

methyKit: User Guide

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1 Introduction

In this manual, we will show how to use the methyKit package. methyKit is an R package for analysis and annotation of DNA methylation information obtained by high-throughput bisulfite sequencing. The package is designed to deal with sequencing data from RRBS and its variants. But it can potentially handle whole-genome bisulfite sequencing data if proper input format is provided.

1.1 DNA methylation

DNA methylation in vertebrates typically occurs at CpG dinucleotides, however non-CpG Cs are also methylated in certain tissues such as embryonic stem cells. DNA Methylation can act as an epigenetic control mechanism for gene regulation. Methylation can hinder binding of transcription factors and/or methylated bases can be bound by methyl-binding-domain proteins which can recruit chromatin remodeling factors. In both cases, the transcription of the regulated gene will be effected. In addition, aberrant DNA methylation patterns have been associated with many human malignancies and can be used in a predictive manner. In malignant tissues, DNA is either hypo-methylated or hyper-methylated compared to the normal tissue. The location of hyper- and hypo-methylated sites gives a distinct signature to many diseases. Traditionally, hypo-methylation is associated with gene transcription (if it is on a regulatory region such as promoters) and hyper-methylation is associated with gene repression.

1.2 High-throughput bisulfite sequencing

Bisulfite sequencing is a technique that can determine DNA methylation patterns. The major difference from regular sequencing experiments is that, in bisulfite sequencing DNA is treated with bisulfite which converts cytosine residues to uracil, but leaves 5-methylcytosine residues unaffected. By sequencing and aligning those converted DNA fragments it is possible to call methylation status of a base. Usually, the methylation status of a base determined by a high-throughput bisulfite sequencing will not be a binary score, but it will be a percentage. The percentage simply determines how many of the bases that are aligning to a given cytosine location in the genome have actual C bases in the reads. Since bisulfate treatment leaves methylated Cs intact, that percentage will give us percent methylation score on that base. The reasons why we will not get a binary response are 1) the probable sequencing errors in high-throughput sequencing experiments 2) incomplete bisulfite conversion 3) (and a more likely scenario) is heterogeneity of samples and heterogeneity of paired chromosomes from the same sample 4) the other reasons you can think of (Homework for the reader :))

2 Basics

2.1 Reading the methylation call files

We start by reading in the methylation call data from bisulfite sequencing with `read` function. Reading in the data this way will return a `methylRawList` object which stores methylation information per sample for each covered base. The methylation call files are basically text files that contain percent methylation score per base. A typical methylation call file looks like this:

##	chrBase	chr	base	strand	coverage	freqC	freqT
## 1	chr21.9764539	chr21	9764539	R	12	25.00	75.00
## 2	chr21.9764513	chr21	9764513	R	12	0.00	100.00
## 3	chr21.9820622	chr21	9820622	F	13	0.00	100.00
## 4	chr21.9837545	chr21	9837545	F	11	0.00	100.00
## 5	chr21.9849022	chr21	9849022	F	124	72.58	27.42

Most of the time bisulfite sequencing experiments have test and control samples. The test samples can be from a disease tissue while the control samples can be from a healthy tissue. You can read a set of methylation call files that have test/control conditions giving `treatment` vector option as follows:

```
library(methylKit)
file.list <- list(system.file("extdata", "test1.myCpG.txt",
                             package = "methylKit"), system.file("extdata",
                             "test2.myCpG.txt",
                             package = "methylKit"), system.file("extdata",
                             "control1.myCpG.txt",
                             package = "methylKit"), system.file("extdata",
                             "control2.myCpG.txt",
                             package = "methylKit"))

# read the files to a methylRawList object: myobj
myobj <- read(file.list, sample.id = list("test1", "test2",
                                          "ctrl1", "ctrl2"), assembly = "hg18", treatment = c(1, 1, 0,
0), context = "CpG")
```

2.2 Reading the methylation calls from sorted Bismark alignments

Alternatively, methylation percentage calls can be calculated from sorted SAM file(s) from Bismark aligner and read-in to the memory. Bismark is a popular aligner for bisulfite sequencing reads [1]. `read.bismark` function is designed to read-in Bismark SAM files as `methylRaw` or `methylRawList` objects which store per base methylation calls. SAM files must be sorted by chromosome and read position columns, using 'sort' command in unix-like machines will accomplish such a sort easily.

The following command reads a sorted SAM file and creates a `methylRaw` object for CpG methylation. The user has the option to save the methylation call files to a folder given by `save.folder` option. The saved files can be read-in using the `read` function when needed.

```
my.methRaw <- read.bismark(location = system.file("extdata",
  "test.fastq_bismark.sorted.min.sam", package = "methylKit"),
  sample.id = "test1", assembly = "hg18", read.context = "CpG",
  save.folder = getwd())
```

It is also possible to read multiple SAM files at the same time, check `read.bismark` documentation.

