

Analysis of Bead Summary Data using beadarray

September 27, 2007

Introduction

There are two methods for describing the results of a BeadArray experiment. Firstly, we can use *bead-level data* whereby the position and intensity of each individual bead on an array is known

Bead summary data can also be used whereby a summary intensity for each bead type on an array is given. The summarised values for a particular bead type can then be compared between different arrays within an experiment. This is the format of the data output by Illumina's BeadStudio application. The methods described within this document are for the analysis of bead summary expression data which can be obtained using either the BeadChip (6 or 8 arrays on a slide) or SAM (arrays organised in 96 well plates) technologies.

1 Citing beadarray

If you use *beadarray* for the analysis or pre-processing of BeadArray data please cite:

Dunning MJ, Smith ML, Ritchie ME, Tavaré S, **beadarray: R classes and methods for Illumina bead-based data**, *Bioinformatics*, **23**(16):2183-2184

2 Getting help with beadarray

Wherever possible, questions about *beadarray* should be sent to the Bioconductor mailing list (bioconductor@stat.math.ethz.ch). Therefore all problems and solutions will be kept in a searchable archive. When posting to this mailing list, please state the version of *beadarray* and R to help to diagnose the problem. This can be done by pasting the output of running the command `sessionInfo()`.

3 Importing Bead Summary Data

The *beadarray* package is able to read the output of BeadStudio versions 1, 2 and 3 which comes in the form of a text file. We assume the file to have one row for each probe and a set of columns for each array, depending on which columns have been exported from BeadStudio. We prefer that the annotation columns are not exported from BeadStudio. These columns often contain unusual characters which cannot be easily read into R. If required, annotation information can be imported at a later time through other Bioconductor packages.

An example data set is included with the *beadarray* package and can be found as a zip file (*BeadSummaryExample.zip*) inside the *inst/demodata* directory of the *beadarray* download. Inside this zip you will find the raw non-normalised data, a sample sheet and a quality control file for an example experiment. These data were obtained as part of a pilot study into BeadArray technology and comprises of 3 Human-6 BeadChips with 6 different samples, I, MC, MD, MT, P and Norm hybridised. MC, MD, MT and P are all tumours whereas Norm is a normal sample and I is a sample provided by Illumina. The normalised data and quality control information was produced using BeadStudio version 1.

3.1 Description of Files

We now describe the included files in more detail.

- `raw_data.csv` (*required*) - This contains the raw, non-normalised bead summary values as output by BeadStudio. Inside the file are several lines of header information followed by a data matrix with some 48,000 rows. Each row is a different gene in the experiment and the columns give different measurements for the gene. For each array, we record the summarised expression level (AVG_Signal), standard error of the bead replicates (BEAD_STDEV), Number of beads used (Avg_NBEADS) and a Detection score which estimates the probability of a gene being detected above the background. When exporting this file from BeadStudio, the user is able to choose which columns to export. `beadarray` is able to read any combination of these columns.

With versions 2 and 3 of BeadStudio it is possible to export annotation information. We recommend this data not be exported if the file is to be read into `beadarray`, as some of the special characters used in the annotation fields cause problems for the `readBeadSummaryData` function. This information can be retrieved later on from other Bioconductor packages, such as `illuminaHumanv1`.

- `raw_data_sample_sheet.csv` (*optional*) - Defines the array IDs and samples placed on each array. In order for this information to be read into `beadarray`, we require that the 4th column is a unique identifier for each array in the experiment. This is a file format that Illumina recommend for users of BeadStudio to specify the contents of each array. This file is created by the user.
- `raw_data_qcinfo.csv` (*optional*) - Gives the summarised data for each of the controls on each array, which may be useful for diagnostic purposes. This file was produced using BeadStudio version 1. The format of the quality control files differs slightly between BeadStudio versions 1 and 2. Version 1 of the software gives one averaged value for each control type, whereas version 2 gives summarised values for each control of a particular type. The user does not have to know the version of BeadStudio used to generate the file. Refer to the Illumina documentation for information on what each control measures.
- `FullControlInfo.txt` (*optional*) - Quality control information exported by BeadStudio version 2.

The following code can be used to read the example data into R. First make sure that the contents of `BeadSummaryExample.zip` are extracted to the current working directory. If the quality control file and sample sheet are not available, then the raw data can be read in on it's own.

The function `readBeadSummaryData` can be made to read the output of either versions 1, 2 or 3 of BeadStudio. The default settings will read BeadStudio version 3 output. Users may need to change the argument `sep`, which specifies if the file is comma or tab delimited and `skip` which specifies the number of lines of header information at the top of the file. Equivalent arguments are used to read the quality control file (`qc.skip` and `qc.sep`). The name of the columns containing standard errors may also change between `BEAD_STDEV` and `BEAD_STDERR`.

The `columns` argument is used to decide which column headings to read from the file and where to store the data in the object created by the function (see later).

