

**limma:**  
Linear Models for Microarray Data  
User's Guide  
(Now Including RNA-Seq Data Analysis)

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<p>This free open-source software implements academic research by the authors and co-workers. If you use it, please support the project by citing the appropriate journal articles listed in Section 2.1.</p>
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# Contents

<b>1</b>	<b>Introduction</b>	<b>5</b>
<b>2</b>	<b>Preliminaries</b>	<b>7</b>
2.1	Citing limma . . . . .	7
2.2	Installation . . . . .	9
2.3	How to get help . . . . .	9
<b>3</b>	<b>Quick Start</b>	<b>11</b>
3.1	A brief introduction to R . . . . .	11
3.2	Sample limma Session . . . . .	12
3.3	Data Objects . . . . .	13
<b>4</b>	<b>Reading Microarray Data</b>	<b>15</b>
4.1	Scope of this Chapter . . . . .	15
4.2	Recommended Files . . . . .	15
4.3	The Targets Frame . . . . .	15
4.4	Reading Two-Color Intensity Data . . . . .	17
4.5	Reading Single-Channel Agilent Intensity Data . . . . .	19
4.6	Reading Illumina BeadChip Data . . . . .	20
4.7	Image-derived Spot Quality Weights . . . . .	21
4.8	Reading Probe Annotation . . . . .	22
4.9	Printer Layout . . . . .	22
4.10	The Spot Types File . . . . .	23
<b>5</b>	<b>Quality Assessment</b>	<b>25</b>
<b>6</b>	<b>Pre-Processing Two-Color Data</b>	<b>27</b>
6.1	Background Correction . . . . .	27
6.2	Within-Array Normalization . . . . .	29
6.3	Between-Array Normalization . . . . .	31
6.4	Using Objects from the marray Package . . . . .	34
<b>7</b>	<b>Filtering</b>	<b>35</b>

<b>8</b>	<b>Linear Models Overview</b>	<b>36</b>
8.1	Introduction . . . . .	36
8.2	Single-Channel Designs . . . . .	37
8.3	Common Reference Designs . . . . .	38
8.4	Direct Two-Color Designs . . . . .	39
<b>9</b>	<b>Single-Channel Experimental Designs</b>	<b>41</b>
9.1	Introduction . . . . .	41
9.2	Two Groups . . . . .	41
9.3	Several Groups . . . . .	43
9.4	Additive Models and Blocking . . . . .	44
	9.4.1 Paired Samples . . . . .	44
	9.4.2 Blocking . . . . .	44
9.5	Interaction Models: $2 \times 2$ Factorial Designs . . . . .	44
	9.5.1 Questions of Interest . . . . .	44
	9.5.2 Analysing as for a Single Factor . . . . .	45
	9.5.3 A Nested Interaction Formula . . . . .	46
	9.5.4 Classic Interaction Models . . . . .	47
9.6	Time Course Experiments . . . . .	48
	9.6.1 Replicated time points . . . . .	48
	9.6.2 Many time points . . . . .	50
9.7	Multi-level Experiments . . . . .	51
<b>10</b>	<b>Two-Color Experiments with a Common Reference</b>	<b>53</b>
10.1	Introduction . . . . .	53
10.2	Two Groups . . . . .	53
10.3	Several Groups . . . . .	55
<b>11</b>	<b>Direct Two-Color Experimental Designs</b>	<b>57</b>
11.1	Introduction . . . . .	57
11.2	Simple Comparisons . . . . .	57
	11.2.1 Replicate Arrays . . . . .	57
	11.2.2 Dye Swaps . . . . .	58
11.3	A Correlation Approach to Technical Replication . . . . .	59
<b>12</b>	<b>Separate Channel Analysis of Two-Color Data</b>	<b>61</b>
<b>13</b>	<b>Statistics for Differential Expression</b>	<b>63</b>
13.1	Summary Top-Tables . . . . .	63
13.2	Fitted Model Objects . . . . .	64
13.3	Multiple Testing Across Contrasts . . . . .	65

<b>14 Array Quality Weights</b>	<b>67</b>
14.1 Introduction . . . . .	67
14.2 Example 1 . . . . .	67
14.3 Example 2 . . . . .	69
14.4 When to Use Array Weights . . . . .	71
<b>15 RNA-seq Data</b>	<b>72</b>
15.1 Introduction . . . . .	72
15.2 Making a count matrix . . . . .	72
15.3 Differential expression . . . . .	72
15.4 Differential splicing . . . . .	73
<b>16 Two-Color Case Studies</b>	<b>75</b>
16.1 Swirl Zebrafish: A Single-Group Experiment . . . . .	75
16.2 Apo1 Knockout Mice: A Two-Group Common-Reference Experiment . . . . .	86
16.3 Weaver Mutant Mice: A Composite 2x2 Factorial Experiment . . . . .	89
16.3.1 Background . . . . .	89
16.3.2 Sample Preparation and Hybridizations . . . . .	90
16.3.3 Data input . . . . .	90
16.3.4 Annotation . . . . .	91
16.3.5 Quality Assessment and Normalization . . . . .	92
16.3.6 Setting Up the Linear Model . . . . .	94
16.3.7 Probe Filtering and Array Quality Weights . . . . .	95
16.3.8 Differential expression . . . . .	95
16.4 Bob1 Mutant Mice: Arrays With Duplicate Spots . . . . .	96
<b>17 Single-Channel Case Studies</b>	<b>101</b>
17.1 Lrp Mutant Ecoli: Two Group Experiment with Affymetrix Arrays . . . . .	101
17.2 Effect of Estrogen on Breast Cancer Tumor Cells: A 2x2 Factorial Experiment with Affymetrix Arrays . . . . .	104
17.3 Comparing Mammary Progenitor Cell Populations with Illumina BeadChips . . . . .	108
17.3.1 Introduction . . . . .	108
17.3.2 The target RNA samples . . . . .	109
17.3.3 The expression profiles . . . . .	110
17.3.4 How many probes are truly expressed? . . . . .	111
17.3.5 Normalization and filtering . . . . .	111
17.3.6 Within-patient correlations . . . . .	112
17.3.7 Differential expression between cell types . . . . .	113
17.3.8 Signature genes for luminal progenitor cells . . . . .	113
17.4 Time Course Effects of Corn Oil on Rat Thymus with Agilent 4x44K Arrays . . . . .	114

<b>18 RNA-Seq Case Studies</b>	<b>118</b>
18.1 Profiles of Unrelated Nigerian Individuals . . . . .	118
18.1.1 Background . . . . .	118
18.1.2 Loading the data . . . . .	118
18.1.3 DGEList object . . . . .	119
18.1.4 Filtering . . . . .	119
18.1.5 Scale normalization . . . . .	120
18.1.6 Linear modeling . . . . .	120
18.1.7 Gene set testing . . . . .	122
18.2 Differential Splicing after Pasilla Knockdown . . . . .	125
18.2.1 Background . . . . .	125
18.2.2 GEO samples and SRA Files . . . . .	125
18.2.3 Mapping reads to the reference genome . . . . .	126
18.2.4 Read counts for exons . . . . .	127
18.2.5 Assemble DGEList and sum counts for technical replicates . . . . .	127
18.2.6 Gene annotation . . . . .	128
18.2.7 Filtering . . . . .	129
18.2.8 Scale normalization . . . . .	129
18.2.9 Linear modelling . . . . .	130
18.2.10 Alternate splicing . . . . .	132
18.2.11 Session information . . . . .	136
18.2.12 Acknowledgements . . . . .	137

# Chapter 1

## Introduction

Limma is a package for the analysis of gene expression data arising from microarray or RNA-Seq technologies. A core capability is the use of linear models to assess differential expression in the context of multifactor designed experiments. Limma provides the ability to analyze comparisons between many RNA targets simultaneously. It has features that make the analyses stable even for experiments with small number of arrays—this is achieved by borrowing information across genes. It is specially designed for analysing complex experiments with a variety of experimental conditions and predictors. The linear model and differential expression functions are applicable to data from any microarray platform, including single-channel or two-color microarray platforms. The methods are also applicable to expression data from non-microarray platforms, such as quantitative PCR or RNA-Seq, provided that a suitable matrix of expression values can be provided.

This guide gives a tutorial-style introduction to the main limma features but does not describe every feature of the package. A full description of the package is given by the individual function help documents available from the R online help system. To access the online help, type `help(package=limma)` at the R prompt or else start the html help system using `help.start()` or the Windows drop-down help menu.

Limma provides a strong suite of functions for reading, exploring and pre-processing data from two-color microarrays. The Bioconductor package `marray` provides alternative functions for reading and normalizing spotted two-color microarray data. The `marray` package provides flexible location and scale normalization routines for log-ratios from two-color arrays. The limma package overlaps with `marray` in functionality but is based on a more general concept of within-array and between-array normalization as separate steps. If you are using limma in conjunction with `marray`, see Section 6.4.

Limma can read output data from a variety of image analysis software platforms, including GenePix, ImaGene etc. Either one-channel or two-channel formats can be processed.

The Bioconductor package `affy` provides functions for reading and normalizing Affymetrix microarray data. Advice on how to use limma with the `affy` package is given throughout the User's Guide, see for example Section 8.2 and the *E. coli* and estrogen case studies.

Functions for reading and pre-processing expression data from Illumina BeadChips were introduced in limma 3.0.0. See the case study in Section 17.3 for an example of these. Limma

can also be used in conjunction with the **vst** or **beadarray** packages for pre-processing Illumina data.

From version 3.9.19, **limma** includes functions to analyse RNA-Seq experiments, demonstrated in Case Study 11.8. The approach is to convert a table of sequence read counts into an expression object which can then be analysed as for microarray data.

This guide describes **limma** as a command-driven package. Graphical user interfaces to the most commonly used functions in **limma** are available through the packages **limmaGUI** [47], for two-color data, or **affyImGUI** [46], for Affymetrix data. Both packages are available from Bioconductor.

This user's guide should be correct for R Versions 2.8.0 through 3.1.0 and **limma** versions 2.16.0 through 3.20.0. The **limma** homepage is <http://bioinf.wehi.edu.au/limma>.

# Chapter 2

## Preliminaries

### 2.1 Citing limma

Limma is an implementation of a body of methodological research by the authors and co-workers. Please try to cite the appropriate methodological papers when you use results from the `limma` software in a publication, as such citations are the main means by which the authors receive professional credit for their work.

If you use `limma` for differential expression analysis, please cite:

Smyth, G. K. (2004). Linear models and empirical Bayes methods for assessing differential expression in microarray experiments. *Statistical Applications in Genetics and Molecular Biology*, Vol. 3, No. 1, Article 3.  
<http://www.bepress.com/sagmb/vol3/iss1/art3>

The above article describes the linear modeling approach implemented by `lmFit` and the empirical Bayes statistics implemented by `eBayes`, `topTable` etc.

If you use `limma` with duplicate spots or technical replication, please cite

Smyth, G. K., Michaud, J., and Scott, H. (2005). The use of within-array replicate spots for assessing differential expression in microarray experiments. *Bioinformatics* **21**(9), 2067–2075.  
<http://bioinformatics.oxfordjournals.org/content/21/9/2067>

The above article describes the theory behind the `duplicateCorrelation` function.

If you use `limma` for normalization of two-color microarray data, please cite:

Smyth, G. K., and Speed, T. P. (2003). Normalization of cDNA microarray data. *Methods* **31**, 265–273.

The above article describes the functions `read.maimages`, `normalizeWithinArrays`, `normalizeBetweenArrays` etc, including the use of spot quality weights.

If you use the `backgroundCorrect` function, please cite:



Ritchie, M. E., Silver, J., Oshlack, A., Silver, J., Holmes, M., Diyagama, D., Holloway, A., and Smyth, G. K. (2007). A comparison of background correction methods for two-colour microarrays. *Bioinformatics* 23, 2700–2707.  
<http://bioinformatics.oxfordjournals.org/content/23/20/2700>

This paper in particular describes the *normexp* background correction method.

If you use *limma* to estimate array quality weights, please cite:

Ritchie, M. E., Diyagama, D., Neilson, van Laar, R., J., Dobrovic, A., Holloway, A., and Smyth, G. K. (2006). Empirical array quality weights in the analysis of microarray data. *BMC Bioinformatics* 7, 261.  
<http://www.biomedcentral.com/1471-2105/7/261>

The above article describes the functions `arrayWeights`, `arrayWeightsSimple` etc.

If you use *limma* to pre-process Illumina BeadChip data, please cite:

Shi, W, Oshlack, A, and Smyth, GK (2010). Optimizing the noise versus bias trade-off for Illumina Whole Genome Expression BeadChips. *Nucleic Acids Research* 38, e204.  
<http://nar.oxfordjournals.org/content/38/22/e204>

This article describes the `read.ilmn`, `nec` and `neqc` functions.

If you use the separate channel analysis (`lmscFit`), please cite:

Smyth, GK, and Altman, NS (2013). Separate-channel analysis of two-channel microarrays: recovering inter-spot information. *BMC Bioinformatics* 14, 165.  
<http://www.biomedcentral.com/1471-2105/14/165>

If you use *limma* for RNA-seq analysis (`voom`), please cite:

Law, CW, Chen, Y, Shi, W, Smyth, GK (2014). Voom: precision weights unlock linear model analysis tools for RNA-seq read counts. *Genome Biology* 5, R29.  
<http://genomebiology.com/2014/15/2/R29>

The *limma* software itself can be cited as:

Smyth, G. K. (2005). *Limma: linear models for microarray data*. In: *Bioinformatics and Computational Biology Solutions using R and Bioconductor*, R. Gentleman, V. Carey, S. Dudoit, R. Irizarry, W. Huber (eds.), Springer, New York, pages 397–420.

The above article describes the software package in the context of the Bioconductor project and surveys the range of experimental designs for which the package can be used, including spot-specific dye-effects. The pre-processing capabilities of the package are also described but more briefly, with examples of background correction, spot quality weights and filtering with control spots.

Finally, if you are using one of the menu-driven interfaces to the software, please cite the appropriate one of

Wettenhall, J. M., and Smyth, G. K. (2004). limmaGUI: a graphical user interface for linear modeling of microarray data. *Bioinformatics*, **20**, 3705–3706.

Wettenhall, J. M., Simpson, K. M., Satterley, K., and Smyth, G. K. (2006). affyImGUI: a graphical user interface for linear modeling of single channel microarray data. *Bioinformatics* **22**, 897–899.

## 2.2 Installation

Limma is a package for the R computing environment and it is assumed that you have already installed R. See the R project at <http://www.r-project.org>. To install the latest version of limma, you will need to be using the latest version of R.

Limma is part of the Bioconductor project at <http://www.bioconductor.org>. (Prior to R 2.6.0, limma was also available from the R project CRAN site.) It is one of a default set of packages installed by biocLite. You can install a set of core Bioconductor packages by

```
> source("http://www.bioconductor.org/biocLite.R")
> biocLite()
```

To get just limma alone (much quicker) you can use

```
> biocLite("limma")
```

This will allow you do to perform many basic analyses, although you'll probably want

```
> biocLite("statmod")
```

as well.

Bioconductor works on a 6-monthly official release cycle, lagging each major R release by a short time. As with other Bioconductor packages, there are always two versions of limma. Most users will use the current official release version, which will be installed by biocLite if you are using the current version of R. There is also a developmental version of limma that includes new features due for the next official release. The developmental version will be installed if you are using the developmental version of R. The official release version always has an even second number (for example 3.6.5), whereas the developmental version has an odd second number (for example 3.7.7).

Limma is updated frequently. Once you have installed limma, the change-log can also be viewed from the R prompt. To see the most recent 20 lines type:

```
> changeLog(n=20)
```

## 2.3 How to get help

Most questions about limma will hopefully be answered by the documentation or references. If you've run into a question which isn't addressed by the documentation, or you've found

a conflict between the documentation and software itself, then there is an active support community which can offer help.

The authors of the package always appreciate receiving reports of bugs in the package functions or in the documentation. The same goes for well-considered suggestions for improvements.

Any other questions or problems concerning `limma` should be sent to the Bioconductor mailing list `bioconductor@stat.math.ethz.ch`. To subscribe to the mailing list, see <https://stat.ethz.ch/mailman/listinfo/bioconductor>. Please send requests for general assistance and advice to the mailing list rather than to the individual authors. Users posting to the mailing list for the first time should read the helpful posting guide at <http://www.bioconductor.org/doc/postingGuide.html>. Note that each function in `limma` has its own online help page, as described in the next section. Mailing list etiquette requires that you read the relevant help page carefully before posting a problem to the list.

# Chapter 3

## Quick Start

### 3.1 A brief introduction to R

R is a program for statistical computing. It is a command-driven language meaning that you have to type commands into it rather than pointing and clicking using a mouse. In this guide it will be assumed that you have successfully downloaded and installed R from <http://www.r-project.org>. A good way to get started is to type

```
> help.start()
```

at the R prompt or, if you're using R for Windows, to follow the drop-down menu items **Help**  $\succ$  **Html help**. Following the links **Packages**  $\succ$  **limma** from the html help page will lead you to the contents page of help topics for functions in **limma**.

Before you can use any **limma** commands you have to load the package by typing

```
> library(limma)
```

at the R prompt. You can get help on any function in any loaded package by typing `?` and the function name at the R prompt, for example

```
> ?read.maimages
```

or equivalently

```
> help("read.maimages")
```

for detailed help on the `read.maimages` function. The individual function help pages are especially important for listing all the arguments which a function will accept and what values the arguments can take.

A key to understanding R is to appreciate that anything that you create in R is an “object”. Objects might include data sets, variables, functions, anything at all. For example

```
> x <- 2
```

will create a variable `x` and will assign it the value 2. At any stage of your R session you can type

```
> objects()
```

to get a list of all the objects you have created. You can see the contents of any object by typing the name of the object at the prompt, for example either of the following commands will print out the contents of `x`:

```
> show(x)
> x
```

We hope that you can use `limma` without having to spend a lot of time learning about the R language itself but a little knowledge in this direction will be very helpful, especially when you want to do something not explicitly provided for in `limma` or in the other Bioconductor packages. For more details about the R language see *An Introduction to R* which is available from the online help. For more background on using R for statistical analyses see [6].

## 3.2 Sample `limma` Session

This is a quick overview of what an analysis might look like. The first example assumes four replicate two-color arrays, the second and fourth of which are dye-swapped. We assume that the images have been analyzed using GenePix to produce a `.gpr` file for each array and that a targets file `targets.txt` has been prepared with a column containing the names of the `.gpr` files.

```
> library(limma)
> targets <- readTargets("targets.txt")
```

Set up a filter so that any spot with a flag of  $-99$  or less gets zero weight.

```
> f <- function(x) as.numeric(x$Flags > -99)
```

Read in the data.

```
> RG <- read.maimages(targets, source="genepix", wt.fun=f)
```

The following command implements a type of adaptive background correction. This is optional but recommended for GenePix data.

```
> RG <- backgroundCorrect(RG, method="normexp", offset=50)
```

Print-tip loess normalization:

```
> MA <- normalizeWithinArrays(RG)
```

Estimate the fold changes and standard errors by fitting a linear model for each gene. The design matrix indicates which arrays are dye-swaps.

```
> fit <- lmFit(MA, design=c(-1,1,-1,1))
```

Apply empirical Bayes smoothing to the standard errors.

```
> fit <- eBayes(fit)
```

Show statistics for the top 10 genes.

```
> topTable(fit)
```

The second example assumes Affymetrix arrays hybridized with either wild-type (wt) or mutant (mu) RNA. There should be three or more arrays in total to ensure some replication. The targets file is now assumed to have another column **Genotype** indicating which RNA source was hybridized on each array.

```
> library(gcrma)
> library(limma)
> targets <- readTargets("targets.txt")
```

Read and pre-process the Affymetrix CEL file data.

```
> ab <- ReadAffy(filename=targets$FileName)
> eset <- gcrma(ab)
```

Form an appropriate design matrix for the two RNA sources and fit linear models. The design matrix has two columns. The first represents log-expression in the wild-type and the second represents the log-ratio between the mutant and wild-type samples. See Section 9.2 for more details on the design matrix.

```
> design <- cbind(WT=1, MUvsWT=targets$Genotype=="mu")
> fit <- lmFit(eset, design)
> fit <- eBayes(fit)
> topTable(fit, coef="MUvsWT")
```

This code fits the linear model, smooths the standard errors and displays the top 10 genes for the mutant versus wild-type comparison.

### 3.3 Data Objects

There are six main types of data objects created and used in **limma**:

**EListRaw**. Raw Expression list. A class used to store single-channel raw intensities prior to normalization. Intensities are unlogged. Objects of this class contain one row for each probe and one column for each array. The function `read.ilmn()` for example creates an object of this class.

**EList**. Expression list. Contains background corrected and normalized log-intensities. Usually created from an **EListRaw** object using `normalizeBetweenArrays()` or `neqc()`.

**RGList**. Red-Green list. A class used to store raw two-color intensities as they are read in from an image analysis output file, usually by `read.maimages()`.

**MAList.** Two-color intensities converted to M-values and A-values, i.e., to within-spot and whole-spot contrasts on the log-scale. Usually created from an **RGList** using **MA.RG()** or **normalizeWithinArrays()**. Objects of this class contain one row for each spot. There may be more than one spot and therefore more than one row for each probe.

**MArrayLM.** MicroArray Linear Model. Store the result of fitting gene-wise linear models to the normalized intensities or log-ratios. Usually created by **lmFit()**. Objects of this class normally contain one row for each unique probe.

**TestResults.** Store the results of testing a set of contrasts equal to zero for each probe. Usually created by **decideTests()**. Objects of this class normally contain one row for each unique probe.

All these objects can be treated like any list in R. For example, **MA\$M** extracts the matrix of M-values if **MA** is an **MAList** object, or **fit\$coef** extracts the coefficient estimates if **fit** is an **MArrayLM** object. **names(MA)** shows what components are contained in the object. For those who are familiar with matrices in R, all these objects are also designed to obey many analogies with matrices. In the case of **RGList** and **MAList**, rows correspond to spots and columns to arrays. In the case of **MarrayLM**, rows correspond to unique probes and columns to parameters or contrasts. The functions **summary**, **dim**, **length**, **ncol**, **nrow**, **dimnames**, **rownames**, **colnames** have methods for these classes. For example

```
> dim(RG)
[1] 11088 4
```

shows that the **RGList** object **RG** contains data for 11088 spots and 4 arrays.

```
> colnames(RG)
```

will give the names of the filenames or arrays in the object, while if **fit** is an **MArrayLM** object then

```
> colnames(fit)
```

would give the names of the coefficients in the linear model fit.

Objects of any of these classes may be subsetted, so that **RG[,j]** means the data for array **j** and **RG[i,]** means the data for probes indicated by the index **i**. Multiple data objects may be combined using **cbind**, **rbind** or **merge**. Hence

```
> RG1 <- read.maimages(files[1:2], source="genepix")
> RG2 <- read.maimages(files[3:5], source="genepix")
> RG <- cbind(RG1, RG2)
```

is equivalent to

```
> RG <- read.maimages(files[1:5], source="genepix")
```

Alternatively, if control status has been set in the **MAList** object then

```
> i <- MA$genes$Status=="Gene"
> MA[i,]
```

might be used to eliminate control spots from the data object prior to fitting a linear model.

# Chapter 4

## Reading Microarray Data

### 4.1 Scope of this Chapter

This chapter covers most microarray types other than Affymetrix. To read data from Affymetrix GeneChips, please use the `affy`, `gcrma` or `aroma.affymetrix` packages to read and normalize the data.

### 4.2 Recommended Files

We assume that an experiment has been conducted with one or more microarrays, all printed with the same library of probes. Each array has been scanned to produce a TIFF image. The TIFF images have then been processed using an image analysis program such as ArrayVision, ImaGene, GenePix, QuantArray or SPOT to acquire the red and green foreground and background intensities for each spot. The spot intensities have then been exported from the image analysis program into a series of text files. There should be one file for each array or, in the case of Imogene, two files for each array.

You will need to have the image analysis output files. In most cases these files will include the IDs and names of the probes and possibly other annotation information. A few image analysis programs, for example SPOT, do not write the probe IDs into the output files. In this case you will also need a *genelist file* which describes the probes. In most cases it is also desirable to have a *targets file* which describes which RNA sample was hybridized to each channel of each array. A further optional file is the *spot types file* which identifies special probes such as control spots.

### 4.3 The Targets Frame

The first step in preparing data for input into `limma` is usually to create a targets file which lists the RNA target hybridized to each channel of each array. It is normally in tab-delimited text format and should contain a row for each microarray in the experiment. The file can



have any name but the default is `Targets.txt`. If it has the default name, it can be read into the R session using

```
> targets <- readTargets()
```

Once read into R, it becomes the *targets frame*.

