

methyAnalysis: an R package for DNA methylation data analysis and visualization

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1 Introduction

The `methyAnalysis` package aims to provide functionalities of analyzing and visualizing the DNA methylation data.

As most DNA-methylation data is still array-based, most public analysis tools use traditional probe-based analysis methods. However, with the increase of probe density, considering the probe spatial information becomes more and more important for better understanding the data. To meet this need, we developed this package for chromosome location based DNA methylation analysis. The current version of the package mainly focus on analyzing the Illumina Infinium methylation array data preprocessed by the `lumi` package [1], but most methods can be generalized to other methylation array or sequencing data. Functions specifically designed for DNA methylation sequencing data will be added in the near future.

The package mainly provides functions in the following aspects:

1. Defines a new class, *MethyGenoSet*, and related methods for the chromosome-location based DNA methylation analysis.
2. Provides functions related with differential methylation analysis, slide-window smoothing of DNA methylation levels, DMR (Differentially Methylation Region) detection and annotation.
3. Visualization of the DNA methylation data.

2 MethyGenoSet-class

In order to keep the chromosome location information together with the data, we defined a new *MethyGenoSet* class as a direct extension of the *GenoSet* class in the `genoset` package. The *GenoSet* class is an extension of *eSet* class. It keeps the chromosome location information in an additional `locData` slot, a *RangedData* object. For convenience of retrieving the methylation data, we keeps the DNA methylation data (using M-value [2] by default) in the `exprs` assayData element. Users can easily retrieve the methylation data by using *exprs* method.

2.1 Example dataset

For better understanding the package, we created a small example dataset, `exampleMethyGenoSet`. The `exampleMethyGenoSet` consists of eight random selected cancer cell line samples from two tissues. To save space, only probes in chromosome 21 were included.

```
> library(methyAnalysis)
> ## load the example data
> data(exampleMethyGenoSet)
> ## show MethyGenoSet class
> slotNames(exampleMethyGenoSet)
```

```

[1] "history"          "locData"
[3] "assayData"        "phenoData"
[5] "featureData"      "experimentData"
[7] "annotation"       "protocolData"
[9] ".__classVersion__"

> # showClass('MethyGenoSet')
>
> ## get chromosome location information
> head(locData(exampleMethyGenoSet))

RangedData with 6 rows and 0 value columns across 1 space
      space      ranges |
      <factor>    <IRanges> |
cg17035109      21 [10882029, 10882029] |
cg06187584      21 [10883548, 10883548] |
cg12459059      21 [10884748, 10884748] |
cg25450479      21 [10884967, 10884967] |
cg23347501      21 [10884969, 10884969] |
cg03661019      21 [10885409, 10885409] |

> ## retrieve methylation data
> dim(exprs(exampleMethyGenoSet))

[1] 4243      8

> ## Sample information
> pData(exampleMethyGenoSet)

      SampleType
Sample1      Type1
Sample2      Type1
Sample3      Type1
Sample4      Type1
Sample5      Type2
Sample6      Type2
Sample7      Type2
Sample8      Type2

```

3 Identifying Differentially Methylated Regions (DMR)

One common DNA methylation analysis task is to identify Differentially Methylated Regions (DMR) between two comparison groups. Similar as the expression microarray analysis, many existing differential test methods can be used here. However, most of these methods do not consider the probe spatial information and assuming probe measurements are independent to each other.