The following code shows how to read version 1 output by adjusting `sep` and `skip`. Version 3 output can be read by running `readBeadSummaryData` without having to specify any additional parameters.

```
> library(beadarray)
> dataFile = "raw_data.csv"
> sampleSheet = "raw_data_sample_sheet.csv"
> qcFile = "raw_data_qcinfo.csv"
> BSData = readBeadSummaryData(dataFile,
```

```

+   qcFile = qcFile, sampleSheet = sampleSheet,
+   skip = 7, columns = list(exprs = "AVG_Signal",
+     se.exprs = "BEAD_STDEV",
+     NoBeads = "Avg_NBEADS"),
+   qc.columns = list(exprs = "AVG.Signal",
+     se.exprs = "SeqVAR"),
+   qc.sep = ",", sep = ",",
+   qc.skip = 7)

```

4 The BSData object

BSData is an object of type ExpressionSetIllumina which is an extension of the ExpressionSet class developed by the Biocore team used as a container for high-throughput assays. Objects of this type use a series of slots to store data.

```
> BSData
```

```

ExpressionSetIllumina (storageMode: list)
assayData: 47293 features, 18 samples
  element names: exprs, se.exprs, NoBeads, Detection, Narrays, arrayStDev, DiffScore
phenoData
  rowNames: 1, 2, ..., 18 (18 total)
  varLabels and varMetadata description:
    Sample_Name: Sample_Name
    Sample_Well: Sample_Well
    ...: ...
    Sentrix_Position: Sentrix_
  Position
  (7 total)
featureData
  featureNames:
  fvarLabels and fvarMetadata description: none
experimentData: use 'experimentData(object)'
Annotation:
QC Information
  Available Slots:  exprs se.exprs Detection NoBeads controlType
  featureNames:  AVG.Signal.biotin, AVG.Signal.cy3_hyb_high, ..., AVG.Signal.low_stringency_hyb_pm, AVG
  sampleNames:  1475542110_F, 1475542113_E, ..., 1475542113_D, 1475542113_F

```

```
> slotNames(BSData)
```

```

[1] "QC"
[2] "assayData"
[3] "phenoData"
[4] "featureData"
[5] "experimentData"
[6] "annotation"
[7] ".__classVersion__"

```

```
> names(assayData(BSData))
```

```

[1] "exprs"      "se.exprs"
[3] "NoBeads"    "Detection"

```

```
[5] "Narrays"      "arrayStDev"  
[7] "DiffScore"
```

```
> dim(assayData(BSData)$exprs)
```

```
[1] 47293    18
```

```
> dim(assayData(BSData)$se.exprs)
```

```
[1] 47293    18
```

```
> dim(assayData(BSData)$Narrays)
```

```
[1] 0 0
```

```
> exprs(BSData)[1:10, 1:2]
```

	IH-1	IC-1
GI_10047089-S	87.8	131.8
GI_10047091-S	161.8	130.8
GI_10047093-S	481.2	401.4
GI_10047099-S	633.7	483.8
GI_10047103-S	1535.6	1186.5
GI_10047105-S	247.5	210.2
GI_10047121-S	113.0	101.3
GI_10047123-S	453.9	306.8
GI_10047133-A	103.6	114.5
GI_10047133-I	118.0	123.1

```
> se.exprs(BSData)[1:10,  
+ 1:2]
```

	IH-1	IC-1
GI_10047089-S	5.1	9.5
GI_10047091-S	12.0	7.9
GI_10047093-S	21.7	24.5
GI_10047099-S	21.6	20.9
GI_10047103-S	42.7	34.5
GI_10047105-S	12.7	11.8
GI_10047121-S	6.4	8.1
GI_10047123-S	14.0	13.1
GI_10047133-A	6.8	6.0
GI_10047133-I	5.6	7.2

```
> pData(BSData)[, c(4, 6)]
```

	Sample_Group	Sentrix_ID
1	IH-1	1475542114
2	IC-1	1475542114
3	IH-2	1475542114
4	MC-1	1475542114
5	MD-1	1475542114
6	MT-1	1475542114
7	IC-2	1475542110

```

8      IH-3 1475542110
9      IC-3 1475542110
10     P-3 1475542110
11     P-3 1475542110
12     Norm-1 1475542110
13     MC-2 1475542113
14     MD-2 1475542113
15     MT-2 1475542113
16     P-1 1475542113
17     Norm-2 1475542113
18     P-2 1475542113

```

```

> QCInfo(BSData)$exprs[1:5,
+   1:4]