The targets frame normally contains a `FileName` column, giving the name of the image-analysis output file, a `Cy3` column giving the RNA type labelled with Cy3 dye for that slide and a `Cy5` column giving the RNA type labelled with Cy5 dye for that slide. Other columns are optional. The targets file can be prepared using any text editor but spreadsheet programs such as Microsoft Excel are convenient. The targets file for the Swirl case study includes optional `SlideNumber` and `Date` columns:

	A	B	C	D	E	F
1	SlideNumber	FileName	Cy3	Cy5	Date	
2	81	swirl.1.spot	swirl	wild type	20/09/2001	
3	82	swirl.2.spot	wild type	swirl	20/09/2001	
4	93	swirl.3.spot	swirl	wild type	8/11/2001	
5	94	swirl.4.spot	wild type	swirl	8/11/2001	
6						

It is often convenient to create short readable labels to associate with each array for use in output and in plots, especially if the file names are long or non-intuitive. A column containing these labels can be included in the targets file, for example the `Name` column used for the ApoA1 case study:

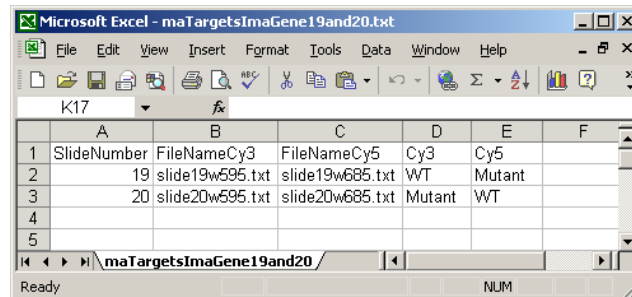
	A	B	C	D	E	F	G
1	SlideNumber	Name	FileName	Cy3	Cy5		
2	1	c1	c1.spot	Ref	wild type		
3	2	c2	c2.spot	Ref	wild type		
4	3	c3	c3.spot	Ref	wild type		
5	4	c4	c4.spot	Ref	wild type		
6	5	c5	c5.spot	Ref	wild type		
7	6	c6	c6.spot	Ref	wild type		
8	7	c7	c7.spot	Ref	wild type		
9	8	c8	c8.spot	Ref	wild type		
10	9	k1	k1.spot	Ref	ApoA1 KO		
11	10	k2	k2.spot	Ref	ApoA1 KO		
12	11	k3	k3.spot	Ref	ApoA1 KO		
13	12	k4	k4.spot	Ref	ApoA1 KO		
14	13	k5	k5.spot	Ref	ApoA1 KO		
15	14	k6	k6.spot	Ref	ApoA1 KO		
16	15	k7	k7.spot	Ref	ApoA1 KO		
17	16	k8	k8.spot	Ref	ApoA1 KO		

This column can be used to created row names for the targets frame by

```
> targets <- readTargets("targets.txt", row.names="Name")
```

The row names can be propagated to become array names in the data objects when these are read in.

For ImaGene files, the `FileName` column is split into a `FileNameCy3` column and a `FileNameCy5` because ImaGene stores red and green intensities in separate files. This is a short example:



	A	B	C	D	E	F
	SlideNumber	FileNameCy3	FileNameCy5	Cy3	Cy5	
1						
2	19	slide19w595.txt	slide19w685.txt	WT	Mutant	
3	20	slide20w595.txt	slide20w685.txt	Mutant	WT	
4						
5						

## 4.4 Reading Two-Color Intensity Data

Let `files` be a character vector containing the names of the image analysis output files. The foreground and background intensities can be read into an `RGList` object using a command of the form

```
> RG <- read.maimages(files, source="<imageanalysisprogram>", path="<directory>")
```

where `<imageanalysisprogram>` is the name of the image analysis program and `<directory>` is the full path of the directory containing the files. If the files are in the current R working directory then the argument `path` can be omitted; see the help entry for `setwd` for how to set the current working directory. The file names are usually read from the Targets File. For example, the Targets File `Targets.txt` is in the current working directory together with the SPOT output files, then one might use

```
> targets <- readTargets()
> RG <- read.maimages(targets$FileName, source="spot")
```

Alternatively, and even more simply, one may give the targets frame itself in place of the `files` argument as

```
> RG <- read.maimages(targets, source="spot")
```

In this case the software will look for the column `FileName` in the targets frame.

If the files are GenePix output files then they might be read using

```
> RG <- read.maimages(targets, source="genepix")
```

given an appropriate targets file. Consult the help entry for `read.maimages` to see which other image analysis programs are supported. Files are assumed by default to be tab-delimited, although other separators can be specified using the `sep=` argument.

Reading data from ImaGene software is a little different to that of other image analysis programs because the red and green intensities are stored in separate files. This means that the targets frame should include two filename columns called, say, `FileNameCy3` and `FileNameCy5`, giving the names of the files containing the green and red intensities respectively. An example is given in Section 4.3. Typical code with ImaGene data might be

```
> targets <- readTargets()
> files <- targets[,c("FileNameCy3","FileNameCy5")]
> RG <- read.maimages(files, source="imagine")
```

For ImaGene data, the `files` argument to `read.maimages()` is expected to be a 2-column matrix of filenames rather than a vector.

The following table gives the default estimates used for the foreground and background intensities:

Source	Foreground	Background
agilent	Median Signal	Median Signal
agilent.mean	Mean Signal	Median Signal
agilent.median	Median Signal	Median Signal
bluefuse	AMPCH	None
genepix	F Mean	B Median
genepix.median	F Median	B Median
genepix.custom	Mean	B
imagine	Signal Mean	Signal Median, or Signal Mean if auto segmentation has been used
quantarray	Intensity	Background
scanarrayexpress	Mean	Median
smd.old	I_MEAN	B_MEDIAN
smd	Intensity (Mean)	Background (Median)
spot	mean	morph
spot.close.open	mean	morph.close.open

The default estimates can be over-ridden by specifying the `columns` argument to `read.maimages()`. Suppose for example that GenePix has been used with a custom background method, and you wish to use median foreground estimates. This combination of foreground and background is not provided as a pre-set choice in `limma`, but you can specify it by

```
> RG <- read.maimages(files,source="genepix",
+   columns=list(R="F635 Median",G="F532 Median",Rb="B635",Gb="B532"))
```

What should you do if your image analysis program is not in the above list? If the image output files are in standard format, then you can supply the annotation and intensity column names yourself. For example,

```
> RG <- read.maimages(files,
+   columns=list(R="F635 Mean",G="F532 Mean",Rb="B635 Median",Gb="B532 Median"),
+   annotation=c("Block","Row","Column","ID","Name"))
```

is exactly equivalent to `source="genepix"`. “Standard format” means here that there is a unique column name identifying each column of interest and that there are no lines in the file following the last line of data. Header information at the start of the file is acceptable, but extra lines at the end of the file will cause the read to fail.

It is a good idea to look at your data to check that it has been read in correctly. Type

```
> show(RG)
```

to see a print out of the first few lines of data. Also try

```
> summary(RG$R)
```

to see a five-number summary of the red intensities for each array, and so on.

It is possible to read the data in several steps. If `RG1` and `RG2` are two data sets corresponding to different sets of arrays then

```
> RG <- cbind(RG1, RG2)
```

will combine them into one large data set. Data sets can also be subsetted. For example `RG[,1]` is the data for the first array while `RG[1:100,]` is the data on the first 100 genes.

## 4.5 Reading Single-Channel Agilent Intensity Data

Reading single-channel data is similar to two-color data, except that the argument `green.only=TRUE` should be added to tell `read.maimages()` not to expect a red channel. Single-channel Agilent intensities, as produced by Agilent’s Feature Extraction software, can be read by

```
> x <- read.maimages(files, source="agilent", green.only=TRUE)
```

or

```
> x <- read.maimages(targets, source="agilent", green.only=TRUE)
```

As for two-color data, the `path` argument is used:

```
> x <- read.maimages(files, source="agilent", path="<directory>", green.only=TRUE)
```

if the data files are not in the current working directory. The `green.only` argument tells `read.maimages()` to output an `EList` object instead an `RGList`. The raw intensities will be stored in the `E` component of the data object, and can be checked for example by

```
> summary(x$E)
```

Agilent’s Feature Extraction software has the ability to estimate the foreground and background signals for each spot using either the mean or the median of the foreground and background pixels. The default for `read.maimages` is to read the median signal for both foreground and background. Alternatively

```
> x <- read.maimages(targets, source="agilent.mean", green.only=TRUE)
```

would read the mean foreground signal while still using median for the background. The possible values for `source` are:

Source	Foreground	Background
agilent	Median Signal	Median Signal
agilent.mean	Mean Signal	Median Signal
agilent.median	Median Signal	Median Signal

As for two-color data, the default choices for the foreground and background estimates can be over-ridden by specifying the `columns` argument to `read.maimages()`.

Agilent Feature Extraction output files contain probe annotation columns as well as intensity columns. By default, `read.maimages()` will read the following annotation columns, if they exist: `Row`, `Col`, `Start`, `Sequence`, `SwissProt`, `GenBank`, `Primate`, `GenPept`, `ProbeUID`, `ControlType`, `ProbeName`, `GeneName`, `SystematicName`, `Description`.

See Section 17.4 for a complete worked case study with single-channel Agilent data.

## 4.6 Reading Illumina BeadChip Data

Illumina whole-genome BeadChips require special treatment. Illumina images are scanned by BeadScan software, and Illumina's BeadStudio or GenomeStudio software can be used to export probe summary profiles. The probe summary profiles are tab-delimited files containing the intensity data. Typically, all the arrays processed at one time are written to a single file, with several columns corresponding to each array. We recommend that intensities should be exported from GenomeStudio without background correction or normalization, as these pre-processing steps can be better done by limma functions. GenomeStudio can also be asked to export profiles for the control probes, and we recommend that this be done as well.

Illumina files differ from other platforms in that each image output file contains data from multiple arrays and in that intensities for control probes are written to a separate file from the regular probes. There are other features of these files that can optionally be used for pre-processing and filtering. Illumina probe summary files can be read by the `read.ilmn` function. A typical usage is

```
> x <- read.ilmn("probe profile.txt", ctrlfiles="control probe profile.txt")
```

where `probe profile.txt` is the name of the main probe summary profile file and `control probe profile.txt` is the name of the file containing profiles for control probes.

If there are multiple probe summary profiles to be read, and the samples are summarized in a `targets` frame, then the `read.ilmn.targets` function can be used.

Reading the control probe profiles is optional but recommended. If the control probe profiles are available, then the Illumina data can be favorably background corrected and normalized using the `neqc` or `nec` functions. Otherwise, Illumina data is background corrected and normalized as for other single channel platforms.

See Section 17.3 for a fully worked case study with Illumina microarray data.

## 4.7 Image-derived Spot Quality Weights

Image analysis programs typically output a lot of information, in addition to the foreground and background intensities, which provides information on the quality of each spot. It is sometimes desirable to use this information to produce a quality index for each spot which can be used in the subsequent analysis steps. One approach is to remove all spots from consideration which do not satisfy a certain quality criterion. A more sophisticated approach is to produce a quantitative quality index which can be used to up or downweight each spot in a graduated way depending on its perceived reliability. `limma` provides an approach to spot weights which supports both of these approaches.

The `limma` approach is to compute a quantitative quality weight for each spot. Weights are treated similarly in `limma` as they are treated in most regression functions in R such as `lm()`. A zero weight indicates that the spot should be ignored in all analysis as being unreliable. A weight of 1 indicates normal quality. A spot quality weight greater or less than one will result in that spot being given relatively more or less weight in subsequent analyses. Spot weights less than zero are not meaningful.

The quality information can be read and the spot quality weights computed at the same time as the intensities are read from the image analysis output files. The computation of the quality weights is defined by the `wt.fun` argument to the `read.maimages()` function. This argument is a function which defines how the weights should be computed from the information found in the image analysis files. Deriving good spot quality weights is far from straightforward and depends very much on the image analysis software used. `limma` provides a few examples which have been found to be useful by some researchers.

Some image analysis programs produce a quality index as part of the output. For example, GenePix produces a column called **Flags** which is zero for a “normal” spot and takes increasingly negative values for different classes of problem spot. If you are reading GenePix image analysis files, the call

```
> RG <- read.maimages(files,source="genepix",wt.fun=wtflags(weight=0,cutoff=-50))
```

will read in the intensity data and will compute a matrix of spot weights giving zero weight to any spot with a **Flags**-value less than  $-50$ . The weights are stored in the `weights` component of the `RGList` data object. The weights are used automatically by functions such as `normalizeWithinArrays` which operate on the `RG`-list.

Sometimes the ideal size, in terms of image pixels, is known for a perfectly circular spot. In this case it may be useful to downweight spots which are much larger or smaller than this ideal size. If SPOT image analysis output is being read, the following call

```
> RG <- read.maimages(files,source="spot",wt.fun=wtarea(100))
```

gives full weight to spots with area exactly 100 pixels and down-weights smaller and larger spots. Spots which have zero area or are more than twice the ideal size are given zero weight.

The appropriate way to computing spot quality weights depends on the image analysis program used. Consult the help entry `QualityWeights` to see what quality weight functions are available. The `wt.fun` argument is very flexible and allows you to construct your own

weights. The `wt.fun` argument can be any function which takes a data set as argument and computes the desired weights. For example, if you wish to give zero weight to all GenePix flags less than -50 you could use

```
> myfun <- function(x) as.numeric(x$Flags > -50.5)
> RG <- read.maimages(files, source="genepix", wt.fun=myfun)
```

The `wt.fun` facility can be used to compute weights based on any number of columns in the image analysis files. For example, some researchers like to filter out spots if the foreground mean and median from GenePix for a given spot differ by more than a certain threshold, say 50. This could be achieved by

```
> myfun <- function(x, threshold=50) {
+   okred <- abs(x[, "F635 Median"] - x[, "F635 Mean"]) < threshold
+   okgreen <- abs(x[, "F532 Median"] - x[, "F532 Mean"]) < threshold
+   as.numeric(okgreen & okred)
+}
> RG <- read.maimages(files, source="genepix", wt.fun=myfun)
```

Then all the “bad” spots will get weight zero which, in `limma`, is equivalent to flagging them out. The definition of `myfun` here could be replaced with any other code to compute weights using the columns in the GenePix output files.

## 4.8 Reading Probe Annotation

The `RGList` read by `read.maimages()` will almost always contain a component called `genes` containing the IDs and other annotation information associated with the probes. The only exceptions are SPOT data, `source="spot"`, or when reading generic data, `source="generic"`, without setting the annotation argument, `annotation=NULL`. Try

```
> names(RG$genes)
```

to see if the `genes` component has been set.

If the `genes` component is not set, the probe IDs will need to be read from a separate file. If the arrays have been scanned with an Axon scanner, then the probes IDs will be available in a tab-delimited GenePix Array List (GAL) file. If the GAL file has extension “gal” and is in the current working directory, then it may be read into a `data.frame` by

```
> RG$genes <- readGAL()
```

Non-GenePix gene lists can be read into R using the function `read.delim` from R base.

## 4.9 Printer Layout

The printer layout is the arrangement of spots and blocks of spots on the arrays. Knowing the printer layout is especially relevant for old-style academic spotted arrays printed with a mechanical robot with a multi-tip print-head. The blocks are sometimes called print-tip groups

or pin-groups or meta rows and columns. Each block corresponds to a print tip on the print-head used to print the arrays, and the layout of the blocks on the arrays corresponds to the layout of the tips on the print-head. The number of spots in each block is the number of times the print-head was lowered onto the array. Where possible, for example for Agilent, GenePix or ImaGene data, `read.maimages` will set the printer layout information in the component `printer`. Try

```
> names(RG$printer)
```

to see if the printer layout information has been set.

If you've used `readGAL` to set the `genes` component, you may also use `getLayout` to set the `printer` information by

```
> RG$printer <- getLayout(RG$genes)
```

Note this will work only for GenePix GAL files, not for general gene lists.

## 4.10 The Spot Types File

The Spot Types file (STF) is another optional tab-delimited text file that allows you to identify different types of probes from the entries appearing in the gene list. It is especially useful for identifying different types of control probes. The STF is used to set the control status of each probe on the arrays so that plots may highlight different types of spots in an appropriate way. It is typically used to distinguish control probes from regular probes corresponding to genes, and to distinguish positive from negative controls, ratio from calibration controls and so on. The STF should have a `SpotType` column giving the names of the different spot-types. One or more other columns should have the same names as columns in the gene list and should contain patterns or regular expressions sufficient to identify the spot-type. Any other columns are assumed to contain plotting attributes, such as colors or symbols, to be associated with the spot-types. There is one row for each spot-type to be distinguished.

The STF uses simplified regular expressions to match patterns. For example, `AA*` means any string starting with `AA`, `*AA` means any code ending with `AA`, `AA` means exactly these two letters, `*AA*` means any string containing `AA`, `AA.` means `AA` followed by exactly one other character and `AA\.` means exactly `AA` followed by a period and no other characters. For those familiar with regular expressions, any other regular expressions are allowed but the codes `^` for beginning of string and `$` for end of string should be excluded. Note that the patterns are matched sequentially from first to last, so more general patterns should be included first. The first row should specify the default spot-type and should have pattern `*` for all the pattern-matching columns.

Here is a short STF appropriate for the ApoAI data:



	A	B	C	D	E	F
1	SpotType	ID	Name	Color		
2	cDNA	*	*	black		
3	BLANK	BLANK	*	brown		
4	Blank	Blank	*	orange		
5	Control	Control	*	blue		
6						
7						
8						
9						

In this example, the columns **ID** and **Name** are found in the gene-list and contain patterns to match. The asterisks are wildcards which can represent anything. Be careful to use upper or lower case as appropriate and don't insert any extra spaces. The remaining column gives colors to be associated with the different types of points. This code assumes of that the probe annotation data.frame includes columns **ID** and **Name**. This is usually so if GenePix has been used for the image analysis, but other image analysis software may use other column names.

Here is a STF below appropriate for arrays with Lucidea Universal ScoreCard control spots.

	A	B	C	D	E	F
1	SpotType	ID	Name	Color		
2	gene	*	*	black		
3	ratio	*	Ratio*	red		
4	calibration	*	Calibr*	blue		
5	utility	*	Utility*	pink		
6	negative	*	Negative*	brown		
7	buffer	*	Buffer	orange		
8	blank	blank	*	yellow		
9						

If the STF has default name `SpotTypes.txt` then it can be read using

```
> spottypes <- readSpotTypes()
```

It is typically used as an argument to the `controlStatus()` function to set the status of each spot on the array, for example

```
> RG$genes$Status <- controlStatus(spottypes, RG)
```

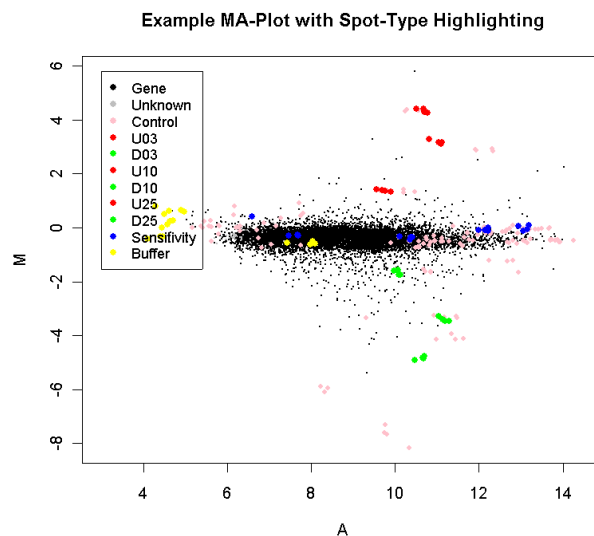
# Chapter 5

## Quality Assessment

An essential step in the analysis of any microarray data is to check the quality of the data from the arrays. For two-color array data, an essential step is to view the MA-plots of the unnormalized data for each array. The `plotMA()` function produces plots for individual arrays. The `plotMA3by2()` function gives an easy way to produce MA-plots for all the arrays in a large experiment. This functions writes plots to disk as png files, 6 plots to a page.

The usefulness of MA-plots is enhanced by highlighting various types of control probes on the arrays, and this is facilitated by the `controlStatus()` funtion. The following is an example MA-Plot for an Incyte array with various spike-in and other controls. (Data courtesy of Dr Steve Gerondakis, Walter and Eliza Hall Institute of Medical Research.) The data shows high-quality data with long comet-like pattern of non-differentially expressed probes and a small proportion of highly differentially expressed probes. The plot was produced using

```
> spottypes <- readSpotTypes()
> RG$genes$Status <- controlStatus(spottypes, RG)
> plotMA(RG)
```



The array includes spike-in ratio controls which are 3-fold, 10-fold and 25-fold up and down regulated, as well as non-differentially expressed sensitivity controls and negative controls.

The background intensities are also a useful guide to the quality characteristics of each array. Boxplots of the background intensities from each array

```
> boxplot(data.frame(log2(RG$Gb)),main="Green background")
> boxplot(data.frame(log2(RG$Rb)),main="Red background")
```

will highlight any arrays unusually with high background intensities.

Spatial heterogeneity on individual arrays can be highlighted by examining imageplots of the background intensities, for example

```
> imageplot(log2(RG$Gb[,1]),RG$printer)
```

plots the green background for the first array. The function `imageplot3by2()` gives an easy way to automate the production of plots for all arrays in an experiment.

If the plots suggest that some arrays are of lesser quality than others, it may be useful to estimate array quality weights to be used in the linear model analysis, see Section 14.

# Chapter 6

## Pre-Processing Two-Color Data

### 6.1 Background Correction

The default background correction action is to subtract the background intensity from the foreground intensity for each spot. If the `RGList` object has not already been background corrected, then `normalizeWithinArrays` will do this by default. Hence

```
> MA <- normalizeWithinArrays(RG)
```

is equivalent to

```
> RGb <- backgroundCorrect(RG, method="subtract")
> MA <- normalizeWithinArrays(RGb)
```

However there are many other background correction options which may be preferable in certain situations, see Ritchie et al [30].

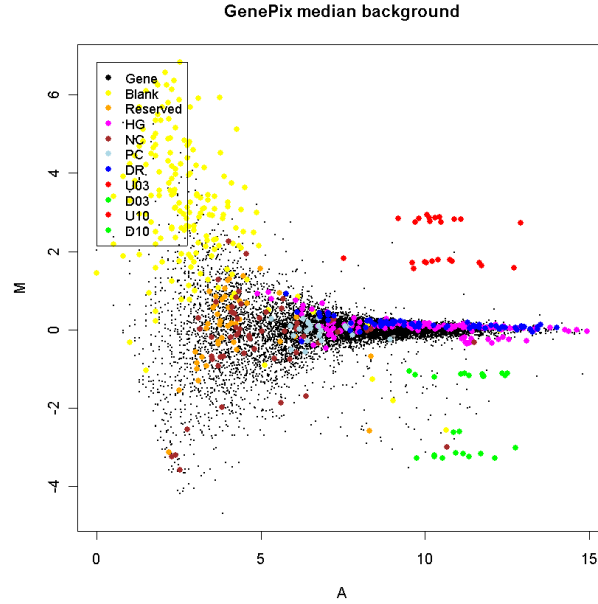
For the purpose of assessing differential expression, we often find

```
> RG <- backgroundCorrect(RG, method="normexp", offset=50)
```

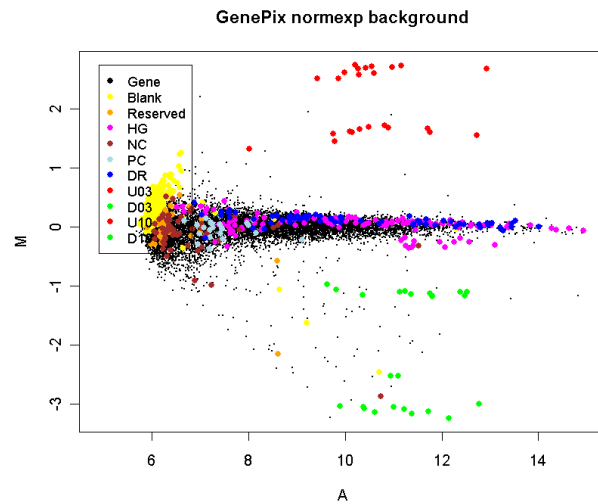
to be preferable to the simple background subtraction when using output from most image analysis programs. This method adjusts the foreground adaptively for the background intensities and results in strictly positive adjusted intensities, i.e., negative or zero corrected intensities are avoided. The use of an offset damps the variation of the log-ratios for very low intensities spots towards zero.

To illustrate some differences between the different background correction methods we consider one cDNA array which was self-self hybridized, i.e., the same RNA source was hybridized to both channels. For this array there is no actual differential expression. The array was printed with a human 10.5k library and hybridized with Jurkatt RNA on both channels. (Data courtesy Andrew Holloway and Dileepa Diyagama, Peter MacCallum Cancer Centre, Melbourne.) The array included a selection of control spots which are highlighted on the plots. Of particular interest are the spike-in ratio controls which should show up and down fold changes of 3 and 10. The first plot displays data acquired with GenePix software and background corrected by subtracting the median local background, which is the default with

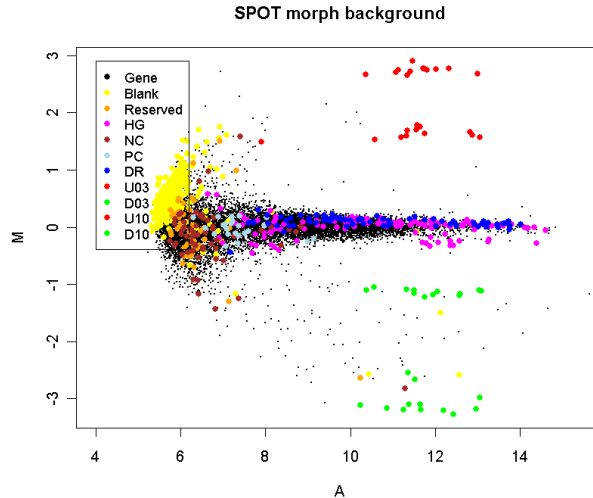
GenePix data. The plot shows the typical wedge shape with fanning of the M-values at low intensities. The range of observed M-values dominates the spike-in ratio controls. There are also 1148 spots not shown on the plot because the background corrected intensities were zero or negative.