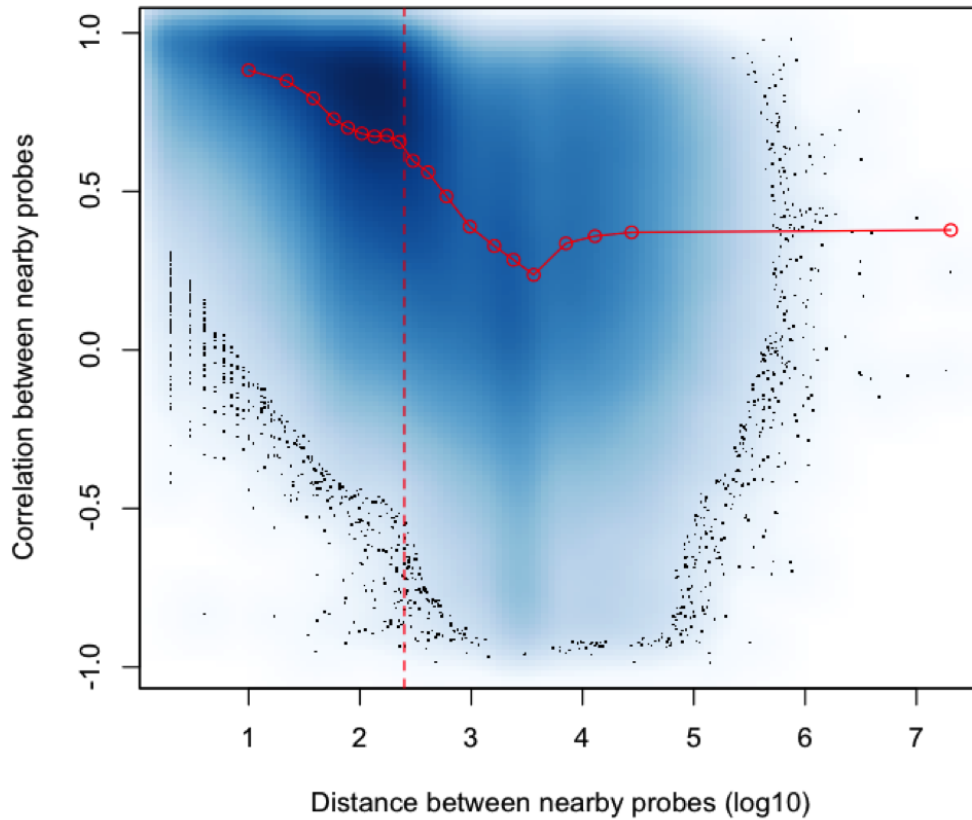


Figure 1: DNA methylation correlation between nearby CpG-sites

3.1 DNA methylation correlation between nearby CpG-sites

For DNA methylation data, we observed strong correlation between nearby CpG-sites. Figure 1 shows the correlation between nearby CpG-sites. The x-axis is the distance between nearby CpG-sites and the y-axis is the Pearson correlation of the related methylation profiles of 49 cell line samples (data not shown). The red dots are the median correlation of the 5 percentile cut (ranked by the distance between nearby CpG-sites (x-axis)). We can see the correlation is very strong when the CpG-sites are close to each other.

On the other hand, due to the sequence variation across samples and fixed probe designs, the array-based DNA-methylation data also tends to be noisy. By considering the observed strong correlation between nearby CpG-sites, we can reduce the measurement noise by using sliding-window smoothing. `smoothMethyData` function is designed for this purpose. By default, we set `winSize` (half-window size) as 250bp, which is selected based on Figure 1.

```
> methyGenoSet.sm <- smoothMethyData(exampleMethyGenoSet, winSize = 250)
```

```
Smoothing Chromosome 21 ...
```

```
> ## winsize is kept as an attribute
> attr(methyGenoSet.sm, 'windowSize')
```

```
[1] 250
```

3.2 Differential methylation test

Function `detectDMR.slideWin` is designed to perform differential methylation test. The function will automatically check whether the methylation data has been smoothed or not. If not, slide window smoothing will be performed first. The current version only implement 't-test' and wilcox test for the differential methylation test. A more flexible (lm)-based method will be added in the future version.

```
> ## get sample type information
> sampleType <- pData(exampleMethyGenoSet)$SampleType
> ## Do differential test
> allResult <- detectDMR.slideWin(exampleMethyGenoSet, sampleType=sampleType)
```