```

```

                                     1475542110_F
AVG.Signal.biotin                    7551.0
AVG.Signal.cy3_hyb_high              32436.0
AVG.Signal.cy3_hyb_low               816.6
AVG.Signal.cy3_hyb_med              11178.2
AVG.Signal.gene                      205.8
                                     1475542113_E
AVG.Signal.biotin                    6137.2
AVG.Signal.cy3_hyb_high              28081.0
AVG.Signal.cy3_hyb_low               739.4
AVG.Signal.cy3_hyb_med              9158.1
AVG.Signal.gene                      176.6
                                     1475542114_A
AVG.Signal.biotin                    10255.0
AVG.Signal.cy3_hyb_high              41451.7
AVG.Signal.cy3_hyb_low               1040.9
AVG.Signal.cy3_hyb_med              13176.7
AVG.Signal.gene                      320.3
                                     1475542114_C
AVG.Signal.biotin                    9358.7
AVG.Signal.cy3_hyb_high              41116.9
AVG.Signal.cy3_hyb_low               1100.0
AVG.Signal.cy3_hyb_med              13109.2
AVG.Signal.gene                      395.2

```

The data from the the raw_data file has been written to the assayData slot of the object. This slot contains a number of matrices, each of which has a column for each array in the experiment and a row for each probe. There is a matrix for each column that can be exported from BeadStudio, although only the columns that we choose to read using the columns parameter in readBeadSummaryData will be filled.

For consistency with the definition of other *ExpressionSet* objects, we now refer to the expression values as the *exprs* matrix which can be accessed using *exprs* and subset in the usual manner. Similarly, the *se.exprs* matrix can be accessed using *se.exprs*. The rows of *exprs* are named according to the row names of the original raw_data file.

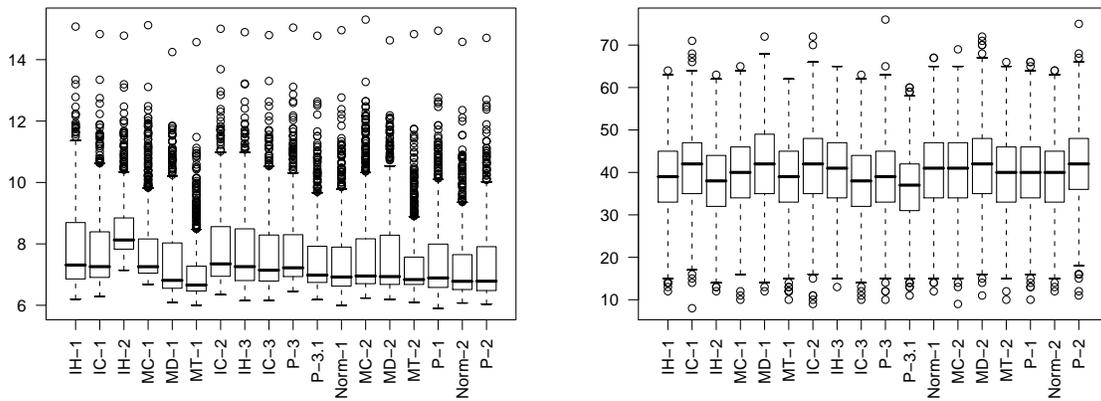
Phenotypic data for the experiment can be accessed using *pData* and the QC slot contains the quality control information.

Boxplots of expression may be useful for quality control. Below we show the code to produce boxplots of the log2 intensities of each array in the experiment. Recall that there are 6 arrays per BeadChip and

that differences between chip hybridised on different days may be seen. In this example the differences in intensity between arrays on the same chip and different chips do not seem too large. However, we can see that the first BeadChip seems to be more variable than the others and in particular the third array on the first BeadChip could be an outlier.

Boxplots of the other slots in BSData can be easily plotted.¹

```
> par(mfrow = c(1, 2))
> boxplot(log2(exprs(BSData)[1:1000,
+         ]), las = 2)
> boxplot(NoBeads(BSData)[1:1000,
+         ], las = 2)
```

