Liver-Treg-R1"
## [5] "Liver-Treg-R2"    "Liver-Treg-R3"    "Skin-Treg-R1"     "Skin-Treg-R2"
## [9] "Skin-Treg-R3"     "Lymph-N-Tcon-R1"  "Lymph-N-Tcon-R2"  "Lymph-N-Tcon-R3"
## [13] "Lymph-N-Treg-R1" "Lymph-N-Treg-R2" "Lymph-N-Treg-R3"
```

The data contains 15 samples: 3 (unmatched) replicates of mouse Tregs from fat, liver, skin and lymph node, plus a group of 3 CD4+ conventional lymph node T cells (Tcon). We will annotate the BSmooth object to reflect this phenotypic information:

```
bsseq::pData(bis_1072) <- data.frame(replicate=gsub(".*-", "", colnames(bis_1072)),
                                     tissue=substr(colnames(bis_1072), 1,
                                                    nchar(colnames(bis_1072))-3),
                                     row.names=colnames(bis_1072))
colData(bis_1072)$tissue <- gsub("-", "_", colData(bis_1072)$tissue)
as.data.frame(colData(bis_1072))

##           replicate      tissue
## Fat-Treg-R1         R1   Fat_Treg
## Fat-Treg-R2         R2   Fat_Treg
## Fat-Treg-R3         R3   Fat_Treg
## Liver-Treg-R1        R1  Liver_Treg
## Liver-Treg-R2        R2  Liver_Treg
## Liver-Treg-R3        R3  Liver_Treg
## Skin-Treg-R1         R1   Skin_Treg
## Skin-Treg-R2         R2   Skin_Treg
## Skin-Treg-R3         R3   Skin_Treg
## Lymph-N-Tcon-R1      R1 Lymph_N_Tcon
## Lymph-N-Tcon-R2      R2 Lymph_N_Tcon
## Lymph-N-Tcon-R3      R3 Lymph_N_Tcon
## Lymph-N-Treg-R1      R1 Lymph_N_Treg
## Lymph-N-Treg-R2      R2 Lymph_N_Treg
## Lymph-N-Treg-R3      R3 Lymph_N_Treg
```

For standardisation purposes (and for `DMR.plot` to recognise the genome) we will change the chromosome naming convention to UCSC:

```
library(GenomeInfoDb)
bis_1072 <- renameSeqlevels(bis_1072, mapSeqlevels(seqlevels(bis_1072), "UCSC"))
```

For demonstration purposes, we will retain CpGs on chromosome 19 only:

```
bis_1072 <- bis_1072[seqnames(bis_1072)=="chr19",]
bis_1072

## An object of type 'BSseq' with
## 558056 methylation loci
## 15 samples
## has been smoothed with
## BSmooth (ns = 70, h = 1000, maxGap = 100000000)
## All assays are in-memory
```

Now we can prepare the model to be fit for `sequencing.annotate()`. The arguments are equivalent to `cpg.annotate()` but for a couple of exceptions:

- There is an extra argument `all.cov` giving an option whether to retain only CpGs where *all* samples have non-zero coverage, or whether to retain CpGs with only partial sample representation.
- The design matrix should be constructed to reflect the 2-factor structure of methylated and unmethylated reads. Fortunately, `edgeR::modelMatrixMeth()` can take a regular design matrix and transform it into the appropriate structure ready for model fitting.

```
tissue <- factor(pData(bis_1072)$tissue)
tissue <- relevel(tissue, "Liver_Treg")

#Regular matrix design
design <- model.matrix(~tissue)
colnames(design) <- gsub("tissue", "", colnames(design))
colnames(design)[1] <- "Intercept"
rownames(design) <- colnames(bis_1072)
design
```

	Intercept	Fat_Treg	Lymph_N_Tcon	Lymph_N_Treg	Skin_Treg
## Fat-Treg-R1	1	1	0	0	0
## Fat-Treg-R2	1	1	0	0	0
## Fat-Treg-R3	1	1	0	0	0
## Liver-Treg-R1	1	0	0	0	0
## Liver-Treg-R2	1	0	0	0	0
## Liver-Treg-R3	1	0	0	0	0
## Skin-Treg-R1	1	0	0	0	1
## Skin-Treg-R2	1	0	0	0	1

