Managing and analyzing multiple NGS samples with Bioconductor bamViews objects: application to RNA-seq

VJ Carey

November 10, 2010

Contents

1 Introduction

We consider a lightweight approach to Bioconductor-based management and interrogation of multiple samples to which NGS methods have been applied.

The basic data store is the binary SAM (BAM) format (Li et al., 2009). This format is widely used in the 1000 genomes project, and transformations between SAM/BAM and output formats of various popular alignment programs are well-established. Bioconductor's *Rsamtools* package allows direct use of important SAM data interrogation facilities from R.

2 Basic design

A collection of NGS samples is represented through the associated set of BAM files and BAI index files. These can be stored in the inst/bam folder of an R package to facilitate documented programmatic access through R file navigation facilities, or the BAM/BAI files can be accessed through arbitrary path or URL references.

The bamViews class is defined to allow reliable fine-grained access to the NGS data along with relevant metadata. A bamViews instance contains access path information for a set of related BAM/BAI files, along with sample metadata and an optional specification of genomic ranges of interest.

A key design aspect of the bamViews class is preservation of semantics of the `X[G, S]` idiom familiar from *ExpressionSet* objects for management of multiple microarrays. With `ExpressionSet` instances, `G` is a predicate specifying selection of microarray probes of interest. With *bamViews* instances, `G` is a predicate specifying selection of genomic features of interest. At present, for *bamViews*, selection using `G` involves ranges of genomic coordinates.

3 Illustration

Data from four samples from a yeast RNA-seq experiment (two wild type, two 'RLP' mutants) are organized in the *leeBamViews* package. The data are collected to allow regeneration of aspects of Figure 8 of Lee et al. (2008). We obtained all reads between bases 800000 and 900000 of yeast chromosome XIII.

We have not yet addressed durable serialization of manager objects, so the *bamViews* instance is created on the fly.

```
> library(leeBamViews)  # bam files stored in package
> bpaths = dir(system.file("bam", package="leeBamViews"), full=TRUE, patt="bam$")
> #
> # extract genotype and lane information from filenames
> #
> gt = gsub(".*/", "", bpaths)
```

```
> gt = gsub("_.*", "", gt)
> lane = gsub(".*(.)$", "\\1", gt)
> geno = gsub(".$", "", gt)
> #
> # format the sample-level information appropriately
> #
> pd = DataFrame(geno=geno, lane=lane, row.names=paste(geno,lane,sep="."))
> prd = new("DataFrame")  # protocol data could go here
> #
> # create the views object, adding some arbitrary experiment-level information
> #
> bs1 = BamViews(bamPaths=bpaths, bamSamples=pd,
+         bamExperiment=list(annotation="org.Sc.sgd.db"))
> bs1

BamViews dim: 0 ranges x 8 samples
names: isowt.5 isowt.6 ... xrn.1 xrn.2
detail: use bamPaths(), bamSamples(), bamRanges(), ...

> #
> # get some sample-level data
> #
> bamSamples(bs1)$geno

[1] "isowt" "isowt" "rlp"   "rlp"   "ssr"   "ssr"   "xrn"   "xrn"
```

We would like to operate on specific regions of chr XIII for all samples. Note that the aligner in use (bowtie) employed "Scchr13" to refer to this chromosome. We add a *GRanges* instance to the view to identify the region of interest.

```
> START = c(861250, 863000)
> END = c(862750, 864000)
> exc = GRanges(seqnames = "Scchr13", IRanges(start = START, end = END),
+     strand = "+")
> bamRanges(bs1) = exc
> bs1

BamViews dim: 2 ranges x 8 samples
names: isowt.5 isowt.6 ... xrn.1 xrn.2
detail: use bamPaths(), bamSamples(), bamRanges(), ...
```