The second plot shows the same array background corrected with `method="normexp"` and `offset=50`. The spike-in ratio controls now stand out clearly from the range of the M-values. All spots on the array are shown on the plot because there are now no missing M-values.



The third plot shows the same array quantified with SPOT software and with “morph” background subtracted. This background estimator produces a similar effect to that with `normexp`.



The effect of using “morph” background or using `method="normexp"` with an offset is to stabilize the variability of the M-values as a function of intensity. The empirical Bayes methods implemented in the `limma` package for assessing differential expression will yield most benefit when the variabilities are as homogeneous as possible between genes. This can best be achieved by reducing the dependence of variability on intensity as far as possible [30].

## 6.2 Within-Array Normalization

`Limma` implements a range of normalization methods for spotted microarrays. Smyth and Speed [39] describe some of the most commonly used methods. The methods may be broadly classified into methods which normalize the M-values for each array separately (within-array normalization) and methods which normalize intensities or log-ratios to be comparable across arrays (between-array normalization). This section discusses mainly within-array normalization, which all that is usually required for the traditional log-ratio analysis of two-color data. Between-array normalization is discussed further in Section 6.3.

Print-tip loess normalization [53] is the default normalization method and can be performed by

```
> MA <- normalizeWithinArrays(RG)
```

There are some notable cases where this is not appropriate. For example, Agilent arrays do not have print-tip groups, so one should use global loess normalization instead:

```
> MA <- normalizeWithinArrays(RG, method="loess")
```

Print-tip loess is also unreliable for small arrays with less than, say, 150 spots per print-tip group. Even larger arrays may have particular print-tip groups which are too small for print-tip loess normalization if the number of spots with non-missing M-values is small for one or more of the print-tip groups. In these cases one should either use global “loess” normalization or else use robust spline normalization

```
> MA <- normalizeWithinArrays(RG, method="robustspline")
```

which is an empirical Bayes compromise between print-tip and global loess normalization, with 5-parameter regression splines used in place of the loess curves.

Loess normalization assumes that the bulk of the probes on the array are not differentially expressed. It doesn't assume that there are equal numbers of up and down regulated genes or that differential expression is symmetric about zero, provided that the loess fit is implemented in a robust fashion, but it is necessary that there be a substantial body of probes which do not change expression levels. Oshlack et al [23] show that loess normalization can tolerate up to about 30% asymmetric differential expression while still giving good results. This assumption can be suspect for boutique arrays where the total number of unique genes on the array is small, say less than 150, particularly if these genes have been selected for being specifically expressed in one of the RNA sources. In such a situation, the best strategy is to include on the arrays a series of non-differentially expressed control spots, such as a titration series of whole-library-pool spots, and to use the up-weighting method discussed below [23]. A whole-library-pool means that one makes a pool of a library of probes, and prints spots from the pool at various concentrations [52]. The library should be sufficiently large than one can be confident that the average of all the probes is not differentially expressed. The larger the library the better. Good results have been obtained with library pools with as few as 500 clones. In the absence of such control spots, normalization of boutique arrays requires specialist advice.

Any spot quality weights found in `RG` will be used in the normalization by default. This means for example that spots with zero weight (flagged out) will not influence the normalization of other spots. The use of spot quality weights will not however result in any spots being removed from the data object. Even spots with zero weight will be normalized and will appear in the output object, such spots will simply not have any influence on the other spots. If you do not wish the spot quality weights to be used in the normalization, their use can be over-ridden using

```
> MA <- normalizeWithinArrays(RG, weights=NULL)
```

The output object `MA` will still contain any spot quality weights found in `RG`, but these weights are not used in the normalization step.

It is often useful to make use of control spots to assist the normalization process. For example, if the arrays contain a series of spots which are known in advance to be non-differentially expressed, these spots can be given more weight in the normalization process. Spots which are known in advance to be differentially expressed can be down-weighted. Suppose for example that the `controlStatus()` has been used to identify spike-in spots which are differentially expressed and a titration series of whole-library-pool spots which should not be differentially expressed. Then one might use

```
> w <- modifyWeights(RG$weights, RG$genes$Status, c("spikein","titration"), c(0,2))
> MA <- normalizeWithinArrays(RG, weights=w)
```

to give zero weight to the spike-in spots and double weight to the titration spots. This process is automated by the "control" normalization method, for example

```
> csi <- RG$genes$Status=="titration"
> MA <- normalizeWithinArrays(RG, method="control", controlspots=csi)
```

In general, `csi` is an index vector specifying the non-differentially expressed control spots [23].

The idea of up-weighting the titration spots is in the same spirit as the composite normalization method proposed by [52] but is more flexible and generally applicable. The above code assumes that `RG` already contains spot quality weights. If not, one could use

```
> w <- modifyWeights(array(1,dim(RG)), RG$genes$Status, c("spikein","titration"), c(0,2))
> MA <- normalizeWithinArrays(RG, weights=w)
```

instead.

Limma contains some more sophisticated normalization methods. In particular, some between-array normalization methods are discussed in Section 6.3 of this guide.

## 6.3 Between-Array Normalization

This section explores some of the methods available for between-array normalization of two-color arrays. A feature which distinguishes most of these methods from within-array normalization is the focus on the individual red and green intensity values rather than merely on the log-ratios. These methods might therefore be called *individual channel* or *separate channel* normalization methods. Individual channel normalization is typically a prerequisite to individual channel analysis methods such as that provided by `lmscFit()`. Further discussion of the issues involved is given by [55]. This section shows how to reproduce some of the results given in [55]. The Apo1 data set from Section 16.2 will be used to illustrate these methods. We assume that the Apo1 data has been loaded and background corrected as follows:

```
> load("Apo1.RData")
```

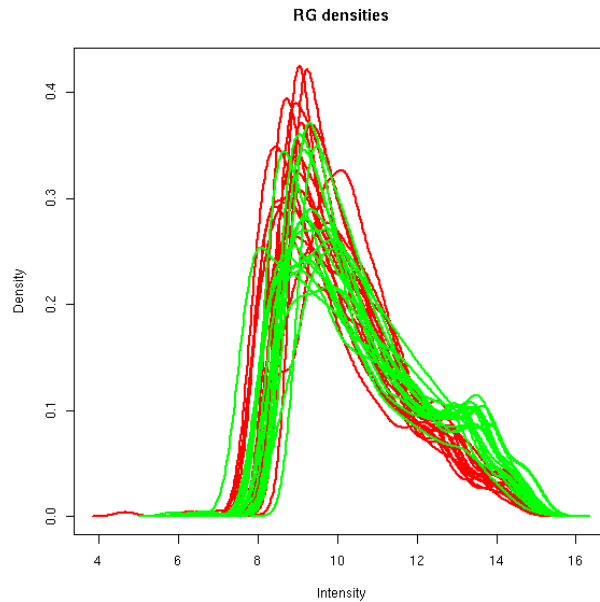
An important issue to consider before normalizing between arrays is how background correction has been handled. For between-array normalization to be effective, it is important to avoid missing values in log-ratios which might arise from negative or zero corrected intensities. The function `backgroundCorrect()` gives a number of useful options. For the purposes of this section, the data has been corrected using the "minimum" method:

```
> RG.b <- backgroundCorrect(RG,method="minimum")
```

`plotDensities` displays smoothed empirical densities for the individual green and red channels on all the arrays. Without any normalization there is considerable variation between both channels and between arrays:

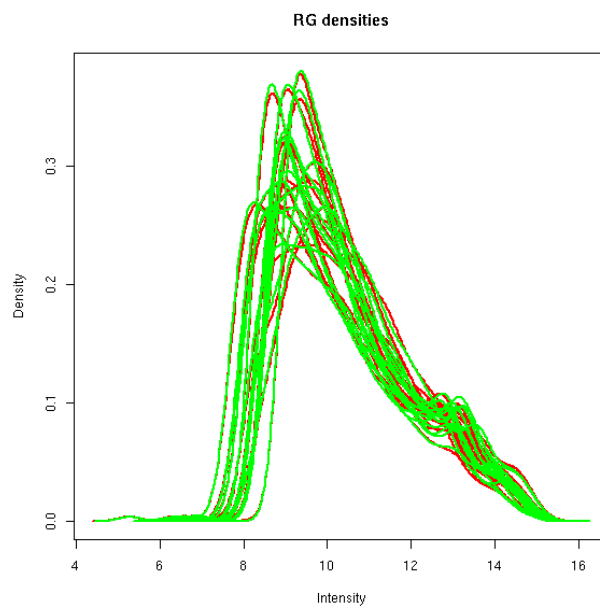
```
> plotDensities(RG.b)
```





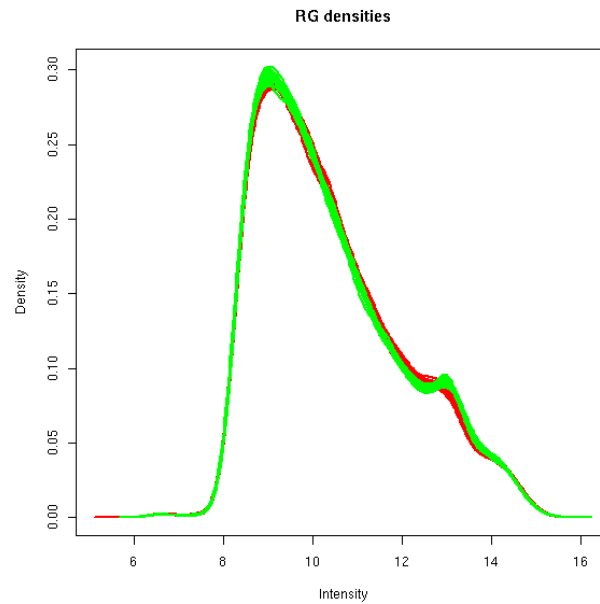
After loess normalization of the M-values for each array the red and green distributions become essentially the same for each array, although there is still considerable variation between arrays:

```
> MA.p <-normalizeWithinArrays(RG.b)
> plotDensities(MA.p)
```



Loess normalization doesn't affect the A-values. Applying quantile normalization to the A-values makes the distributions essentially the same across arrays as well as channels:

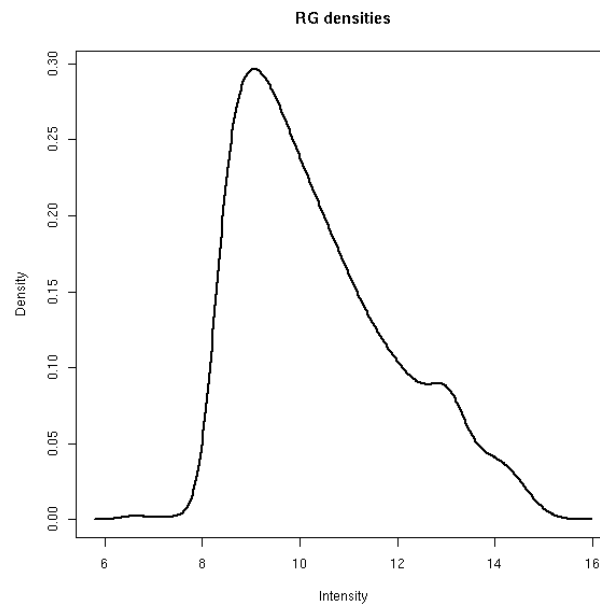
```
> MA.pAq <- normalizeBetweenArrays(MA.p, method="Aquantile")
> plotDensities(MA.pAq)
```



Applying quantile normalization directly to the individual red and green intensities produces a similar result but is somewhat noisier:

```
> MA.q <- normalizeBetweenArrays(RG.b, method="quantile")
> plotDensities(MA.q, col="black")
```

Warning message:  
number of groups=2 not equal to number of col in: plotDensities(MA.q, col = "black")



There are other between-array normalization methods not explored here. For example `normalizeBetweenArrays` with `method="vsn"` gives an interface to the variance-stabilizing normalization methods of the `vsn` package.

## 6.4 Using Objects from the `marray` Package

The package `marray` is a well known R package for pre-processing of two-color microarray data. `Marray` provides functions for reading, normalization and graphical display of data. `Marray` and `limma` are both descendants of the earlier and path-breaking `sma` package available from <http://www.stat.berkeley.edu/users/terry/zarray/Software/smacode.html> but `limma` has maintained and built upon the original data structures whereas `marray` has converted to a fully formal data class representation. For this reason, `Limma` is backwardly compatible with `sma` while `marray` is not.

Normalization functions in `marray` focus on a flexible approach to location and scale normalization of M-values, rather than the within and between-array approach of `limma`. `Marray` provides some normalization methods which are not in `limma` including 2-D loess normalization and print-tip-scale normalization. Although there is some overlap between the normalization functions in the two packages, both providing print-tip loess normalization, the two approaches are largely complementary. `Marray` also provides highly developed functions for graphical display of two-color microarray data.

Read functions in `marray` produce objects of class `marrayRaw` while normalization produces objects of class `marrayNorm`. Objects of these classes may be converted to and from `limma` data objects using the `convert` package. `marrayRaw` objects may be converted to `RGList` objects and `marrayNorm` objects to `MAList` objects using the `as` function. For example, if `Data` is an `marrayNorm` object then

```
> library(convert)
> MA <- as(Data, "MAList")
```

converts to an `MAList` object.

`marrayNorm` objects can also be used directly in `limma` without conversion, and this is generally recommended. If `Data` is an `marrayNorm` object, then

```
> fit <- lmFit(Data, design)
```

fits a linear model to `Data` as it would to an `MAList` object. One difference however is that the `marray` read functions tend to populate the `maW` slot of the `marrayNorm` object with qualitative spot quality flags rather than with quantitative non-negative weights, as expected by `limma`. If this is so then one may need

```
> fit <- lmFit(Data, design, weights=NULL)
```

to turn off use of the spot quality weights.

# Chapter 7

## Filtering

We usually recommend that all probes on the microarray platform be used for the normalization step.

For downstream analysis, it is usually worthwhile to remove probes that appear not be expressed in any of the experimental conditions. This is called filtering. We generally recommend that this is done before the linear modelling and empirical Bayes steps, but after normalization.

There are a number of ways that filtering can be done. One way is to keep probes that are expressed above background on at least  $n$  arrays, where  $n$  is the smallest number of replicates assigned to any of the treatment combinations. See for example Case studies 15.3 or 15.4 in the limma User's Guide.

Note that filtering methods involving variances should not be used. The limma algorithm analyses the spread of the genewise variances. Any filtering method based on genewise variances will change the distribution of variances, will interfere with the limma algorithm and hence will give poor results.

# Chapter 8

## Linear Models Overview

### 8.1 Introduction

The package `limma` uses an approach called *linear models* to analyze designed microarray experiments. This approach allows very general experiments to be analyzed just as easily as a simple replicated experiment. The approach is outlined in [36, 54]. The approach requires one or two matrices to be specified. The first is the *design matrix* which indicates in effect which RNA samples have been applied to each array. The second is the *contrast matrix* which specifies which comparisons you would like to make between the RNA samples. For very simple experiments, you may not need to specify the contrast matrix.

The philosophy of the approach is as follows. You have to start by fitting a linear model to your data which fully models the systematic part of your data. The model is specified by the design matrix. Each row of the design matrix corresponds to an array in your experiment and each column corresponds to a coefficient that is used to describe the RNA sources in your experiment. With Affymetrix or single-channel data, or with two-color with a common reference, you will need as many coefficients as you have distinct RNA sources, no more and no less. With direct-design two-color data you will need one fewer coefficient than you have distinct RNA sources, unless you wish to estimate a dye-effect for each gene, in which case the number of RNA sources and the number of coefficients will be the same. Any set of independent coefficients will do, providing they describe all your treatments. The main purpose of this step is to estimate the variability in the data, hence the systematic part needs to be modelled so it can be distinguished from random variation.

In practice the requirement to have exactly as many coefficients as RNA sources is too restrictive in terms of questions you might want to answer. You might be interested in more or fewer comparisons between the RNA source. Hence the contrasts step is provided so that you can take the initial coefficients and compare them in as many ways as you want to answer any questions you might have, regardless of how many or how few these might be.

If you have data from Affymetrix experiments, from single-channel spotted microarrays or from spotted microarrays using a common reference, then linear modeling is the same as ordinary analysis of variance or multiple regression except that a model is fitted for every gene. With data of this type you can create design matrices as one would do for ordinary

modeling with univariate data. If you have data from spotted microarrays using a direct design, i.e., a connected design with no common reference, then the linear modeling approach is very powerful but the creation of the design matrix may require more statistical knowledge.

For statistical analysis and assessing differential expression, `limma` uses an empirical Bayes method to moderate the standard errors of the estimated log-fold changes. This results in more stable inference and improved power, especially for experiments with small numbers of arrays [36]. For arrays with within-array replicate spots, `limma` uses a pooled correlation method to make full use of the duplicate spots [38].

## 8.2 Single-Channel Designs

Affymetrix data will usually be normalized using the `affy` package. We will assume here that the data is available as an `ExpressionSet` object called `eset`. Such an object will have an slot containing the log-expression values for each gene on each array which can be extracted using `exprs(eset)`. Affymetrix and other single-channel microarray data may be analyzed very much like ordinary linear models or anova models. The difference with microarray data is that it is almost always necessary to extract particular contrasts of interest and so the standard parametrizations provided for factors in R are not usually adequate.

There are many ways to approach the analysis of a complex experiment in `limma`. A straightforward strategy is to set up the simplest possible design matrix and then to extract from the fit the contrasts of interest.

Suppose that there are three RNA sources to be compared. Suppose that the first three arrays are hybridized with RNA1, the next two with RNA2 and the next three with RNA3. Suppose that all pair-wise comparisons between the RNA sources are of interest. We assume that the data has been normalized and stored in an `ExpressionSet` object, for example by

```
> data <- ReadAffy()
> eset <- rma(data)
```

An appropriate design matrix can be created and a linear model fitted using

```
> design <- model.matrix(~ 0+factor(c(1,1,1,2,2,3,3,3)))
> colnames(design) <- c("group1", "group2", "group3")
> fit <- lmFit(eset, design)
```

To make all pair-wise comparisons between the three groups the appropriate contrast matrix can be created by

```
> contrast.matrix <- makeContrasts(group2-group1, group3-group2, group3-group1, levels=design)
> fit2 <- contrasts.fit(fit, contrast.matrix)
> fit2 <- eBayes(fit2)
```

A list of top genes differential expressed in group2 versus group1 can be obtained from

```
> topTable(fit2, coef=1, adjust="BH")
```

The outcome of each hypothesis test can be assigned using

```
> results <- decideTests(fit2)
```

A Venn diagram showing numbers of genes significant in each comparison can be obtained from

```
> vennDiagram(results)
```

## 8.3 Common Reference Designs

Now consider two-color microarray experiments in which a common reference has been used on all the arrays. Such experiments can be analyzed very similarly to Affymetrix experiments except that allowance must be made for dye-swaps. The simplest method is to setup the design matrix using the `modelMatrix()` function and the targets file. As an example, we consider part of an experiment conducted by Joëlle Michaud, Catherine Carmichael and Dr Hamish Scott at the Walter and Eliza Hall Institute to compare the effects of transcription factors in a human cell line. The targets file is as follows:

```
> targets <- readTargets("runxtargets.txt")
```

```
> targets
```

	SlideNumber	Cy3	Cy5
1	2144	EGFP	AML1
2	2145	EGFP	AML1
3	2146	AML1	EGFP
4	2147	EGFP	AML1.CBFb
5	2148	EGFP	AML1.CBFb
6	2149	AML1.CBFb	EGFP
7	2158	EGFP	CBFb
8	2159	CBFb	EGFP
9	2160	EGFP	AML1.CBFb
10	2161	AML1.CBFb	EGFP
11	2162	EGFP	AML1.CBFb
12	2163	AML1.CBFb	EGFP
13	2166	EGFP	CBFb
14	2167	CBFb	EGFP

In the experiment, green fluorescent protein (EGFP) has been used as a common reference. An adenovirus system was used to transport various transcription factors into the nuclei of HeLa cells. Here we consider the transcription factors AML1, CBFbeta or both. A simple design matrix was formed and a linear model fit:

```
> design <- modelMatrix(targets,ref="EGFP")
```

```
> design
```

	AML1	AML1.CBFb	CBFb
1	1	0	0
2	1	0	0
3	-1	0	0
4	0	1	0
5	0	1	0
6	0	-1	0

```

7      0      0      1
8      0      0     -1
9      0      1      0
10     0     -1      0
11     0      1      0
12     0     -1      0
13     0      0      1
14     0      0     -1
> fit <- lmFit(MA, design)

```

It is of interest to compare each of the transcription factors to EGFP and also to compare the combination transcription factor with AML1 and CBFb individually. An appropriate contrast matrix was formed as follows:

```

> contrast.matrix <- makeContrasts(AML1,CBFb,AML1.CBFb,AML1.CBFb-AML1,AML1.CBFb-CBFb,
+      levels=design)
> contrast.matrix
      AML1 CBFb AML1.CBFb AML1.CBFb - AML1 AML1.CBFb - CBFb
AML1      1   0       0          -1          0
AML1.CBFb 0   0       1           1           1
CBFb      0   1       0           0          -1

```

The linear model fit can now be expanded and empirical Bayes statistics computed:

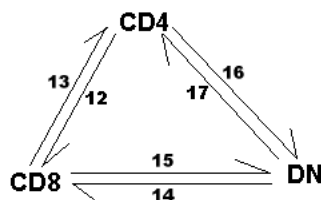
```

> fit2 <- contrasts.fit(fit, contrasts.matrix)
> fit2 <- eBayes(fit2)

```

## 8.4 Direct Two-Color Designs

Two-color designs without a common reference require the most statistical knowledge to choose the appropriate design matrix. A direct design is one in which there is no single RNA source which is hybridized to every array. As an example, we consider an experiment conducted by Dr Mireille Lahoud at the Walter and Eliza Hall Institute to compare gene expression in three different populations of dendritic cells (DC).



Arrow heads represent Cy5, i.e. arrows point in the Cy3 to Cy5 direction.

This experiment involved six cDNA microarrays in three dye-swap pairs, with each pair used to compare two DC types. The design is shown diagrammatically above. The targets file was as follows:



```
> targets
      SlideNumber   FileName Cy3 Cy5
ml12med          12 ml12med.spot CD4 CD8
ml13med          13 ml13med.spot CD8 CD4
ml14med          14 ml14med.spot  DN CD8
ml15med          15 ml15med.spot CD8  DN
ml16med          16 ml16med.spot CD4  DN
ml17med          17 ml17med.spot  DN CD4
```

There are many valid choices for a design matrix for such an experiment and no single correct choice. We chose to setup the design matrix as follows:

```
> design <- modelMatrix(targets, ref="CD4")
Found unique target names:
  CD4 CD8 DN
> design
      CD8 DN
ml12med   1  0
ml13med  -1  0
ml14med   1 -1
ml15med  -1  1
ml16med   0  1
ml17med   0 -1
```

In this design matrix, the CD8 and DN populations have been compared back to the CD4 population. The coefficients estimated by the linear model will correspond to the log-ratios of CD8 vs CD4 (first column) and DN vs CD4 (second column).

After appropriate normalization of the expression data, a linear model was fit using

```
> fit <- lmFit(MA, design)
```

The linear model can now be interrogated to answer any questions of interest. For this experiment it was of interest to make all pairwise comparisons between the three DC populations. This was accomplished using the contrast matrix

```
> contrast.matrix <- cbind("CD8-CD4"=c(1,0),"DN-CD4"=c(0,1),"CD8-DN"=c(1,-1))
> rownames(contrast.matrix) <- colnames(design)
> contrast.matrix
      CD8-CD4 DN-CD4 CD8-DN
CD8          1      0       1
DN           0      1      -1
```

The contrast matrix can be used to expand the linear model fit and then to compute empirical Bayes statistics:

```
> fit2 <- contrasts.fit(fit, contrast.matrix)
> fit2 <- eBayes(fit2)
```

# Chapter 9

## Single-Channel Experimental Designs

### 9.1 Introduction

Unlike the early days of microarrays, most data is now of the single channel type. Single channel data is generated from popular microarray technologies such as Affymetrix, Illumina or Agilent. The new technology of RNA-Seq also generates single channel data, so everything in this chapter can be applied to RNA-Seq analyses when the data has been pre-processed using the `voom` function [15]. Single-channel data may be analyzed very much like ordinary univariate linear models or analysis of variance. The difference with microarray data is that it is almost always necessary to extract particular contrasts of interest and so the standard parametrizations provided for factors in R are not usually adequate.

We will assume for our examples here that the data has been suitably pre-processed normalized and is available as an `ExpressionSet` or `EList` object called `eset`. Such an object will have an slot containing the log-expression values for each gene on each array which can be extracted using `exprs(eset)`.

### 9.2 Two Groups

The simplest possible single channel experiment is to compare two groups. Suppose that we wish to compare two wild type (Wt) mice with three mutant (Mu) mice:

FileName	Target
File1	WT
File2	WT
File3	Mu
File4	Mu
File5	Mu

There are two different ways to form the design matrix. We can either

1. create a design matrix which includes a coefficient for the mutant vs wild type difference,  
or

2. create a design matrix which includes separate coefficients for wild type and mutant mice and then extract the difference as a contrast.