```

## Skin-Treg-R3          1      0      0      0      1
## Lymph-N-Tcon-R1       1      0      1      0      0
## Lymph-N-Tcon-R2       1      0      1      0      0
## Lymph-N-Tcon-R3       1      0      1      0      0
## Lymph-N-Treg-R1       1      0      0      1      0
## Lymph-N-Treg-R2       1      0      0      1      0
## Lymph-N-Treg-R3       1      0      0      1      0
## attr("assign")
## [1] 0 1 1 1 1
## attr("contrasts")
## attr("contrasts")$tissue
## [1] "contr.treatment"

#Methylation matrix design
methdesign <- edgeR::modelMatrixMeth(design)
methdesign

##      Sample1 Sample2 Sample3 Sample4 Sample5 Sample6 Sample7 Sample8 Sample9
## 1          1      0      0      0      0      0      0      0      0
## 2          1      0      0      0      0      0      0      0      0
## 3          0      1      0      0      0      0      0      0      0
## 4          0      1      0      0      0      0      0      0      0
## 5          0      0      1      0      0      0      0      0      0
## 6          0      0      1      0      0      0      0      0      0
## 7          0      0      0      1      0      0      0      0      0
## 8          0      0      0      1      0      0      0      0      0
## 9          0      0      0      0      1      0      0      0      0
## 10         0      0      0      0      1      0      0      0      0
## 11         0      0      0      0      0      1      0      0      0
## 12         0      0      0      0      0      1      0      0      0
## 13         0      0      0      0      0      0      1      0      0
## 14         0      0      0      0      0      0      1      0      0
## 15         0      0      0      0      0      0      0      1      0
## 16         0      0      0      0      0      0      0      1      0
## 17         0      0      0      0      0      0      0      0      1
## 18         0      0      0      0      0      0      0      0      1
## 19         0      0      0      0      0      0      0      0      0
## 20         0      0      0      0      0      0      0      0      0
## 21         0      0      0      0      0      0      0      0      0
## 22         0      0      0      0      0      0      0      0      0
## 23         0      0      0      0      0      0      0      0      0
## 24         0      0      0      0      0      0      0      0      0
## 25         0      0      0      0      0      0      0      0      0
## 26         0      0      0      0      0      0      0      0      0
## 27         0      0      0      0      0      0      0      0      0
## 28         0      0      0      0      0      0      0      0      0

```

##	29	0	0	0	0	0	0	0	0	0
##	30	0	0	0	0	0	0	0	0	0
##		Sample10	Sample11	Sample12	Sample13	Sample14	Sample15	Intercept	Fat_Treg	
##	1	0	0	0	0	0	0	1	1	
##	2	0	0	0	0	0	0	0	0	
##	3	0	0	0	0	0	0	1	1	
##	4	0	0	0	0	0	0	0	0	
##	5	0	0	0	0	0	0	1	1	
##	6	0	0	0	0	0	0	0	0	
##	7	0	0	0	0	0	0	1	0	
##	8	0	0	0	0	0	0	0	0	
##	9	0	0	0	0	0	0	1	0	
##	10	0	0	0	0	0	0	0	0	
##	11	0	0	0	0	0	0	1	0	
##	12	0	0	0	0	0	0	0	0	
##	13	0	0	0	0	0	0	1	0	
##	14	0	0	0	0	0	0	0	0	
##	15	0	0	0	0	0	0	1	0	
##	16	0	0	0	0	0	0	0	0	
##	17	0	0	0	0	0	0	1	0	
##	18	0	0	0	0	0	0	0	0	
##	19	1	0	0	0	0	0	1	0	
##	20	1	0	0	0	0	0	0	0	
##	21	0	1	0	0	0	0	1	0	
##	22	0	1	0	0	0	0	0	0	
##	23	0	0	1	0	0	0	1	0	
##	24	0	0	1	0	0	0	0	0	
##	25	0	0	0	1	0	0	1	0	
##	26	0	0	0	1	0	0	0	0	
##	27	0	0	0	0	1	0	1	0	
##	28	0	0	0	0	1	0	0	0	
##	29	0	0	0	0	0	1	1	0	
##	30	0	0	0	0	0	1	0	0	
##		Lymph_N_Tcon	Lymph_N_Treg	Skin_Treg						
##	1	0	0	0						
##	2	0	0	0						
##	3	0	0	0						
##	4	0	0	0						
##	5	0	0	0						
##	6	0	0	0						
##	7	0	0	0						
##	8	0	0	0						
##	9	0	0	0						
##	10	0	0	0						
##	11	0	0	0						

