

Some Basic Analysis of ChIP-Seq Data

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Our goal is to describe the use of Bioconductor software to perform some basic tasks in the analysis of ChIP-Seq data. We will use several functions in the as-yet-unreleased `chipseq` package, which provides convenient interfaces to other powerful packages such as `ShortRead` and `IRanges`. We will also use the `lattice` package for visualization.

```
> library(chipseq)
> library(lattice)
```

Example data

The `alignedLocs` data set, provided in the file `alignedLocs.rda`, contains data from three Solexa lanes. The raw reads were aligned to the reference genome (mouse in this case) using an external program (MAQ), and the results read in using the `ShortRead` package. We then removed all duplicate reads and applied a quality score cutoff. The remaining data were reduced to a set of alignment start positions (including orientation).

```
> load("../data/alignedLocs.rda")
> alignedLocs

'AlignedList' with 3 lanes:
control sample1 sample2
1114023 1344740 2175087

Chromosomes: chr1, chr2, chr3, chr4, chr5, chr6, chr7, chr8, chr9, chr10, chr11, chr12,
chr13, chr14, chr15, chr16, chr17, chr18, chr19

Strands: -, +
```

`alignedLocs` has a list-like structure, each component representing data from one lane.

```
> alignedLocs$sample1

Mmusculus 'GenomeList' with 19 chromosomes:
```

Class of children: list

Each of these are themselves lists:

```
> str(head(alignedLocs$sample1, 2))

List of 2
 $ chr1 :List of 2
   ..$ -: int [1:50584] 3013802 3026308 3035525 3039158 3060684 ...
   ..$ +: int [1:50181] 3001001 3018535 3041392 3055167 3064081 ...
 $ chr10:List of 2
   ..$ -: int [1:38604] 3013702 3019386 3021977 3022708 3031335 3032387 ...
   ..$ +: int [1:38627] 3012735 3013613 3019737 3020950 3022283 3022648 ...
```

The mouse genome

The data we have refer to alignments to a genome, and only makes sense in that context. Bioconductor has genome packages containing the full sequences of several genomes. The one relevant for us is

```
> library(BSgenome.Mmusculus.UCSC.mm9)
> mouse.chromlens <- seqlengths(Mmusculus)
> head(mouse.chromlens)

  chr1      chr2      chr3      chr4      chr5      chr6
197195432 181748087 159599783 155630120 152537259 149517037
```

We will only make use of the chromosome lengths, but the actual sequence will be needed for motif finding, etc.

Extending reads

Solexa gives us the first few (35 in our data) bases of each fragment it sequences, but the actual fragment is longer. By design, the sites of interest (transcription factor binding sites) should be somewhere in the fragment, but not necessarily in its initial part. Although the actual lengths of fragments vary, extending the alignment of the short read by a fixed amount in the appropriate direction, depending on whether the alignment was to the positive or negative strand, makes it more likely that we cover the actual site of interest.

We extend all reads to be 200 bases long. This is done using the `extendReads()` function, which can work on data from one chromosome in one lane.

```
> ext <- extendReads(alignedLocs$sample1$chr5, readLen = 35, seqLen = 200)
> head(ext)

IRanges object:
  start     end width
1 3018808 3019007   200
2 3025021 3025220   200
3 3030072 3030271   200
4 3041363 3041562   200
5 3047643 3047842   200
6 3052628 3052827   200
```

The result is essentially a collection of intervals (ranges) over the reference genome.

Coverage, islands, and depth

A useful summary of this information is the *coverage*, that is, how many times each base in the genome was covered by one of these intervals.

```
> cov <- coverage(ext, start = 1, end = mouse.chromlens["chr5"])
> cov

152537259-integer "XRleInteger" instance
[1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
```

For efficiency, the result is stored in a run-length encoded form.

The regions of interest are contiguous segments of non-zero coverage, also known as *islands*.

For each island, we can compute the number of reads in the island, and the maximum coverage depth within that island.

```

> viewSums(head(islands))
[1] 200 400 200 200 200 200 200

> viewMaxs(head(islands))
[1] 1 2 1 1 1 1 1

> nread.tab <- table(viewSum)
> depth.tab <- table(viewMax)
> head(nread.tab, 10)

      1        2        3        4
52396 10885  2855    901    38

> head(depth.tab, 10)

      1        2        3        4
52423 11647  2652    626    28

```

Processing multiple lanes

Although data from one chromosome within one lane is often the natural unit to work with, we typically want to apply any procedure to all chromosomes in all lanes. A function that is useful for this purpose is `summarizeReads`, which recursively applies a summary function to a full dataset. The summary function must produce a data frame. Here is a simple summary function that computes the frequency distribution of the number of reads.

```
> islandReadSummary <- function(x)
+ {
+   g <- extendReads(x)
+   s <- slice(coverage(g, 1, max(end(g))), lower = 1)
+   tab <- table(viewSums(s) / 200)
+   ans <- data.frame(nread = as.numeric(names(tab)), count = as.numeric(tab))
+   ans
+ }
```

Applying it to our test-case, we get

```
> head(islandReadSummary(alignedLocs$sample1$chr5))
```

nread	count
1	52396
2	10885
3	2855
4	901
5	355
6	174

We can now use it to summarize the full dataset.