For the first approach, the treatment-contrasts parametrization, the design matrix should be as follows:

```
> design

      WT MUvsWT
Array1  1      0
Array2  1      0
Array3  1      1
Array4  1      1
Array5  1      1
```

Here the first coefficient estimates the mean log-expression for wild type mice and plays the role of an intercept. The second coefficient estimates the difference between mutant and wild type. Differentially expressed genes can be found by

```
> fit <- lmFit(eset, design)
> fit <- eBayes(fit)
> topTable(fit, coef="MUvsWT", adjust="BH")
```

where `eset` is an `ExpressionSet` or `matrix` object containing the log-expression values. For the second approach, the design matrix should be

```
      WT MU
Array1  1  0
Array2  1  0
Array3  0  1
Array4  0  1
Array5  0  1
```

Differentially expressed genes can be found by

```
> fit <- lmFit(eset, design)
> cont.matrix <- makeContrasts(MUvsWT=MU-WT, levels=design)
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
> topTable(fit2, adjust="BH")
```

For the first approach, the treatment-contrasts parametrization, the design matrix can be computed by

```
> design <- cbind(WT=1,MUvsWT=c(0,0,1,1,1))
```

or by

```
> Group <- factor(targets$Target, levels=c("WT","Mu"))
> design <- model.matrix(~Group)
> colnames(design) <- c("WT","MUvsWT")
```

For the second approach, the group-means parametrization, the design matrix can be computed by

```
> design <- cbind(WT=c(1,1,0,0,0,MU=c(0,0,1,1,1))
```

or by

```
> design <- model.matrix(~0+Group)
> colnames(design) <- c("WT","MU")
```

## 9.3 Several Groups

The above approaches for two groups extend easily to any number of groups. Suppose that three RNA targets to be compared. Suppose that the three targets are called “RNA1”, “RNA2” and “RNA3” and that the column `targets$Target` indicates which one was hybridized to each array. An appropriate design matrix can be created using

```
> f <- factor(targets$Target, levels=c("RNA1","RNA2","RNA3"))
> design <- model.matrix(~0+f)
> colnames(design) <- c("RNA1","RNA2","RNA3")
```

To make all pair-wise comparisons between the three groups one could proceed

```
> fit <- lmFit(eset, design)
> contrast.matrix <- makeContrasts(RNA2-RNA1, RNA3-RNA2, RNA3-RNA1,
+                                levels=design)
> fit2 <- contrasts.fit(fit, contrast.matrix)
> fit2 <- eBayes(fit2)
```

A list of top genes for RNA2 versus RNA1 can be obtained from

```
> topTable(fit2, coef=1, adjust="BH")
```

The outcome of each hypothesis test can be assigned using

```
> results <- decideTests(fit2)
```

A Venn diagram showing numbers of genes significant in each comparison can be obtained from

```
> vennDiagram(results)
```

The statistic `fit2$F` and the corresponding `fit2$F.p.value` combine the three pair-wise comparisons into one  $F$ -test. This is equivalent to a one-way ANOVA for each gene except that the residual mean squares have been moderated between genes. To find genes which vary between the three RNA targets in any way, look for genes with small  $p$ -values. To find the top 30 genes:

```
> topTableF(fit2, number=30)
```

## 9.4 Additive Models and Blocking

### 9.4.1 Paired Samples

Paired samples occur when we compare two treatments and each sample given one treatment is naturally paired with a particular sample given the other treatment. This is a special case of blocking with blocks of size two. The classical test associated with this situation is the paired  $t$ -test.

Suppose an experiment is conducted to compare a new treatment (T) with a control (C). Six dogs are used from three sib-ships. For each sib-pair, one dog is given the treatment while the other dog is a control. This produces the targets frame:

FileName	SibShip	Treatment
File1	1	C
File2	1	T
File3	2	C
File4	2	T
File5	3	C
File6	3	T

A moderated paired  $t$ -test can be computed by allowing for sib-pair effects in the linear model:

```
> SibShip <- factor(targets$SibShip)
> Treat <- factor(targets$Treatment, levels=c("C","T"))
> design <- model.matrix(~SibShip+Treat)
> fit <- lmFit(eset, design)
> fit <- eBayes(fit)
> topTable(fit, coef="TreatT")
```

### 9.4.2 Blocking

The above approach used for paired samples can be applied in any situation where there are batch effects or where the experiment has been conducted in blocks. The treatments can be adjusted for differences between the blocks by using a model formula of the form:

```
> design <- model.matrix(~Block+Treatment)
```

In this type of analysis, the treatments are compared only within each block.

## 9.5 Interaction Models: $2 \times 2$ Factorial Designs

### 9.5.1 Questions of Interest

Factorial designs are those where more than one experimental dimension is being varied and each combination of treatment conditions is observed. Suppose that cells are extracted from wild type and mutant mice and these cells are either stimulated (S) or unstimulated (U). RNA

from the treated cells is then extracted and hybridized to a microarray. We will assume for simplicity that the arrays are single-color arrays such as Affymetrix. Consider the following targets frame:

FileName	Strain	Treatment
File1	WT	U
File2	WT	S
File3	Mu	U
File4	Mu	S
File5	Mu	S

The two experimental dimensions or *factors* here are Strain and Treatment. Strain specifies the genotype of the mouse from which the cells are extracted and Treatment specifies whether the cells are stimulated or not. All four combinations of Strain and Treatment are observed, so this is a factorial design. It will be convenient for us to collect the Strain/Treatment combinations into one vector as follows:

```
> TS <- paste(targets$Strain, targets$Treatment, sep=".")
> TS
[1] "WT.U" "WT.S" "Mu.U" "Mu.S" "Mu.S"
```

It is especially important with a factorial design to decide what are the comparisons of interest. We will assume here that the experimenter is interested in

1. which genes respond to stimulation in wild-type cells,
2. which genes respond to stimulation in mutant cells, and
3. which genes respond differently in mutant compared to wild-type cells.

as these are the questions which are most usually relevant in a molecular biology context. The first of these questions relates to the WT.S vs WT.U comparison and the second to Mu.S vs Mu.U. The third relates to the difference of differences, i.e.,  $(\text{Mu.S} - \text{Mu.U}) - (\text{WT.S} - \text{WT.U})$ , which is called the *interaction* term.

### 9.5.2 Analysing as for a Single Factor

We describe first a simple way to analyze this experiment using limma commands in a similar way to that in which two-sample designs were analyzed. Then we will go on to describe the more classical statistical approaches using factorial model formulas. All the approaches considered are equivalent and yield identical bottom-line results. The most basic approach is to fit a model with a coefficient for each of the four factor combinations and then to extract the comparisons of interest as contrasts:

```
> TS <- factor(TS, levels=c("WT.U", "WT.S", "Mu.U", "Mu.S"))
> design <- model.matrix(~0+TS)
> colnames(design) <- levels(TS)
> fit <- lmFit(eset, design)
```

This fits a model with four coefficients corresponding to WT.U, WT.S, Mu.U and Mu.S respectively. Our three contrasts of interest can be extracted by

```
> cont.matrix <- makeContrasts(
+   SvsUinWT=WT.S-WT.U,
+   SvsUinMu=Mu.S-Mu.U,
+   Diff=(Mu.S-Mu.U)-(WT.S-WT.U),
+   levels=design)
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
```

We can use `topTable()` to look at lists of differentially expressed genes for each of three contrasts, or else

```
> results <- decideTests(fit2)
> vennDiagram(results)
```

to look at all three contrasts simultaneously.

This approach is recommended for most users, because the contrasts that are being tested are formed explicitly.

### 9.5.3 A Nested Interaction Formula

Model formulas in R are very flexible, and offer lots of possible shortcuts for setting up the design matrix. However they also require a high level of statistical understanding in order to use reliably, and they are not completely described in the main R documentation. If we only wanted to test the first two questions above, an easy to to setup the design matrix would be to use a nested interaction term:

```
> Strain <- factor(targets$Strain, levels=c("WT","Mu"))
> Treatment <- factor(targets$Treatment, levels=c("U","S"))
> design <- model.matrix(~Strain+Strain:Treatment)
> colnames(design)
[1] "(Intercept)"          "StrainMu"              "StrainWT:TreatmentS" "StrainMu:TreatmentS"
```

The first term in the model formula is an effect for Strain. This introduces an intercept column to the design matrix, which estimates the average log-expression level for wild-type unstimulated cells, and a column for Strain which estimates the mutant vs wildtype difference in the unstimulated state. The second term in the model formula represents the interaction between stimulation and strain. Because there is no main effect for treatment in the model, the interaction is fitted in a nested sense. It introduces a third and a fourth column to the design matrix which represent the effect of stimulation for wild-type and for mutant mice respectively, exactly the same as the contrasts `SvsUinWT` and `SvsUinMu` define in the previous section. After

```
> fit <- lmFit(eset, design)
> fit <- eBayes(fit)
```

then

```
> topTable(fit, coef=3)
```

will find those genes responding to stimulation in wild-type mice, and

```
> topTable(fit, coef=4)
```

will find those genes responding to stimulation in mutant mice. Finally, we could extract the interaction contrast `Diff` considered above by

```
> fit2 <- contrasts.fit(fit, c(0,0,-1,1))
> fit2 <- eBayes(fit2)
> topTable(fit2)
```

This finds genes that respond differently to the stimulus in mutant vs wild-type mice.

## 9.5.4 Classic Interaction Models

The analysis of factorial designs has a long history in statistics and a system of factorial *model formulas* has been developed to facilitate the analysis of complex designs. It is important to understand though that the above three molecular biology questions do not correspond to any of the classic parametrizations used in statistics for factorial designs. Hence we generally recommend the approaches already considered above for microarray analysis.

Suppose for example that we proceed in the usual statistical way,

```
> design <- model.matrix(~Strain*Treatment)
```

This creates a design matrix which defines four coefficients with the following interpretations:

Coefficient	Comparison	Interpretation
Intercept	WT.U	Baseline level of unstimulated WT
StrainMu	Mu.U-WT.U	Difference between unstimulated strains
TreatmentS	WT.S-WT.U	Stimulation effect for WT
StrainMu:TreatmentS	(Mu.S-Mu.U)-(WT.S-WT.U)	Interaction

This is called the *treatment-contrast* parametrization. Notice that one of our comparisons of interest,  $\text{Mu.S}-\text{Mu.U}$ , is not represented and instead the comparison  $\text{Mu.U}-\text{WT.U}$ , which might not be of direct interest, is included. We need to use contrasts to extract all the comparisons of interest:

```
> fit <- lmFit(eset, design)
> cont.matrix <- cbind(SvsUinWT=c(0,0,1,0),SvsUinMu=c(0,0,1,1),Diff=c(0,0,0,1))
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
```

This extracts the WT stimulation effect as the third coefficient and the interaction as the fourth coefficient. The mutant stimulation effect is extracted as the sum of the third and fourth coefficients of the original model. This analysis yields exactly the same results as the previous analysis.

An even more classical statistical approach to the factorial experiment would be to use the *sum to zero* parametrization. In R this is achieved by



```
> contrasts(Strain) <- contr.sum(2)
> contrasts(Treatment) <- contr.sum(2)
> design <- model.matrix(~Strain*Treatment)
```

This defines four coefficients with the following interpretations:

Coefficient	Comparison	Interpretation
Intercept	$(WT.U + WT.S + Mu.U + Mu.S)/4$	Grand mean
Strain1	$(WT.U + WT.S - Mu.U - Mu.S)/4$	Strain main effect
Treatment1	$(WT.U - WT.S + Mu.U - Mu.S)/4$	Treatment main effect
Strain1:Treatment1	$(WT.U - WT.S - Mu.U + Mu.S)/4$	Interaction

This parametrization has many appealing mathematical properties and is the classical parametrization used for factorial designs in much experimental design theory. However it defines only one coefficient which is directly of interest to us, namely the interaction. Our three contrasts of interest could be extracted using

```
> fit <- lmFit(eset, design)
> cont.matrix <- cbind(SvsUinWT=c(0,0,-2,-2),SvsUinMu=c(0,0,-2,2),Diff=c(0,0,0,4))
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
```

The results will be identical to those for the previous three approaches.

The various approaches described here for the  $2 \times 2$  factorial problem are equivalent and differ only in the parametrization chosen for the linear model. The fitted model objects `fit` will differ only in the `coefficients` and associated components. The residual standard deviations `fit$sigma`, residual degrees of freedom `fit$df.residual` and all components of `fit2` will be identical regardless of parametrization used. Since the approaches are equivalent, users are free to choose whichever one is most intuitive or convenient.

## 9.6 Time Course Experiments

### 9.6.1 Replicated time points

Time course experiments are those in which RNA is extracted at several time points after the onset of some treatment or stimulation. How best to analyse a time course experiment depends on the nature of the experiment, and especially on the number of distinct time points. We consider first experiments with a relative small number of replicated time points. Simple time course experiments of this type are similar to experiments with several groups covered in Section 9.3.

As an example, we consider here a two-way experiment in which time course profiles are to be compared for two genotypes. Consider the targets frame

FileName	Target
File1	wt.0hr
File2	wt.0hr
File3	wt.6hr
File4	wt.24hr
File5	mu.0hr
File6	mu.0hr
File7	mu.6hr
File8	mu.24hr

The targets are RNA samples collected from wild-type and mutant animals at 0, 6 and 24 hour time points. This can be viewed as a factorial experiment but a simpler approach is to use the group-mean parametrization.

```
> lev <- c("wt.0hr","wt.6hr","wt.24hr","mu.0hr","mu.6hr","mu.24hr")
> f <- factor(targets$Target, levels=lev)
> design <- model.matrix(~0+f)
> colnames(design) <- lev
> fit <- lmFit(eset, design)
```

Which genes respond at either the 6 hour or 24 hour times in the wild-type? We can find these by extracting the contrasts between the wild-type times.

```
> cont.wt <- makeContrasts(
+   "wt.6hr-wt.0hr",
+   "wt.24hr-wt.6hr",
+   levels=design)
> fit2 <- contrasts.fit(fit, cont.wt)
> fit2 <- eBayes(fit2)
> topTableF(fit2, adjust="BH")
```

Any two contrasts between the three times would give the same result. The same gene list would be obtained had "wt.24hr-wt.0hr" been used in place of "wt.24hr-wt.6hr" for example.

Which genes respond (i.e., change over time) in the mutant?

```
> cont.mu <- makeContrasts(
+   "mu.6hr-mu.0hr",
+   "mu.24hr-mu.6hr",
+   levels=design)
> fit2 <- contrasts.fit(fit, cont.mu)
> fit2 <- eBayes(fit2)
> topTableF(fit2, adjust="BH")
```

Which genes respond *differently* over time in the mutant relative to the wild-type?

```
> cont.dif <- makeContrasts(
+   Dif6hr =(mu.6hr-mu.0hr)-(wt.6hr-wt.0hr),
+   Dif24hr=(mu.24hr-mu.6hr)-(wt.24hr-wt.6hr),
+   levels=design)
> fit2 <- contrasts.fit(fit, cont.dif)
> fit2 <- eBayes(fit2)
> topTableF(fit2, adjust="BH")
```

The method of analysis described in this section was used for a six-point time course experiment on histone deacetylase inhibitors [24].

### 9.6.2 Many time points

Now we consider an example with many time points for each group. When there are many time points, it is reasonable to assume that expression changes smoothly over time rather than making discrete jumps from one time point to another. This type of time course can be analysed by fitting a temporal trend using a regression spline or a polynomial.

Consider the following targets frame, with 32 rows:

FileName	Group	Time
File1	Control	1
File2	Control	2
⋮	⋮	⋮
File16	Control	16
File17	Treat	1
File18	Treat	2
⋮	⋮	⋮
File32	Treat	16

It might be reasonable to represent a time course for a particular gene in a particular condition using a cubic spline curve with a modest number of knots. Choosing effective degrees of freedom to be in range 3–5 is reasonable. Setup a basis for a natural regression spline:

```
> library(splines)
> X <- ns(targets$Time, df=5)
```

Then fit separate curves for the control and treatment groups:

```
> Group <- factor(targets$Group)
> design <- model.matrix(~Group*X)
> fit <- lmFit(y, design)
> fit <- eBayes(fit)
```

This creates a model with 12 parameters, with the last 5 corresponding to interaction, i.e., to differences in the curves between groups. To detect genes with different time trends for treatment vs control:

```
> topTable(fit, coef=8:12)
```

This conducts a moderated F-test for each gene on 5 df, which can detect very general differences between the treatment and control curves.

Note that for this analysis, it is not necessary to have replicates, nor is it necessary for the two treatment groups to be observed at identical time points.

## 9.7 Multi-level Experiments

We have considered paired comparisons, and we have considered comparisons between two independent groups. There are however experiments that combine both of these types of comparisons.

Consider a single-channel experiment with the following targets frame:

FileName	Subject	Condition	Tissue
File01	1	Diseased	A
File02	1	Diseased	B
File03	2	Diseased	A
File04	2	Diseased	B
File05	3	Diseased	A
File06	3	Diseased	B
File07	4	Normal	A
File08	4	Normal	B
File09	5	Normal	A
File10	5	Normal	B
File11	6	Normal	A
File12	6	Normal	B

This experiment involves 6 subjects, including 3 patients who have the disease and 3 normal subjects. From each subject, we have expression profiles of two tissue types, A and B.

In analysing this experiment, we want to compare the two tissue types. This comparison can be made within subjects, because each subject yields a value for both tissues. We also want to compare diseased subjects to normal subjects, but this comparison is between subjects.

If we only wanted to compare the two tissue types, we could do a paired samples comparison. If we only wanted to compared diseased to normal, we could do an ordinary two group comparison. Since we need to make comparisons both within and between subjects, it is necessary to treat Patient as a random effect. This can be done in limma using the `duplicateCorrelation` function.

The two experimental factors Condition and Tissue could be handled in many ways. Here we will assume that it is convenient to join the two into a combined factor:

```
> Treat <- factor(paste(targets$Condition,targets$Tissue,sep="."))
> design <- model.matrix(~0+Treat)
> colnames(design) <- levels(Treat)
```

Then we estimate the correlation between measurements made on the same subject:

```
> corfit <- duplicateCorrelation(eset,design,block=targets$Subject)
> corfit$consensus
```

Then this inter-subject correlation is input into the linear model fit:

```
> fit <- lmFit(eset,design,block=targets$Subject,correlation=corfit$consensus)
```

Now we can make any comparisons between the experimental conditions in the usual way, example:

```
> cm <- makeContrasts(  
+       DiseasedvsNormalForTissueA = Diseased.A-Normal.A,  
+       DiseasedvsNormalForTissueB = Diseased.B-Normal.B,  
+       TissueAvsTissueBForNormal = Normal.B-Normal.A,  
+       TissueAvsTissueBForDiseased = Diseased.B-Diseased.A,  
+ levels=design)
```

Then compute these contrasts and moderated t-tests:

```
> fit2 <- contrasts.fit(fit, cm)  
> fit2 <- eBayes(fit2)
```

Then

```
> topTable(fit2, coef="DiseasedvsNormalForTissueA")
```

will find those genes that are differentially expressed between the normal and diseased subjects in the A tissue type. And so on.

This experiment has two levels of variability. First, there is the variation from person to person, which we call the between-subject strata. Then there is the variability of repeat measurements made on the same subject, the within-subject strata. The between-subject variation is always expected to be larger than within-subject, because the latter is adjusted for baseline differences between the subjects. Here the comparison between tissues can be made within subjects, and hence should be more precise than the comparison between diseased and normal, which must be made between subjects.

# Chapter 10

## Two-Color Experiments with a Common Reference

### 10.1 Introduction

Now consider two-color microarray experiments in which a common reference has been used on all the arrays. If the same channel has been used for the common reference throughout the experiment, then the expression log-ratios may be analysed exactly as if they were log-expression values from a single channel experiment. In these cases, the design matrix can be formed as for a single channel experiment.

When the common reference is dye-swapped, the simplest method is to setup the design matrix using the `modelMatrix()` function and the targets file.

### 10.2 Two Groups

Suppose now that we wish to compare two wild type (Wt) mice with three mutant (Mu) mice using arrays hybridized with a common reference RNA (Ref):

FileName	Cy3	Cy5
File1	Ref	WT
File2	Ref	WT
File3	Ref	Mu
File4	Ref	Mu
File5	Ref	Mu

The interest here is in the comparison between the mutant and wild type mice. There are two major ways in which this comparison can be made. We can either

1. create a design matrix which includes a coefficient for the mutant vs wild type difference, or
2. create a design matrix which includes separate coefficients for wild type and mutant mice and then extract the difference as a contrast.

For the first approach, the design matrix should be as follows

```
> design
```

	WTvsREF	MUvsWT
Array1	1	0
Array2	1	0
Array3	1	1
Array4	1	1
Array5	1	1

Here the first coefficient estimates the difference between wild type and the reference for each probe while the second coefficient estimates the difference between mutant and wild type. For those not familiar with model matrices in linear regression, it can be understood in the following way. The matrix indicates which coefficients apply to each array. For the first two arrays the fitted values will be just the **WTvsREF** coefficient, which is correct. For the remaining arrays the fitted values will be **WTvsREF + MUvsWT**, which is equivalent to mutant vs reference, also correct. For reasons that will be apparent later, this is sometimes called the *treatment-contrasts* parametrization. Differentially expressed genes can be found by

```
> fit <- lmFit(MA, design)
> fit <- eBayes(fit)
> topTable(fit, coef="MUvsWT", adjust="BH")
```

There is no need here to use `contrasts.fit()` because the comparison of interest is already built into the fitted model. This analysis is analogous to the classical *pooled two-sample t-test* except that information has been borrowed between genes.

For the second approach, the design matrix should be

	WT	MU
Array1	1	0
Array2	1	0
Array3	0	1
Array4	0	1
Array5	0	1

The first coefficient now represents wild-type vs the reference and the second represents mutant vs the reference. Our comparison of interest is the difference between these two coefficients. We will call this the *group-means* parametrization. Differentially expressed genes can be found by

```
> fit <- lmFit(MA, design)
> cont.matrix <- makeContrasts(MUvsWT=MU-WT, levels=design)
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
> topTable(fit2, adjust="BH")
```

The results will be exactly the same as for the first approach.

The design matrix can be constructed

1. manually,
2. using the limma function `modelMatrix()`, or
3. using the built-in R function `model.matrix()`.

Let `Group` be the factor defined by

```
> Group <- factor(c("WT","WT","Mu","Mu","Mu"), levels=c("WT","Mu"))
```

For the first approach, the treatment-contrasts parametrization, the design matrix can be computed by

```
> design <- cbind(WTvsRef=1,MUvsWT=c(0,0,1,1,1))
```

or by

```
> param <- cbind(WTvsRef=c(-1,1,0),MUvsWT=c(0,-1,1))
> rownames(param) <- c("Ref","WT","Mu")
> design <- modelMatrix(targets, parameters=param)
```

or by

```
> design <- model.matrix(~Group)
> colnames(design) <- c("WTvsRef","MUvsWT")
```

all of which produce the same result. For the second approach, the group-means parametrization, the design matrix can be computed by

```
> design <- cbind(WT=c(1,1,0,0,0),MU=c(0,0,1,1,1))
```

or by

```
> param <- cbind(WT=c(-1,1,0),MU=c(-1,0,1))
> rownames(param) <- c("Ref","WT","Mu")
> design <- modelMatrix(targets, parameters=param)
```

or by

```
> design <- model.matrix(~0+Group)
> colnames(design) <- c("WT","Mu")
```

all of which again produce the same result.

## 10.3 Several Groups

The above approaches for two groups extend easily to any number of groups. Suppose that the experiment has been conducted to compare three RNA sources, “RNA1”, “RNA2” and “RNA3”. For example the targets frame might be



FileName	Cy3	Cy5
File1	Ref	RNA1
File2	RNA1	Ref
File3	Ref	RNA2
File4	RNA2	Ref
File5	Ref	RNA3

For this experiment the design matrix could be formed by

```
> design <- modelMatrix(targets, ref="Ref")
```

after which the analysis would be exactly as for the equivalent single channel experiment in Section 9.3. For example, to make all pair-wise comparisons between the three groups one could proceed

```
> fit <- lmFit(eset, design)
> contrast.matrix <- makeContrasts(RNA2-RNA1, RNA3-RNA2, RNA3-RNA1, levels=design)
> fit2 <- contrasts.fit(fit, contrast.matrix)
> fit2 <- eBayes(fit2)
```

and so on.

# Chapter 11

## Direct Two-Color Experimental Designs

### 11.1 Introduction

Direct two-color designs are those in which there is no common reference, but the RNA samples are instead compared directly by competitive hybridization on the same arrays. Direct two-color designs can be very efficient and powerful, but they require the most statistical knowledge to choose the appropriate design matrix.

### 11.2 Simple Comparisons

#### 11.2.1 Replicate Arrays

The simplest possible microarray experiment is one with a series of replicate two-color arrays all comparing the same two RNA sources. For a three-array experiment comparing wild type (wt) and mutant (mu) RNA, the targets file might contain the following entries:

FileName	Cy3	Cy5
File1	wt	mu
File2	wt	mu
File3	wt	mu

A list of differentially expressed probes might be found for this experiment by

```
> fit <- lmFit(MA)
> fit <- eBayes(fit)
> topTable(fit)
```

where `MA` holds the normalized data. The default design matrix used here is just a single column of ones. The experiment here measures the fold change of mutant over wild type. Genes which have positive M-values are more highly expressed in the mutant RNA while genes with negative M-values are more highly expressed in the wild type. The analysis is analogous

to the classical single-sample  $t$ -test except that we have used empirical Bayes methods to borrow information between genes.

## 11.2.2 Dye Swaps

A simple modification of the above experiment would be to swap the dyes for one of the arrays. The targets file might now be

FileName	Cy3	Cy5
File1	wt	mu
File2	mu	wt
File3	wt	mu

Now the analysis would be

```
> design <- c(1,-1,1)
> fit <- lmFit(MA, design)
> fit <- eBayes(fit)
> topTable(fit)
```

Alternatively the design matrix could be set, replacing the first of the above code lines, by

```
> design <- modelMatrix(targets, ref="wt")
```

where **targets** is the data frame holding the targets file information.