Smoothing Chromosome 21 ...

```
> head(allResult)
```

GRanges with 6 ranges and 10 metadata columns:

	seqnames	ranges	strand
	<Rle>	<IRanges>	<Rle>
cg17035109	21	[10882029, 10882029]	*
cg06187584	21	[10883548, 10883548]	*
cg12459059	21	[10884748, 10884748]	*
cg25450479	21	[10884967, 10884967]	*
cg23347501	21	[10884969, 10884969]	*
cg03661019	21	[10885409, 10885409]	*
	PROBEID	difference	p.value
	<factor>	<numeric>	<numeric>
cg17035109	cg17035109	-1.8411605	0.06276449
cg06187584	cg06187584	-0.4566059	0.41601486
cg12459059	cg12459059	-0.3591179	0.36542152
cg25450479	cg25450479	-0.3591179	0.36542152
cg23347501	cg23347501	-0.3591179	0.36542152
cg03661019	cg03661019	-0.3532662	0.38065600
	p.adjust	startWinIndex	endWinIndex
	<numeric>	<numeric>	<numeric>
cg17035109	0.1886706	1	1
cg06187584	0.6148210	2	2
cg12459059	0.5624436	3	5

cg25450479	0.5624436	3	5
cg23347501	0.5624436	3	5
cg03661019	0.5786899	6	6
	startLocation	endLocation	mean_Type1
	<integer>	<integer>	<numeric>
cg17035109	10882029	10882029	-2.4183775
cg06187584	10883548	10883548	-2.2297567
cg12459059	10884748	10884969	0.2594151
cg25450479	10884748	10884969	0.2594151
cg23347501	10884748	10884969	0.2594151
cg03661019	10885409	10885409	-0.4170363
	mean_Type2		
	<numeric>		
cg17035109	-0.57721699		
cg06187584	-1.77315084		
cg12459059	0.61853304		
cg25450479	0.61853304		
cg23347501	0.61853304		
cg03661019	-0.06377013		

seqlengths:			
	21		
	NA		

3.3 Define differentially methylated regions

We define a differentially methylated region (DMR) as a region, in which most measured CpG-sites are differentially methylated. To identify DMRs, we first determine the differential methylation status of each probe, then merge them as a continuous region. The `identifySigDMR` function is a wrapper function for all of these. The `getContinuousRegion` function is called by `identifySigDMR` to detection continous regions. Its input is a `GRanges` object with a "status" column to show whether the probe is differentially methylated or not. Its output is also a `GRanges` object indicating the identified DMRs. The `identifySigDMR` function returns a list of two `GRanges` objects. `sigDMRInfo` includes the identified DMRs, and `sigDataInfo` includes all differentially methylated probe information.

```
> ## Identify the DMR (Differentially Methylated Region) by setting proper parameters.
> ## Here we just use default ones
> allDMRInfo = identifySigDMR(allResult)
> names(allDMRInfo)

[1] "sigDMRInfo" "sigDataInfo"
```

4 Annotating DMRs

To understand what genes or gene elements (promoters or exons) are overlapping with these identified DMRs, we need to do annotate. The `annotateDMRInfo` is defined for this purpose. A *TranscriptDb* annotation package is required for the annotation process. Here we use the `TxDb.Hsapiens.UCSC.hg19.knownGene` package for the annotation. The `TxDb.Hsapiens.UCSC.hg19.knownGene` package includes the Homo Sapiens data from UCSC build hg19 based on the knownGene Track. Other *TranscriptDb* annotation packages, *TranscriptDb* or *GRanges* objects can also be used as *annotationDatabase*. The `export.DMRInfo` function is to output the annotated DMR information as .csv files.

```
> ## Annotate significant DMR info
> DMRInfo.ann <- annotateDMRInfo(allDMRInfo, 'TxDb.Hsapiens.UCSC.hg19.knownGene')
> ## output the DMR information
> export.DMRInfo(DMRInfo.ann, savePrefix='testExample')
```

5 Visualizing DNA methylation data

As the DNA methylation levels are chromosome location dependent. The methylation patterns can be pretty different between different gene elements, like promoter, exon1, intron and exons. The methylation patterns within the CpG-islands usually are also different from other regions. In order to better understanding these difference, we need to visualize the DNA methylation data. Two visualization options are supported in the `methyAnalysis` package.