```
## 12      0      0      0
## 13      0      0      1
## 14      0      0      0
## 15      0      0      1
## 16      0      0      0
## 17      0      0      1
## 18      0      0      0
## 19      1      0      0
## 20      0      0      0
## 21      1      0      0
## 22      0      0      0
## 23      1      0      0
## 24      0      0      0
## 25      0      1      0
## 26      0      0      0
## 27      0      1      0
## 28      0      0      0
## 29      0      1      0
## 30      0      0      0
```

Just like for `cpg.annotate()`, we can specify a contrast matrix to find our comparisons of interest.

```
cont.mat <- limma::makeContrasts(treg_vs_tcon=Lymph_N_Treg-Lymph_N_Tcon,
                                fat_vs_ln=Fat_Treg-Lymph_N_Treg,
                                skin_vs_ln=Skin_Treg-Lymph_N_Treg,
                                fat_vs_skin=Fat_Treg-Skin_Treg,
                                levels=methdesign)

cont.mat

##           Contrasts
## Levels      treg_vs_tcon fat_vs_ln skin_vs_ln fat_vs_skin
## Sample1              0          0          0          0
## Sample2              0          0          0          0
## Sample3              0          0          0          0
## Sample4              0          0          0          0
## Sample5              0          0          0          0
## Sample6              0          0          0          0
## Sample7              0          0          0          0
## Sample8              0          0          0          0
## Sample9              0          0          0          0
## Sample10             0          0          0          0
## Sample11             0          0          0          0
## Sample12             0          0          0          0
## Sample13             0          0          0          0
## Sample14             0          0          0          0
```

##	Sample15	0	0	0	0
##	Intercept	0	0	0	0
##	Fat_Treg	0	1	0	1
##	Lymph_N_Tcon	-1	0	0	0
##	Lymph_N_Treg	1	-1	-1	0
##	Skin_Treg	0	0	1	-1

Say we want to find DMRs between the regulatory and conventional T cells from the lymph node. First we would fit the model, where `sequencing.annotate()` transforms counts into log2CPMs (via `limma::voom()`) and uses `limma` under the hood to generate per-CpG  $t$ -statistics, indexing the FDR at 0.05:

```
seq_annot <- sequencing.annotate(bis_1072, methdesign, all.cov = TRUE,
                                contrasts = TRUE, cont.matrix = cont.mat,
                                coef = "treg_vs_tcon", fdr=0.05)

## Filtering out all CpGs where at least one sample has zero coverage...
## Processing BSseq object...
## Transforming counts...
## Fitting model...
## Your contrast returned 157 individually significant CpGs. We recommend
## the default setting of pcutoff in dmrcate().

seq_annot

## CpGannotated object describing 506908 CpG sites, with independent
## CpG threshold indexed at fdr=0.05 and 157 significant CpG sites.
```

And then, just like before, we can call DMRs with `dmrcate()`:

```
dmrcate.res <- dmrcate(seq_annot, C=2, min.cpgs = 5)

## Fitting chr19...
## Demarcating regions...
## Done!

dmrcate.res

## DMResults object with 9 DMRs.
## Use extractRanges() to produce a GRanges object of these.

treg_vs_tcon.ranges <- extractRanges(dmrcate.res, genome="mm10")