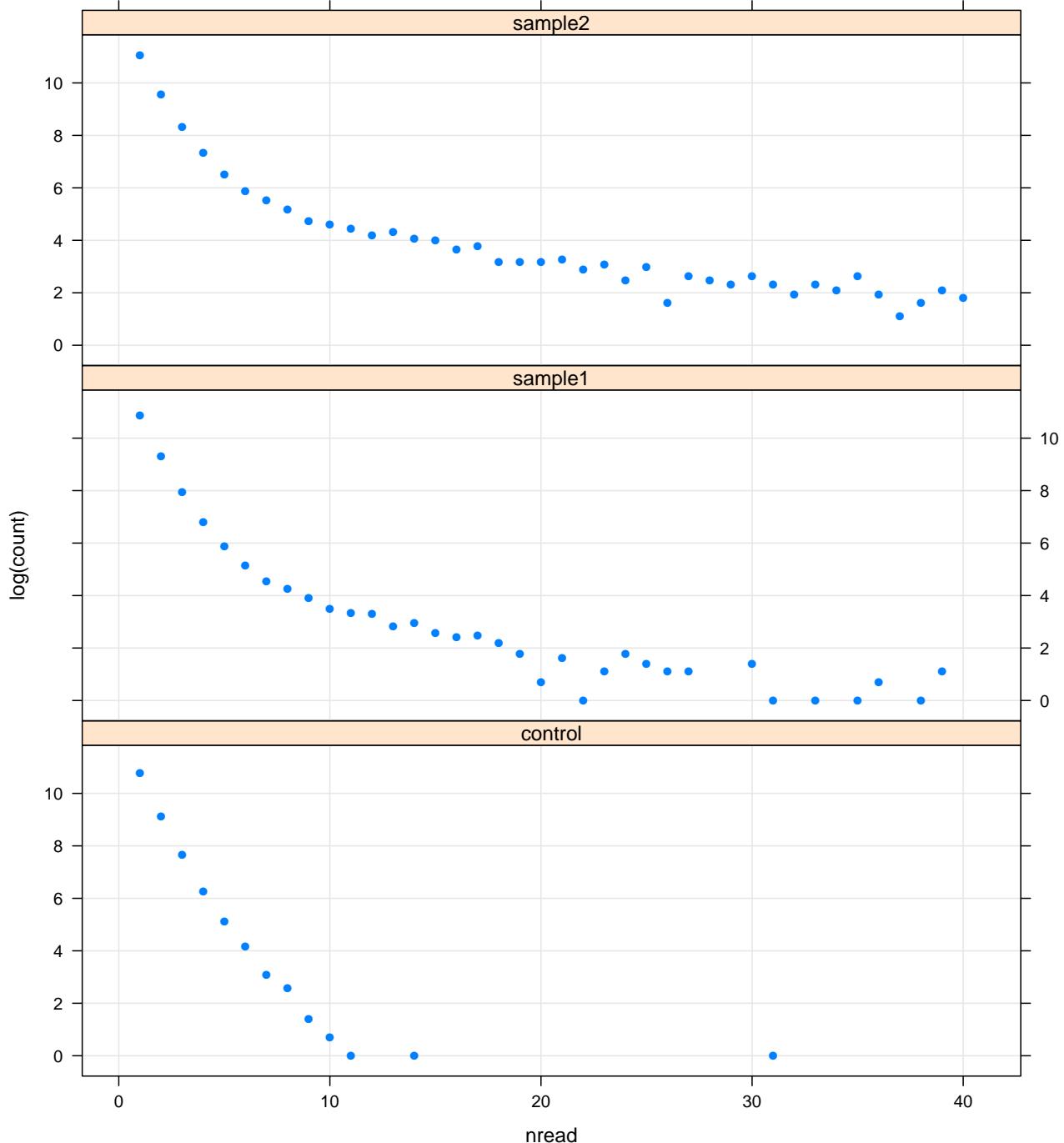
```
> nread.islands <- summarizeReads(alignedLocs, summary.fun = islandReadSummary)
> head(nread.islands)
```

	nread	count	chromosome	lane
control.chr1.1	1	61711	chr1	control
control.chr1.2	2	10117	chr1	control
control.chr1.3	3	2033	chr1	control
control.chr1.4	4	487	chr1	control
control.chr1.5	5	144	chr1	control
control.chr1.6	6	46	chr1	control

```

> xyplot(log(count) ~ nread / lane, nread.islands,
+         subset = (chromosome == "chr5" & nread <= 40),
+         layout = c(1, 3), pch = 16, type = c("p", "g"))