5.1 Export data for external visualization

One easier option is to export the DNA methylation data in certain formats, and visualize these files using some genome browser tools, like IGV (<http://www.broadinstitute.org/igv/>) and IGB (<http://bioviz.org/igb/index.html>). Users can use `export.methyGenoSet` to output the `MethyGenoSet` object. The current implementation supports two output formats: ".gct" and ".bw" files. ".gct" includes all samples in a single file. It is only supported by IGV genome browser. The BigWig format (".bw") is a more general format supported by many visualization tools. Each BigWig file represents one single sample. So it is more flexible for the users only interested in a subset of samples.

```
> ## output in IGV supported "gct" file
> export.methyGenoSet(exampleMethyGenoSet, file.format='gct', savePrefix='test')
> ## output in BigWig files
> export.methyGenoSet(exampleMethyGenoSet, file.format='bw', savePrefix='test')
```

5.2 Plot methylation heatmap by chromosome location

Another visualization option is to show a focused regions, like DMRs, as a chromosome location based heatmap. `heatmapByChromosome` is designed for this. It is adapted based

on the `plotTracks` function in `Gviz` package. The function is designed for different types of data with chromosome location information. Figure 2 shows an example plot of gene `SIM2` (Entrez Gene ID:6493), which overlaps with the identified DMRs shown above. Users can also provide a *GRanges* object to specify a plot region.

```
> ## plot the DNA methylation heatmap by chromosome location
> heatmapByChromosome(exampleMethyGenoSet, gene='6493',
  genomicFeature='TxDb.Hsapiens.UCSC.hg19.knownGene', includeGeneBody=TRUE)
```

Another wrapper function, `plotMethylationHeatmapByGene`, is specifically designed for the methylation data. Users can add phenotypes or matched gene expression data to the right panel of the plot. Figure legends can be also added, as shown in Figure 3. By default, the `plotMethylationHeatmapByGene` plots methylation Beta-values [2] (in the range of 0 to 1) instead of M-values. Users can set *useBetaValue* as `FALSE` if they want to change to M-values.

```
> ## plot the DNA methylation heatmap by gene of selected GRanges
> plotMethylationHeatmapByGene('6493', methyGenoSet=exampleMethyGenoSet,
  phenoData=pData(exampleMethyGenoSet), includeGeneBody=TRUE,
  genomicFeature='TxDb.Hsapiens.UCSC.hg19.knownGene')
```

6 sessionInfo

```
> toLatex(sessionInfo())
```

- R version 3.0.0 (2013-04-03), x86_64-apple-darwin10.8.0
- Locale: C
- Base packages: base, datasets, grDevices, graphics, grid, methods, parallel, stats, utils
- Other packages: AnnotationDbi 1.22.1, Biobase 2.20.0, BiocGenerics 0.6.0, DBI 0.2-5, GenomicFeatures 1.12.0, GenomicRanges 1.12.1, IRanges 1.18.0, RSQLite 0.11.2, TxDb.Hsapiens.UCSC.hg19.knownGene 2.9.0, methyAnalysis 1.2.0, org.Hs.eg.db 2.9.0
- Loaded via a namespace (and not attached): BSgenome 1.28.0, BiocInstaller 1.10.0, Biostrings 2.28.0, Gviz 1.4.0, Hmisc 3.10-1, KernSmooth 2.23-10, MASS 7.3-26, Matrix 1.0-12, R.methodsS3 1.4.2, RColorBrewer 1.0-5, RCurl 1.95-4.1, Rsamtools 1.12.0, XML 3.96-1.1, affy 1.38.0, affyio 1.28.0, annotate 1.38.0, beanplot 1.1, biomaRt 2.16.0, biovizBase 1.8.0, bitops 1.0-5, cluster 1.14.4, colorspace 1.2-1, dichromat 2.0-0, genefilter 1.42.0, genoset 1.12.0, illuminaio 0.2.0, labeling 0.1, lattice 0.20-15, limma 3.16.1, lumi 2.12.0, matrixStats 0.6.2, mclust 4.0, methylumi 2.6.1, mgcv 1.7-22, minfi 1.6.0, multtest 2.16.0, munsell 0.4, nleqslv 2.0, nlme 3.1-109, nor1mix 1.1-3, plyr 1.8, preprocessCore 1.22.0, reshape 0.8.4, rtracklayer 1.20.0, scales 0.2.3, siggenes 1.34.0, splines 3.0.0, stats4 3.0.0, stringr 0.6.2, survival 2.37-4, tools 3.0.0, xtable 1.7-1, zlibbioc 1.6.0