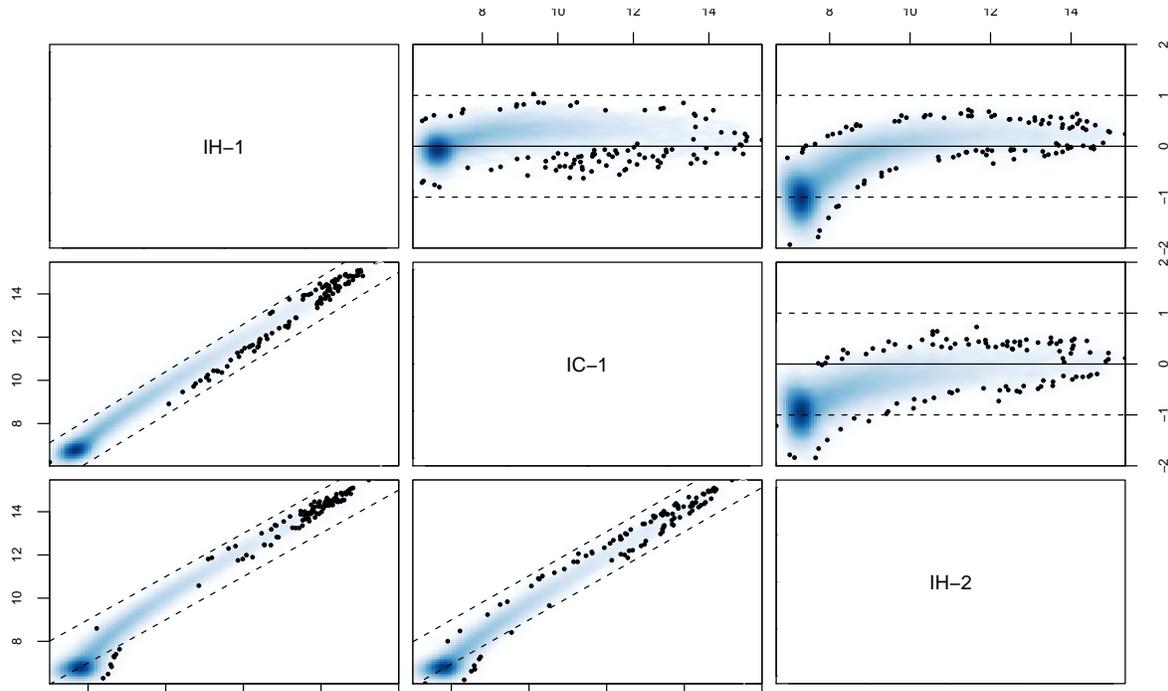


5 Normalisation and Quality Control

In the boxplots we notice that there are differences in expression level across a chip and between chips. Therefore we might want to normalise the arrays in the experiment comparable. We also see the the 3rd array has a higher intensity than the others. The sample on this array is replicated three times on the first chip, so comparing the MA and XY plots for the replicates of this sample can be informative.

```
> plotMAXY(exprs(BSData),
+         arrays = 1:3, labels = as.character(pData(BSData)[1:3,
+         4]), pch = 16)
```

¹We have restricted the number of points plotted in order to keep the size of this vignette small.



In the top right corner we see the MA plots for all pairwise comparisons involving the 3 arrays. On an MA plot, for each gene we plot the average of the expression levels on the two arrays on the x axis and the difference in the measurements on the y axis. For replicate arrays we would expect all genes to be unchanged between the two samples and hence most points on the plot to lie along the line $y=0$. In the lower left corner of the MAXY plot we see the XY plot and for replicate arrays we would expect to see most points along the diagonal $y = x$. From this MAXY plot it is obvious that the third array is different to the other replicates and normalisation is required.

Both XY and MA plots for a particular comparison of arrays are available separately using `plotXY` and `plotMA`

6 Using Quality Control Information

Quality control information from Illumina experiments can be exported from the BeadStudio application. This information can be read into beadarray using the `readBeadSummaryData` function or at a later time using `readQC`.

The quality control information which is read in by `readBeadSummaryData` can be plotted to provide useful diagnostic information. To retrieve this quality control data we can use the `QCInfo` function. Alternatively, quality control information can be read using `readQC`. QC is a list object and each item can be accessed using the `$` operator to give a matrix. The row names of the matrix indicates the control types. In the following example we plot the values of the Biotin control across all arrays.

```
> QC = QCInfo(BSData)
> QC$exprs[1:3, ]
```

	1475542110_F
AVG.Signal.biotin	7551.0
AVG.Signal.cy3_hyb_high	32436.0
AVG.Signal.cy3_hyb_low	816.6
	1475542113_E