## see ?DMRcatedata and browseVignettes('DMRcatedata') for documentation
## loading from cache

treg_vs_tcon.ranges
```

```
## GRanges object with 9 ranges and 8 metadata columns:
##      seqnames      ranges strand |   no.cpgs min_smoothed_fdr
##      <Rle>        <IRanges> <Rle> | <integer>      <numeric>
## [1]   chr19 29270611-29272005     * |      16      4.32351e-94
## [2]   chr19 36378257-36379597     * |      27      1.53747e-76
## [3]   chr19 40808208-40809554     * |      26      3.43873e-63
## [4]   chr19 46653280-46654180     * |      19      3.94008e-59
## [5]   chr19 26683453-26684174     * |      12      1.77927e-57
## [6]   chr19 32276886-32278089     * |      13      1.74620e-56
## [7]   chr19 29374953-29375393     * |      12      1.48257e-54
## [8]   chr19 41874401-41874895     * |      22      2.75829e-39
## [9]   chr19 57092365-57092646     * |      10      3.80468e-36
##      Stouffer      HMFDR      Fisher      maxdiff      meandiff      overlapping.genes
##      <numeric>      <numeric>      <numeric> <numeric> <numeric>      <character>
## [1] 7.30413e-50 1.53438e-06 9.06017e-52 -6.40482 -4.22353      Jak2
## [2] 5.11228e-45 5.32893e-06 6.32480e-49 -6.09625 -3.03550      Pcgf5
## [3] 1.57979e-50 7.52023e-05 1.44219e-45 -4.83855 -3.07494      Cc2d2b
## [4] 6.97298e-34 5.32893e-06 1.28153e-35  5.18388  2.93152      Wbp11
## [5] 3.23045e-25 3.29036e-07 1.30324e-30 -6.40328 -3.53692      Smarca2
## [6] 2.50713e-38 5.32893e-06 1.55805e-36  5.81470  3.93201      Sgms1
## [7] 7.68507e-20 3.13417e-06 3.83714e-26 -6.10902 -3.02083      Cd274, Gm36043
## [8] 1.15140e-30 6.23899e-05 7.96953e-30  4.57011  2.56520      Rrp12
## [9] 1.28763e-24 7.32179e-06 6.36706e-23 -4.67645 -3.36472      Ablim1
## -----
##      seqinfo: 1 sequence from an unspecified genome; no seqlengths
```

Looks like the top DMR is associated with the *Jak2* locus and hypomethylated in the Treg cells (since `meandiff < 0`). We can plot it like so:

```
cols <- as.character(plyr::mapvalues(tissue, unique(tissue),
                                     c("darkorange", "maroon", "blue",
                                       "black", "magenta")))
names(cols) <- tissue

DMR.plot(treg_vs_tcon.ranges, dmr = 1,
         CpGs=bis_1072[,tissue %in% c("Lymph_N_Tcon", "Lymph_N_Treg")],
         phen.col = cols[tissue %in% c("Lymph_N_Tcon", "Lymph_N_Treg")],
         genome="mm10")
```





Now, let's find DMRs between fat and skin Tregs.

```
seq_annot <- sequencing.annotate(bis_1072, methdesign, all.cov = TRUE,
                                contrasts = TRUE, cont.matrix = cont.mat,
                                coef = "fat_vs_skin", fdr=0.05)

## Filtering out all CpGs where at least one sample has zero coverage...
## Processing BSseq object...
## Transforming counts...
## Fitting model...
## Your contrast returned 5 individually significant CpGs; a small
but real effect. Consider increasing the 'fdr' parameter using changeFDR(),
but be warned there is an increased risk of Type I errors.
```

Because this comparison is a bit more subtle, there are very few significantly differential CpGs at this threshold. So we can use `changeFDR()` to relax the

FDR to 0.25, taking into account that there is an increased risk of false positives.