```



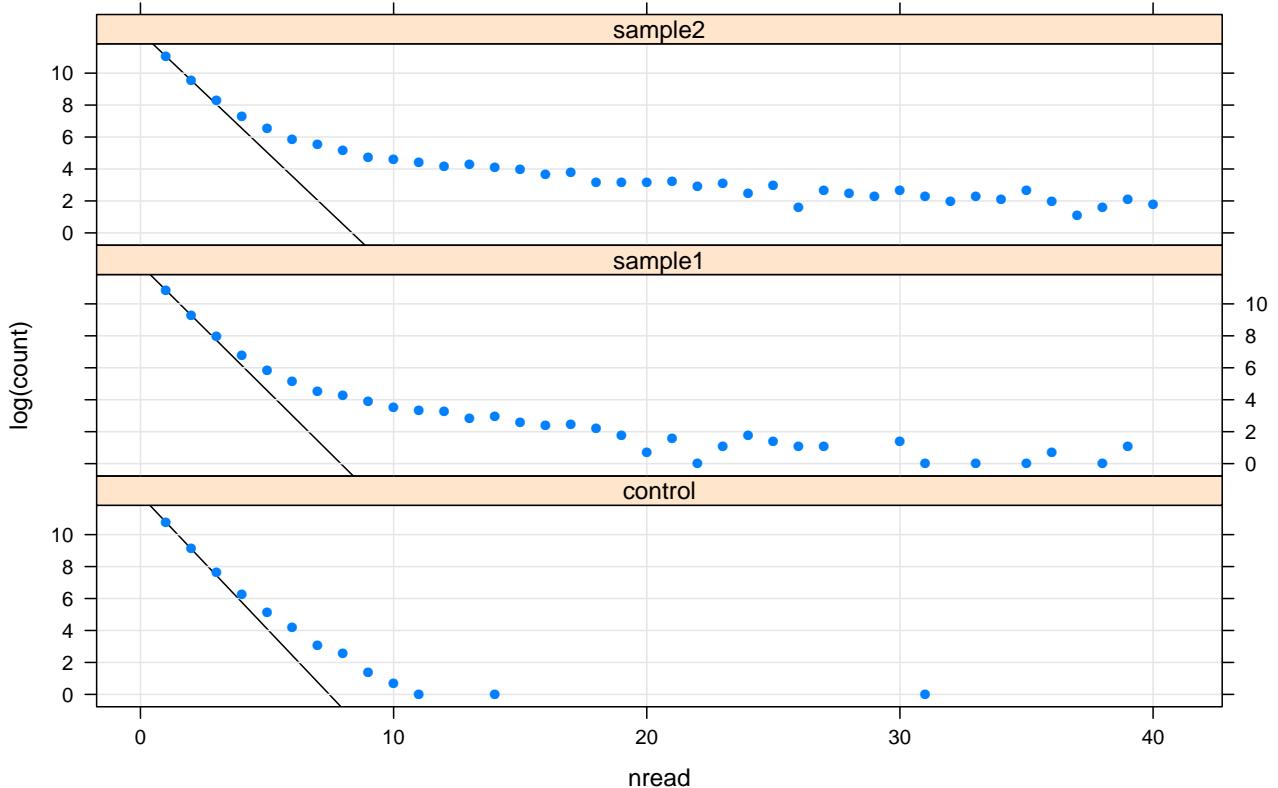
If reads were sampled randomly from the genome, then the null distribution number of reads per island would have a geometric distribution; that is,

$$P(X = k) = p^{k-1}(1 - p)$$

In other words, $\log P(X = k)$ is linear in k . Although our samples are not random, the islands with just one or two reads may be representative of the null distribution.