2.3 Descriptive statistics on samples

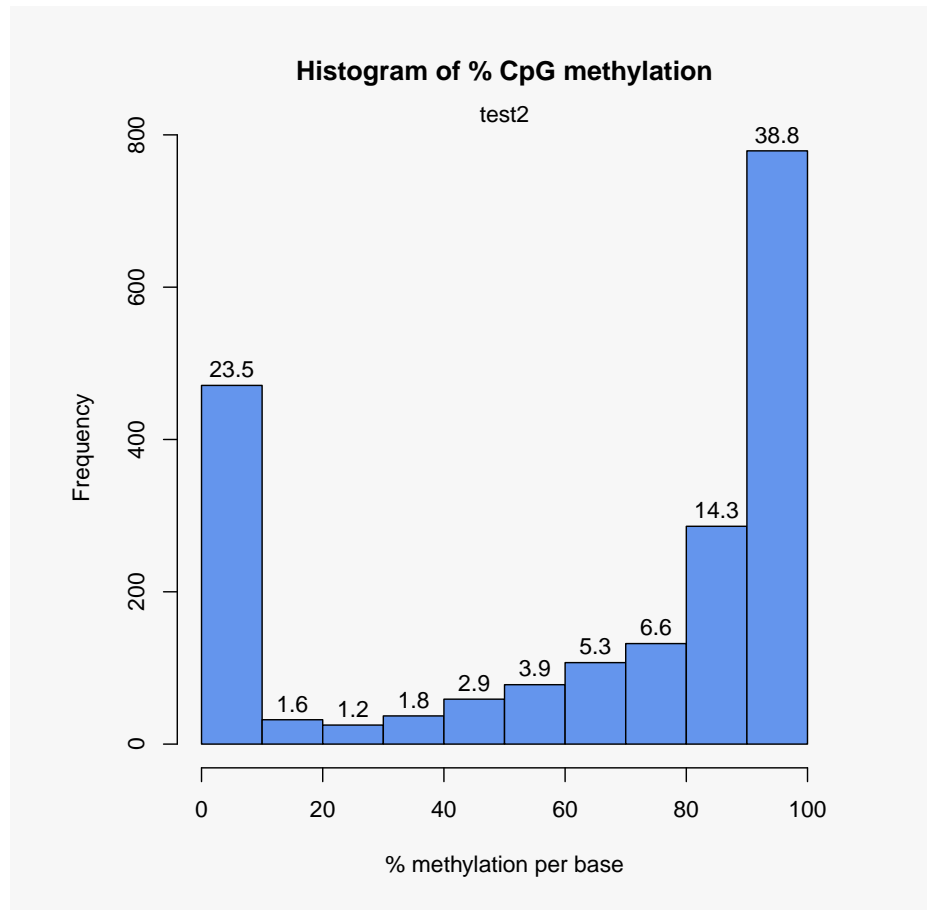
Since we read the methylation data now, we can check the basic stats about the methylation data such as coverage and percent methylation. We now have a `methylRawList` object which contains methylation information per sample. The following command prints out percent methylation statistics for second sample: "test2"

```
getMethylationStats(myobj[[2]], plot = F, both.strands = F)

## methylation statistics per base
## summary:
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.0   20.0   82.8   63.2   94.7   100.0
## percentiles:
##      0%    10%    20%    30%    40%    50%    60%    70%    80%    90%    95%    99%
##      0.00   0.00   0.00  48.39  70.00  82.79  90.00  93.33  96.43 100.00 100.00 100.00
##      99.5%  99.9%  100%
##      100.00 100.00 100.00
##
```