AVG.Signal.biotin	6137.2
AVG.Signal.cy3_hyb_high	28081.0
AVG.Signal.cy3_hyb_low	739.4
1475542114_A	
AVG.Signal.biotin	10255.0
AVG.Signal.cy3_hyb_high	41451.7
AVG.Signal.cy3_hyb_low	1040.9
1475542114_C	
AVG.Signal.biotin	9358.7
AVG.Signal.cy3_hyb_high	41116.9
AVG.Signal.cy3_hyb_low	1100.0
1475542110_B	
AVG.Signal.biotin	9595.1
AVG.Signal.cy3_hyb_high	41957.6
AVG.Signal.cy3_hyb_low	1017.8
1475542114_B	
AVG.Signal.biotin	10818.4
AVG.Signal.cy3_hyb_high	44276.0
AVG.Signal.cy3_hyb_low	1039.5
1475542110_A	
AVG.Signal.biotin	11483.9
AVG.Signal.cy3_hyb_high	47204.4
AVG.Signal.cy3_hyb_low	1037.6
1475542110_C	
AVG.Signal.biotin	9977.0
AVG.Signal.cy3_hyb_high	45043.8
AVG.Signal.cy3_hyb_low	953.8
1475542114_D	
AVG.Signal.biotin	7727.4
AVG.Signal.cy3_hyb_high	34646.3
AVG.Signal.cy3_hyb_low	868.5
1475542113_A	
AVG.Signal.biotin	8822.6
AVG.Signal.cy3_hyb_high	36889.3
AVG.Signal.cy3_hyb_low	944.4
1475542114_E	
AVG.Signal.biotin	7835.9
AVG.Signal.cy3_hyb_high	33330.6
AVG.Signal.cy3_hyb_low	820.0
1475542113_B	
AVG.Signal.biotin	8588.6
AVG.Signal.cy3_hyb_high	40451.8
AVG.Signal.cy3_hyb_low	967.3
1475542114_F	
AVG.Signal.biotin	6559.4
AVG.Signal.cy3_hyb_high	27580.2
AVG.Signal.cy3_hyb_low	697.4
1475542113_C	
AVG.Signal.biotin	8527.5
AVG.Signal.cy3_hyb_high	39325.6
AVG.Signal.cy3_hyb_low	949.6

```

1475542110_D
AVG.Signal.biotin      7908.9
AVG.Signal.cy3_hyb_high 33515.9
AVG.Signal.cy3_hyb_low  901.8

1475542110_E
AVG.Signal.biotin      7134.3
AVG.Signal.cy3_hyb_high 31132.7
AVG.Signal.cy3_hyb_low  797.9

1475542113_D
AVG.Signal.biotin      6706.2
AVG.Signal.cy3_hyb_high 30452.9
AVG.Signal.cy3_hyb_low  828.7

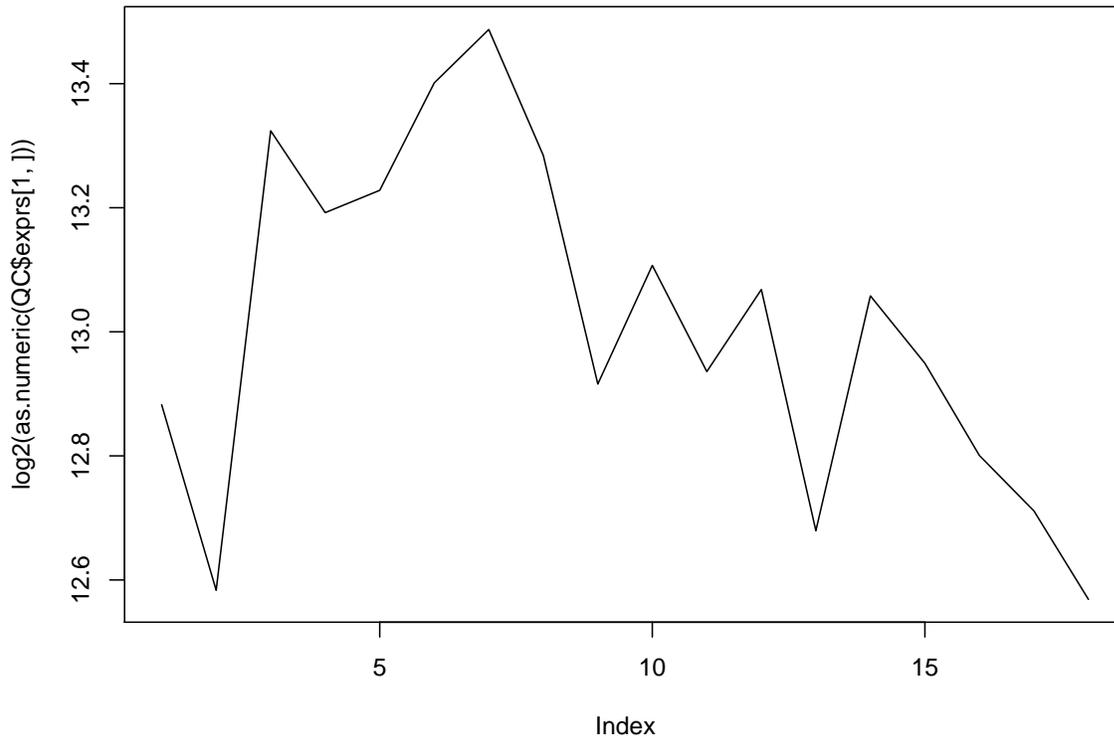
1475542113_F
AVG.Signal.biotin      6075.0
AVG.Signal.cy3_hyb_high 25584.2
AVG.Signal.cy3_hyb_low  730.8

```

```

> plot(log2(as.numeric(QC$exprs[1,
+           ])), type = "l")

```



It is possible to use the normalisation methods available in the *affy* or *lumi* packages.

```

> library(affy)
> library(lumi)

```

```

> BSData.quantile = normaliseIllumina(BSData,
+   method = "quantile",
+   transform = "log2")
> BSData.lumi = normaliseIllumina(BSData,
+   method = "quantile",
+   transform = "vst")

```

7 Differential Expression

Research into the best method for detecting differential expression for BeadArray data is still work in progress. In the meantime, users are able to use the `lmFit` and `eBayes` functions from `limma` on the matrix `exprs(BSData)` with a \log_2 transformation applied.