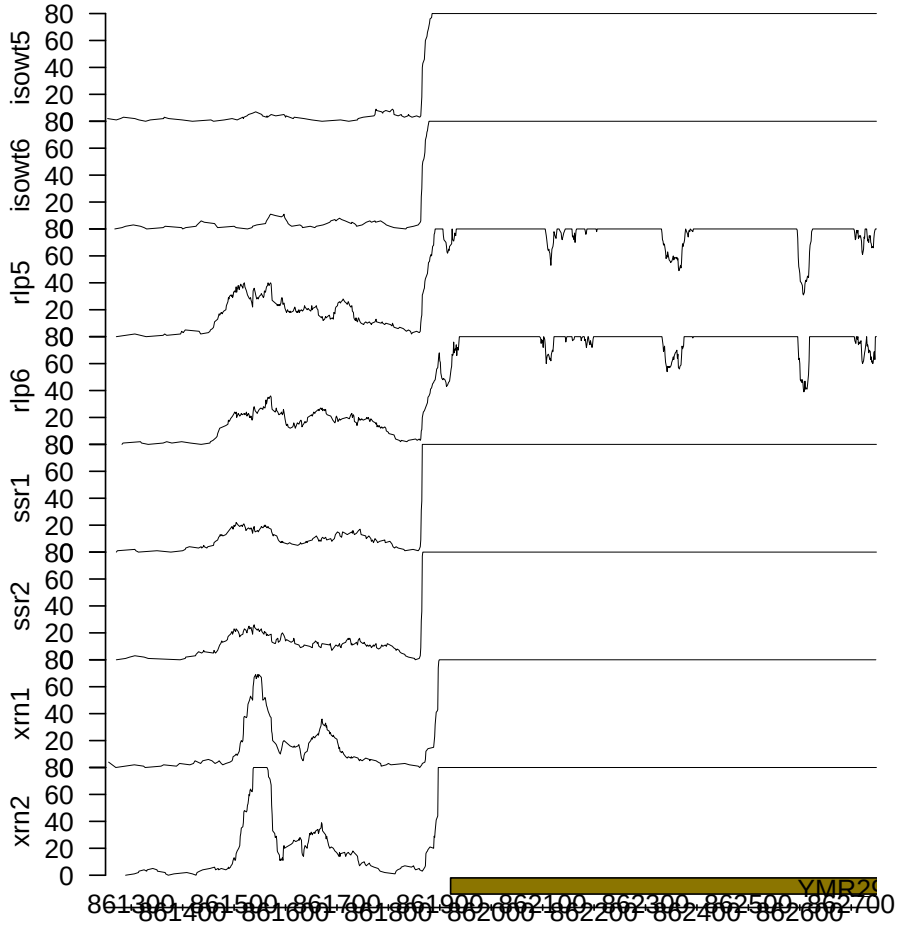
A common operation will be to extract coverage information. We use a transforming method, `readGappedAlignments`, from the *GenomicRanges* package to extract reads and metadata for each region and each sample.

```
> covex = RleList(lapply(bamPaths(bs1), function(x) coverage(readGappedAlignments(x))
> names(covex) = gsub(".bam$", "", basename(bamPaths(bs1)))
> head(covex, 3)

SimpleRleList of length 3
$isowt5_13e
'integer' Rle of length 900030 with 21818 runs
  Lengths: 799974      2      2      1      6 ...      1     10      7      1
  Values :      0      1      2      3      4 ...      5      4      3      2

$isowt6_13e
'integer' Rle of length 900035 with 21798 runs
  Lengths: 799976      2      3     14     13 ...      1     17      1      4
  Values :      0      1      2      3      4 ...      4      3      2      1

$rlp5_13e
'integer' Rle of length 900032 with 23036 runs
  Lengths: 799974      2      6     25      3 ...      3      4      2     30
  Values :      0      1      2      3      4 ...      2      3      2      1
```