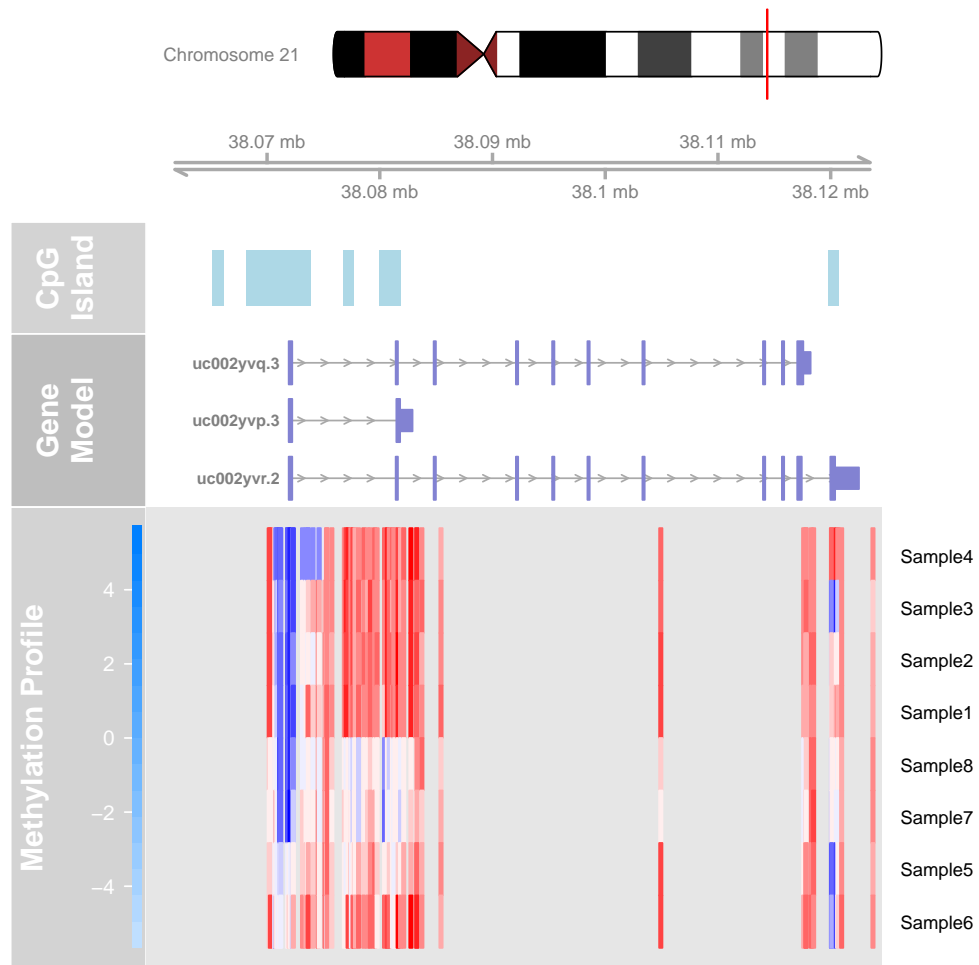


Figure 2: DNA methylation heatmap by chromosome location

Plotting SIM2 (GeneID:6493)