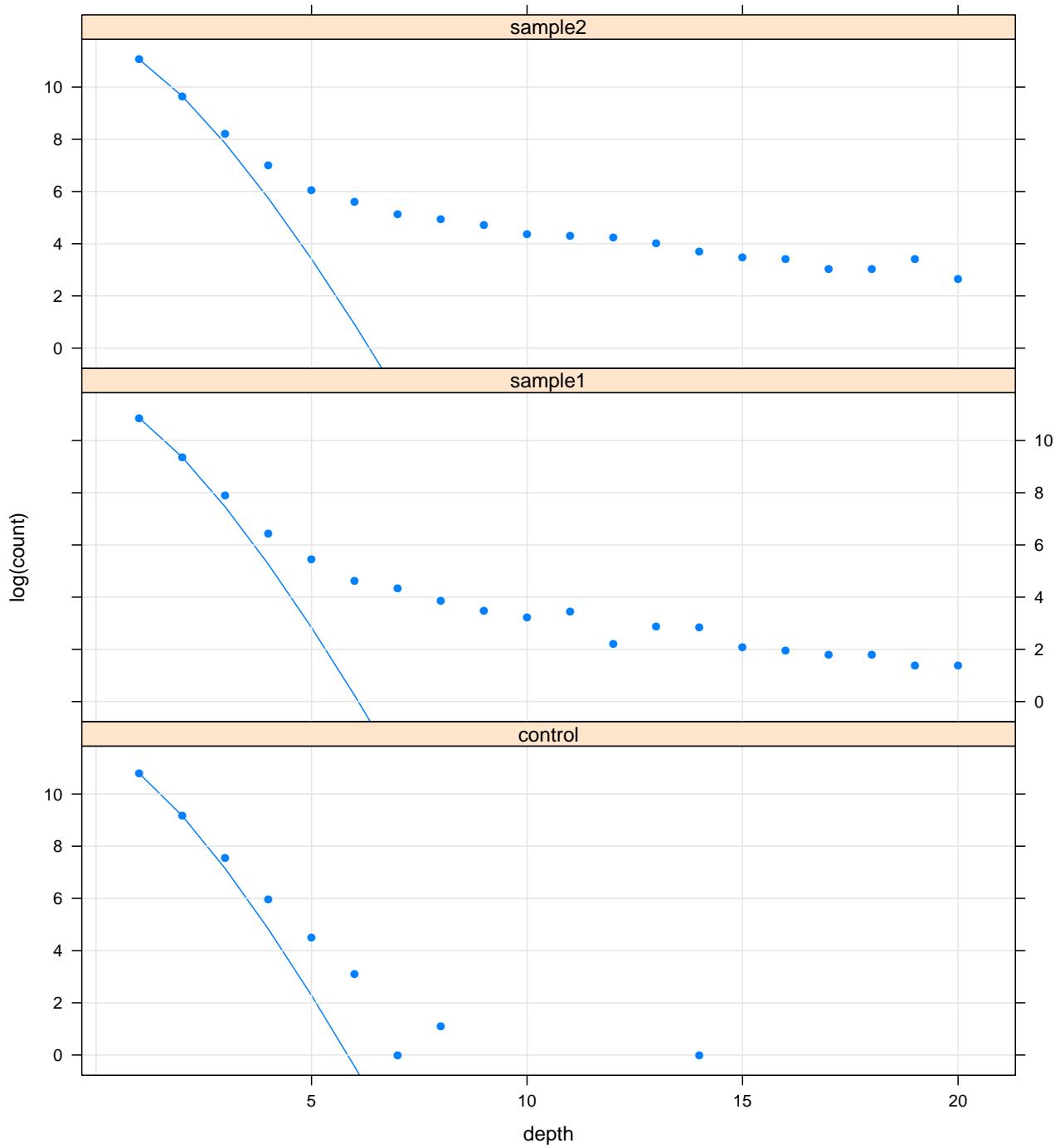
```
> xyplot(log(count) ~ nread / lane, nread.islands,
+         subset = (chromosome == "chr5" & nread <= 40),
+         layout = c(1, 3), pch = 16, type = c("p", "g"),
+         panel = function(x, y, ...) {
+             panel.lmline(x[1:2], y[1:2])
+             panel.xyplot(x, y, ...)
+         })

```



We can create a similar plot of the distribution of depths.

```
> islandDepthSummary <- function(x)
+ {
+   g <- extendReads(x)
+   s <- slice(coverage(g, 1, max(end(g))), lower = 1)
+   tab <- table(viewMaxs(s))
+   ans <- data.frame(depth = as.numeric(names(tab)), count = as.numeric(tab))
+   ans
+ }
> depth.islands <- summarizeReads(alignedLocs, summary.fun = islandDepthSummary)
> xyplot(log(count) ~ depth | lane, depth.islands,
+         subset = (chromosome == "chr5" & depth <= 20),
+         layout = c(1, 3), pch = 16, type = c("p", "g"),
+         panel = function(x, y, ...) {
+           lambda <- 2 * exp(y[2]) / exp(y[1])
+           null.est <- function(xx) {
+             xx * log(lambda) - lambda - lgamma(xx + 1)
+           }
+           log.N.hat <- null.est(1) - y[1]
+           panel.lines(1:10, -log.N.hat + null.est(1:10))
+           panel.xyplot(x, y, ...)
+         })
}
```



Peaks

Going back to our example of chr5 of the first sample, we can define “peaks” to be regions of the genome where coverage is 8 or more.