Let's visualize what we have so far. We use *GenomeGraphs* and add some supporting software.

```
> library(GenomeGraphs)
> cov2baseTrack = function(rle, start, end, dp = DisplayPars(type = "l",
+     lwd = 0.5, color = "black"), countTx = function(x) log10(x +
+     1)) {
+     require(GenomeGraphs)
+     if (!is(rle, "Rle"))
+         stop("requires instance of Rle")
+     dat = runValue(rle)
+     loc = cumsum(runLength(rle))
+     ok = which(loc >= start & loc <= end)
+     makeBaseTrack(base = loc[ok], value = countTx(dat[ok]), dp = dp)
+ }
> trs = lapply(covex, function(x) cov2baseTrack(x, START[1], END[1],
+     countTx = function(x) pmin(x, 80)))
> ac = as.character
> names(trs) = paste(ac(bamSamples(bs1)$geno), ac(bamSamples(bs1)$lane),
+     sep = "")
> library(biomaRt)
> mart = useMart("ensembl", "scerevisiae_gene_ensembl")
> gr = makeGeneRegion(START, END, chromosome = "XIII", strand = "+",
```

```
+     biomart = mart, dp = DisplayPars(plotId = TRUE, idRotation = 0,
+         idColor = "black"))
> trs[[length(trs) + 1]] = gr
> trs[[length(trs) + 1]] = makeGenomeAxis()

> print(gdPlot(trs, minBase = START[1], maxBase = END[1]))

NULL
```



We can encapsulate this to something like:

```
> plotStrains = function(bs, query, start, end, snames, mart, chr,
+     strand = "+") {
+     filtbs = bs[query, ]
+     cov = lapply(filtbs, coverage)
+     covtrs = lapply(cov, function(x) cov2baseTrack(x[[1]], start,
+         end, countTx = function(x) pmin(x, 80)))
+     names(covtrs) = snames
```

```
+     gr = makeGeneRegion(start, end, chromosome = chr, strand = strand,
+         biomart = mart, dp = DisplayPars(plotId = TRUE, idRotation = 0,
+             idColor = "black"))
+     grm = makeGeneRegion(start, end, chromosome = chr, strand = "-",
+         biomart = mart, dp = DisplayPars(plotId = TRUE, idRotation = 0,
+             idColor = "black"))
+     covtrs[[length(covtrs) + 1]] = gr
+     covtrs[[length(covtrs) + 1]] = makeGenomeAxis()
+     covtrs[[length(covtrs) + 1]] = grm
+     gdPlot(covtrs, minBase = start, maxBase = end)
+ }
```

4 Comparative counts in a set of regions of interest

4.1 Counts in a regular partition

The supplementary information for the Lee paper includes data on unnannotated transcribed regions reported in other studies. We consider the study of David et al., confining attention to chromosome XIII. If you wanted to study their intervals you could use code like:

```
> data(leeUnn)
> names(leeUnn)
> leeUnn[1:4, 1:8]
> table(leeUnn$study)
> l13 = leeUnn[leeUnn$chr == 13, ]
> l13d = na.omit(l13[l13$study == "David", ])
> d13r = GRanges(seqnames = "Scchr13", IRanges(l13d$start, l13d$end),
+     strand = ifelse(l13d$strand == 1, "+", ifelse(l13d$strand ==
+         "0", "*", "-")))
> elementMetadata(d13r)$name = paste("dav13x", 1:length(d13r),
+     sep = ".")
> bamRanges(bs1) = d13r
> d13tab = tabulateReads(bs1)
```