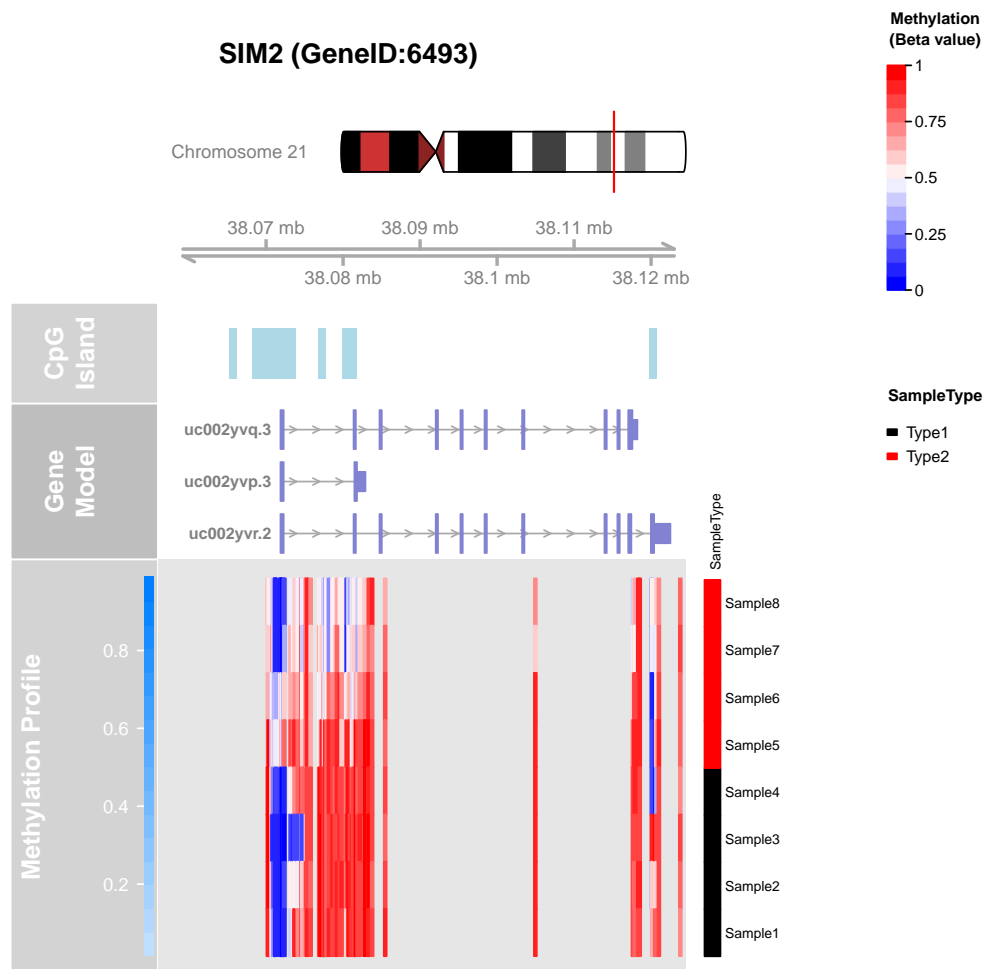


Figure 3: DNA methylation heatmap by chromosome location with phenotype information

7 References

1. Du P, Kibbe WA and Lin SM: "lumi: a Bioconductor package for processing Illumina microarray" *Bioinformatics* 2008 24(13):1547-1548
2. Du P, Zhang X, Huang CC, Jafari N, Kibbe WA, Hou L, and Lin SM: "Comparison of Beta-value and M-value methods for quantifying methylation levels by microarray analysis", *BMC Bioinformatics* 2010, 11:587