The following code shows how to set up a design matrix for the example experiment combining the I, MC, MD, MT, P and Normal samples together. We then define contrasts comparing the I samples to the P samples and I to Normal and perform an empirical bayes shrinkage. In this particular experiment, the I and P samples are completely different so we would expect to see plenty of differentially expressed genes.

For more information about `lmFit` and `eBayes` please see the comprehensive `limma` documentation.

```

> design = matrix(nrow = 18,
+   ncol = 6, 0)
> colnames(design) = c("I",
+   "MC", "MD", "MT", "P",
+   "Norm")
> design[which(strtrim(colnames(exprs(BSData))),
+   1) == "I", 1] = 1
> design[which(strtrim(colnames(exprs(BSData))),
+   2) == "MC", 2] = 1
> design[which(strtrim(colnames(exprs(BSData))),
+   2) == "MD", 3] = 1
> design[which(strtrim(colnames(exprs(BSData))),
+   2) == "MT", 4] = 1
> design[which(strtrim(colnames(exprs(BSData))),
+   1) == "P", 5] = 1
> design[which(strtrim(colnames(exprs(BSData))),
+   1) == "N", 6] = 1
> design

```

	I	MC	MD	MT	P	Norm
[1,]	1	0	0	0	0	0
[2,]	1	0	0	0	0	0
[3,]	1	0	0	0	0	0
[4,]	0	1	0	0	0	0
[5,]	0	0	1	0	0	0
[6,]	0	0	0	1	0	0
[7,]	1	0	0	0	0	0
[8,]	1	0	0	0	0	0
[9,]	1	0	0	0	0	0
[10,]	0	0	0	0	1	0
[11,]	0	0	0	0	1	0
[12,]	0	0	0	0	0	1
[13,]	0	1	0	0	0	0
[14,]	0	0	1	0	0	0

```
[15,] 0 0 0 1 0 0
[16,] 0 0 0 0 1 0
[17,] 0 0 0 0 0 1
[18,] 0 0 0 0 1 0
```

```
> ids = rownames(exprs(BSData))
> controlids = c("lysA",
+ "pheA", "thrB", "trpF")
> controlind = match(controlids,
+ ids)
> fit = lmFit(exprs(BSData.quantile)[-controlind,
+ ], design)
> cont.matrix = makeContrasts(IvsP = I -
+ P, IvsNorm = I - Norm,
+ PvsNorm = P - Norm,
+ levels = design)
> fit = contrasts.fit(fit,
+ cont.matrix)
> ebFit = eBayes(fit)
> topTable(ebFit, genelist = ids[-controlind])
```

	ProbeID
9260	GI_28302132-S
13743	GI_34304351-S
21840	GI_4501988-S
22143	GI_4503886-S
9259	GI_28302130-S
2128	GI_15149480-S
19978	GI_42542384-S
22144	GI_4503888-S
3117	GI_18375521-A
9257	GI_28302128-S
	IvsP
9260	7.05124284
13743	-6.41967544
21840	5.50531799
22143	5.12600762
9259	6.82821239
2128	-6.21848978
19978	5.20822549
22144	4.59044439
3117	-4.89612179
9257	0.07101028
	IvsNorm
9260	6.775686661
13743	-3.060012038
21840	5.134115849
22143	5.115005439
9259	6.576394085
2128	-6.293353109
19978	4.977646454
22144	4.530531990
3117	-0.001238405

```

9257 -6.325215556
      PvsNorm      F
9260 -0.27555618 6324.087
13743 3.35966341 5562.350
21840 -0.37120215 4661.143
22143 -0.01100219 4360.251
9259 -0.25181830 4338.271
2128 -0.07486333 3874.901
19978 -0.23057903 3754.780
22144 -0.05991240 3323.952
3117 4.89488338 3310.720
9257 -6.39622584 3062.805
      P.Value
9260 5.413714e-38
13743 3.266853e-37
21840 3.879873e-36
22143 9.871758e-36
9259 1.059516e-35
2128 5.145356e-35
19978 7.992802e-35
22144 4.393341e-34
3117 4.645256e-34
9257 1.378672e-33
      adj.P.Val
9260 2.560091e-33
13743 7.724312e-33
21840 6.115845e-32
22143 1.002069e-31
9259 1.002069e-31
2128 4.055312e-31
19978 5.399594e-31
22144 2.440772e-30
3117 2.440772e-30
9257 6.519604e-30