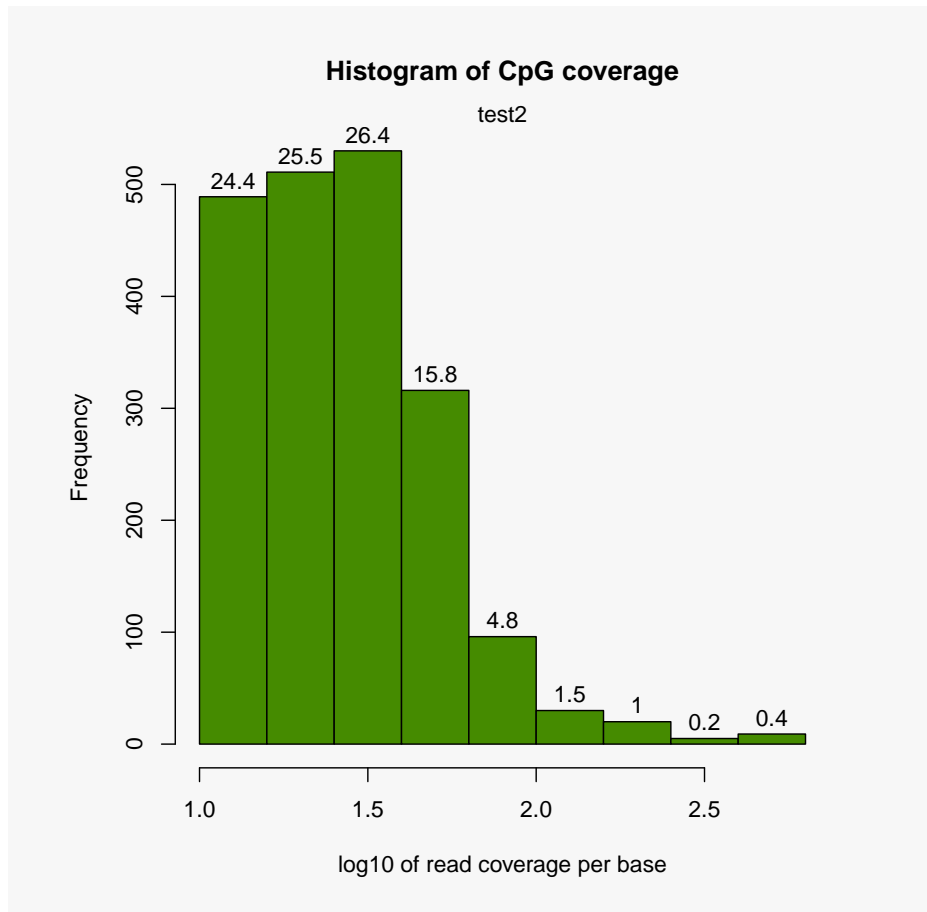
The following command plots the histogram for percent methylation distribution. The figure below is the histogram and numbers on bars denote what percentage of locations are contained in that bin. Typically, percent methylation histogram should have two peaks on both ends. In any given cell, any given base are either methylated or not. Therefore, looking at many cells should yield a similar pattern where we see lots of locations with high methylation and lots of locations with low methylation.

```
library("graphics")
getMethylationStats(myobj[[2]], plot = T, both.strands = F)
```



We can also plot the read coverage per base information in a similar way, again numbers on bars denote what percentage of locations are contained in that bin. Experiments that are highly suffering from PCR duplication bias will have a secondary peak towards the right hand side of the histogram.

```
library("graphics")  
getCoverageStats(myobj[[2]], plot = T, both.strands = F)
```



2.4 Filtering samples based on read coverage

It might be useful to filter samples based on coverage. Particularly, if our samples are suffering from PCR bias it would be useful to discard bases with very high read coverage. Furthermore, we would also like to discard bases that have low read coverage, a high enough read coverage will increase the power of the statistical tests. The code below filters a `methyRawList` and discards bases that have coverage below 10X and also discards the bases that have more than 99.9th percentile of coverage in each sample.

```
filtered.myobj <- filterByCoverage(myobj, lo.count = 10,  
  lo.perc = NULL, hi.count = NULL, hi.perc = 99.9)
```

3 Comparative analysis

3.1 Merging samples

In order to do further analysis, we will need to get the bases covered in all samples. The following function will merge all samples to one object for base-pair locations that are covered in all samples. Setting `destrand=TRUE` (the default is `FALSE`) will merge reads on both strands of a CpG dinucleotide. This provides better coverage, but only advised when looking at CpG methylation (for CpH methylation this will cause wrong results in subsequent analyses). In addition, setting `destrand=TRUE` will only work when operating on base-pair resolution, otherwise setting this option `TRUE` will have no effect. The `unite()` function will return a `methyBase` object which will be our main object for all comparative analysis. The `methyBase` object contains methylation information for regions/bases that are covered in all samples.

```
meth <- unite(myobj, destrand = FALSE)
```

Let us take a look at the data content of `methyBase` object:

```
head(meth)
```