If there are at least two arrays with each dye-orientation, then it is possible to estimate and adjust for any probe-specific dye effects. The dye-effect is estimated by an intercept term. If the experiment was

FileName	Cy3	Cy5
File1	wt	mu
File2	mu	wt
File3	wt	mu
File4	mu	wt

then we could set

```
> design <- cbind(DyeEffect=1,MUvsWT=c(1,-1,1,-1))
> fit <- lmFit(MA, design)
> fit <- eBayes(fit)
```

The genes which show dye effects can be seen by

```
> topTable(fit, coef="DyeEffect")
```

The genes which are differentially expressed in the mutant are obtained by

```
> topTable(fit, coef="MUvsWT")
```

The fold changes and significant tests in this list are corrected for dye-effects. Including the dye-effect in the model in this way uses up one degree of freedom which might otherwise be used to estimate the residual variability, but it is valuable if many genes show non-negligible dye-effects.

## 11.3 A Correlation Approach to Technical Replication

In the previous sections we have assumed that all arrays are biological replicates. Now consider an experiment in which two wild-type and two mice from the same mutant strain are compared using two arrays for each pair of mice. The targets might be

FileName	Cy3	Cy5
File1	wt1	mu1
File2	wt1	mu1
File3	wt2	mu2
File4	wt2	mu2

The first and second and third and fourth arrays are *technical replicates*. It would not be correct to treat this experiment as comprising four replicate arrays because the technical replicate pairs are not independent, in fact they are likely to be positively correlated.

One way to analyze these data is the following:

```
> biolrep <- c(1, 1, 2, 2)
> corfit <- duplicateCorrelation(MA, ndups = 1, block = biolrep)
> fit <- lmFit(MA, block = biolrep, cor = corfit$consensus)
> fit <- eBayes(fit)
> topTable(fit, adjust = "BH")
```

The vector `biolrep` indicates the two blocks corresponding to biological replicates. The value `corfit$consensus` estimates the average correlation within the blocks and should be positive. This analysis is analogous to *mixed model* analysis of variance [21, Chapter 18] except that information has been borrowed between genes. Information is borrowed by constraining the within-block correlations to be equal between genes and by using empirical Bayes methods to moderate the standard deviations between genes [38].

If the technical replicates were in dye-swap pairs as

FileName	Cy3	Cy5
File1	wt1	mu1
File2	mu1	wt1
File3	wt2	mu2
File4	mu2	wt2

then one might use

```
> design <- c(1, -1, 1, -1)
> corfit <- duplicateCorrelation(MA, design, ndups = 1, block = biolrep)
> fit <- lmFit(MA, design, block = biolrep, cor = corfit$consensus)
> fit <- eBayes(fit)
> topTable(fit, adjust = "BH")
```

In this case the correlation `corfit$consensus` should be negative because the technical replicates are dye-swaps and should vary in opposite directions.

This method of handling technical replication using `duplicateCorrelation()` is somewhat limited for two-color experiments. If for example one technical replicate was dye-swapped and the other not,

FileName	Cy3	Cy5
File1	wt1	mu1
File2	mu1	wt1
File3	wt2	mu2
File4	wt2	mu2

then there is no way to use `duplicateCorrelation()` because the technical replicate correlation will be negative for the first pair but positive for the second. In this case, there is no good alternative to treating the technical replicates as if they were biological, so that that the experiment would be analysed as a simple comparison with dye-swaps. Beware however that treating technical replicates as biological gives  $p$ -values that are smaller than they should be.

# Chapter 12

## Separate Channel Analysis of Two-Color Data

Separate channel analysis is a way to analyse two-color data in terms of the individual channel intensities [41]. In effect, separate channel analysis converts a two-color experiment into a single channel experiment with twice as many arrays but with a technical pairing between the two channels that originated from the same array.

Consider an experiment comparing young and old animals for both both wild-type and mutant genotypes.

FileName	Cy3	Cy5
File1	wt.young	wt.old
File2	wt.old	wt.young
File3	mu.young	mu.old
File4	mu.old	mu.young

Each of the arrays in this experiment makes a direct comparison between young and old RNA targets. There are no arrays which compare wild-type and mutant animals. This is an example of an *unconnected* design in that there are no arrays linking the wild-type and mutant targets. It is not possible to make comparisons between wild-type and mutant animals on the basis of log-ratios alone. So to do this it is necessary to analyze the red and green channels intensities separately, i.e., to analyze log-intensities instead of log-ratios. It is possible to do this using a mixed model representation which treats each spot as a randomized block [48, 37]. **Limma** implements mixed model methods for separate channel analysis which make use of shrinkage methods to ensure stable and reliable inference with small numbers of arrays [37]. **Limma** also provides between-array normalization to prepare for separate channel analysis, for example

```
> MA <- normalizeBetweenArrays(MA, method="Aquantile")
```

scales the intensities so that *A*-values have the same distribution across arrays.

The first step in the differential expression analysis is to convert the targets frame to be channel rather than array orientated.

```
> targets2 <- targetsA2C(targets)
> targets2
```

	channel.col	FileName	Target
File1.1	1	File1	wt.young
File1.2	2	File1	wt.old
File2.1	1	File2	wt.old
File2.2	2	File2	wt.young
File3.1	1	File3	mu.young
File3.2	2	File3	mu.old
File4.1	1	File4	mu.old
File4.2	2	File4	mu.young

The following code produces a design matrix with eight rows and four columns:

```
> u <- unique(targets2$Target)
> f <- factor(targets2$Target, levels=u)
> design <- model.matrix(~0+f)
> colnames(design) <- u
```

Inference proceeds as for within-array replicate spots except that the correlation to be estimated is that between the two channels for the same spot rather than between replicate spots.

```
> corfit <- intraspotCorrelation(MA, design)
> fit <- lmscFit(MA, design, correlation=corfit$consensus)
```

Subsequent steps proceed as for log-ratio analyses. For example if we want to compare wild-type young to mutant young animals, we could extract this contrast by

```
> cont.matrix <- makeContrasts("mu.young-wt.young",levels=design)
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
> topTable(fit2, adjust="BH")
```

# Chapter 13

## Statistics for Differential Expression

### 13.1 Summary Top-Tables

Limma provides functions `topTable()` and `decideTests()` which summarize the results of the linear model, perform hypothesis tests and adjust the  $p$ -values for multiple testing. Results include (log2) fold changes, standard errors,  $t$ -statistics and  $p$ -values. The basic statistic used for significance analysis is the *moderated  $t$ -statistic*, which is computed for each probe and for each contrast. This has the same interpretation as an ordinary  $t$ -statistic except that the standard errors have been moderated across genes, i.e., shrunk towards a common value, using a simple Bayesian model. This has the effect of borrowing information from the ensemble of genes to aid with inference about each individual gene [36]. Moderated  $t$ -statistics lead to  $p$ -values in the same way that ordinary  $t$ -statistics do except that the degrees of freedom are increased, reflecting the greater reliability associated with the smoothed standard errors. The effectiveness of the moderated  $t$  approach has been demonstrated on test data sets for which the differential expression status of each probe is known [12].

A number of summary statistics are presented by `topTable()` for the top genes and the selected contrast. The `logFC` column gives the value of the contrast. Usually this represents a log<sub>2</sub>-fold change between two or more experimental conditions although sometimes it represents a log<sub>2</sub>-expression level. The `AveExpr` column gives the average log<sub>2</sub>-expression level for that gene across all the arrays and channels in the experiment. Column `t` is the moderated  $t$ -statistic. Column `P.Value` is the associated  $p$ -value and `adj.P.Value` is the  $p$ -value adjusted for multiple testing. The most popular form of adjustment is "BH" which is Benjamini and Hochberg's method to control the false discovery rate [1]. The adjusted values are often called  $q$ -values if the intention is to control or estimate the false discovery rate. The meaning of "BH"  $q$ -values is as follows. If all genes with  $q$ -value below a threshold, say 0.05, are selected as differentially expressed, then the expected proportion of false discoveries in the selected group is controlled to be less than the threshold value, in this case 5%. This procedure is equivalent to the procedure of Benjamini and Hochberg although the original paper did not formulate the method in terms of adjusted  $p$ -values.

The  $B$ -statistic (`lods` or `B`) is the log-odds that the gene is differentially expressed [36, Section 5]. Suppose for example that  $B = 1.5$ . The odds of differential expression is



$\exp(1.5)=4.48$ , i.e., about four and a half to one. The probability that the gene is differentially expressed is  $4.48/(1+4.48)=0.82$ , i.e., the probability is about 82% that this gene is differentially expressed. A  $B$ -statistic of zero corresponds to a 50-50 chance that the gene is differentially expressed. The  $B$ -statistic is automatically adjusted for multiple testing by assuming that 1% of the genes, or some other percentage specified by the user in the call to `eBayes()`, are expected to be differentially expressed. The  $p$ -values and  $B$ -statistics will normally rank genes in the same order. In fact, if the data contains no missing values or quality weights, then the order will be precisely the same.

As with all model-based methods, the  $p$ -values depend on normality and other mathematical assumptions which are never exactly true for microarray data. It has been argued that the  $p$ -values are useful for ranking genes even in the presence of large deviations from the assumptions [40, 38]. Benjamini and Hochberg's control of the false discovery rate assumes independence between genes, although Reiner et al [27] have argued that it works for many forms of dependence as well. The  $B$ -statistic probabilities depend on the same assumptions but require in addition a prior guess for the proportion of differentially expressed probes. The  $p$ -values may be preferred to the  $B$ -statistics because they do not require this prior knowledge.

The `eBayes()` function computes one more useful statistic. The moderated  $F$ -statistic ( $F$ ) combines the  $t$ -statistics for all the contrasts into an overall test of significance for that gene.

The  $F$ -statistic tests whether any of the contrasts are non-zero for that gene, i.e., whether that gene is differentially expressed on any contrast. The denominator degrees of freedom is the same as that of the moderated- $t$ . Its  $p$ -value is stored as `fit$F.p.value`. It is similar to the ordinary  $F$ -statistic from analysis of variance except that the denominator mean squares are moderated across genes.

A frequently asked question relates to the occasional occurrence that all of the adjusted  $p$ -values are equal to 1. This is not an error situation but rather an indication that there is no evidence of differential expression in the data after adjusting for multiple testing. This can occur even though many of the raw  $p$ -values may seem highly significant when taken as individual values. This situation typically occurs when none of the raw  $p$ -values are less than  $1/G$ , where  $G$  is the number of probes included in the fit. In that case the adjusted  $p$ -values are typically equal to 1 using any of the adjustment methods except for `adjust="none"`.

## 13.2 Fitted Model Objects

The output from `lmFit()` is an object of class `MArrayLM`. This section gives some mathematical details describing what is contained in such objects. This section can be skipped by readers not interested in such details.

The linear model for gene  $j$  has residual variance  $\sigma_j^2$  with sample value  $s_j^2$  and degrees of freedom  $d_j$ . The output from `lmFit()`, `fit` say, holds the  $s_j$  in component `fit$sigma` and the  $d_j$  in `fit$df.residual`. The covariance matrix of the estimated  $\hat{\beta}_j$  is  $\sigma_j^2 C^T (X^T V_j X)^{-1} C$  where  $V_j$  is a weight matrix determined by prior weights, any covariance terms introduced by correlation structure and any iterative weights introduced by robust estimation. The square-roots of the diagonal elements of  $C^T (X^T V_j X)^{-1} C$  are called unscaled standard deviations and

are stored in `fit$stdev.unscaled`. The ordinary  $t$ -statistic for the  $k$ th contrast for gene  $j$  is  $t_{jk} = \hat{\beta}_{jk}/(u_{jk}s_j)$  where  $u_{jk}$  is the unscaled standard deviation. The ordinary  $t$ -statistics can be recovered by

```
> tstat.ord <- fit$coef/fit$stdev.unscaled/fit$sigma
```

after fitting a linear model if desired.

The empirical Bayes method assumes an inverse Chisquare prior for the  $\sigma_j^2$  with mean  $s_0^2$  and degrees of freedom  $d_0$ . The posterior values for the residual variances are given by

$$\tilde{s}_j^2 = \frac{d_0 s_0^2 + d_j s_j^2}{d_0 + d_j}$$

where  $d_j$  is the residual degrees of freedom for the  $j$ th gene. The output from `eBayes()` contains  $s_0^2$  and  $d_0$  as `fit$s2.prior` and `fit$df.prior` and the  $\tilde{s}_j^2$  as `fit$s2.post`. The moderated  $t$ -statistic is

$$\tilde{t}_{jk} = \frac{\hat{\beta}_{jk}}{u_{jk}\tilde{s}_j}$$

This can be shown to follow a  $t$ -distribution on  $d_0 + d_j$  degrees of freedom if  $\beta_{jk} = 0$  [36]. The extra degrees of freedom  $f_0$  represent the extra information which is borrowed from the ensemble of genes for inference about each individual gene. The output from `eBayes()` contains the  $\tilde{t}_{jk}$  as `fit$t` with corresponding  $p$ -values in `fit$p.value`.

### 13.3 Multiple Testing Across Contrasts

The output from `topTable` includes adjusted  $p$ -values, i.e., it performs multiple testing for the contrast being considered. If several contrasts are being tested simultaneously, then the issue arises of multiple testing for the entire set of hypotheses being considered, across contrasts as well as probes. The function `decideTests()` offers a number of strategies for doing this.

The simplest multiple testing method is `method="separate"`. This method does multiple testing for each contrast separately. This method is the default because it is equivalent to using `topTable()`. Using this method, testing a set of contrasts together will give the same results as when each contrast is tested on its own. The great advantage of this method is that it gives the same results regardless of which set of contrasts are tested together. The disadvantage of this method is that it does not do any multiple testing adjustment between contrasts. Another disadvantage is that the raw  $p$ -value cutoff corresponding to significance can be very different for different contrasts, depending on the number of DE probes. This method is recommended when different contrasts are being analysed to answer more or less independent questions.

`method="global"` is recommended when a set of closely related contrasts are being tested. This method simply appends all the tests together into one long vector of tests, i.e., it treats all the tests as equivalent regardless of which probe or contrast they relate to. An advantage is that the raw  $p$ -value cutoff is consistent across all contrasts. For this reason, `method="global"` is recommended if you want to compare the number of DE genes found for different contrasts,

for example interpreting the number of DE genes as representing the strength of the contrast. However users need to be aware that the number of DE genes for any particular contrasts will depend on which other contrasts are tested at the same time. Hence one should include only those contrasts which are closely related to the question at hand. Unnecessary contrasts should be excluded as these would affect the results for the contrasts of interest. Another more theoretical issue is that there is no theorem which proves that `adjust.method="BH"` in combination with `method="global"` will correctly control the false discovery rate for combinations of negatively correlated contrasts, however simulations, experience and some theory suggest that the method is safe in practice.

The `"hierarchical"` method offers power advantages when used with `adjust.method="holm"` to control the family-wise error rate. However its properties are not yet well understood with `adjust="BH"`.

`method="nestedF"` has a more specialised aim to give greater weight to probes which are significant for two or more contrasts. Most multiple testing methods tend to underestimate the number of such probes. There is some practical experience to suggest that `method="nestedF"` gives less conservative results when finding probes which respond to several different contrasts at once. However this method should still be viewed as experimental. It provides formal false discovery rate control at the probe level only, not at the contrast level.

# Chapter 14

## Array Quality Weights

### 14.1 Introduction

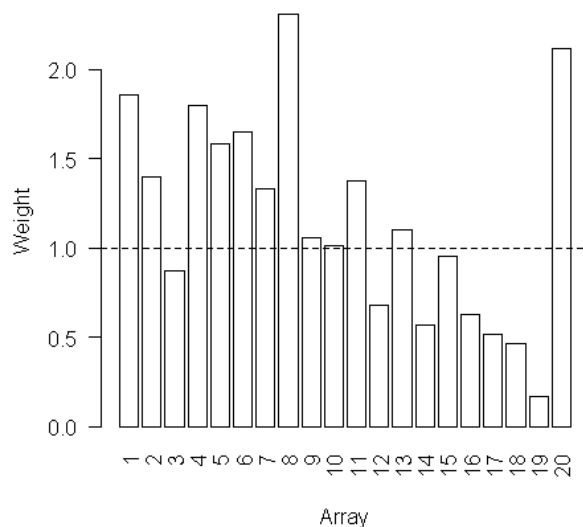
Given an appropriate design matrix, the relative reliability of each array in an experiment can be estimated by measuring how well the expression values for that array follow the linear model. This empirical approach of assessing array quality can be applied to both two-color and single-channel microarray data and is described in [29].

The method is implemented in the `arrayWeights` function, which fits a heteroscedastic model to the expression values for each gene by calling the function `lm.wfit`. (See also `arrayWeightsSimple` which does the same calculation more quickly when there are no probe-level quality weights.) The dispersion model is fitted to the squared residuals from the mean fit, and is set up to have array specific coefficients, which are updated in either full REML scoring iterations, or using an efficient gene-by-gene update algorithm. The final estimates of these array variances are converted to weights which can be used in `lmFit`. This method offers a graduated approach to quality assessment by allowing poorer quality arrays, which would otherwise be discarded, to be included in an analysis but down-weighted.

### 14.2 Example 1

We consider the array quality weights applied to the spike-in controls from a quality control data set courtesy of Andrew Holloway, Ryan van Laar and Dileepa Diyagama from the Peter MacCallum Cancer Centre in Melbourne. This collection of arrays (described in [29]) consists of 100 replicate hybridizations and we will use data from the first 20 arrays. The object `MAlms` stores the loess normalized data for the 120 spike-in control probes on each array. Since these arrays are replicate hybridizations, the default design matrix of a single column of ones is used.

```
> arrayw <- arrayWeights(MAlms)
> barplot(arrayw, xlab="Array", ylab="Weight", col="white", las=2)
> abline(h=1, lwd=1, lty=2)
```

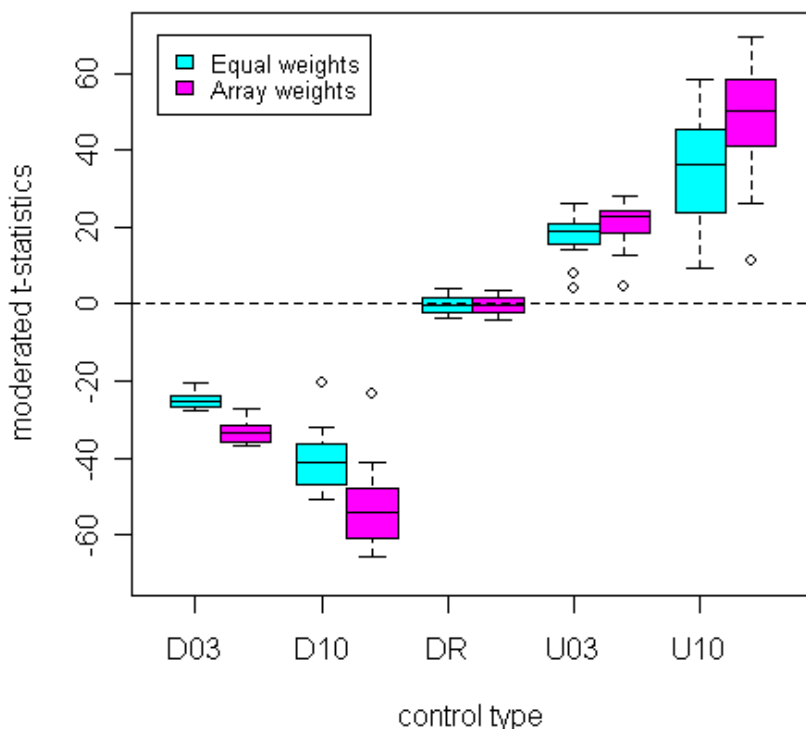


The empirical array weights vary from a minimum of 0.16 for array 19 to a maximum of 2.31 for array 8. These weights can be used in the linear model analysis.

```
> fitw <- lmFit(MAlms, weights=arrayw)
> fitw <- eBayes(fitw)
```

In this example the ratio control spots should show three-fold or ten-fold changes while the dynamic range spots should not be differentially expressed. To compare the moderated *t*-statistics before and after applying array weights, use the following:

```
> fit <- lmFit(MAlms)
> fit <- eBayes(fit)
> boxplot(fit$t~MAlms$genes$Status, at=1:5-0.2, col=5, boxwex=0.4, xlab="control type",
+         ylab="moderated t-statistics", pch=".", ylim=c(-70, 70), medlwd=1)
> boxplot(fitw$t~MAlms$genes$Status, at=1:5+0.2, col=6, boxwex=0.4,
+         add=TRUE, yaxt="n", xaxt="n", medlwd=1, pch=".")
> abline(h=0, col="black", lty=2, lwd=1)
> legend(0.5, 70, legend=c("Equal weights", "Array weights"), fill=c(5,6), cex=0.8)
```



The boxplots show that the  $t$ -statistics for all classes of ratio controls (D03, D10, U03 and U10) move further from zero when array weights are used while the distribution of  $t$ -statistics for the dynamic range controls (DR) does not noticeably change. This demonstrates that the array quality weights increase statistical power to detect true differential expression without increasing the false discovery rate.

The same heteroscedastic model can also be fitted at the print-tip group level using the `printtipWeights` function. If there are  $p$  print-tip groups across  $n$  arrays, the model fitting procedure described in [29] is repeated  $p$  times to produce a weight for each print-tip group on each array for use in `lmFit`. This method can be applied to two-color microarray data where the probes are organized into print-tip groups whose size is specified by the `printer` component of the `MAList`.

## 14.3 Example 2

Below is an example of applying this method to the `Apoa1` data.

```
> ptw <- printtipWeights(MA, design, layout=MA$printer)
> zlim <- c(min(ptw), max(ptw))
> par(mfrow=c(3,2))
```

```
> for(i in seq(7,12,by=1))
+   imageplot(ptw[,i], layout=MA$printer, zlim=zlim, main=colnames(MA)[i])
```

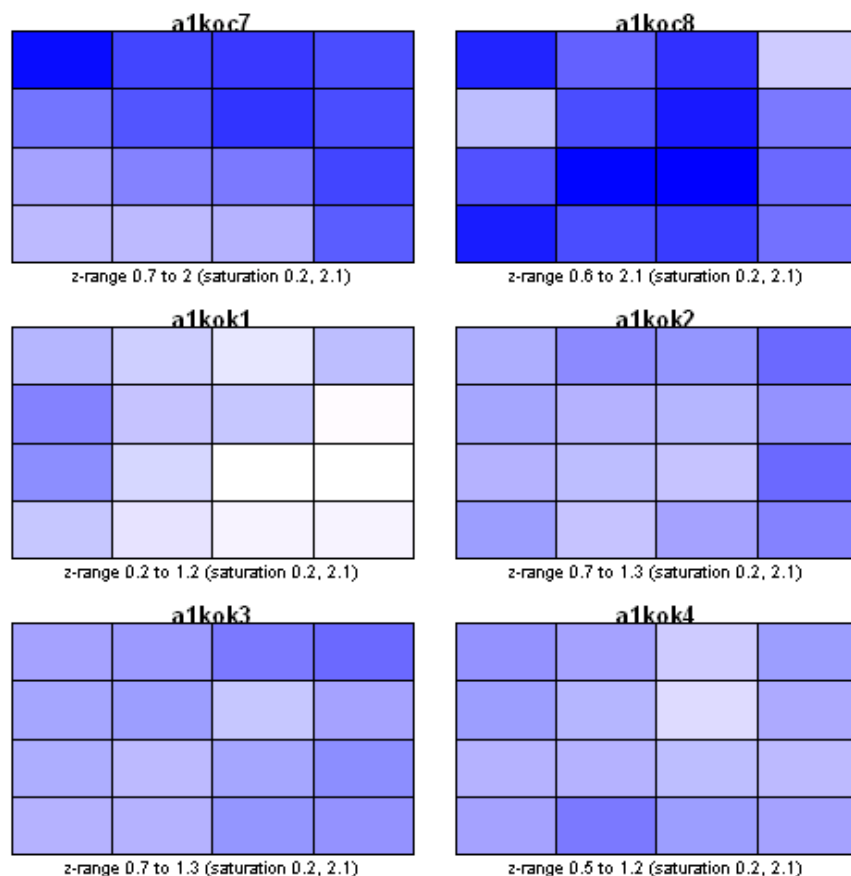


Image plots of the print-tip weights for arrays 7 through to 12 are shown above, with lighter shades indicating print-tip groups which have been assigned lower weights. A corner of array 9 (a1kok1) is measured to be less reproducible than the same region on other arrays, which may be indicative of a spatial artefact. Using these weights in the linear model analysis increases the *t*-statistics of the top ranking genes compared to an analysis without weights (compare the results table below with the table in section 16.2).

```
> fitptw <- lmFit(MA, design, weights=ptw)
> fitptw <- eBayes(fitptw)
> options(digits=3)
> topTable(fitptw,coef=2,number=15,genelist=fitptw$genes$NAME)
```

	ID	logFC	AveExpr	t	P.Value	adj.P.Val	B
2149	ApoAI,lipid-Img	-3.151	12.47	-25.64	1.21e-15	7.73e-12	16.4206
540	EST,HighlysimilartoA	-2.918	12.28	-14.49	2.22e-11	7.09e-08	12.4699
5356	CATECHOLO-METHYLTRAN	-1.873	12.93	-13.16	1.10e-10	2.34e-07	11.5734
4139	EST,WeaklysimilartoC	-0.981	12.61	-11.71	7.28e-10	1.16e-06	10.3623
1739	ApoCIII,lipid-Img	-0.933	13.74	-10.58	3.66e-09	4.67e-06	9.4155
1496	est	-0.949	12.23	-9.92	9.85e-09	1.05e-05	8.6905
2537	ESTs,Highlysimilarto	-1.011	13.63	-9.56	1.75e-08	1.60e-05	8.2587

4941	similartoyeaststerol	-0.873	13.29	-6.88	1.93e-06	1.54e-03	4.6875
947	EST,WeaklysimilartoF	-0.566	10.54	-5.08	7.78e-05	5.52e-02	1.6112
2812	5'similartoPIR:S5501	-0.514	11.65	-4.30	4.31e-04	2.75e-01	0.1242
6073	estrogenrec	0.412	9.79	4.21	5.27e-04	3.06e-01	-0.0497
1347	Musmusculustranscrip	-0.412	10.18	-4.07	7.09e-04	3.47e-01	-0.3106
634	MDB1376	-0.380	9.32	-4.07	7.11e-04	3.47e-01	-0.3123
2	Cy5RT	0.673	10.65	4.04	7.61e-04	3.47e-01	-0.3745
5693	Meox2	0.531	9.77	3.84	1.19e-03	4.74e-01	-0.7649

For example, the moderated  $t$ -statistic of the top ranked gene, ApoA1, which has been knocked-out in this experiment, increases in absolute terms from -23.98 when equal weights are used to -25.64 with print-tip weights. The  $t$ -statistic of the related gene ApoCIII also increases in absolute value (moderated  $t$ -statistic of -9.83 before weighting and -10.58 after). This analysis provides a further example that a graduated approach to quality control can improve power to detect differentially expressed genes.