```

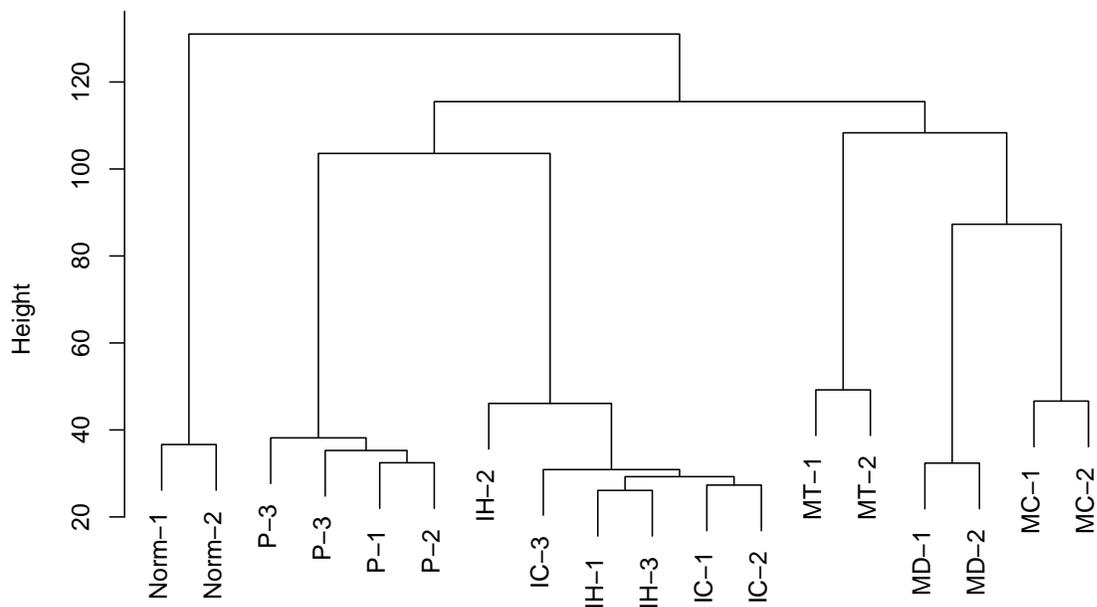
8 Further Analysis

The clustering functionality available in BeadStudio can be easily performed through R using the `h1cust` once a distance matrix has been defined. In this example we see that the clusters correspond well to the different sample types. The `heatmap` function could also be used in a similar manner and principal components analysis is possible using `princomp`.

```

> d = dist(t(exprs(BSData.quantile)))
> p1clust(h1cust(d), labels = pData(BSData)[,
+       4])

```



```

d
hclust (*, "complete")

```

So far, the results returned by the limma analysis are in terms of probes with Illumina IDs. This alone is not very useful for drawing biologically meaningful conclusions from the experiment. More useful information about each can be obtained using the `illuminaHumanv1` package. In the following code, we show how to obtain chromosomal information and gene names for every probe. The rows of the expression matrix are used as a key to extract the relevant information from the environment. Note that some probes on Illumina arrays will not have a matching gene name or RefSeq ID.

```

> library(illuminaHumanv1)
> illuminaHumanv1()

```

```

Quality control information for illuminaHumanv1
Date built: Created: Wed Apr 4 10:51:36 2007

```

```

Number of probes: 47297

```

```

Probe number mismatch: illuminaHumanv1ACCNUM; illuminaHumanv1CHRLOC; illuminaHumanv1CHR; illuminaHumanv1ENTREZID; illuminaHumanv1ENZYME; illuminaHumanv1GENENAME; illuminaHumanv1GO

```

```

Probe mismatch: None

```

```

Mappings found for probe based rda files:

```

```

illuminaHumanv1ACCNUM found 26092 of 47297
illuminaHumanv1CHRLOC found 18648 of 47297
illuminaHumanv1CHR found 19255 of 47297
illuminaHumanv1ENTREZID found 19258 of 47297
illuminaHumanv1ENZYME found 2147 of 47297
illuminaHumanv1GENENAME found 18182 of 47297
illuminaHumanv1GO found 16772 of 47297

```

```

illuminaHumanv1MAP found 19160 of 47297
illuminaHumanv1OMIM found 12692 of 47297
illuminaHumanv1PATH found 4630 of 47297
illuminaHumanv1PMID found 19001 of 47297
illuminaHumanv1REFSEQ found 19258 of 47297
illuminaHumanv1SUMFUNC found 0 of 47297
illuminaHumanv1SYMBOL found 19258 of 47297
illuminaHumanv1UNIGENE found 19023 of 47297

```

Mappings found for non-probe based rda files:

```

illuminaHumanv1CHRLNGTHS found 25
illuminaHumanv1ENZYME2PROBE found 785
illuminaHumanv1GO2ALLPROBES found 8265
illuminaHumanv1GO2PROBE found 6093
illuminaHumanv1ORGANISM found 1
illuminaHumanv1PATH2PROBE found 192
illuminaHumanv1PFAM found 15279
illuminaHumanv1PMID2PROBE found 139948
illuminaHumanv1PROSITE found 10793

```

```

> ids = rownames(exprs(BSData))
> chr = mget(ids, illuminaHumanv1CHR,
+   ifnotfound = NA)
> chrloc = mget(ids, illuminaHumanv1CHRLOC,
+   ifnotfound = NA)
> refseq = mget(ids, illuminaHumanv1REFSEQ,
+   ifnotfound = NA)
> genename = mget(ids, illuminaHumanv1GENENAME,
+   ifnotfound = NA)
> anno = cbind(Ill_ID = as.character(ids),
+   Chr = as.character(chr),
+   Loc = as.character(chrloc),
+   RefSeq = as.character(refseq),
+   Name = as.character(genename))
> ebFit$genes = anno
> topTable(ebFit)