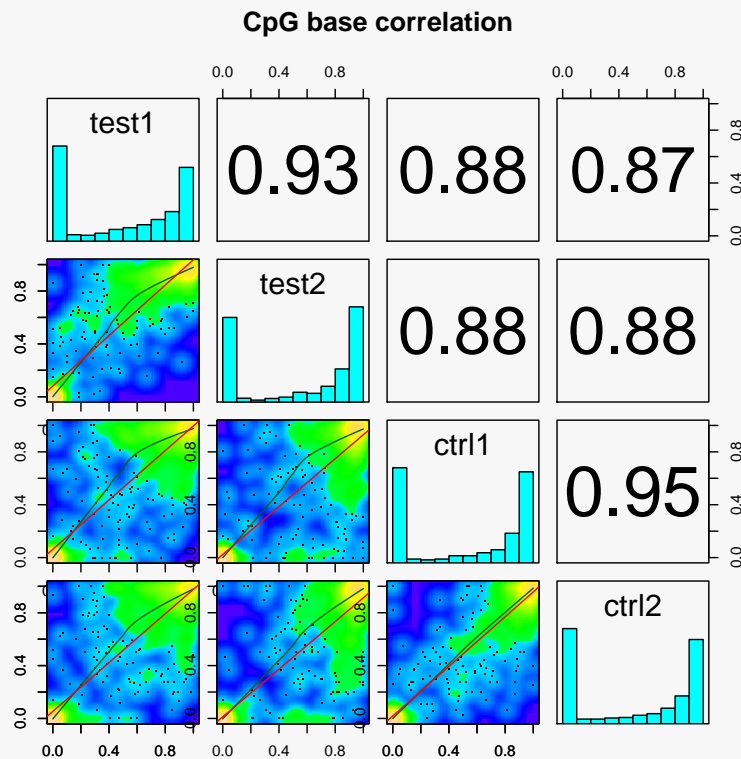
##		id	chr	start	end	strand	coverage1	numCs1	numTs1	coverage2
## 1	chr21.10011833	chr21	10011833	10011833	+	174	173	1	18	
## 2	chr21.10011841	chr21	10011841	10011841	+	173	164	9	20	
## 3	chr21.10011855	chr21	10011855	10011855	+	175	175	0	21	
## 4	chr21.10011858	chr21	10011858	10011858	+	175	131	44	21	
## 5	chr21.10011861	chr21	10011861	10011861	+	174	147	27	20	
## 6	chr21.10011872	chr21	10011872	10011872	+	167	160	7	20	
##	numCs2	numTs2	coverage3	numCs3	numTs3	coverage4	numCs4	numTs4		
## 1	18	0	40	34	6	14	14	0		
## 2	19	1	40	18	22	14	8	6		
## 3	21	0	39	29	10	14	12	2		
## 4	20	1	39	31	8	13	8	5		
## 5	15	5	39	13	26	13	9	4		
## 6	19	1	39	34	5	14	8	6		

3.2 Sample Correlation

We can check the correlation between samples using `getCorrelation`. This function will either plot scatter plot and correlation coefficients or just print a correlation matrix

```
getCorrelation(meth, plot = T)
```

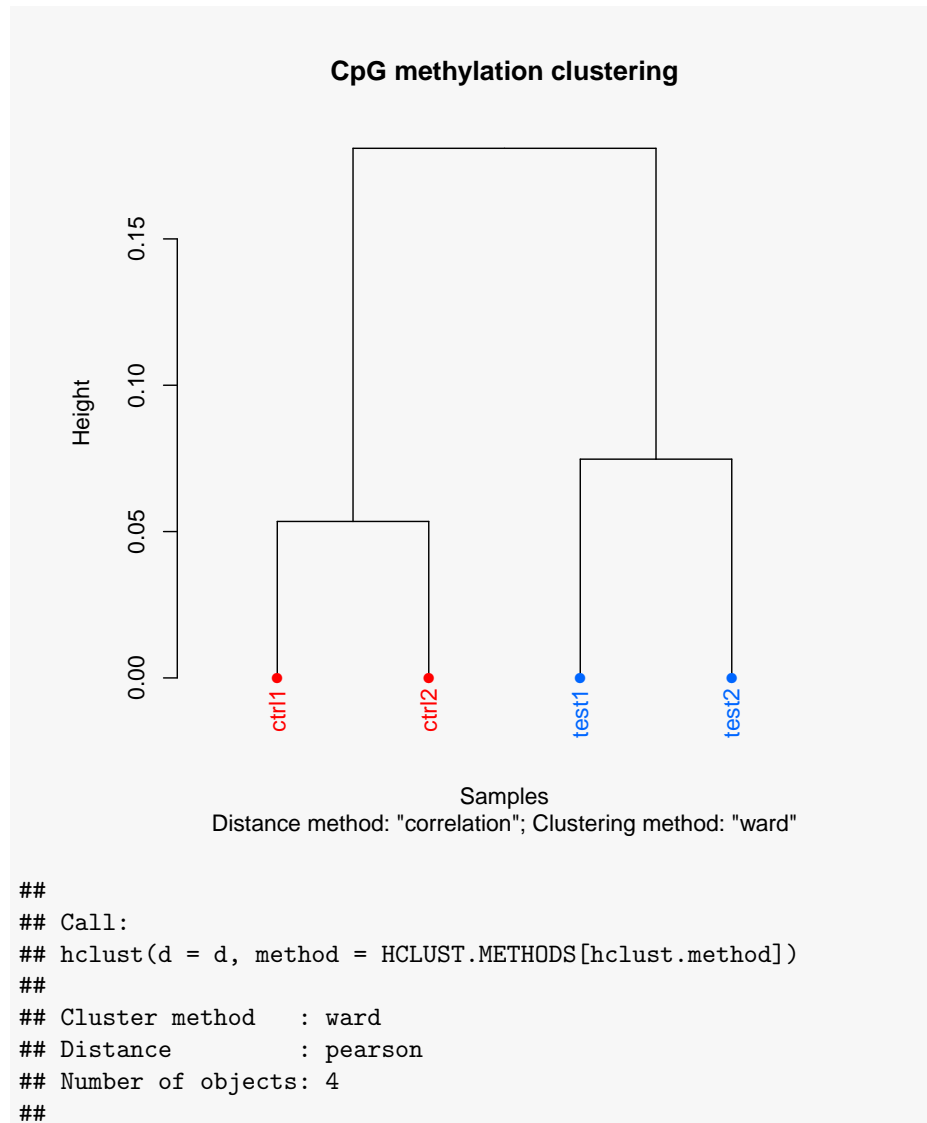
```
##          test1 test2 ctrl1 ctrl2
## test1  1.0000 0.9253 0.8768 0.8738
## test2  0.9253 1.0000 0.8792 0.8802
## ctrl1  0.8768 0.8792 1.0000 0.9465
## ctrl2  0.8738 0.8802 0.9465 1.0000
```