## 14.4 When to Use Array Weights

Array weights are generally useful when there is some reason to expect variable array quality. For example, RNA samples from human clinical patients are typically variable in quality, so array weights might be used routinely with human *in vivo* data, see for example Ellis et al [9]. If array quality plots suggest a problem, then array weights are indicated. If RNA is plentiful, e.g., from cell lines or model organisms, and quality plots of the arrays don't suggest problems, then array weights are usually not needed.

In gross cases where an array is clearly bad or wrong, it should be removed, rather than downweighted. However this action should be reserved for extreme cases.

If most genes are not differentially expressed, then the design matrix for arrayWeights does not need to be as complex as for the final linear model. For example, in a two-group comparison with just 2 replicates in each group, the array weights should be estimated with the default (intercept) design matrix, otherwise each array is compared only to its partner rather than to the other 3 arrays.



# Chapter 15

## RNA-seq Data

### 15.1 Introduction

The limma approach to RNA-seq explained in the article by Law et al [15]. The voom transformation is applied to the read counts. This converts the counts to log-counts per million with associated precision weights. After this, the RNA-seq data can be analyzed as if it was microarray data. This means for example that any of the linear modelling or gene set testing methods in the limma package can be applied to RNA-seq data.

### 15.2 Making a count matrix

RNA-seq data usually arrives in the form of FastQ or BAM files of unaligned reads. The reads need to be mapped to a reference genome or transcriptome, then summarized at the exon or gene level to produce a matrix of counts. We find the Rsubread package [18] to be convenient, fast and effective for this purpose. Other popular methods include RSEM [16] and HTseq. A runnable example with complete code showing how to use subread and featureCounts with limma is provided at <http://bioinf.wehi.edu.au/RNAseqCaseStudy>.

### 15.3 Differential expression

Suppose that a matrix of read counts `counts` has been created, with rows for genes and columns for samples. The limma-voom method assumes that rows with zero or very low counts have been removed.

It is usual to apply scale normalization to RNA-seq read counts, and the TMM normalization method [31] in particular has been found to perform well in comparative studies. To apply TMM normalization, it is convenient to create a `DGEList` object using the edgeR package:

```
> dge <- DGEList(counts=counts)
> dge <- calcNormFactors(dge)
```

The voom transformation is then applied:

```
v <- voom(dge,design,plot=TRUE)
```

The voom transformation uses the experiment design matrix, and produces an `EList` object.

It is also possible to give a matrix of counts directly to voom without TMM normalization, by

```
> v <- voom(counts,design,plot=TRUE)
```

If the data are very noisy, one can apply the same between-array normalization methods as would be used for microarrays, for example:

```
> v <- voom(counts,design,plot=TRUE,normalize="quantile")
```

After this, the usual limma pipelines for differential expression can be applied, for example:

```
> fit <- lmFit(v,design)
> fit <- eBayes(fit)
> topTable(fit,coef=ncol(design))
```

Or, to give more weight to fold-changes in the ranking, one could use say:

```
> fit <- treat(fit,lfc=log2(1.2))
> topTreat(fit,coef=ncol(design))
```

## 15.4 Differential splicing

limma can also detect genes that show evidence of differential splicing between conditions. One can test for differential splicing associated with any contrast for a linear model.

In this case, the matrix of counts should be at the exon level, with a row for each exon. For example,

```
> dge <- DGEList(counts=counts)
> dge$genes$GeneID <- GeneID
```

where `counts` is a matrix of exon-level counts, and `GeneID` identifies which gene each exon belongs to. Then filter and normalize:

```
> A <- rowSums(dge$counts)
> dge <- dge[A>10,,keep.lib.sizes=FALSE]
> dge <- calcNormFactors(dge)
```

Then apply the voom transformation and fit a linear model:

```
> v <- voom(dge,design,plot=TRUE)
> fit <- lmFit(v,design)
```

Now we can test for differential splicing associated with any coefficient in the linear model. First run the `diffSplice` function:

```
> ex <- diffSplice(fit, geneid="GeneID")
```

Then

```
> topSplice(ex,coef=2,level="gene")
```

will find genes that show evidence of differential splicing associated with the second coefficient in the linear model. The output is similar that from the limma topTable function. More detail can be obtained by

```
> topSplice(ex,coef=2,level="exon")
```

which will show individual exons that are enriched or depleted relative to other exons in the same gene. To display the pattern of exons in the top genes:

```
> plotSplice(ex)
```

# Chapter 16

## Two-Color Case Studies

### 16.1 Swirl Zebrafish: A Single-Group Experiment

In this section we consider a case study in which two RNA sources are compared directly on a set of replicate or dye-swap arrays. The case study includes reading in the data, data display and exploration, as well as normalization and differential expression analysis. The analysis of differential expression is analogous to a classical one-sample test of location for each gene.

In this example we assume that the data is provided as a GAL file called `fish.gal` and raw SPOT output files and that these files are in the current working directory. The data used for this case study can be downloaded from <http://bioinf.wehi.edu.au/limmaGUI/DataSets.html>.

```
> dir()
[1] "fish.gal"          "swirl.1.spot"      "swirl.2.spot"      "swirl.3.spot"      "swirl.4.spot"
[6] "SwirlSample.txt"
```

**Background.** The experiment was carried out using zebrafish as a model organism to study the early development in vertebrates. Swirl is a point mutant in the BMP2 gene that affects the dorsal/ventral body axis. The main goal of the Swirl experiment is to identify genes with altered expression in the Swirl mutant compared to wild-type zebrafish.

**The hybridizations.** Two sets of dye-swap experiments were performed making a total of four replicate hybridizations. Each of the arrays compares RNA from swirl fish with RNA from normal (“wild type”) fish. The experimenters have prepared a tab-delimited targets file called `SwirlSamples.txt` which describes the four hybridizations:

```
> library(limma)
> targets <- readTargets("SwirlSample.txt")
> targets
  SlideNumber  FileName      Cy3      Cy5      Date
1           81 swirl.1.spot  swirl wild type 2001/9/20
2           82 swirl.2.spot wild type      swirl 2001/9/20
3           93 swirl.3.spot  swirl wild type 2001/11/8
4           94 swirl.4.spot wild type      swirl 2001/11/8
```

We see that slide numbers 81, 82, 93 and 94 were used to make the arrays. On slides 81 and 93, swirl RNA was labelled with green (Cy3) dye and wild type RNA was labelled with red (Cy5) dye. On slides 82 and 94, the labelling was the other way around.

Each of the four hybridized arrays was scanned on an Axon scanner to produce a TIFF image, which was then processed using the image analysis software SPOT. The data from the arrays are stored in the four output files listed under `FileName`. Now we read the intensity data into an `RGList` object in R. The default for SPOT output is that `Rmean` and `Gmean` are used as foreground intensities and `morphR` and `morphG` are used as background intensities:

```
> RG <- read.maimages(targets, source="spot")
Read swirl.1.spot
Read swirl.2.spot
Read swirl.3.spot
Read swirl.4.spot
> RG
An object of class "RGList"
$R
      swirl.1  swirl.2  swirl.3  swirl.4
[1,] 19538.470 16138.720 2895.1600 14054.5400
[2,] 23619.820 17247.670 2976.6230 20112.2600
[3,] 21579.950 17317.150 2735.6190 12945.8500
[4,]  8905.143  6794.381  318.9524   524.0476
[5,]  8676.095  6043.542  780.6667   304.6190
8443 more rows ...

$G
      swirl.1  swirl.2  swirl.3  swirl.4
[1,] 22028.260 19278.770 2727.5600 19930.6500
[2,] 25613.200 21438.960 2787.0330 25426.5800
[3,] 22652.390 20386.470 2419.8810 16225.9500
[4,]  8929.286  6677.619  383.2381   786.9048
[5,]  8746.476  6576.292  901.0000   468.0476
8443 more rows ...

$Rb
      swirl.1 swirl.2 swirl.3 swirl.4
[1,]      174      136      82      48
[2,]      174      133      82      48
[3,]      174      133      76      48
[4,]      163      105      61      48
[5,]      140      105      61      49
8443 more rows ...

$Gb
      swirl.1 swirl.2 swirl.3 swirl.4
[1,]      182      175      86      97
[2,]      171      183      86      85
[3,]      153      183      86      85
[4,]      153      142      71      87
[5,]      153      142      71      87
8443 more rows ...
```

```

$targets
  SlideNumber   FileName      Cy3      Cy5      Date
1           81 swirl.1.spot  swirl wild type 2001/9/20
2           82 swirl.2.spot wild type      swirl 2001/9/20
3           93 swirl.3.spot  swirl wild type 2001/11/8
4           94 swirl.4.spot wild type      swirl 2001/11/8

$source
[1] "spot"

```

**The arrays.** The microarrays used in this experiment were printed with 8448 probes (spots), including 768 control spots. The array printer uses a print head with a 4x4 arrangement of print-tips and so the microarrays are partitioned into a 4x4 grid of tip groups. Each grid consists of 22x24 spots that were printed with a single print-tip.

Unlike most image analysis software, SPOT does not store probe annotation in the output files, so we have to read it separately. The gene name associated with each spot is recorded in a GenePix array list (GAL) file:

```

> RG$genes <- readGAL("fish.gal")
> RG$genes[1:30,]

```

	Block	Row	Column	ID	Name
1	1	1	1	control	geno1
2	1	1	2	control	geno2
3	1	1	3	control	geno3
4	1	1	4	control	3XSSC
5	1	1	5	control	3XSSC
6	1	1	6	control	EST1
7	1	1	7	control	geno1
8	1	1	8	control	geno2
9	1	1	9	control	geno3
10	1	1	10	control	3XSSC
11	1	1	11	control	3XSSC
12	1	1	12	control	3XSSC
13	1	1	13	control	EST2
14	1	1	14	control	EST3
15	1	1	15	control	EST4
16	1	1	16	control	3XSSC
17	1	1	17	control	Actin
18	1	1	18	control	Actin
19	1	1	19	control	3XSSC
20	1	1	20	control	3XSSC
21	1	1	21	control	3XSSC
22	1	1	22	control	3XSSC
23	1	1	23	control	Actin
24	1	1	24	control	Actin
25	1	2	1	control	ath1
26	1	2	2	control	Cad-1
27	1	2	3	control	DeltaB
28	1	2	4	control	Dlx4

```

29      1    2      5 control ephrinA4
30      1    2      6 control   FGF8

```

Because we are using SPOT output, the 4x4x22x24 print layout also needs to be set. The easiest way to do this is to infer it from the GAL file:

```
> RG$printer <- getLayout(RG$genes)
```

**Image plots.** It is interesting to look at the variation of background values over the array. Consider image plots of the red and green background for the first array:

```

> imageplot(log2(RG$Rb[,1]), RG$printer, low="white", high="red")
> imageplot(log2(RG$Gb[,1]), RG$printer, low="white", high="green")

```

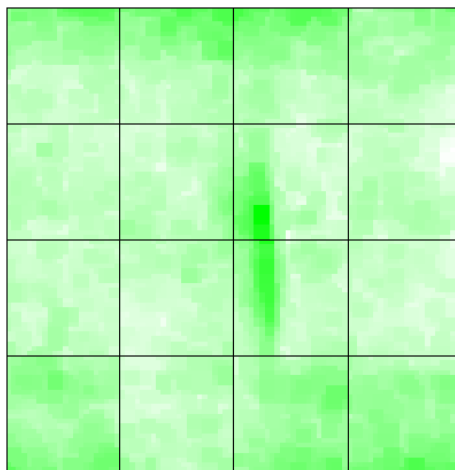
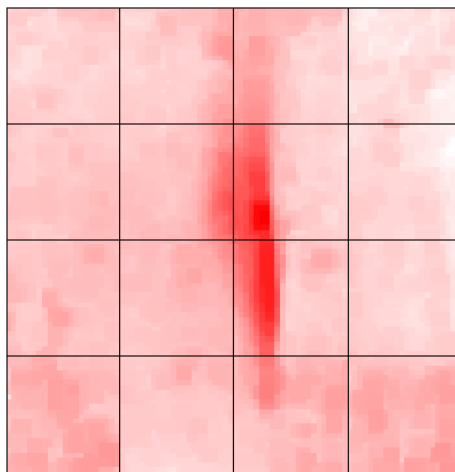
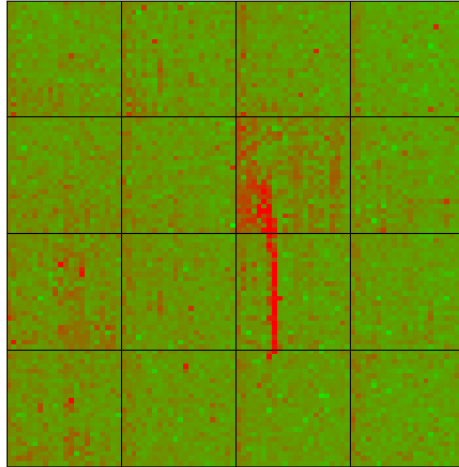


Image plot of the un-normalized log-ratios or M-values for the first array:

```

> MA <- normalizeWithinArrays(RG, method="none")
> imageplot(MA$M[,1], RG$printer, zlim=c(-3,3))

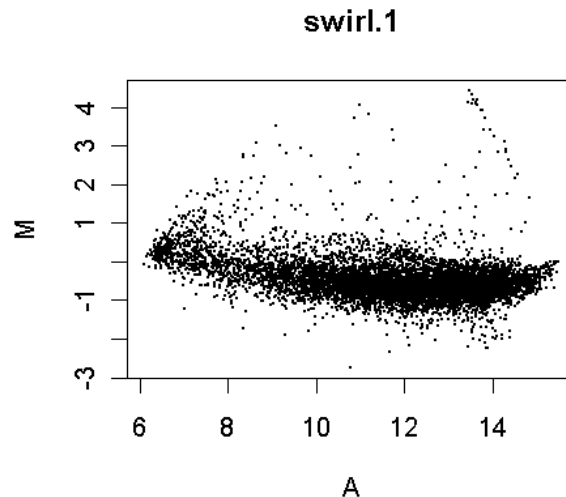
```



The `imageplot` function lies the slide on its side, so the first print-tip group is bottom left in this plot. We can see a red streak across the middle two grids of the 3rd row caused by a scratch or dust on the array. Spots which are affected by this artefact will have suspect M-values. The streak also shows up as darker regions in the background plots.

**MA-plots.** An MA-plot plots the log-ratio of R vs G against the overall intensity of each spot. The log-ratio is represented by the M-value,  $M = \log_2(R) - \log_2(G)$ , and the overall intensity by the A-value,  $A = (\log_2(R) + \log_2(G))/2$ . Here is the MA-plot of the un-normalized values for the first array:

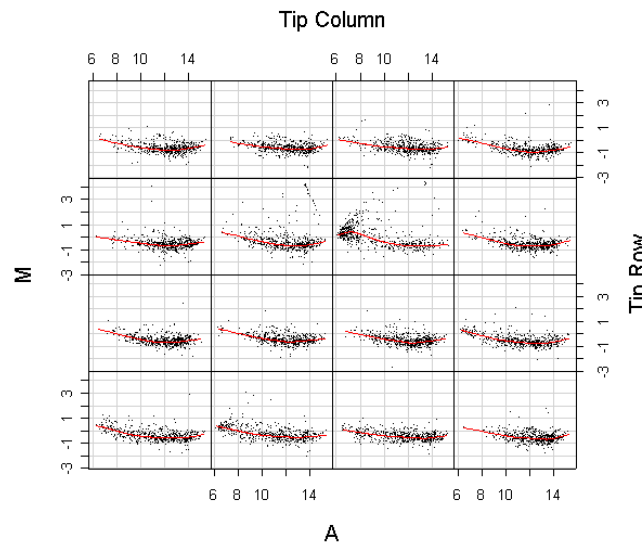
```
> plotMA(MA)
```



The red streak seen on the image plot can be seen as a line of spots in the upper right of this plot. Now we plot the individual MA-plots for each of the print-tip groups on this array, together with the loess curves which will be used for normalization:

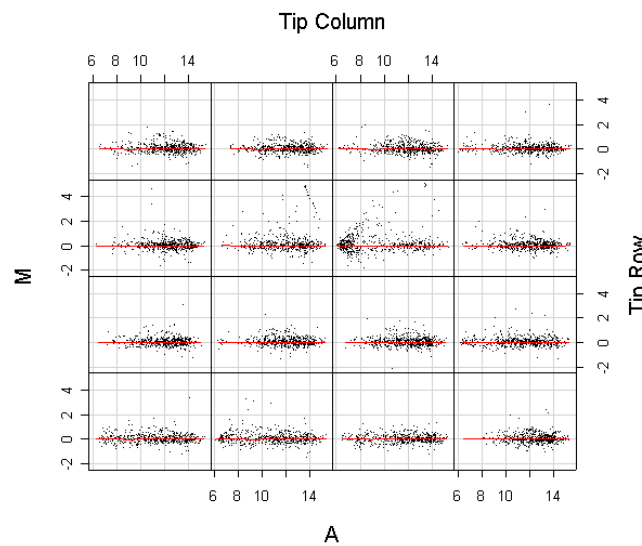


```
> plotPrintTipLoess(MA)
```



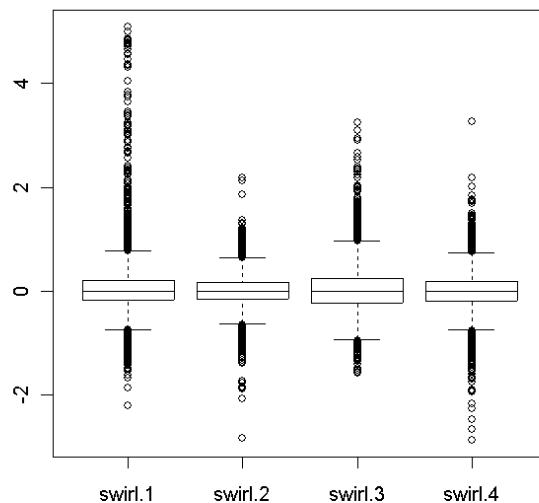
**Normalization.** Print-tip loess normalization:

```
> MA <- normalizeWithinArrays(RG)
> plotPrintTipLoess(MA)
```



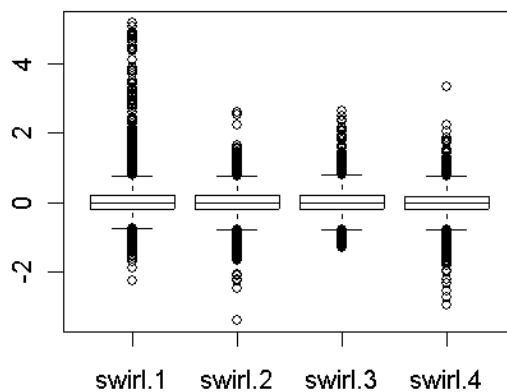
We have normalized the M-values with each array. A further question is whether normalization is required between the arrays. The following plot shows overall boxplots of the M-values for the four arrays.

```
> boxplot(MA$M~col(MA$M),names=colnames(MA$M))
```



There is evidence that the different arrays have different spreads of M-values, so we will scale normalize between the arrays.

```
> MA <- normalizeBetweenArrays(MA,method="scale")
> boxplot(MA$M~col(MA$M),names=colnames(MA$M))
```



Note that scale-normalization is not done routinely for all two-color data sets, in fact it is rarely done with newer platforms. However it does give good results on this data set. It should only be done when there is good evidence of a scale difference in the M-values.

**Linear model.** First setup an appropriate design matrix. The negative numbers in the design matrix indicate the dye-swaps:

```

> design <- modelMatrix(targets, ref="wild type")
Found unique target names:
  swirl wild type
> design
      swirl
swirl.1  -1
swirl.2   1
swirl.3  -1
swirl.4   1

```

Now fit a simple linear model for each gene. This has the effect of estimating the average M-value for each gene, adjusting for the dye-swaps.

```

> fit <- lmFit(MA,design)
> fit
An object of class "MArrayLM"
$coefficients
[1] -0.3556298 -0.3283455 -0.3455845 -0.2254783 -0.3175470
8443 more rows ...

$rank
[1] 1

$assign
NULL

$qr
$qr
      [,1]
[1,]  2.0
[2,] -0.5
[3,]  0.5
[4,] -0.5

$qraux
[1] 1.5

$pivot
[1] 1

$tol
[1] 1e-07

$rank
[1] 1

$df.residual
[1] 3 3 3 3 3
8443 more elements ...

$sigma

```

```
[1] 0.2873571 0.3115307 0.3699258 0.3331054 0.2689609
8443 more elements ...
```

```
$cov.coefficients
[,1]
[1,] 0.25
```

```
$stdev.unscaled
[1] 0.5 0.5 0.5 0.5 0.5
8443 more rows ...
```

```
$pivot
[1] 1
```

```
$genes
  Block Row Column      ID Name
1     1   1      1 control geno1
2     1   1      2 control geno2
3     1   1      3 control geno3
4     1   1      4 control 3XSSC
5     1   1      5 control 3XSSC
8443 more rows ...
```

```
$Amean
[1] 13.44500 13.65700 13.40297 10.71737 10.83383
8443 more elements ...
```

```
$method
[1] "ls"
```

```
$design
[,1]
[1,] -1
[2,]  1
[3,] -1
[4,]  1
```

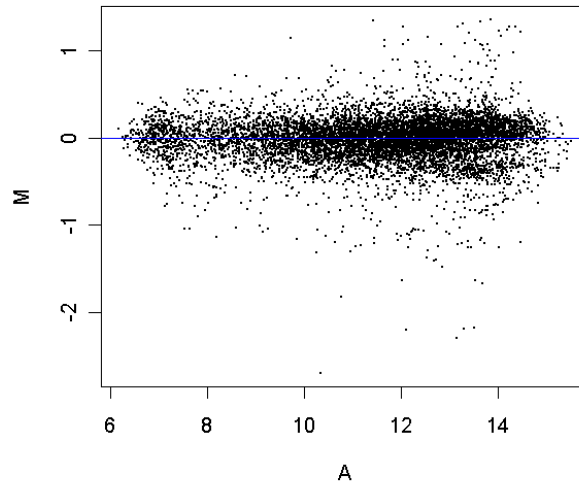
In the above fit object, `coefficients` is the average M-value for each gene and `sigma` is the sample standard deviations for each gene. Ordinary *t*-statistics for comparing mutant to wt could be computed by

```
> ordinary.t <- fit$coef / fit$stdev.unscaled / fit$sigma
```

We prefer though to use empirical Bayes moderated *t*-statistics which are computed below.