but our object `bs1` is too restricted in its coverage. Instead, we illustrate with a small set of subintervals of the basic interval in use:

```
> myrn = GRanges(seqnames = "Scchr13", IRanges(start = seq(861250,
+     862750, 100), width = 100), strand = "+")
> elementMetadata(myrn)$name = paste("til", 1:length(myrn), sep = ".")
> bamRanges(bs1) = myrn
> tabulateReads(bs1, "+")
```

```
         til.1  til.2  til.3  til.4  til.5  til.6  til.7  til.8  til.9 til.10
start   861250 861350 861450 861550 861650 861750 861850 861950 862050 862150
end     861349 861449 861549 861649 861749 861849 861949 862049 862149 862249
isowt.5      1      1      3      6      2      7    299    605    408    380
isowt.6      2      6      9     12      7      4    306    666    458    382
rlp.5        1      5     65     53     36     11    158    247    186    145
rlp.6        3      2     47     48     37     16    123    238    163    159
ssr.1        2      6     35     27     21      8    423    700    541    496
ssr.2        2      6     43     37     26     13    443    839    616    509
xrn.1        7      8     75     78     24      5    180    446    357    288
xrn.2        4      9     96    110     31      8    225    611    465    356
        til.11 til.12 til.13 til.14 til.15 til.16
start   862250 862350 862450 862550 862650 862750
end     862349 862449 862549 862649 862749 862849
isowt.5    482    554    895    631    643    702
isowt.6    446    517    870    689    691    701
rlp.5      174    180    316    251    239    277
rlp.6      190    215    336    270    269    281
ssr.1      573    596    966    737    669    771
ssr.2      576    606    987    775    742    811
xrn.1      349    484    678    549    396    342
xrn.2      430    578    837    643    453    420
```

4.2 Counts in annotated intervals: genes

We can use Bioconductor annotation resources to acquire boundaries of yeast genes on our subregion of chromosome 13.

In the following chunk we generate annotated ranges of genes on the Watson strand.

```
> library(org.Sc.sgd.db)
> library(IRanges)
> c13g = get("13", revmap(org.Sc.sgdCHR))  # all genes on chr13
> c13loc = unlist(mget(c13g, org.Sc.sgdCHRLOC))  # their 'start' addresses
> c13locend = unlist(mget(c13g, org.Sc.sgdCHRLOCEND))
> c13locp = c13loc[c13loc>0]     # confine attention to + strand
> c13locendp = c13locend[c13locend>0]
> ok = !is.na(c13locp) & !is.na(c13locendp)
> c13pr = GRanges(seqnames="Scchr13", IRanges(c13locp[ok], c13locendp[ok]),
+     strand="+")   # store and clean up names
> elementMetadata(c13pr)$name = gsub(".13$", "", names(c13locp[ok]))
> c13pr
GRanges with 297 ranges and 1 elementMetadata value
      seqnames           ranges strand   |        name
```

```
        <Rle>        <IRanges>  <Rle>   | <character>
  [1]  Scchr13 [268031, 268149]      +   |       CEN13
  [2]  Scchr13 [923539, 924429]      +   |      TEL13R
  [3]  Scchr13 [924305, 924429]      +   |   TEL13R-TR
  [4]  Scchr13 [923539, 924003]      +   |   TEL13R-XC
  [5]  Scchr13 [924004, 924304]      +   |   TEL13R-XR
  [6]  Scchr13 [267174, 267800]      +   |     YML001W
  [7]  Scchr13 [264541, 266754]      +   |     YML002W
  [8]  Scchr13 [263483, 264355]      +   |     YML003W
  [9]  Scchr13 [260221, 261609]      +   |     YML005W
  ...      ...               ...    ... ...         ...
[289]  Scchr13 [297277, 297363]      +   |       snR78
[290]  Scchr13 [626348, 626653]      +   |       snR83
[291]  Scchr13 [463553, 463624]      +   |    tD(GUC)M
[292]  Scchr13 [290800, 290871]      +   |    tE(UUC)M
[293]  Scchr13 [352279, 352369]      +   |    tF(GAA)M
[294]  Scchr13 [363063, 363134]      +   |    tH(GUG)M
[295]  Scchr13 [504894, 505007]      +   |    tL(CAA)M
[296]  Scchr13 [168795, 168883]      +   |   tY(GUA)M1
[297]  Scchr13 [837927, 838015]      +   |   tY(GUA)M2

seqlengths
 Scchr13
      NA
```

```
> c13pro = c13pr[ order(ranges(c13pr)), ]
```