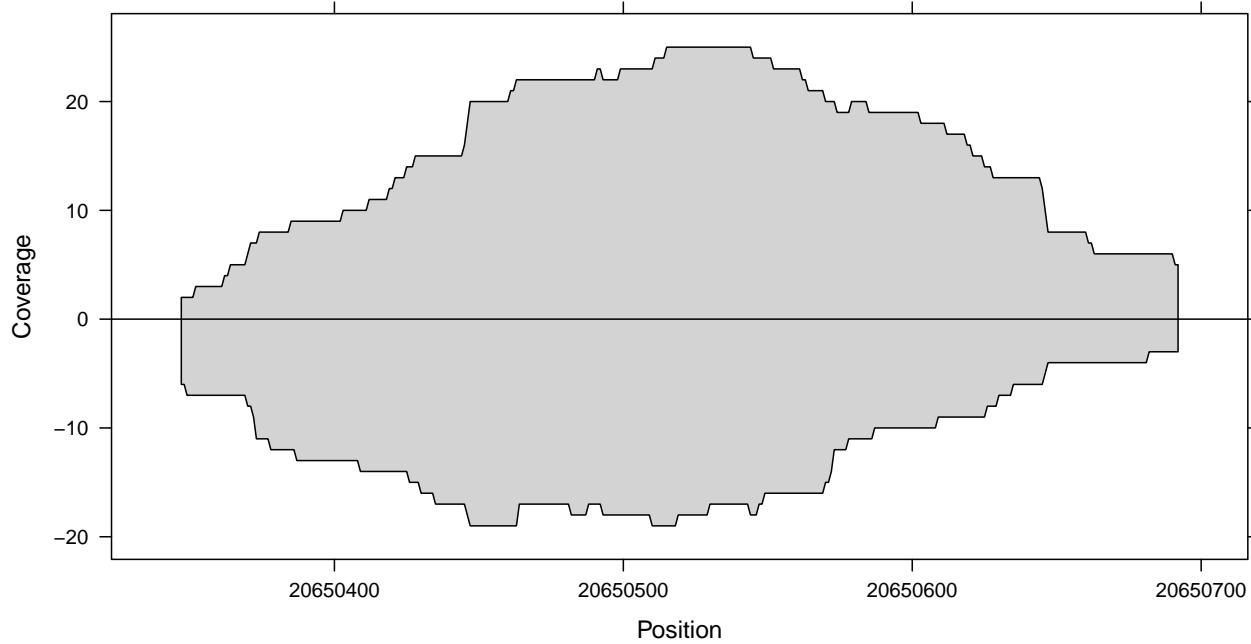
It is meaningful to ask about the contribution of each strand to each peak, as the sequenced region of pull-down fragments would be on opposite sides of a binding site depending on which strand it matched. We can compute strand-specific coverage, and look at the individual coverages under the combined peaks as follows:

```
> peak.depths <- viewMaxs(peaks)
> cov.pos <- coverage(extendReads(alignedLocs$sample1$chr5, strand = "+"),
+                         start = 1, end = mouse.chromlens["chr5"])
> cov.neg <- coverage(extendReads(alignedLocs$sample1$chr5, strand = "-"),
+                         start = 1, end = mouse.chromlens["chr5"])
> peaks.pos <- copyIRanges(peaks, cov.pos)
> peaks.neg <- copyIRanges(peaks, cov.neg)
> which(peak.depths >= 40)

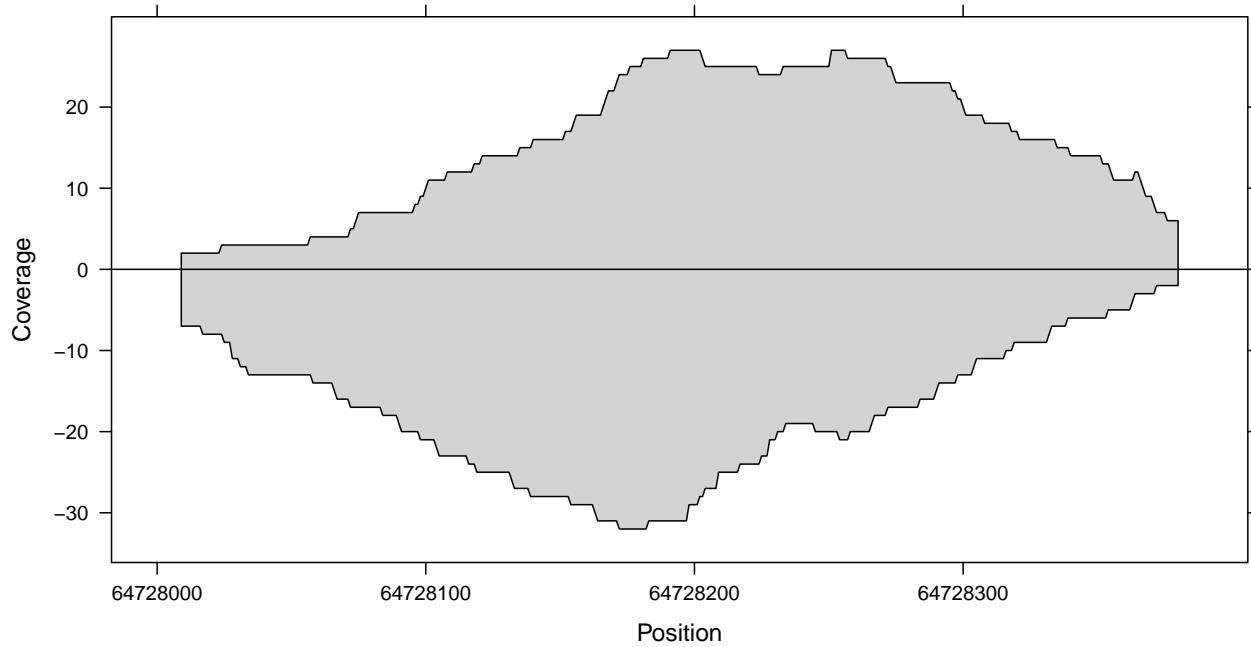
[1] 6 96 126 173
```