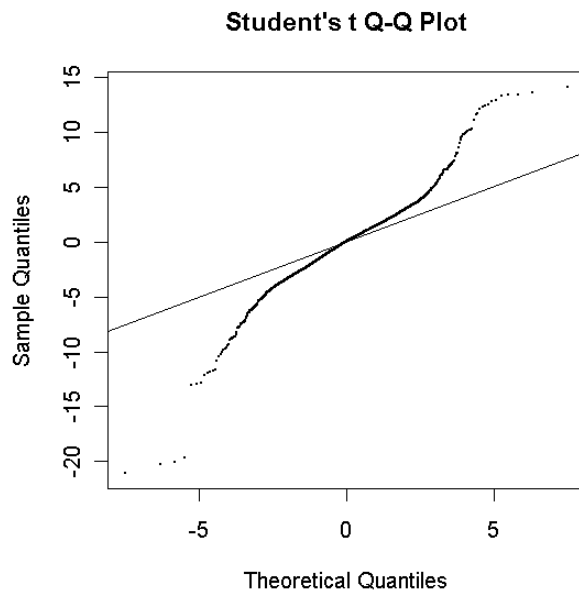
Now create an MA-plot of the average M and A-values for each gene.

```
> plotMA(fit)
> abline(0,0,col="blue")
```



**Empirical Bayes analysis.** We will now go on and compute empirical Bayes statistics for differential expression. The moderated  $t$ -statistics use sample standard deviations which have been shrunk towards a pooled standard deviation value.

```
> fit <- eBayes(fit)
> qqf(fit$t,df=fit$df.prior+fit$df.residual,pch=16,cex=0.2)
> abline(0,1)
```



Visually there seems to be plenty of genes which are differentially expressed. We will obtain a summary table of some key statistics for the top genes.

```

> options(digits=3)
> topTable(fit,number=30,adjust="BH")

```

	Block	Row	Column	ID	Name	logFC	AveExpr	t	P.Value	adj.P.Val	B
3721	8	2	1	control	BMP2	-2.21	12.1	-21.1	1.03e-07	0.000357	7.96
1609	4	2	1	control	BMP2	-2.30	13.1	-20.3	1.34e-07	0.000357	7.78
3723	8	2	3	control	Dlx3	-2.18	13.3	-20.0	1.48e-07	0.000357	7.71
1611	4	2	3	control	Dlx3	-2.18	13.5	-19.6	1.69e-07	0.000357	7.62
8295	16	16	15	fb94h06	20-L12	1.27	12.0	14.1	1.74e-06	0.002067	5.78
7036	14	8	4	fb40h07	7-D14	1.35	13.8	13.5	2.29e-06	0.002067	5.54
515	1	22	11	fc22a09	27-E17	1.27	13.2	13.4	2.44e-06	0.002067	5.48
5075	10	14	11	fb85f09	18-G18	1.28	14.4	13.4	2.46e-06	0.002067	5.48
7307	14	19	11	fc10h09	24-H18	1.20	13.4	13.2	2.67e-06	0.002067	5.40
319	1	14	7	fb85a01	18-E1	-1.29	12.5	-13.1	2.91e-06	0.002067	5.32
2961	6	14	9	fb85d05	18-F10	-2.69	10.3	-13.0	3.04e-06	0.002067	5.29
4032	8	14	24	fb87d12	18-N24	1.27	14.2	12.8	3.28e-06	0.002067	5.22
6903	14	2	15	control	Vox	-1.26	13.4	-12.8	3.35e-06	0.002067	5.20
4546	9	14	10	fb85e07	18-G13	1.23	14.2	12.8	3.42e-06	0.002067	5.18
683	2	7	11	fb37b09	6-E18	1.31	13.3	12.4	4.10e-06	0.002182	5.02
1697	4	5	17	fb26b10	3-I20	1.09	13.3	12.4	4.30e-06	0.002182	4.97
7491	15	5	3	fb24g06	3-D11	1.33	13.6	12.3	4.39e-06	0.002182	4.96
4188	8	21	12	fc18d12	26-F24	-1.25	12.1	-12.2	4.71e-06	0.002209	4.89
4380	9	7	12	fb37e11	6-G21	1.23	14.0	12.0	5.19e-06	0.002216	4.80
3726	8	2	6	control	fli-1	-1.32	10.3	-11.9	5.40e-06	0.002216	4.76
2679	6	2	15	control	Vox	-1.25	13.4	-11.9	5.72e-06	0.002216	4.71
5931	12	6	3	fb32f06	5-C12	-1.10	13.0	-11.7	6.24e-06	0.002216	4.63
7602	15	9	18	fb50g12	9-L23	1.16	14.0	11.7	6.25e-06	0.002216	4.63
2151	5	2	15	control	vent	-1.40	12.7	-11.7	6.30e-06	0.002216	4.62
3790	8	4	22	fb23d08	2-N16	1.16	12.5	11.6	6.57e-06	0.002221	4.58
7542	15	7	6	fb36g12	6-D23	1.12	13.5	11.0	9.23e-06	0.003000	4.27
4263	9	2	15	control	vent	-1.41	12.7	-10.8	1.06e-05	0.003326	4.13
6375	13	2	15	control	vent	-1.37	12.5	-10.5	1.33e-05	0.004026	3.91
1146	3	4	18	fb22a12	2-I23	1.05	13.7	10.2	1.57e-05	0.004242	3.76
157	1	7	13	fb38a01	6-I1	-1.82	10.8	-10.2	1.58e-05	0.004242	3.75

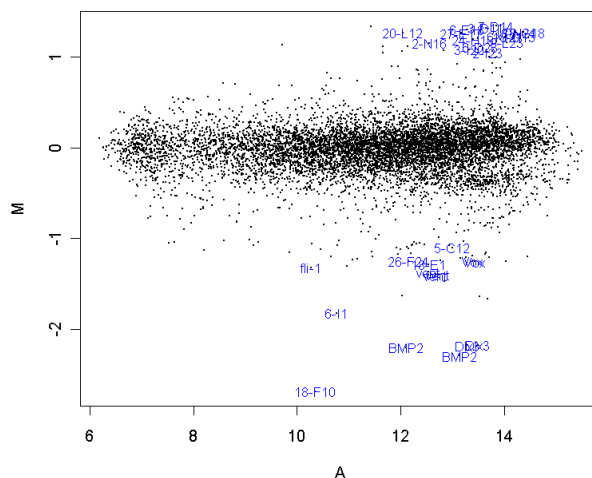
The top gene is BMP2 which is significantly down-regulated in the Swirl zebrafish, as it should be because the Swirl fish are mutant in this gene. Other positive controls also appear in the top 30 genes in terms.

In the table,  $t$  is the empirical Bayes moderated  $t$ -statistic, the corresponding P-values have been adjusted to control the false discovery rate and B is the empirical Bayes log odds of differential expression.

```

> plotMA(fit)
> top30 <- order(fit$lods,decreasing=TRUE)[1:30]
> text(fit$Amean[top30],fit$coef[top30],labels=fit$genes[top30,"Name"],cex=0.8,col="blue")

```



## 16.2 ApoA1 Knockout Mice: A Two-Group Common-Reference Experiment

In this section we consider a case study where two RNA sources are compared through a common reference RNA. The analysis of the log-ratios involves a two-sample comparison of means for each gene.

In this example we assume that the data is available as an `RGList` in the data file `Apoa1.RData`. The data used for this case study can be downloaded from <http://bioinf.wehi.edu.au/limma>.

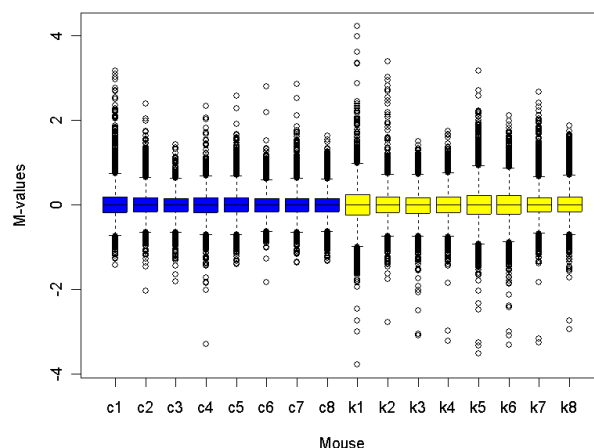
**Background.** The data is from a study of lipid metabolism by [5]. The apolipoprotein AI (Apoa1) gene is known to play a pivotal role in high density lipoprotein (HDL) metabolism. Mice which have the Apoa1 gene knocked out have very low HDL cholesterol levels. The purpose of this experiment is to determine how Apoa1 deficiency affects the action of other genes in the liver, with the idea that this will help determine the molecular pathways through which Apoa1 operates.

**Hybridizations.** The experiment compared 8 ApoA1 knockout mice with 8 normal C57BL/6 ("black six") mice, the control mice. For each of these 16 mice, target mRNA was obtained from liver tissue and labelled using a Cy5 dye. The RNA from each mouse was hybridized to a separate microarray. Common reference RNA was labelled with Cy3 dye and used for all the arrays. The reference RNA was obtained by pooling RNA extracted from the 8 control mice.

Number of arrays	Red	Green
8	Normal “black six” mice	Pooled reference
8	Apoa1 knockout	Pooled reference

This is an example of a single comparison experiment using a common reference. The fact that the comparison is made by way of a common reference rather than directly as for the swirl experiment makes this, for each gene, a two-sample rather than a single-sample setup.

```
> load("Apoa1.RData")
> objects()
[1] "RG"
> names(RG)
[1] "R" "G" "Rb" "Gb" "printer" "genes" "targets"
> RG$targets
      FileName  Cy3      Cy5
c1 a1koc1.spot Pool C57BL/6
c2 a1koc2.spot Pool C57BL/6
c3 a1koc3.spot Pool C57BL/6
c4 a1koc4.spot Pool C57BL/6
c5 a1koc5.spot Pool C57BL/6
c6 a1koc6.spot Pool C57BL/6
c7 a1koc7.spot Pool C57BL/6
c8 a1koc8.spot Pool C57BL/6
k1 a1kok1.spot Pool ApoAI-/-
k2 a1kok2.spot Pool ApoAI-/-
k3 a1kok3.spot Pool ApoAI-/-
k4 a1kok4.spot Pool ApoAI-/-
k5 a1kok5.spot Pool ApoAI-/-
k6 a1kok6.spot Pool ApoAI-/-
k7 a1kok7.spot Pool ApoAI-/-
k8 a1kok8.spot Pool ApoAI-/-
> MA <- normalizeWithinArrays(RG)
> cols <- MA$targets$Cy5
> cols[cols=="C57BL/6"] <- "blue"
> cols[cols=="ApoAI-/-"] <- "yellow"
> boxplot(MA$M~col(MA$M),names=rownames(MA$targets),col=cols,xlab="Mouse",ylab="M-values")
```



Since the common reference here is a pool of the control mice, we expect to see more differences from the pool for the knock-out mice than for the control mice. In terms of the above plot,



this should translate into a wider range of M-values for the knock-out mice arrays than for the control arrays, and we do see this. Since the different arrays are not expected to have the same range of M-values, between-array scale normalization of the M-values is not appropriate here.

Now we can go on to estimate the fold change between the two groups. In this case the design matrix has two columns. The coefficient for the second column estimates the parameter of interest, the log-ratio between knockout and control mice.

```
> design <- cbind("Control-Ref"=1,"KO-Control"=MA$targets$Cy5=="ApoAI-/-")
> design
      Control-Ref KO-Control
[1,]           1           0
[2,]           1           0
[3,]           1           0
[4,]           1           0
[5,]           1           0
[6,]           1           0
[7,]           1           0
[8,]           1           0
[9,]           1           1
[10,]          1           1
[11,]          1           1
[12,]          1           1
[13,]          1           1
[14,]          1           1
[15,]          1           1
[16,]          1           1
> fit <- lmFit(MA, design)
> fit$coef[1:5,]
      Control-Ref KO-Control
[1,]    -0.6595     0.6393
[2,]     0.2294     0.6552
[3,]    -0.2518     0.3342
[4,]    -0.0517     0.0405
[5,]    -0.2501     0.2230
> fit <- eBayes(fit)
> options(digits=3)
```

Normally at this point one would just type

```
> topTable(fit,coef=2)
```

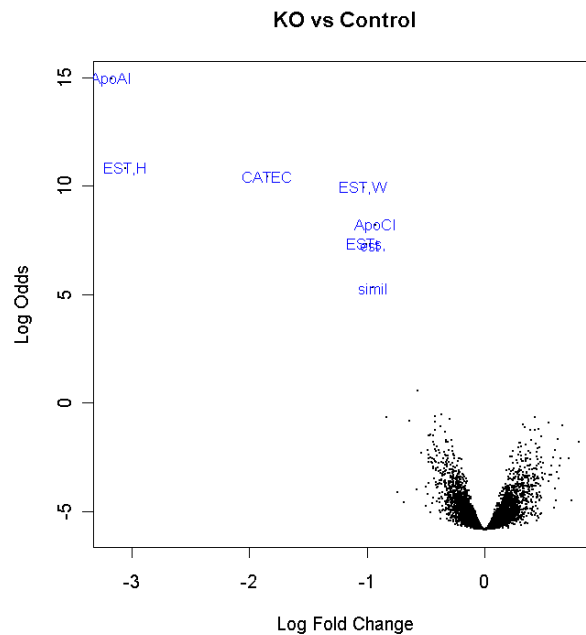
However, the gene annotation is a bit wide for the printed page, so we will tell `topTable()` to show just one column of the annotation information:

```
> topTable(fit,coef=2,number=15,genelist=fit$genes$NAME)
      ID logFC AveExpr      t P.Value adj.P.Val      B
2149  ApoAI,lipid-Img -3.166  12.47 -23.98 4.77e-15  3.05e-11 14.927
540  EST,HighlysimilartoA -3.049  12.28 -12.96 1.57e-10  5.02e-07 10.813
5356 CATECHOLO-METHYLTRAN -1.848  12.93 -12.44 3.06e-10  6.51e-07 10.448
4139 EST,WeaklysimilartoC -1.027  12.61 -11.76 7.58e-10  1.21e-06  9.929
```

1739	ApoCIII,lipid-Img	-0.933	13.74	-9.84	1.22e-08	1.56e-05	8.192
2537	ESTs,Highlysimilar	-1.010	13.63	-9.02	4.53e-08	4.22e-05	7.305
1496	est	-0.977	12.23	-9.00	4.63e-08	4.22e-05	7.290
4941	similartoyeaststerol	-0.955	13.29	-7.44	7.04e-07	5.62e-04	5.311
947	EST,Weaklysimilar	-0.571	10.54	-4.55	2.49e-04	1.77e-01	0.563
5604		-0.366	12.71	-3.96	9.22e-04	5.29e-01	-0.553
4140	APXL2,5q-Img	-0.420	9.79	-3.93	9.96e-04	5.29e-01	-0.619
6073	estrogenrec	0.421	9.79	3.91	1.03e-03	5.29e-01	-0.652
1337	psoriasis-associated	-0.838	11.66	-3.89	1.08e-03	5.29e-01	-0.687
954	Caspase7,heart-Img	-0.302	12.14	-3.86	1.17e-03	5.30e-01	-0.757
563	FATTYACID-BINDINGPRO	-0.637	11.62	-3.81	1.29e-03	5.30e-01	-0.839

Notice that the top gene is ApoA1 itself which is heavily down-regulated. Theoretically the M-value should be minus infinity for ApoA1 because it is the knockout gene. Several of the other genes are closely related. The top eight genes here were confirmed by independent assay subsequent to the microarray experiment to be differentially expressed in the knockout versus the control line.

```
> volcanoplot(fit,coef=2,highlight=8,names=fit$genes$NAME,main="KO vs Control")
```



## 16.3 Weaver Mutant Mice: A Composite 2x2 Factorial Experiment

### 16.3.1 Background

This case study considers a more involved two-color analysis in which the RNA sources have a factorial structure with two factors.

The study examined the development of neurons in wild-type and weaver mutant mice [7]. The weaver mutation affects cerebellar granule neurons, the most numerous cell-type in the central nervous system. Weaver mutant mice are characterized by a weaving gait. Granule cells are generated in the first postnatal week in the external granule layer of the cerebellum. In normal mice, the terminally differentiated granule cells migrate to the internal granule layer but in mutant mice the cells die before doing so, meaning that the mutant mice have strongly reduced numbers of cells in the internal granule layer. The expression level of any gene which is specific to mature granule cells, or is expressed in response to granule cell derived signals, is greatly reduced in the mutant mice.

### 16.3.2 Sample Preparation and Hybridizations

At each time point (P11 = 11 days postnatal and P21 = 21 days postnatal) cerebella were isolated from two wild-type and two mutant littermates and pooled for RNA isolation. RNA was then divided into aliquots and labelled before hybridizing to the arrays. (This means that aliquots are technical replicates, arising from the same mice and RNA extraction. In our analysis here, we will ignore this complication and will instead treat the aliquots as if they were biological replicates. See Yang and Speed (2002) for a detailed discussion of this issue in the context of this experiment.) A pool of RNA was also made by combining the different RNA samples.

There are four different treatment combinations, P11wt, P11mt, P21wt and P21mt, comprising a 2x2 factorial structure. The RNA samples were hybridized to ten two-color microarrays, spotted with a 20k Riken clone library. There are six arrays comparing the four different RNA sources to the RNA pool, and four arrays making direct comparisons between the four treatment combinations.

The microarray images were scanned using SPOT image analysis software.

### 16.3.3 Data input

The data used for this case study can be downloaded from <http://bioinf.wehi.edu.au/limma/data/weaverfull.rar>. The data are provided courtesy of Drs Jean Yang and Elva Diaz.

First read in the targets frame:

```
> library(limma)
> targets <- readTargets("targets.txt")
> rownames(targets) <- removeExt(targets$FileName)
> targets
```

	FileName	Tissue	Mouse	Cy5	Cy3
cbmut.3	cbmut.3.spot	Cerebellum	Weaver	P11wt	Pool
cbmut.4	cbmut.4.spot	Cerebellum	Weaver	P11mt	Pool
cbmut.5	cbmut.5.spot	Cerebellum	Weaver	P21mt	Pool
cbmut.6	cbmut.6.spot	Cerebellum	Weaver	P21wt	Pool
cbmut.15	cbmut.15.spot	Cerebellum	Weaver	P21wt	Pool
cbmut.16	cbmut.16.spot	Cerebellum	Weaver	P21mt	Pool
cb.1	cb.1.spot	Cerebellum	Weaver	P11wt	P11mt

```
cb.2      cb.2.spot Cerebellum Weaver P11mt P21mt
cb.3      cb.3.spot Cerebellum Weaver P21mt P21wt
cb.4      cb.4.spot Cerebellum Weaver P21wt P11wt
```

Exploratory analysis showed that the segmented area for spots for these arrays was quite variable, with a median spot area just over 50 pixels. A small proportion of spots had very small segmented sizes, suggesting that the intensities for these spots might be unreliable. It was therefore decided to set a spot quality weight function, so any spot with an area less than 50 pixels will get reduced weight. The function is set so that any spot with zero area will get zero weight:

```
> wtfun <- function(x) pmin(x$area/50, 1)
```

Then read the SPOT files containing the intensity data using file names recorded in the targets file. The data files are stored in the subdirectory /spot:

```
> RG <- read.maimages(targets, source = "spot", path = "spot", wt.fun = wtfun)
Read spot/cbmut.3.spot
Read spot/cbmut.4.spot
Read spot/cbmut.5.spot
Read spot/cbmut.6.spot
Read spot/cbmut.15.spot
Read spot/cbmut.16.spot
Read spot/cb.1.spot
Read spot/cb.2.spot
Read spot/cb.3.spot
Read spot/cb.4.spot
```

Finally, we set the print-tip layout. These arrays were printed using a print-head with 8 rows and 4 columns of print tips:

```
> RG$printer <- list(ngrid.r = 8, ngrid.c = 4, nspot.r = 25, nspot.c = 24)
```

### 16.3.4 Annotation

Probe annotation is contained a separate file. The rows in the annotation file are as for the intensity data. Columns give Riken chip rearray IDs, GenBank accession numbers and UniGene information.

```
> Annotation <- read.delim("091701RikenUpdatev3.txt", comment.char="", quote="\\"",
+                           check.names=FALSE, stringsAsFactors=FALSE)
> names(Annotation)
[1] "ReArrayID"          "Accession #, GenBank"      "description (Riken)"
[4] "Cluster ID (UniGene)" "2nd description (UniGene)"
```

For our purposes, we will keep the Riken IDs and GenBank accessions, putting these into the data object:

```
> RG$genes <- Annotation[,c(1,2)]
> colnames(RG$genes) <- c("RikenID", "GenBank")
```

Where possible, we find gene symbols corresponding to the GenBank accession numbers, by using the mouse organism package constructed from the NCBI database. Symbols can be found for only a little over 5000 of the probes.

```
> library(org.Mm.eg.db)
```

First we find the Entrez Gene ID for each accession number:

```
> EG.AN <- toTable(org.Mm.egACCNUM)
> i <- match(RG$genes$GenBank, EG.AN[, "accession"])
> EntrezID <- EG.AN[i, "gene_id"]
```

Then convert Entrez Gene IDs to symbols:

```
> EG.Sym <- toTable(org.Mm.egSYMBOL)
> i <- match(EntrezID, EG.Sym[, "gene_id"])
> RG$genes$Symbol <- EG.Sym[i, "symbol"]
```

### 16.3.5 Quality Assessment and Normalization

We also read in a spot-types file and set a range of control spots.

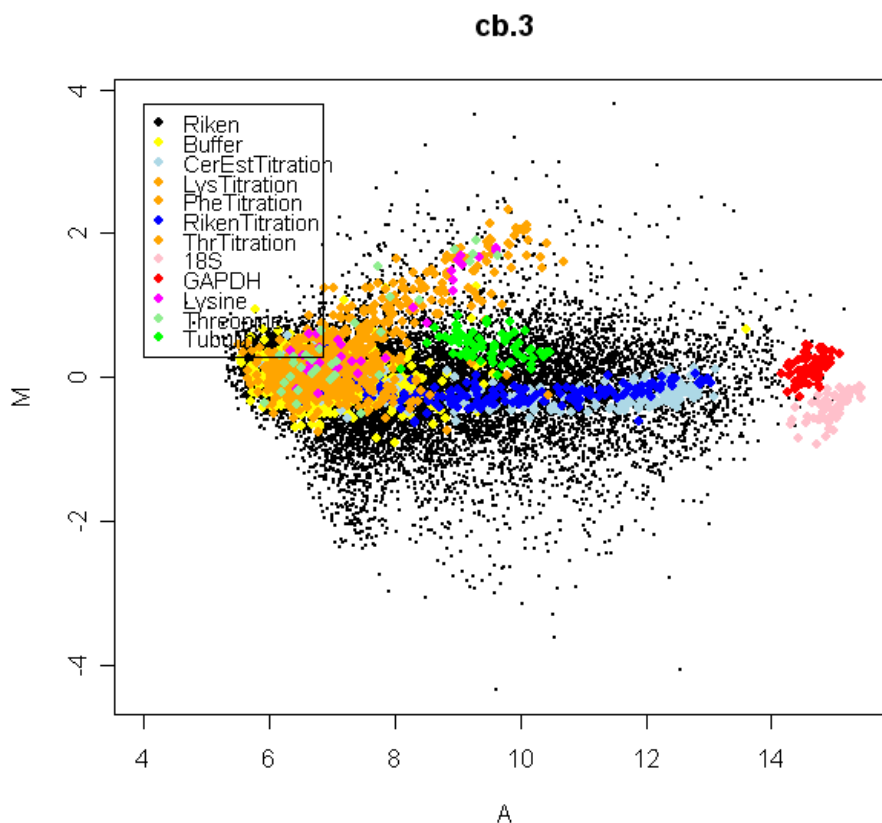
```
> spottypes <- readSpotTypes("spottypes.txt")
> spottypes
```

	SpotType	RikenID	col	cex
1	Control	*	green	1.0
2	Riken	Z*	black	0.2
3	Buffer	3x SSC	yellow	1.0
4	CerEstTitration	cer est \\\(*	lightblue	1.0
5	LysTitration	Lys \\\(*	orange	1.0
6	PheTitration	Phe \\\(*	orange	1.0
7	RikenTitration	Riken est \\\(*	blue	1.0
8	ThrTitration	Thr \\\(*	orange	1.0
9	18S	18S \\\(0.15ug/ul\\)	pink	1.0
10	GAPDH	GAPDH \\\(0.15 ug/ul\\)	red	1.0
11	Lysine	Lysine \\\(0.2 ug/ul\\)	magenta	1.0
12	Threonine	Threonine \\\(0.2ug/ul\\)	lightgreen	1.0
13	Tubulin	Tubulin \\\(0.15 ug/ul\\)	green	1.0

```
> RG$genes$Status <- controlStatus(spottypes, RG)
Matching patterns for: RikenID
Found 19200 Control
Found 16896 Riken
Found 710 Buffer
Found 192 CerEstTitration
Found 224 LysTitration
Found 260 PheTitration
Found 160 RikenTitration
Found 224 ThrTitration
Found 64 18S
Found 64 GAPDH
Found 32 Lysine
Found 32 Threonine
Found 64 Tubulin
Setting attributes: values col cex
```

MA-plots were examined for all the arrays. Here we give the plot for array 9 only:

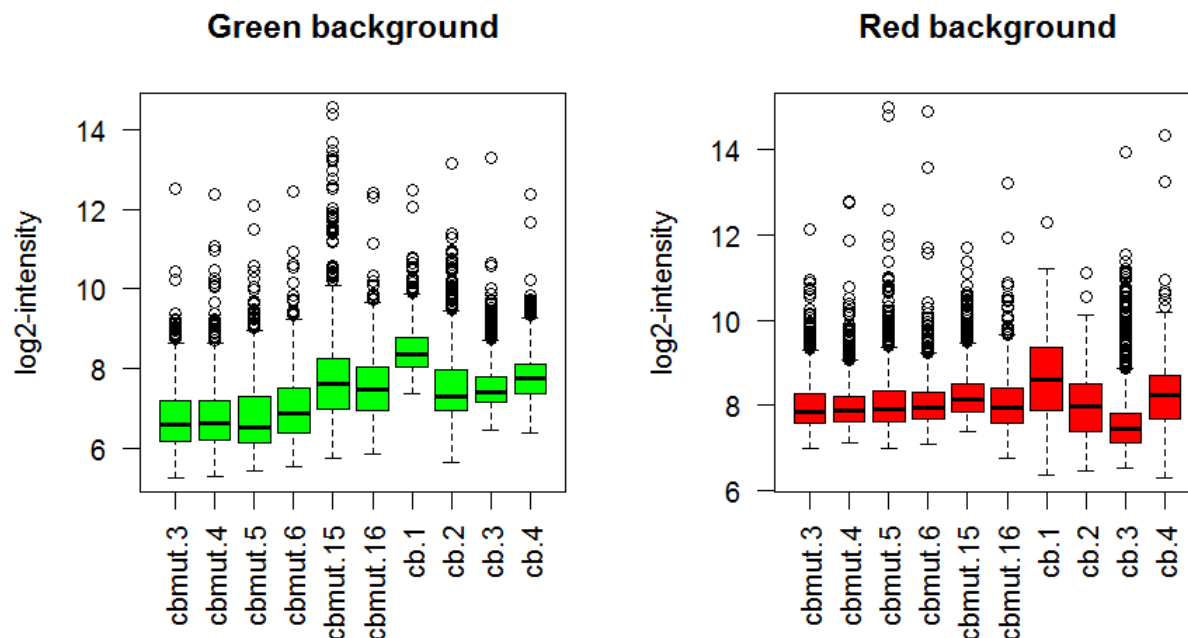
```
> plotMA(RG,array=9,xlim=c(4,15.5))
```



Here Buffer is an obvious negative control while 18S, GAPDH, Lysine, Threonine and Tubulin are single-gene positive controls, sometime called house-keeping genes. RikenTitration is a titration series of a pool of the entire Riken library, and can be reasonably expected to be non-differentially expressed. CerEstTitration is a titration of a pool of a cerebellum EST library. This will show higher expression in later mutant tissues. The Lys, Phe and Thr series are single-gene titration series which were not spiked-in in this case and can therefore be treated as negative controls.