3.3 Clustering samples

We can cluster the samples based on the similarity of their methylation profiles. The following function will cluster the samples and draw a dendrogram.

```
clusterSamples(meth, dist = "correlation", method = "ward",
               plot = TRUE)
```

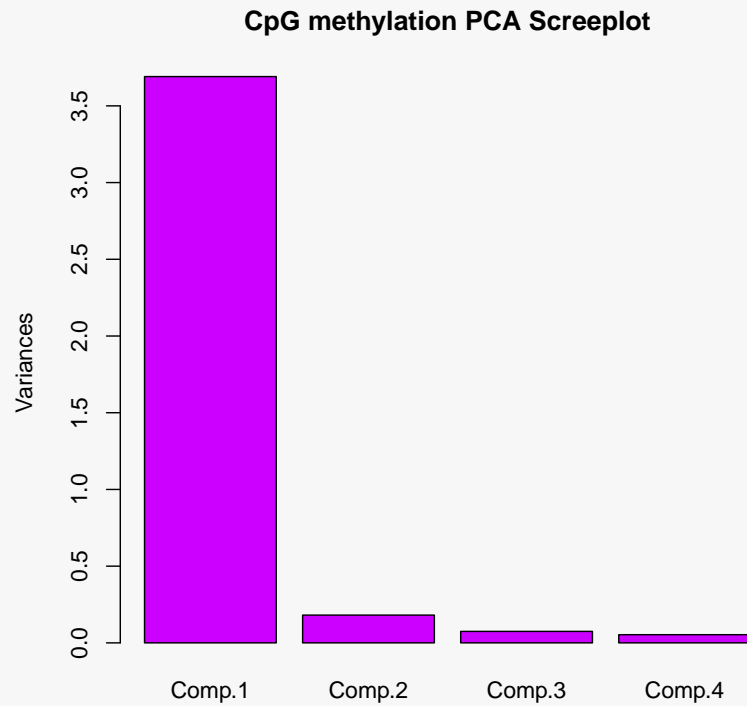



Setting the `plot=FALSE` will return a dendrogram object which can be manipulated by users or fed in to other user functions that can work with dendrograms.

```
hc <- clusterSamples(meth, dist = "correlation", method = "ward",  
  plot = FALSE)
```

We can also do a PCA analysis on our samples. The following function will plot a scree plot for importance of components.

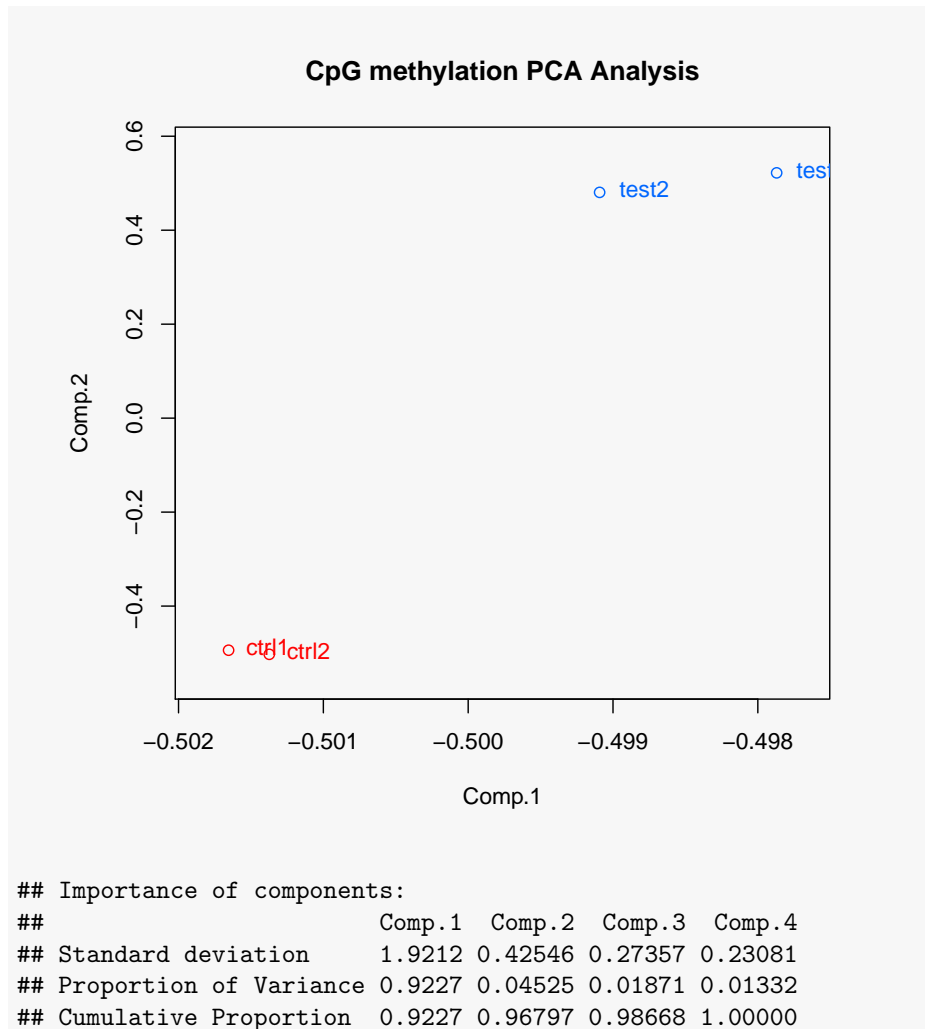
```
PCASamples(meth, screeplot = TRUE)
```



```
## Importance of components:
##               Comp.1  Comp.2  Comp.3  Comp.4
## Standard deviation    1.9212  0.42546  0.27357  0.23081
## Proportion of Variance 0.9227  0.04525  0.01871  0.01332
## Cumulative Proportion 0.9227  0.96797  0.98668  1.00000
```