That's the complete set of genes on the Watson strand of chromosome XIII. In the *leeBamViews* package, we do not have access to all these, but only those lying in a 100kb interval.

```
> lim = GRanges(seqnames = "Scchr13", IRanges(8e+05, 9e+05), strand = "+")
> c13prol = c13pro[which(c13pro %in% lim), ]
```

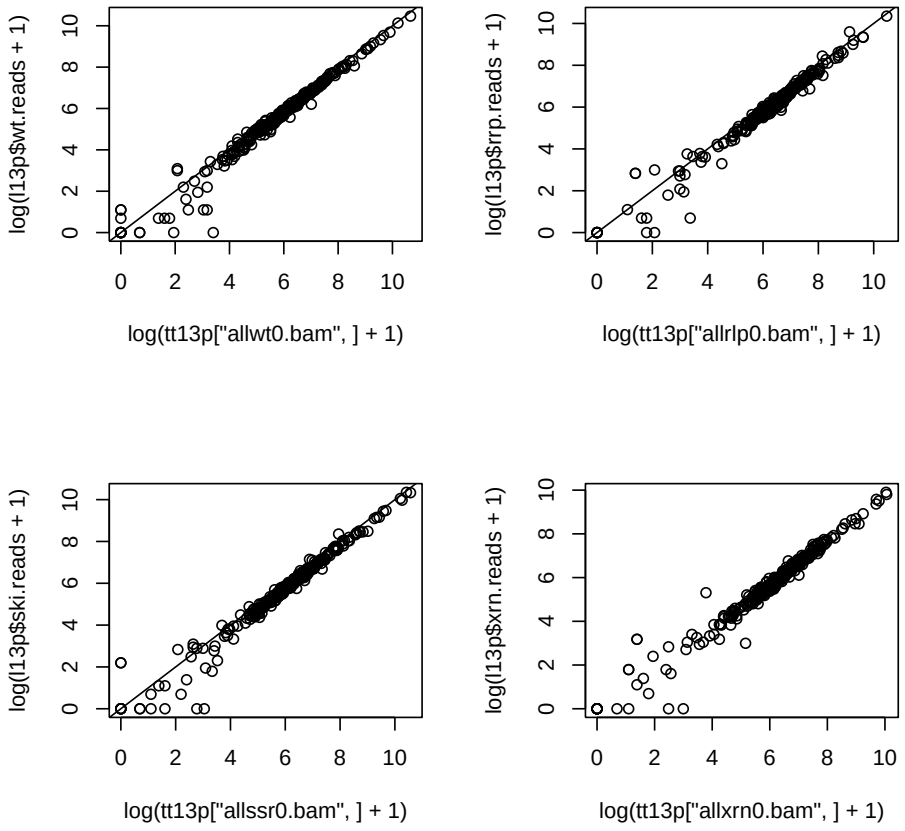
Now that we have a set of annotation-based genomic regions, we can tabulate read counts lying in those regions and obtain an annotated matrix.

```
> bamRanges(bs1) = c13prol
> annotab = tabulateReads(bs1, strandmarker = "+")
```

5 Larger scale sanity check

The following plot compares read counts published with the Lee et al. (2008) paper to those computed by the methods sketched here, for all regions noted on the plus strand of

chromosome XIII. Exact correspondence is not expected because of different approaches to read filtering.