We plot the four highest

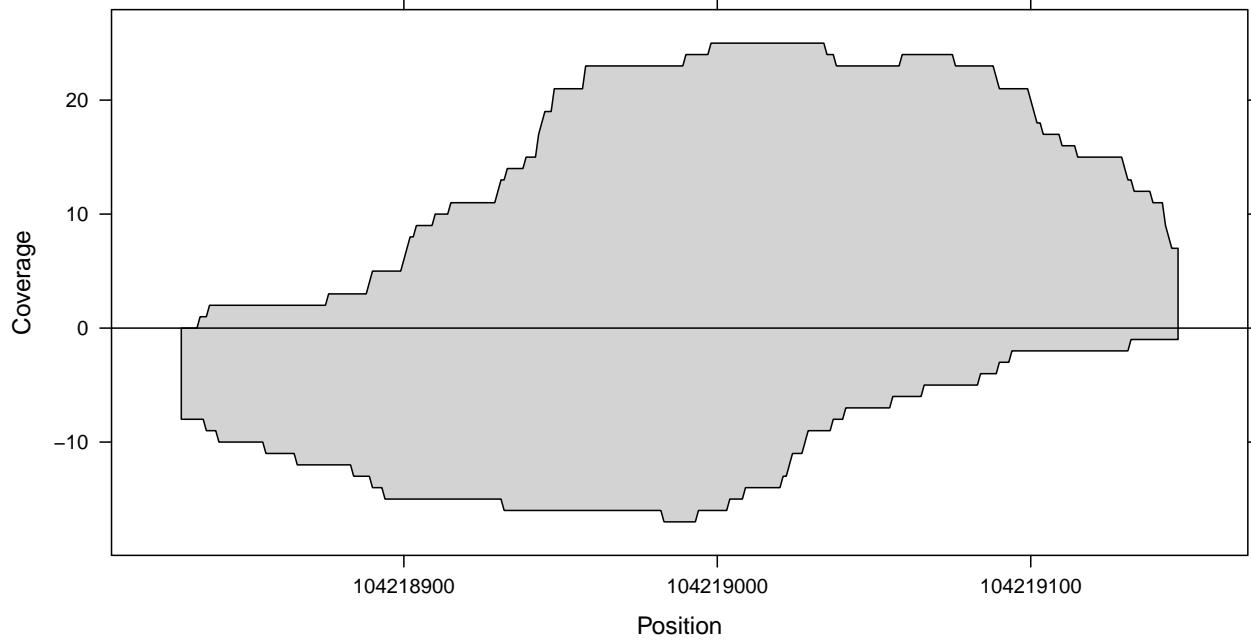
```
> plotPeak(peaks.pos[6], peaks.neg[6])
```



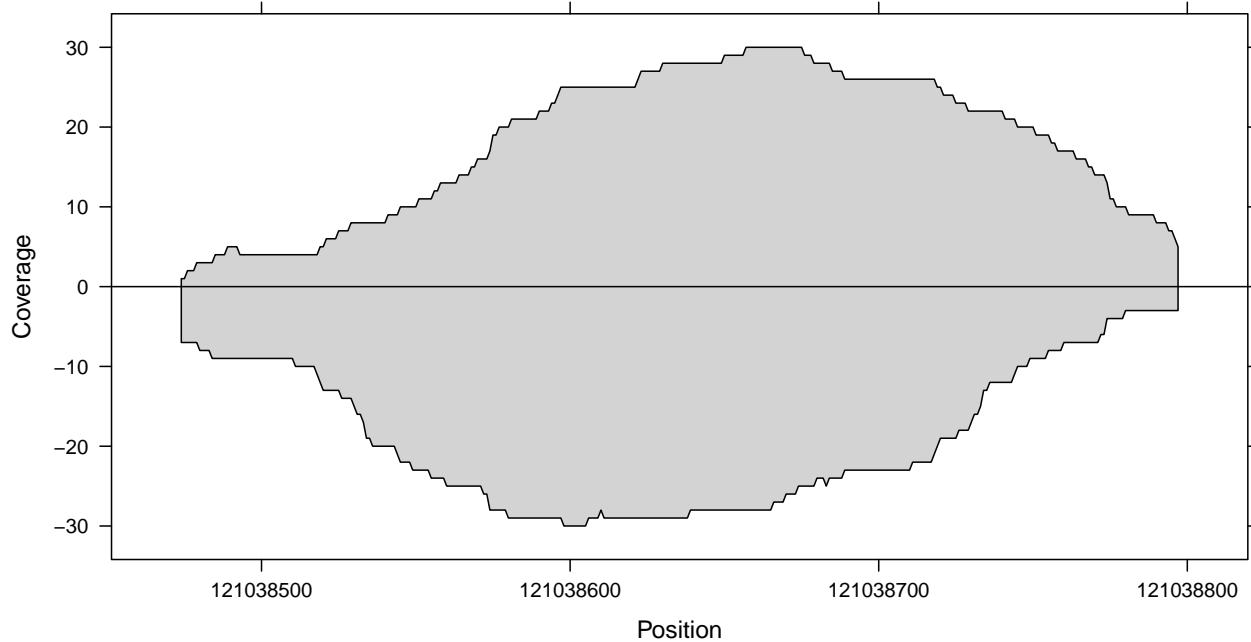
```
> plotPeak(peaks.pos[96], peaks.neg[96])
```



```
> plotPeak(peaks.pos[126], peaks.neg[126])
```