We can also plot PC1 and PC2 axis and a scatter plot of our samples on those axis which will reveal how they cluster.

```
PCASamples(meth)
```



3.4 Tiling windows analysis

For some situations, it might be desirable to summarize methylation information over tiling windows rather than doing base-pair resolution analysis. `methyKit` provides functionality to do such analysis. The function below tiles the genome with windows 1000bp length and 1000bp step-size and summarizes the methylation information on those tiles. In this case, it returns a `methyRawList` object which can be fed into `unite` and `calculateDiffMeth` functions consecutively to get differentially methylated regions.

```

tiles <- tileMethylCounts(myobj, win.size = 1000, step.size =
1000)
head(tiles[[1]])

```

##		id	chr	start	end	strand	coverage	numCs	numTs
## 1	chr21.9764001.9765000	chr21	9764001	9765000	*	24	3	21	
## 2	chr21.9820001.9821000	chr21	9820001	9821000	*	13	0	13	
## 3	chr21.9837001.9838000	chr21	9837001	9838000	*	11	0	11	
## 4	chr21.9849001.9850000	chr21	9849001	9850000	*	124	90	34	
## 5	chr21.9853001.9854000	chr21	9853001	9854000	*	34	22	12	
## 6	chr21.9860001.9861000	chr21	9860001	9861000	*	39	38	1	

3.5 Finding differentially methylated bases or regions

`calculateDiffMeth()` function is the main function to calculate differential methylation. Depending on the sample size per each set it will either use Fisher's exact or logistic regression to calculate P-values. P-values will be adjusted to Q-values using SLIM method [2].

```

myDiff <- calculateDiffMeth(meth)

```

After q-value calculation, we can select the differentially methylated regions/bases based on q-value and percent methylation difference cutoffs. Following bit selects the bases that have q-value \leq 0.01 and percent methylation difference larger than 25%. If you specify `type="hyper"` or `type="hypo"` options, you will get hyper-methylated or hypo-methylated regions/bases.

```

# get hyper methylated bases
myDiff25p.hyper <- get.methylDiff(myDiff, difference = 25,
qvalue = 0.01, type = "hyper")
#
# get hypo methylated bases
myDiff25p.hypo <- get.methylDiff(myDiff, difference = 25,
qvalue = 0.01, type = "hypo")
#
#
# get all differentially methylated bases
myDiff25p <- get.methylDiff(myDiff, difference = 25,
qvalue = 0.01)

```

We can also visualize the distribution of hypo/hyper-methylated bases/regions per chromosome using the following function. In this case, the example set includes only one chromosome. The `list` shows percentages of hypo/hyper methylated bases over all the covered bases in a given chromosome.

```
diffMethPerChr(myDiff, plot = FALSE, qvalue.cutoff = 0.01,
               meth.cutoff = 25)

## $diffMeth.per.chr
##      chr number.of.hypomethylated percentage.of.hypomethylated
## 1 chr21                      59                      6.127
##      number.of.hypermethylated percentage.of.hypermethylated
## 1                      75                      7.788
##
## $diffMeth.all
##      percentage.of.hypermethylated number.of.hypermethylated
## 1                      7.788                      75
##      percentage.of.hypomethylated number.of.hypomethylated
## 1                      6.127                      59
##
```