6 Statistical analyses of differential expression

6.1 Using edgeR

Statistical analysis of read counts via negative binomial distributions with moderated dispersion is developed in Robinson and Smyth (2008). The *edgeR* differential expression statistics are computed using regional read counts, and total library size plays a role. We compute total read counts directly (the operation can be somewhat slow for very large BAM files):

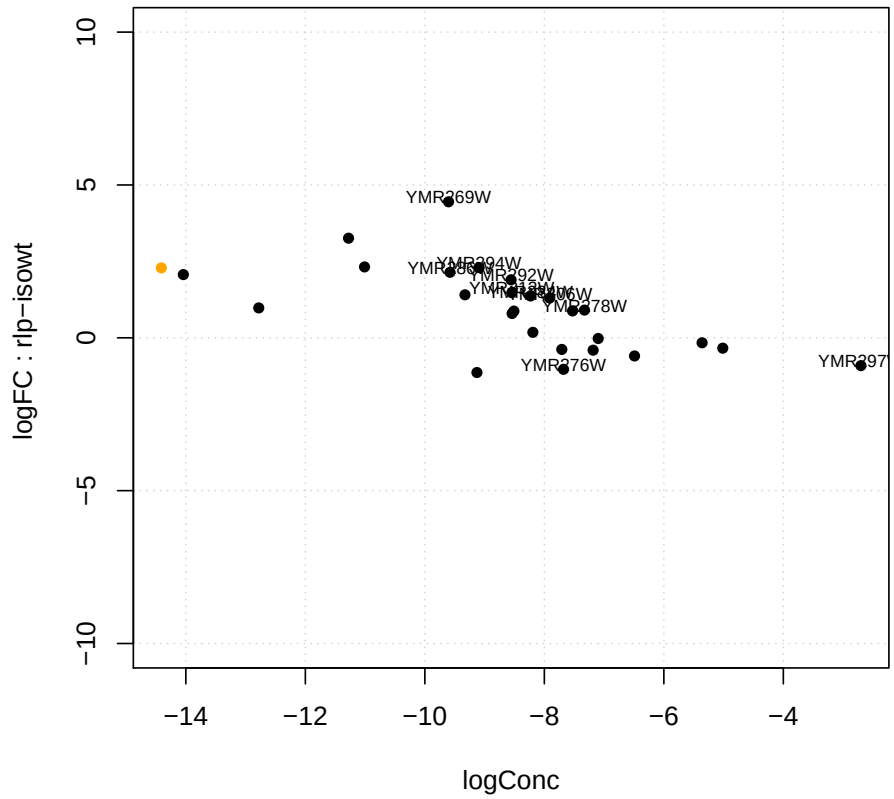
```
> totcnts = totalReadCounts(bs1)
```

In the following demonstration, we will regard multiple lanes from the same genotype as replicates. This is probably inappropriate for this method; the original authors tested for lane effects and ultimately combined counts across lanes within strain.

```
> library(edgeR)
> #
> # construct an edgeR container for read counts, including
> #   genotype and region (gene) metadata
> #
> dgel1 = DGEList( counts=t(annotab)[,-c(1,2)],
+    group=factor(bamSamples(bs1)$geno),
+    lib.size=totcnts, genes=colnames(annotab))
> #
> # compute a dispersion factor for the negative binomial model
> #
> cd = estimateCommonDisp(dgel1)
> #
> # test for differential expression between two groups
> # for each region
> #
> et12 = exactTest(cd)

Comparison of groups:  rlp - isowt

> #
> # display statistics for the comparison
> #
> tt12 = topTags(et12)
> tt12

Comparison of groups: rlp-isowt
          genes   logConc      logFC        PValue           FDR
YMR297W YMR297W -2.701639 -0.9092912 4.001725e-260 1.080466e-258
YMR269W YMR269W -9.603251  4.4504807  9.748151e-88  1.316000e-86
YMR294W YMR294W -9.093662  2.2997348  1.199710e-31  1.079739e-30
YMR292W YMR292W -8.557110  1.8989068  4.386646e-31  2.960986e-30
YMR306W YMR306W -7.909224  1.3029908  5.286705e-23  2.854821e-22
YMR284W YMR284W -8.231637  1.3698208  9.531069e-21  4.288981e-20
YMR286W YMR286W -9.577072  2.1461646  5.032338e-20  1.941045e-19
YMR312W YMR312W -8.544790  1.4744256  2.254859e-19  7.610150e-19
YMR278W YMR278W -7.327946  0.9077038  6.124400e-17  1.837320e-16
YMR276W YMR276W -7.678076 -1.0290934  1.161190e-16  3.135214e-16
```