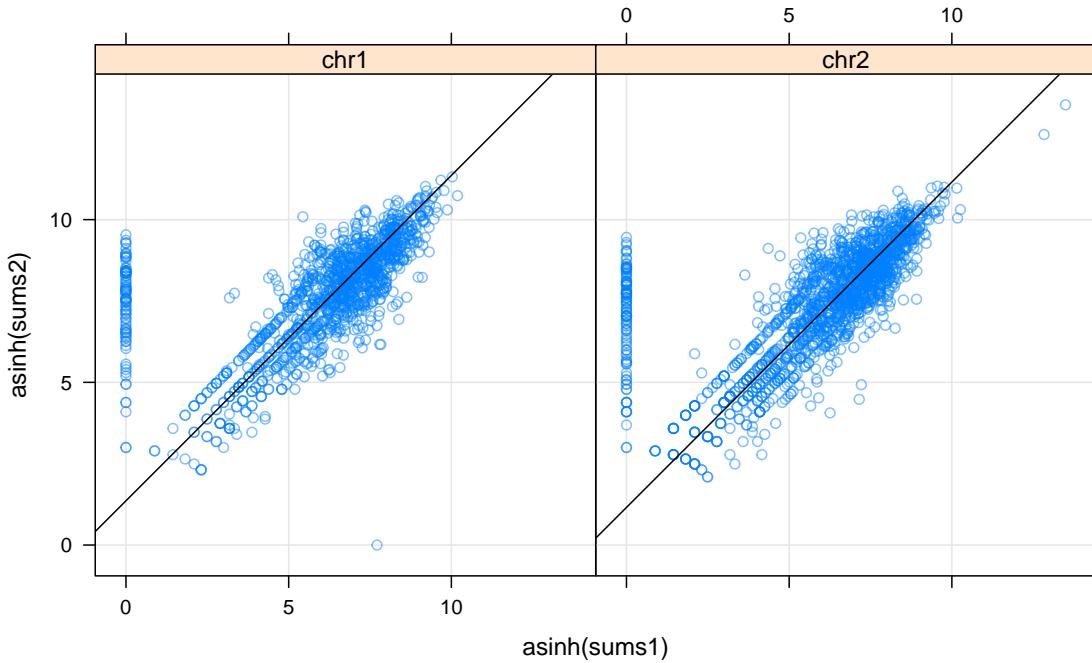
```
> plotPeak(peaks.pos[173], peaks.neg[173])
```



Differential peaks

One common question is: which peaks are different in two samples? One simple strategy is the following: combine data from the two samples, find peaks in the combined data, and compare the contributions of the two samples.

```
> extRanges <- lapply(alignedLocs, extendReads)
> peakSummary <-
+   diffPeakSummary(extRanges$sample1, extRanges$sample2,
+                   chrom.lens = mouse.chromlens, lower = 10)
> xyplot(asinh(sums2) ~ asinh(sums1) | chromosome,
+         data = peakSummary,
+         subset = (chromosome %in% c("chr1", "chr2")),
+         panel = function(x, y, ...) {
+           panel.xyplot(x, y, ...)
+           panel.abline(median(y - x), 1)
+ },
+         type = c("p", "g"), alpha = 0.5, aspect = "iso")
```