3.5.1 Finding differentially methylated bases using multiple-cores

The differential methylation calculation speed can be increased substantially by utilizing multiple-cores in a machine if available. Both Fisher's Exact test and logistic regression based test are able to use multiple-core option. The following piece of code will run differential methylation calculation using 2 cores.

```
myDiff <- calculateDiffMeth(meth, num.cores = 2)
```

4 Annotating differentially methylated bases or regions

We can annotate our differentially methylated regions/bases based on gene annotation. In this example, we read the gene annotation from a bed file and annotate our differentially methylated regions with that information. This will tell us what percentage of our differentially methylated regions are on promoters/introns/exons/intergenic region. Similar gene annotation can be fetched using **GenomicFeatures** package available from Bioconductor.org.

```
gene.obj <- read.transcript.features(system.file("extdata",
        "refseq.hg18.bed.txt", package = "methylKit"))
#
# annotate differentially methylated Cs with
# promoter/exon/intron using annotation data
#
annotate.WithGenicParts(myDiff25p, gene.obj)
```

```
## summary of target set annotation with genic parts
## 133 rows in target set
## -----
## -----
## percentage of target features overlapping with annotation :
##   promoter      exon      intron intergenic
##      27.82      15.04      34.59      57.14
##
##
## percentage of target features overlapping with annotation (with promoter>exon>intron pre
##   promoter      exon      intron intergenic
##      27.82       0.00      15.04      57.14
##
##
## percentage of annotation boundaries with feature overlap :
## promoter      exon      intron
##  0.01813  0.00159  0.01004
##
##
## summary of distances to the nearest TSS :
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      5     828   45200   52000   94600  314000
```

Similarly, we can read the CpG island annotation and annotate our differentially methylated bases/regions with them.

```
# read the shores and flanking regions and name the flanks as
#   shores
# and CpG islands as CpGi
cpg.obj <- read.feature.flank(system.file("extdata",
    "cpgi.hg18.bed.txt", package = "methyKit"),
feature.flank.name = c("CpGi",
    "shores"))
#
#
diffCpGann <- annotate.WithFeature.Flank(myDiff25p, cpg.obj$CpGi,
    cpg.obj$shores, feature.name = "CpGi", flank.name = "shores")
```

4.1 Regional analysis

We can also summarize methylation information over a set of defined regions such as promoters or CpG islands. The function below summarizes the methylation information over a given set of promoter regions and outputs a `methyRaw` or `methyRawList` object depending on the input.

```
promoters <- regionCounts(myobj, gene.obj$promoters)

head(promoters[[1]])
```

##		id	chr	start	end	strand	coverage	numCs	numTs
## 1	chr21.17806094.17808094.NA	chr21	17806094	17808094	+	1834	7	1827	
## 2	chr21.10119796.10121796.NA	chr21	10119796	10121796	-	79	44	35	
## 3	chr21.10011791.10013791.NA	chr21	10011791	10013791	-	3697	2982	715	
## 4	chr21.10119808.10121808.NA	chr21	10119808	10121808	-	79	44	35	
## 5	chr21.15357997.15359997.NA	chr21	15357997	15359997	-	8613	16	8594	
## 6	chr21.16023366.16025366.NA	chr21	16023366	16025366	+	6296	5	6291	

4.2 Convenience functions for annotation objects

After getting the annotation of differentially methylated regions, we can get the distance to TSS and nearest gene name using the `getAssociationWithTSS` function.

```
diffAnn <- annotate.WithGenicParts(myDiff25p, gene.obj)

# target.row is the row number in myDiff25p
head(getAssociationWithTSS(diffAnn))
```

##	target.row	dist.to.feature	feature.name	feature.strand
## 60	1	951	NM_199260	-
## 60.1	2	931	NM_199260	-
## 60.2	3	838	NM_199260	-
## 60.3	4	828	NM_199260	-
## 60.4	5	802	NM_199260	-
## 60.5	6	723	NM_199260	-

It is also desirable to get percentage/number of differentially methylated regions that overlap with intron/exon/promoters

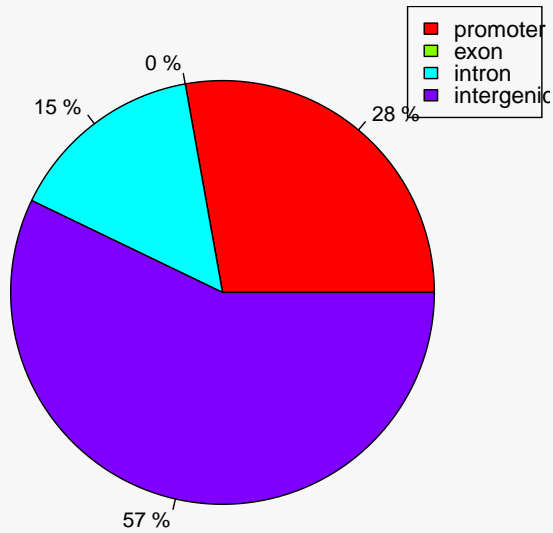
```
getTargetAnnotationStats(diffAnn, percentage = TRUE,
  precedence = TRUE)
```