```
seq_annot <- changeFDR(seq_annot, 0.25)

## Threshold is now set at FDR=0.25, resulting in 63 significantly differential CpGs.
```

```
dmrcate.res <- dmrcate(seq_annot, C=2, min.cpgs = 5)

## Fitting chr19...
## Demarcating regions...
## Done!

fat_vs_skin.ranges <- extractRanges(dmrcate.res, genome="mm10")

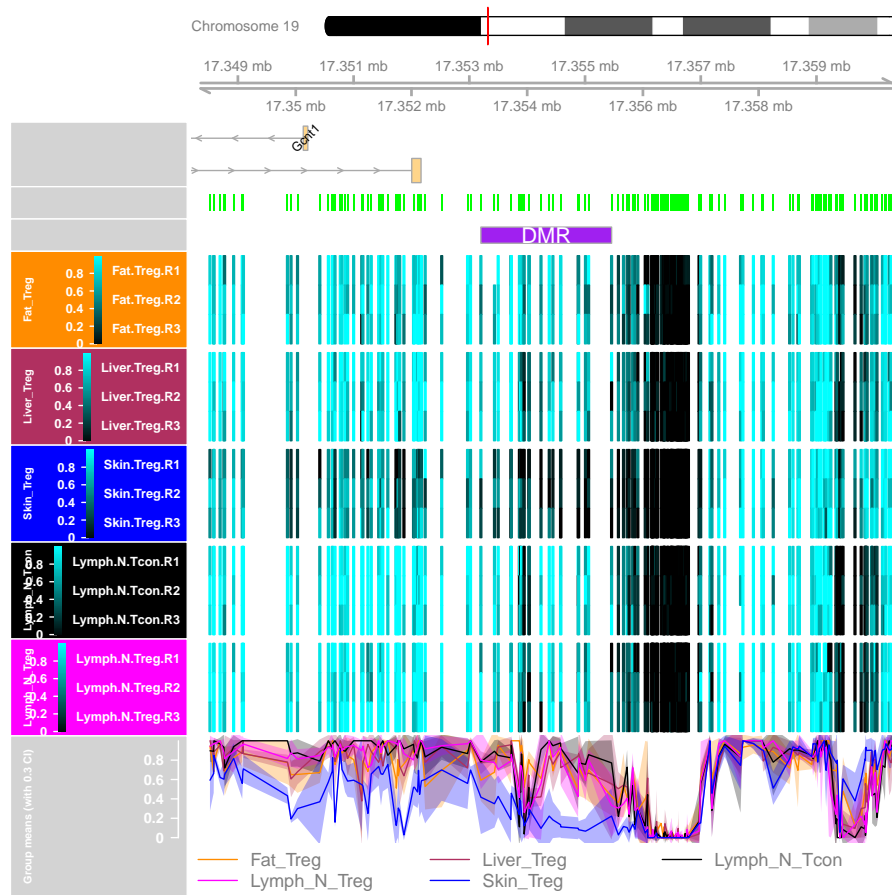
## see ?DMRcatedata and browseVignettes('DMRcatedata') for documentation
## loading from cache
```

Now let's plot the top DMR with not only fat and skin, but with all samples:

```
cols

##      Fat_Treg      Fat_Treg      Fat_Treg      Liver_Treg      Liver_Treg      Liver_Treg
## "darkorange" "darkorange" "darkorange"      "maroon"      "maroon"      "maroon"
##      Skin_Treg      Skin_Treg      Skin_Treg      Lymph_N_Tcon      Lymph_N_Tcon      Lymph_N_Tcon
##          "blue"          "blue"          "blue"          "black"          "black"          "black"
##      Lymph_N_Treg      Lymph_N_Treg      Lymph_N_Treg
##          "magenta"      "magenta"      "magenta"

DMR.plot(fat_vs_skin.ranges, dmr = 1, CpGs=bis_1072, phen.col = cols, genome="mm10")
```



Here we can see the methylation of skin cells over this region near the *Gcnt1* promoter is hypomethylated not only relative to fat, but to the other tissues as well.