An analog of the "MA-plot" familiar from microarray studies is available for this analysis. The 'concentration' is the log proportion of reads present in each gene, and the "log fold change" is the model-based estimate of relative abundance. In the following display we label the top 10 genes (those with smallest FDR).

```
> plotSmear(cd, cex = 0.8, ylim = c(-10, 10))
> text(tt12$table$logConc, tt12$table$logFC + 0.15, as.character(tt12$table$genes),
+     cex = 0.65)
```



7 Summary

- The BAM format provides reasonably compact and comprehensive information about a alignments of short reads obtained in a sequencing experiment. samtools utilities permit efficient random access to read collections of interest.
- *Rsamtools* brings samtools functionality into R, principally through the `scanBam` method, which is richly parameterized so that many details of access to and filtering of reads from BAM files can be controlled in R.
- *Rsamtools* defines the *bamViews* container for management of collections of BAM files. Read data are managed external to R; data on aligned reads can be imported efficiently, and "streaming read" models for scanning large collections of

reads can be used. Many embarrassingly parallel operations can be accomplished concurrently using *multicore* or similar packages.

- The *leeBamViews* package provides small excerpts from BAM files generated after bowtie alignment of FASTQ records available through the NCBI short read archives. These excerpts can be analyzed using code shown in this vignette.

- After the count data have been generated, various approaches to inference on differential expression are available. We consider the moderated negative binomial models of *edgeR* above; more general variance modeling is available in the developmental *DESeq* package.

References

Albert Lee, Kasper Daniel Hansen, James Bullard, Sandrine Dudoit, Gavin Sherlock, and Michael Snyder. Novel low abundance and transient rnas in yeast revealed by tiling microarrays and ultra high–throughput sequencing are not conserved across closely related yeast species. *PLoS Genet*, 4(12):e1000299, Dec 2008. doi: 10.1371/journal.pgen.1000299.t002.

Heng Li, Bob Handsaker, Alec Wysoker, Tim Fennell, Jue Ruan, Nils Homer, Gabor Marth, Goncalo Abecasis, Richard Durbin, and 1000 Genome Project Data Processing Subgroup. The sequence alignment/map format and samtools. *Bioinformatics*, 25(16): 2078–9, Aug 2009. doi: 10.1093/bioinformatics/btp352.

Mark D Robinson and Gordon K Smyth. Small-sample estimation of negative binomial dispersion, with applications to sage data. *Biostatistics (Oxford, England)*, 9(2):321–32, Apr 2008. doi: 10.1093/biostatistics/kxm030. URL `http://biostatistics.oxfordjournals.org/cgi/content/full/9/2/321`.

8 Session data

```
> sessionInfo()

R version 2.13.0 Under development (unstable) (2010-11-01 r53513)
Platform: x86_64-unknown-linux-gnu (64-bit)

locale:
 [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
 [3] LC_TIME=en_US.UTF-8        LC_COLLATE=C
 [5] LC_MONETARY=C              LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_US.UTF-8       LC_NAME=C
```

```
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C

attached base packages:
[1] grid      stats     graphics  grDevices utils     datasets  methods
[8] base

other attached packages:
 [1] edgeR_1.9.4          org.Sc.sgd.db_2.4.6  RSQLite_0.9-3
 [4] DBI_0.2-5            AnnotationDbi_1.13.1 GenomeGraphs_1.11.0
 [7] biomaRt_2.7.0        leeBamViews_0.99.11  BSgenome_1.19.0
[10] Rsamtools_1.3.4      Biostrings_2.19.0    GenomicRanges_1.3.2
[13] IRanges_1.9.8        Biobase_2.11.6

loaded via a namespace (and not attached):
[1] RCurl_1.4-3  XML_3.2-0    limma_3.7.10 tools_2.13.0
```