##	promoter	exon	intron	intergenic
##	27.82	0.00	15.04	57.14

We can also plot the percentage of differentially methylated bases overlapping with exon/intron/promoters

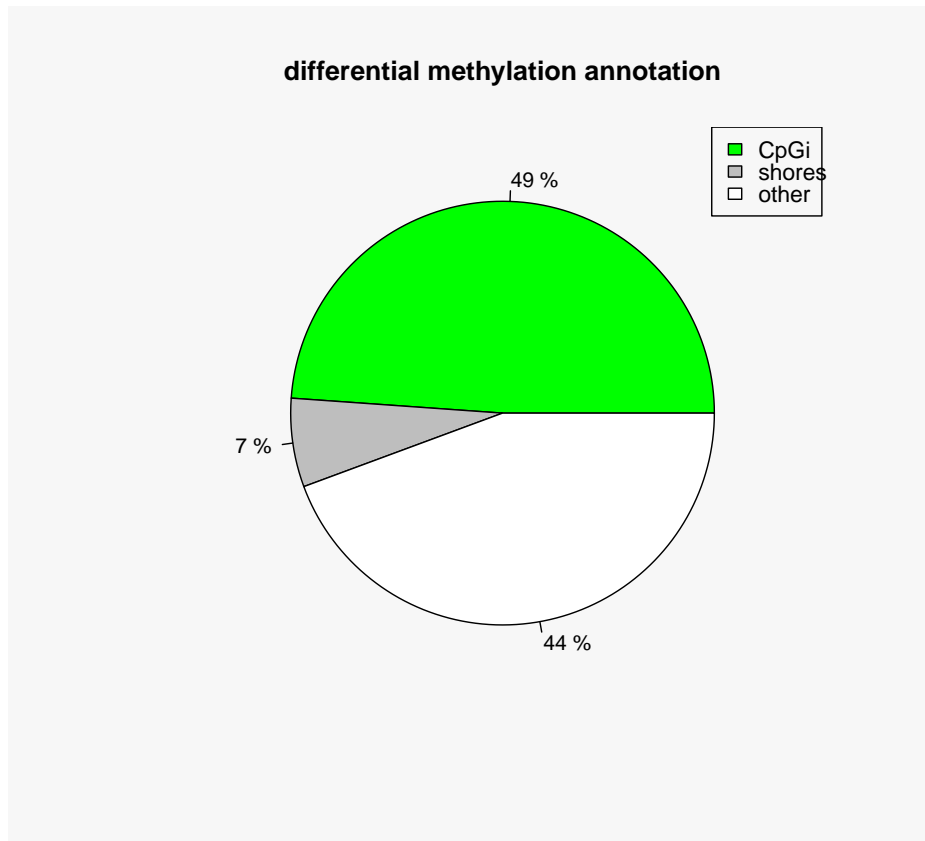
```
plotTargetAnnotation(diffAnn, precedence = TRUE, main =
"differential methylation annotation")
```

differential methylation annotation



We can also plot the CpG island annotation the same way. The plot below shows what percentage of differentially methylated bases are on CpG islands, CpG island shores and other regions.

```
plotTargetAnnotation(diffCpGann, col = c("green", "gray",
"white"), main = "differential methylation annotation")
```

It might be also useful to get percentage of intron/exon/promoters that overlap with differentially methylated bases.

```
getFeatsWithTargetsStats(diffAnn, percentage = TRUE)
```

```
## promoter    exon    intron
## 0.01813    0.00159 0.01004
```

5 R session info

```
sessionInfo()
```

```
## R version 2.14.1 (2011-12-22)
## Platform: x86_64-apple-darwin9.8.0/x86_64 (64-bit)
##
```

```
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
## other attached packages:
## [1] methylKit_0.4 knitr_0.1
##
## loaded via a namespace (and not attached):
## [1] codetools_0.2-8      data.table_1.7.7      digest_0.5.1          evaluate_0.4.1
## [5] formatR_0.3-4        GenomicRanges_1.6.4 highlight_0.3.1        IRanges_1.12.5
## [9] KernSmooth_2.23-7    parser_0.0-14         plyr_1.7.1            Rcpp_0.9.9
## [13] stringr_0.6          tools_2.14.1
```

References

- [1] Felix Krueger and Simon R Andrews. Bismark: a flexible aligner and methylation caller for Bisulfite-Seq applications. *Bioinformatics (Oxford, England)*, 27(11):1571–2, June 2011.
- [2] Hong-Qiang Wang, Lindsey K Tuominen, and Chung-Jui Tsai. SLIM: a sliding linear model for estimating the proportion of true null hypotheses in datasets with dependence structures. *Bioinformatics (Oxford, England)*, 27(2):225–31, January 2011.