```

	Ill_ID	Chr	Loc
	9260	GI_28302132-S	11
	13743	GI_34304351-S	X
	21840	GI_4501988-S	4
	22143	GI_4503886-S	X
	9259	GI_28302130-S	11
	2128	GI_15149480-S	2
	19978	GI_42542384-S	12
	22144	GI_4503888-S	X
	3117	GI_18375521-A	1
	9257	GI_28302128-S	11
			Loc
	9260		-5230996
	13743		152413604
	21840		74520796
	22143	c(49221981, 49212423)	
	9259		-5226077

2128	189547343
19978	-54634156
22144	49103620
3117	-103114611
9257	-5203271

	RefSeq
9260	c("NM_000184", "NP_000175")
13743	c("NM_001711", "NP_001702")
21840	c("NM_001134", "NP_001125")
22143	c("NM_001476", "NP_001467")
9259	c("NM_000559", "NP_000550")
2128	c("NM_000090", "NP_000081")
19978	c("NM_006928", "NP_008859")
22144	c("NM_001477", "NP_001468")
3117	c("NM_001854", "NP_001845", "NM_080629", "NP_542196", "NM_080630", "NP_542197")
9257	c("NM_000518", "NP_000509")

	Name
9260	hemoglobin, gamma G
13743	biglycan
21840	alpha-fetoprotein
22143	G antigen 6
9259	hemoglobin, gamma A
2128	collagen, type III, alpha 1 (Ehlers-Danlos syndrome type IV, autosomal dominant)
19978	silver homolog (mouse)
22144	G antigen 7B
3117	collagen, type XI, alpha 1
9257	hemoglobin, beta

	IvsP
9260	7.05124284
13743	-6.41967544
21840	5.50531799
22143	5.12600762
9259	6.82821239
2128	-6.21848978
19978	5.20822549
22144	4.59044439
3117	-4.89612179
9257	0.07101028

	IvsNorm
9260	6.775686661
13743	-3.060012038
21840	5.134115849
22143	5.115005439
9259	6.576394085
2128	-6.293353109
19978	4.977646454
22144	4.530531990
3117	-0.001238405
9257	-6.325215556

	PvsNorm	F
9260	-0.27555618	6324.087

```
13743 3.35966341 5562.350
21840 -0.37120215 4661.143
22143 -0.01100219 4360.251
9259 -0.25181830 4338.271
2128 -0.07486333 3874.901
19978 -0.23057903 3754.780
22144 -0.05991240 3323.952
3117 4.89488338 3310.720
9257 -6.39622584 3062.805
```

P.Value

```
9260 5.413714e-38
13743 3.266853e-37
21840 3.879873e-36
22143 9.871758e-36
9259 1.059516e-35
2128 5.145356e-35
19978 7.992802e-35
22144 4.393341e-34
3117 4.645256e-34
9257 1.378672e-33
```

adj.P.Val

```
9260 2.560091e-33
13743 7.724312e-33
21840 6.115845e-32
22143 1.002069e-31
9259 1.002069e-31
2128 4.055312e-31
19978 5.399594e-31
22144 2.440772e-30
3117 2.440772e-30
9257 6.519604e-30
```

This vignette was built using the following packages:

```
> sessionInfo()
```

```
R version 2.6.0 Under development (unstable) (2007-08-12 r42483)
x86_64-unknown-linux-gnu
```

locale:

```
LC_CTYPE=en_GB.UTF-8;LC_NUMERIC=C;LC_TIME=en_GB.UTF-8;LC_COLLATE=en_GB.UTF-8;LC_MONETARY=en_GB.UTF-8;L
```

attached base packages:

```
[1] tools      stats
[3] graphics  grDevices
[5] utils      datasets
[7] methods   base
```

other attached packages:

```
[1] illuminaHumanv1_1.2.0
[2] lumi_1.3.34
[3] mgcv_1.3-22
```

```
[4] beadarray_1.5.14
[5] affy_1.15.7
[6] preprocessCore_0.99.12
[7] affyio_1.3.2
[8] geneplotter_1.15.6
[9] lattice_0.14-16
[10] annotate_1.13.4
[11] Biobase_1.15.26
[12] limma_2.11.9
```

loaded via a namespace (and not attached):

```
[1] grid_2.6.0
[2] KernSmooth_2.22-19
[3] RColorBrewer_0.2-3
```

Acknowledgements

We are grateful to Inma Spiteri for providing the BeadChip data set distributed with the `beadarray` package. We also thank Julie Addison, Tom Hardcastle, John Marioni, Inma Spiteri and Anna Git for their helpful feedback on the exercises in this tutorial.