```
sessionInfo()

## R version 4.5.1 (2025-06-13 ucrt)
## Platform: x86_64-w64-mingw32/x64
## Running under: Windows Server 2022 x64 (build 20348)
##
## Matrix products: default
##   LAPACK version 3.12.1
##
## locale:
## [1] LC_COLLATE=C
## [2] LC_CTYPE=English_United States.utf8
```

```

## [3] LC_MONETARY=English_United States.utf8
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.utf8
##
## time zone: America/New_York
## tzcode source: internal
##
## attached base packages:
## [1] parallel stats4 stats graphics grDevices utils datasets
## [8] methods base
##
## other attached packages:
## [1] GenomeInfoDb_1.45.9
## [2] bsseq_1.45.2
## [3] tissueTreg_1.29.0
## [4] IlluminaHumanMethylationEPICv2anno.20a1.hg38_1.0.0
## [5] DMRcatedata_2.27.0
## [6] IlluminaHumanMethylationEPICanno.ilm10b4.hg19_0.6.0
## [7] IlluminaHumanMethylationEPICmanifest_0.3.0
## [8] FlowSorted.Blood.EPIC_2.13.0
## [9] minfi_1.55.1
## [10] bumpHunter_1.51.1
## [11] locfit_1.5-9.12
## [12] iterators_1.0.14
## [13] foreach_1.5.2
## [14] Biostrings_2.77.2
## [15] XVector_0.49.0
## [16] SummarizedExperiment_1.39.1
## [17] Biobase_2.69.0
## [18] MatrixGenerics_1.21.0
## [19] matrixStats_1.5.0
## [20] GenomicRanges_1.61.1
## [21] Seqinfo_0.99.2
## [22] IRanges_2.43.0
## [23] S4Vectors_0.47.0
## [24] ExperimentHub_2.99.5
## [25] AnnotationHub_3.99.6
## [26] BiocFileCache_2.99.5
## [27] dbplyr_2.5.0
## [28] BiocGenerics_0.55.1
## [29] generics_0.1.4
## [30] DMRcate_3.5.1
##
## loaded via a namespace (and not attached):
## [1] splines_4.5.1

```

```
## [2] BiocIO_1.19.0
## [3] bitops_1.0-9
## [4] filelock_1.0.3
## [5] cellranger_1.1.0
## [6] tibble_3.3.0
## [7] R.oo_1.27.1
## [8] preprocessCore_1.71.2
## [9] XML_3.99-0.18
## [10] rpart_4.1.24
## [11] lifecycle_1.0.4
## [12] httr2_1.2.1
## [13] edgeR_4.7.3
## [14] base64_2.0.2
## [15] lattice_0.22-7
## [16] ensemblDb_2.33.1
## [17] MASS_7.3-65
## [18] scribe_1.3.5
## [19] backports_1.5.0
## [20] magrittr_2.0.3
## [21] limma_3.65.2
## [22] Hmisc_5.2-3
## [23] rmarkdown_2.29
## [24] yaml_2.3.10
## [25] doRNG_1.8.6.2
## [26] askpass_1.2.1
## [27] Gviz_1.53.1
## [28] DBI_1.2.3
## [29] RColorBrewer_1.1-3
## [30] abind_1.4-8
## [31] quadprog_1.5-8
## [32] purrr_1.1.0
## [33] R.utils_2.13.0
## [34] AnnotationFilter_1.33.0
## [35] biovizBase_1.57.1
## [36] RCurl_1.98-1.17
## [37] nnet_7.3-20
## [38] VariantAnnotation_1.55.1
## [39] rappdirs_0.3.3
## [40] rentrez_1.2.4
## [41] genefilter_1.91.0
## [42] annotate_1.87.0
## [43] permute_0.9-8
## [44] DelayedMatrixStats_1.31.0
## [45] codetools_0.2-20
## [46] DelayedArray_0.35.2
```