We use a simple cutoff to flag peaks that are different.

```
> peakSummary <-
+   within(peakSummary,
+   {
+     diffs <- asinh(sums2) - asinh(sums1)
+     resids <- (diffs - median(diffs)) / mad(diffs)
+     up <- resids > 2
+     down <- resids < -2
+   })
> head(peakSummary)
```

	start	end	sums1	sums2	maxs1	maxs2	chromosome	down	up
chr1.1	6810057	6810265	1514	1635	9	9	chr1	FALSE	FALSE
chr1.2	6810752	6810759	8	72	1	9	chr1	FALSE	FALSE

```

chr1.3 6810772 6810929      0   1962      0   14      chr1 FALSE  TRUE
chr1.4 7078966 7078982      68   102      4    6      chr1 FALSE FALSE
chr1.5 7078992 7078996      20   30       4    6      chr1 FALSE FALSE
chr1.6 7079000 7079158     549  1187      4    9      chr1 FALSE FALSE
             resids      diff
chr1.1 -1.2944071 0.07688763
chr1.2  0.8245183 2.19338924
chr1.3  6.9129605 8.27486689
chr1.4 -0.9654834 0.40543508
chr1.5 -0.9658005 0.40511836
chr1.6 -0.5994144 0.77108530

```

Placing peaks in genomic context

Locations of individual peaks may be of interest. Alternatively, a global summary might look at classifying the peaks of interest in the context of genomic features such as promoters, upstream regions, etc. The `geneMouse` dataset in the `chipseq` package contains gene location information from UCSC. The `genomic_regions` function converts this into a set of ranges defining promoters, upstream regions, etc.

```

> data(geneMouse)
> gregions <- genomic_regions(genes = geneMouse, proximal = 2000)
> gregions$gene <- as.character(gregions$gene)
> str(gregions)

'data.frame':      49409 obs. of  12 variables:
 $ chrom        : Factor w/ 33 levels "chr1","chr10",...
 $ gene          : chr "uc007aet.1" "uc007aeu.1" "uc007aev.1" "uc007aew.1" ...
 $ promoter.start: int 3203713 3659579 3646985 4397322 4348473 4481816 4484494 4484494 4484494 ...
 $ promoter.end  : int 3207713 3663579 3650985 4401322 4352473 4485816 4488494 4488494 4488494 ...
 $ threeprime.start: int 3193984 3202562 3636391 4278926 4332223 4479008 4479008 4479008 4479008 ...
 $ threeprime.end  : int 3197984 3206562 3640391 4282926 4336223 4483008 4483008 4483008 4483008 ...
 $ upstream.start : int 3207714 3663580 3650986 4401323 4352474 4485817 4488495 4488495 4488495 ...
 $ upstream.end   : int 3215713 3671579 3658985 4409322 4360473 4493816 4496494 4496494 4496494 ...
 $ downstream.start: int 3185984 3194562 3628391 4270926 4324223 4471008 4471008 4471008 4471008 ...
 $ downstream.end  : int 3193983 3202561 3636390 4278925 4332222 4479007 4479007 4479007 4479007 ...
 $ gene.start     : int 3195984 3204562 3638391 4280926 4334223 4481008 4481008 4481008 4481008 ...
 $ gene.end       : int 3205713 3661579 3648985 4399322 4350473 4483816 4486494 4486494 4486494 ...

```

This can be used to obtain a tabulation of the peaks.

```

> ans <- contextDistribution(peakSummary, gregions)
> head(ans)

  type total promoter threeprime upstream downstream gene chromosome
1 all   1257      242        96      163       199     576     chr1
2 up     97       6         6      14        12     38     chr1
3 down    24       3         2       2        2     11     chr1
4 all   1034      261       101      188       187     548     chr10
5 up     77       5         8       7        12     36     chr10
6 down    17       4         0       2        1      6     chr10

> sumtab <-
+   as.data.frame(rbind(total = xtabs(total ~ type, ans),
+                      promoter = xtabs(promoter ~ type, ans),
+                      threeprime = xtabs(threeprime ~ type, ans),
+                      upstream = xtabs(upstream ~ type, ans),

```

```

+
+           downstream = xtabs(downstream ~ type, ans),
+           gene = xtabs(gene ~ type, ans)))
> cbind(sumtab, ratio = round(sumtab[, "down"] / sumtab[, "up"], 3))

      all    up   down ratio
total     18633 1635   281 0.172
promoter  4085  178    76 0.427
threeprime 1765  120    29 0.242
upstream   3174  216    39 0.181
downstream 3311  216    53 0.245
gene       9735  826   122 0.148

```

Version information

```

> sessionInfo()

R version 2.9.0 Under development (unstable) (2008-10-21 r46769)
x86_64-unknown-linux-gnu

locale:
LC_CTYPE=en_US.UTF-8;LC_NUMERIC=C;LC_TIME=en_US.UTF-8;LC_COLLATE=en_US.UTF-8;LC_MONETARY=C;LC_MESSAGES=en_U

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

other attached packages:
[1] BSgenome.Mmusculus.UCSC.mm9_1.3.11 chipseq_0.1.2
[3] ShortRead_1.1.2                  lattice_0.17-15
[5] Biobase_2.3.0                   BSgenome_1.11.0
[7] Biostrings_2.11.0                IRanges_1.1.0

loaded via a namespace (and not attached):
[1] grid_2.9.0        Matrix_0.999375-16

```