```
## [47] xml2_1.3.8
## [48] tidyselect_1.2.1
## [49] UCSC.utils_1.5.0
## [50] farver_2.1.2
## [51] beanplot_1.3.1
## [52] base64enc_0.1-3
## [53] illuminaio_0.51.0
## [54] GenomicAlignments_1.45.2
## [55] jsonlite_2.0.0
## [56] multtest_2.65.0
## [57] Formula_1.2-5
## [58] survival_3.8-3
## [59] missMethyl_1.43.0
## [60] tools_4.5.1
## [61] progress_1.2.3
## [62] Rcpp_1.1.0
## [63] glue_1.8.0
## [64] gridExtra_2.3
## [65] SparseArray_1.9.1
## [66] xfun_0.52
## [67] dplyr_1.1.4
## [68] HDF5Array_1.37.0
## [69] withr_3.0.2
## [70] IlluminaHumanMethylation450kanno.ilmn12.hg19_0.6.1
## [71] BiocManager_1.30.26
## [72] fastmap_1.2.0
## [73] latticeExtra_0.6-30
## [74] rhdf5filters_1.21.0
## [75] openssl_2.3.3
## [76] digest_0.6.37
## [77] R6_2.6.1
## [78] colorspace_2.1-1
## [79] gtools_3.9.5
## [80] jpeg_0.1-11
## [81] dichromat_2.0-0.1
## [82] biomaRt_2.65.0
## [83] RSQLite_2.4.2
## [84] R.methodsS3_1.8.2
## [85] h5mread_1.1.1
## [86] tidyr_1.3.1
## [87] data.table_1.17.8
## [88] rtracklayer_1.69.1
## [89] prettyunits_1.2.0
## [90] httr_1.4.7
## [91] htmlwidgets_1.6.4
```

```
## [92] S4Arrays_1.9.1
## [93] pkgconfig_2.0.3
## [94] gtable_0.3.6
## [95] blob_1.2.4
## [96] siggenes_1.83.0
## [97] htmltools_0.5.8.1
## [98] ProtGenerics_1.41.0
## [99] scales_1.4.0
## [100] png_0.1-8
## [101] knitr_1.50
## [102] rstudioapi_0.17.1
## [103] tzdb_0.5.0
## [104] rjson_0.2.23
## [105] nlme_3.1-168
## [106] checkmate_2.3.2
## [107] curl_6.4.0
## [108] org.Hs.eg.db_3.21.0
## [109] cachem_1.1.0
## [110] rhdf5_2.53.3
## [111] stringr_1.5.1
## [112] BiocVersion_3.22.0
## [113] foreign_0.8-90
## [114] AnnotationDbi_1.71.0
## [115] restfulr_0.0.16
## [116] GEOquery_2.77.1
## [117] pillar_1.11.0
## [118] grid_4.5.1
## [119] reshape_0.8.10
## [120] vctrs_0.6.5
## [121] beachmat_2.25.3
## [122] xtable_1.8-4
## [123] cluster_2.1.8.1
## [124] htmlTable_2.4.3
## [125] evaluate_1.0.4
## [126] readr_2.1.5
## [127] GenomicFeatures_1.61.5
## [128] cli_3.6.5
## [129] compiler_4.5.1
## [130] Rsamtools_2.25.2
## [131] rngtools_1.5.2
## [132] rlang_1.1.6
## [133] crayon_1.5.3
## [134] nor1mix_1.3-3
## [135] mclust_6.1.1
## [136] interp_1.1-6
```

```
## [137] plyr_1.8.9
## [138] stringi_1.8.7
## [139] deldir_2.0-4
## [140] BiocParallel_1.43.4
## [141] lazyeval_0.2.2
## [142] Matrix_1.7-3
## [143] BSgenome_1.77.1
## [144] hms_1.1.3
## [145] sparseMatrixStats_1.21.0
## [146] bit64_4.6.0-1
## [147] ggplot2_3.5.2
## [148] Rhdf5lib_1.31.0
## [149] KEGGREST_1.49.1
## [150] statmod_1.5.0
## [151] highr_0.11
## [152] memoise_2.0.1
## [153] bit_4.6.0
## [154] readxl_1.4.5
```

## References

- [1] Chen Y, Pal B, Visvader JE, Smyth GK. Differential methylation analysis of reduced representation bisulfite sequencing experiments using edgeR. *F1000Research*. 2017 **6**, 2055.
- [2] Delacher M, Imbusch CD, Weichenhan D, Breiling A, Hotz-Wagenblatt A, Trager U, ... Feuerer M. (2017). Genome-wide DNA-methylation landscape defines specialization of regulatory T cells in tissues. *Nature Immunology*. 2017 **18**(10), 1160-1172.