The negative control probe intensities are quite high, especially for the red channel and especially for array 7:

```
> negative <- RG$genes$Status %in% c("Buffer","LysTitration","PheTitration","ThrTitration")
> par(mfrow=c(1,2))
> boxplot(log2(RG$G[negative,]),las=2,main="Green background",ylab="log2-intensity",col="green")
> boxplot(log2(RG$R[negative,]),las=2,main="Red background",ylab="log2-intensity",col="red")
> par(mfrow=c(1,1))
```



Later on, we will investigate setting array quality weights.

Now normalize the data. The Riken titration library, being based on a pool of a large number of non-specific genes, should not be differentially expressed. We can take advantage of this by upweighting these probes in the print-tip normalization step. Here we give double-weight to the titration library probes, although higher weights could also be considered:

```
> w <- modifyWeights(RG$weights, RG$genes$Status, "RikenTitration", 2)
> MA <- normalizeWithinArrays(RG, weights = w)
```

### 16.3.6 Setting Up the Linear Model

The experiment has a composite design, with some arrays comparing back to the RNA pool as a common reference, and other arrays making direct comparisons between the treatment conditions of interest. The simplest design matrix is that which compares all the RNA samples back to the RNA pool.

```
> design <- modelMatrix(targets, ref = "Pool")
Found unique target names:
P11mt P11wt P21mt P21wt Pool
```

We also add an intercept term to extract probe-specific dye effects:

```
> design <- cbind(Dye=1,design)
> design
```

	Dye	P11mt	P11wt	P21mt	P21wt
cbmut.3	1	0	1	0	0
cbmut.4	1	1	0	0	0

```
cbmut.5    1    0    0    1    0
cbmut.6    1    0    0    0    1
cbmut.15   1    0    0    0    1
cbmut.16   1    0    0    1    0
cb.1       1   -1    1    0    0
cb.2       1    1    0   -1    0
cb.3       1    0    0    1   -1
cb.4       1    0   -1    0    1
```

### 16.3.7 Probe Filtering and Array Quality Weights

First we remove control probes, leaving only the regular probes of the Riken library:

```
> regular <- MA$genes$Status=="Riken"
> MA2 <- MA[regular,]
> MA2$genes$Status <- NULL
```

Then we estimate array quality weights:

```
> aw <- arrayWeights(MA2,design)
> options(digits=3)
> aw
      1      2      3      4      5      6      7      8      9     10
1.175 1.457 0.852 1.216 0.371 1.087 1.325 0.856 1.418 0.869
```

The array weights multiply the spot weights already in the data object:

```
> library(statmod)
> w <- matvec(MA2$weights,aw)
```

### 16.3.8 Differential expression

Fit the linear model:

```
> fit <- lmFit(MA2, design, weights=w)
```

Now extract all possible comparisons of interest as contrasts. We look for the mutant vs wt comparisons at 11 and 21 days, the time effects for mutant and wt, and the interaction terms:

```
> cont.matrix <- makeContrasts(
+   WT11.MT11=P11mt-P11wt,
+   WT21.MT21=P21mt-P21wt,
+   WT11.WT21=P21wt-P11wt,
+   MT11.MT21=P21mt-P11mt,
+   Int=(P21mt-P11mt)-(P21wt-P11wt),
+   levels=design)
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
```

Adjustment for multiple testing, using Benjamini and Hochberg's method to control the false discovery rate at 5% across all genes and all contrasts, leads to the following:



```
> results <- decideTests(fit2,method="global")
> summary(results)
      WT11.MT11 WT21.MT21 WT11.WT21 MT11.MT21   Int
-1         28        136        455        765    74
0        16835       16540       16102       15377 16692
1         33         220        339        754   130
```

The probes that show significant interactions are those which develop differently in the mutant compared to the wildtype between days 11 and 21. To see these:

```
> topTable(fit2,coef="Int")
      RikenID  GenBank      Symbol logFC AveExpr      t P.Value adj.P.Val      B
14395 ZX00005I07 AV038977      <NA>  2.71  10.52 11.40 8.56e-08  0.00145 7.66
1473  ZX00028J17 AV076735      <NA>  1.92  11.37 10.11 3.18e-07  0.00215 6.65
14288 ZA00003I15 AV010442      <NA>  2.21   9.50  9.94 3.81e-07  0.00215 6.50
1184  ZX00004J09 AK005530 Tnfrsf12a -2.02   8.47 -9.43 6.74e-07  0.00237 6.03
13843 ZX00003J07 AV033559      <NA> -2.97  12.08 -9.33 7.51e-07  0.00237 5.95
14898 ZX00003H24 AK005382 Tnfrsf12a -2.41   9.40 -9.23 8.43e-07  0.00237 5.86
13520 ZX00020K15 AV088030      <NA>  1.83   9.93  9.09 9.88e-07  0.00238 5.73
10916 ZX00023L14 AV104464      <NA>  2.90  10.49  8.93 1.19e-06  0.00252 5.37
12532 ZX00026E06 AV140268      <NA>  2.75  10.55  8.63 1.71e-06  0.00322 5.27
14250 ZX00048F23 AV122249      <NA>  1.89  10.27  8.41 2.23e-06  0.00377 5.04
```

```
> sessionInfo()
R version 2.13.0 Patched (2011-04-25 r55638)
Platform: i386-pc-mingw32/i386 (32-bit)
```

```
locale:
[1] LC_COLLATE=English_Australia.1252 LC_CTYPE=English_Australia.1252
[3] LC_MONETARY=English_Australia.1252 LC_NUMERIC=C
[5] LC_TIME=English_Australia.1252
```

```
attached base packages:
[1] splines      stats      graphics  grDevices  utils      datasets  methods    base
```

```
other attached packages:
[1] statmod_1.4.11      org.Mm.eg.db_2.5.0  RSQLite_0.9-4      DBI_0.2-5
[5] AnnotationDbi_1.14.0 Biobase_2.12.0      limma_3.9.8
```

## 16.4 Bob1 Mutant Mice: Arrays With Duplicate Spots

In this section we consider a case study in which all genes (ESTs and controls) are printed more than once on the array. This means that there is both within-array and between-array replication for each gene. The structure of the experiment is therefore essentially a randomized block experiment for each gene. The approach taken here is to estimate a common correlation for all the genes for between within-array duplicates. The theory behind the approach is explained in [38]. This approach assumes that all genes are replicated the same number of times on the array and that the spacing between the replicates is entirely regular.

In this example we assume that the data is available as an `RGList`.

**Background.** This data is from a study of transcription factors critical to B cell maturation by Lynn Corcoran and Wendy Dietrich at the WEHI. Mice which have a targeted mutation in the Bob1 (aka Pou2af1 or OBF-1) transcription factor display a number of abnormalities in the B lymphocyte compartment of the immune system. Immature B cells that have emigrated from the bone marrow fail to differentiate into full fledged B cells, resulting in a notable deficit of mature B cells.

**Arrays.** Arrays were printed at the Australian Genome Research Facility with expressed sequence tags (ESTs) from the National Institute of Aging 15k mouse clone library, plus a range of positive, negative and calibration controls. The arrays were printed using a 48 tip print head and 26x26 spots in each tip group. Data from 24 of the tip groups are given here. Every gene (ESTs and controls) was printed twice on each array, side by side by rows. The NIA15k probe IDs have been anonymized in the output presented here.

**Hybridizations.** A retrovirus was used to add Bob back to a Bob deficient cell line. Two RNA sources were compared using 2 dye-swap pairs of microarrays. One RNA source was obtained from the Bob deficient cell line after the retrovirus was used to add GFP ("green fluorescent protein", a neutral protein). The other RNA source was obtained after adding both GFP and Bob protein. RNA from Bob+GFP was labelled with Cy5 in arrays 2 and 4, and with Cy3 in arrays 1 and 4.

**Image analysis.** The arrays were image analyzed using SPOT with "morph" background estimation.

The data used for this case study can be downloaded from <http://bioinf.wehi.edu.au/limma/>. The file should be placed in the working directory of your R session. (This case study was last updated on 29 June 2006 using R 2.3.0 and limma 2.7.5.)

```
> library(limma)
> load("Bob.RData")
> objects()
[1] "design" "RG"
> design
[1] -1  1 -1  1
> names(RG)
[1] "R"      "G"      "Rb"     "Gb"     "genes"  "printer"
> RG$genes[1:40,]
      Library      ID
1  Control      cDNA1.500
2  Control      cDNA1.500
3  Control Printing.buffer
4  Control Printing.buffer
5  Control Printing.buffer
6  Control Printing.buffer
7  Control Printing.buffer
8  Control Printing.buffer
9  Control      cDNA1.500
10 Control      cDNA1.500
11 Control Printing.buffer
12 Control Printing.buffer
```

```

13 Control Printing.buffer
14 Control Printing.buffer
15 Control Printing.buffer
16 Control Printing.buffer
17 Control      cDNA1.500
18 Control      cDNA1.500
19 Control Printing.buffer
20 Control Printing.buffer
21 Control Printing.buffer
22 Control Printing.buffer
23 Control Printing.buffer
24 Control Printing.buffer
25 Control      cDNA1.500
26 Control      cDNA1.500
27 NIA15k      H31
28 NIA15k      H31
29 NIA15k      H32
30 NIA15k      H32
31 NIA15k      H33
32 NIA15k      H33
33 NIA15k      H34
34 NIA15k      H34
35 NIA15k      H35
36 NIA15k      H35
37 NIA15k      H36
38 NIA15k      H36
39 NIA15k      H37
40 NIA15k      H37

```

Although there are only four arrays, we have a total of eight spots for each gene, and more for the controls. Naturally the two M-values obtained from duplicate spots on the same array are highly correlated. The problem is how to make use of the duplicate spots in the best way. The approach taken here is to estimate the spatial correlation between the adjacent spots using REML and then to conduct the usual analysis of the arrays using generalized least squares.

First normalize the data using print-tip loess regression. The SPOT morph background ensures that the default background subtraction can be used without inducing negative intensities.

```
> MA <- normalizeWithinArrays(RG)
```

Then remove the control probes:

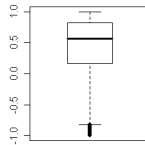
```
> MA2 <- MA[MA$genes$Library=="NIA15k", ]
```

Now estimate the spatial correlation. We estimate a correlation term by REML for each gene, and then take a trimmed mean on the atanh scale to estimate the overall correlation. This command will probably take at least a few minutes depending on the speed of your computer.

```

> options(digits=3)
> corfit <- duplicateCorrelation(MA2,design,ndups=2) # A slow computation!
Loading required package: statmod
> corfit$consensus.correlation
[1] 0.575
> boxplot(tanh(corfit$atanh.correlations))

```



```

> fit <- lmFit(MA2,design,ndups=2,correlation=corfit$consensus)
> fit <- eBayes(fit)
> topTable(fit,n=30,adjust="BH")

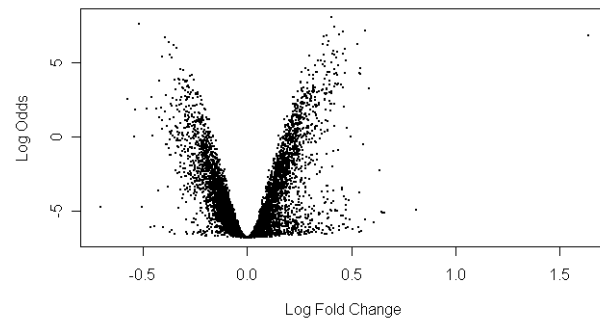
```

	Library	ID	logFC	AveExpr	t	P.Value	adj.P.Val	B
4599	NIA15k	H34599	0.404	10.93	12.92	1.34e-07	0.000443	8.02
1324	NIA15k	H31324	-0.520	7.73	-12.24	2.23e-07	0.000443	7.57
3309	NIA15k	H33309	0.420	10.99	11.99	2.71e-07	0.000443	7.39
440	NIA15k	H3440	0.568	9.96	11.64	3.60e-07	0.000443	7.13
6795	NIA15k	H36795	0.460	10.78	11.56	3.85e-07	0.000443	7.07
121	NIA15k	H3121	0.441	10.48	11.31	4.73e-07	0.000443	6.88
2838	NIA15k	H32838	1.640	12.74	11.26	4.92e-07	0.000443	6.84
6999	NIA15k	H36999	0.381	9.91	11.19	5.21e-07	0.000443	6.79
132	NIA15k	H3132	0.370	10.10	11.17	5.31e-07	0.000443	6.77
6207	NIA15k	H36207	-0.393	8.53	-11.06	5.82e-07	0.000443	6.69
7168	NIA15k	H37168	0.391	9.88	10.76	7.51e-07	0.000493	6.45
1831	NIA15k	H31831	-0.374	9.62	-10.63	8.41e-07	0.000493	6.35
2014	NIA15k	H32014	0.363	9.65	10.49	9.54e-07	0.000493	6.23
7558	NIA15k	H37558	0.532	11.42	10.49	9.58e-07	0.000493	6.22
4471	NIA15k	H34471	-0.353	8.76	-10.41	1.02e-06	0.000493	6.16
126	NIA15k	H3126	0.385	10.59	10.40	1.03e-06	0.000493	6.15
4360	NIA15k	H34360	-0.341	9.37	-10.22	1.21e-06	0.000545	6.00
6794	NIA15k	H36794	0.472	11.33	10.11	1.35e-06	0.000570	5.90
329	NIA15k	H3329	0.413	11.37	9.97	1.53e-06	0.000612	5.78
5017	NIA15k	H35017	0.434	11.41	9.90	1.63e-06	0.000618	5.72
2678	NIA15k	H32678	0.461	10.44	9.74	1.90e-06	0.000618	5.57
2367	NIA15k	H32367	0.409	10.21	9.72	1.93e-06	0.000618	5.56
1232	NIA15k	H31232	-0.372	8.72	-9.70	1.96e-06	0.000618	5.54
111	NIA15k	H3111	0.369	10.42	9.69	1.98e-06	0.000618	5.53
2159	NIA15k	H32159	0.418	10.19	9.67	2.03e-06	0.000618	5.51
4258	NIA15k	H34258	0.299	9.11	9.62	2.12e-06	0.000622	5.47
3192	NIA15k	H33192	-0.410	9.46	-9.55	2.26e-06	0.000638	5.41
6025	NIA15k	H36025	0.427	10.37	9.47	2.45e-06	0.000654	5.33
5961	NIA15k	H35961	-0.362	8.50	-9.46	2.49e-06	0.000654	5.31
1404	NIA15k	H31404	0.474	11.34	9.26	3.00e-06	0.000722	5.13

```

> volcanoplot(fit)

```



# Chapter 17

## Single-Channel Case Studies

### 17.1 Lrp Mutant Ecoli: Two Group Experiment with Affymetrix Arrays

The data are from experiments reported in [11] and are available from the www site <http://visitor.ics.uci.edu/genex/cybert/tutorial/index.html>. The data is also available from the *ecoli*Leucine data package available from the Bioconductor www site under "Experimental Data". Hung et al [11] state that

The purpose of the work presented here is to identify the network of genes that are differentially regulated by the global *E. coli* regulatory protein, leucine-responsive regulatory protein (Lrp), during steady state growth in a glucose supplemented minimal salts medium. Lrp is a DNA-binding protein that has been reported to affect the expression of approximately 55 genes.

Gene expression in two *E. coli* bacteria strains, labelled *lrp*<sup>+</sup> and *lrp*<sup>-</sup>, were compared using eight Affymetrix *ecoli* chips, four chips each for *lrp*<sup>+</sup> and *lrp*<sup>-</sup>.

The following code assumes that the data files for the eight chips are in your current working directory.

```
> dir()
[1] "Ecoli.CDF"           "nolrp_1.CEL"       "nolrp_2.CEL"
[4] "nolrp_3.CEL"         "nolrp_4.CEL"       "wt_1.CEL"
[7] "wt_2.CEL"           "wt_3.CEL"         "wt_4.CEL"
```

The data is read and normalized using the `affy` package. The package `ecolicdf` must also be installed, otherwise the `rma()` function will attempt to download and install it for you—without giving you the opportunity to veto the download.

```
> library(limma)
> library(affy)
Welcome to Bioconductor
  Vignettes contain introductory material.  To view,
  simply type: openVignette()
```

For details on reading vignettes, see  
the openVignette help page.

```
> Data <- ReadAffy()
> eset <- rma(Data)
Background correcting
Normalizing
Calculating Expression
> pData(eset)
```

```
      sample
nolrp_1.CEL      1
nolrp_2.CEL      2
nolrp_3.CEL      3
nolrp_4.CEL      4
wt_1.CEL         5
wt_2.CEL         6
wt_3.CEL         7
wt_4.CEL         8
```

Now we consider differential expression between the lrp+ and lrp- strains.

```
> strain <- c("lrp-", "lrp-", "lrp-", "lrp-", "lrp+", "lrp+", "lrp+", "lrp+")
> design <- model.matrix(~factor(strain))
> colnames(design) <- c("lrp-", "lrp+vs-")
> design
  lrp- lrp+vs-
1     1      0
2     1      0
3     1      0
4     1      0
5     1      1
6     1      1
7     1      1
8     1      1
attr(,"assign")
[1] 0 1
attr(,"contrasts")
attr(,"contrasts")$"factor(strain)"
[1] "contr.treatment"
```

The first coefficient measures  $\log_2$ -expression of each gene in the lrp- strain. The second coefficient measures the  $\log_2$ -fold change of lrp+ over lrp-, i.e., the log-fold change induced by lrp.

```
> fit <- lmFit(eset, design)
> fit <- eBayes(fit)
> options(digits=2)
> topTable(fit, coef=2, n=40, adjust="BH")
      ID logFC AveExpr      t P.Value adj.P.Val      B
4282 IG_821_1300838_1300922_fwd_st -3.32  12.4 -23.1 7.2e-09  5.3e-05  8.017
5365          serA_b2913_st  2.78  12.2  15.8 1.6e-07  6.0e-04  6.603
1389          gltD_b3213_st  3.03  10.9  13.3 6.4e-07  1.6e-03  5.779
4625          lrp_b0889_st  2.30   9.3  11.4 2.3e-06  4.0e-03  4.911
```

1388		gltB_b3212_st	3.24	10.1	11.1	2.8e-06	4.0e-03	4.766
4609		livK_b3458_st	2.35	9.9	10.8	3.5e-06	4.0e-03	4.593
4901		oppB_b1244_st	-2.91	10.7	-10.6	4.0e-06	4.0e-03	4.504
4903		oppD_b1246_st	-1.94	10.4	-10.5	4.4e-06	4.0e-03	4.434
5413		sodA_b3908_st	1.50	10.3	9.7	8.0e-06	6.5e-03	3.958
4900		oppA_b1243_st	-2.98	13.0	-9.1	1.3e-05	9.2e-03	3.601
5217		rmf_b0953_st	-2.71	13.6	-9.0	1.5e-05	9.3e-03	3.474
7300		ytfK_b4217_st	-2.64	11.1	-8.9	1.5e-05	9.3e-03	3.437
5007		pntA_b1603_st	1.58	10.1	8.3	2.5e-05	1.4e-02	3.019
4281	IG_820_1298469_1299205_fwd_st	-2.45	10.7	-8.1	3.1e-05	1.6e-02	2.843	
4491		ilvI_b0077_st	0.95	10.0	7.4	6.3e-05	2.9e-02	2.226
5448		stpA_b2669_st	1.79	10.0	7.4	6.4e-05	2.9e-02	2.210
611		b2343_st	-2.12	10.8	-7.1	7.9e-05	3.4e-02	2.028
5930		ybfA_b0699_st	-0.91	10.5	-7.0	8.7e-05	3.5e-02	1.932
1435		grxB_b1064_st	-0.91	9.8	-6.9	1.0e-04	3.8e-02	1.810
4634		lysU_b4129_st	-3.30	9.3	-6.9	1.1e-04	3.9e-02	1.758
4829		ndk_b2518_st	1.07	11.1	6.7	1.2e-04	4.3e-02	1.616
2309	IG_1643_2642304_2642452_rev_st	0.83	9.6	6.7	1.3e-04	4.3e-02	1.570	
4902		oppC_b1245_st	-2.15	10.7	-6.3	1.9e-04	5.9e-02	1.238
4490		ilvH_b0078_st	1.11	9.9	5.9	2.9e-04	8.8e-02	0.820
1178		fimA_b4314_st	3.40	11.7	5.9	3.2e-04	8.8e-02	0.743
6224		ydgR_b1634_st	-2.35	9.8	-5.8	3.3e-04	8.8e-02	0.722
4904		oppF_b1247_st	-1.46	9.9	-5.8	3.3e-04	8.8e-02	0.720
792		b3914_st	-0.77	9.5	-5.7	3.9e-04	1.0e-01	0.565
5008		pntB_b1602_st	1.47	12.8	5.6	4.1e-04	1.0e-01	0.496
4610		livM_b3456_st	1.04	8.5	5.5	4.7e-04	1.1e-01	0.376
5097		ptsG_b1101_st	1.16	12.2	5.5	4.8e-04	1.1e-01	0.352
4886		nupC_b2393_st	0.79	9.6	5.5	4.9e-04	1.1e-01	0.333
4898		ompT_b0565_st	2.67	10.5	5.4	5.6e-04	1.2e-01	0.218
5482		tdh_b3616_st	-1.61	10.5	-5.3	6.3e-04	1.3e-01	0.092
1927	IG_13_14080_14167_fwd_st	-0.55	8.4	-5.3	6.4e-04	1.3e-01	0.076	
6320		yeeF_b2014_st	0.88	9.9	5.3	6.5e-04	1.3e-01	0.065
196		atpG_b3733_st	0.60	12.5	5.2	7.2e-04	1.4e-01	-0.033
954		cydB_b0734_st	-0.76	11.0	-5.0	9.3e-04	1.8e-01	-0.272
1186		fimI_b4315_st	1.15	8.3	5.0	9.5e-04	1.8e-01	-0.298
4013	IG_58_107475_107629_fwd_st	-0.49	10.4	-4.9	1.1e-03	2.0e-01	-0.407	

The column `logFC` gives the  $\log_2$ -fold change while the column `AveExpr` gives the average  $\log_2$ -intensity for the probe-set. Positive M-values mean that the gene is up-regulated in `lrp+`, negative values mean that it is repressed.

It is interesting to compare this table with Tables III and IV in [11]. Note that the top-ranked gene is an intergenic region (IG) tRNA gene. The knock-out gene itself is in position four. Many of the genes in the above table, including the `ser`, `glt`, `liv`, `opp`, `lys`, `ilv` and `fim` families, are known targets of `lrp`.



## 17.2 Effect of Estrogen on Breast Cancer Tumor Cells: A 2x2 Factorial Experiment with Affymetrix Arrays

This data is from the `estrogen` package on Bioconductor. A subset of the data is also analyzed in the `factDesign` package vignette. To repeat this case study you will need to have the R packages `affy`, `estrogen` and `hgu95av2cdf` installed.

The data gives results from a 2x2 factorial experiment on MCF7 breast cancer cells using Affymetrix HGU95av2 arrays. The factors in this experiment were estrogen (present or absent) and length of exposure (10 or 48 hours). The aim of the study is to identify genes which respond to estrogen and to classify these into early and late responders. Genes which respond early are putative direct-target genes while those which respond late are probably downstream targets in the molecular pathway.

First load the required packages:

```
> library(limma)
> library(affy)
Welcome to Bioconductor
  Vignettes contain introductory material. To view,
  simply type: openVignette()
  For details on reading vignettes, see
  the openVignette help page.
> library(hgu95av2cdf)
```

The data files are contained in the `extdata` directory of the `estrogen` package:

```
> datadir <- file.path(.find.package("estrogen"), "extdata")
> dir(datadir)
[1] "00Index"      "bad.cel"      "high10-1.cel" "high10-2.cel" "high48-1.cel"
[6] "high48-2.cel" "low10-1.cel"  "low10-2.cel"  "low48-1.cel"  "low48-2.cel"
[11] "phenoData.txt"
```

The targets file is called `phenoData.txt`. We see there are two arrays for each experimental condition, giving a total of 8 arrays.

```
> targets <- readTargets("phenoData.txt", path=datadir, sep="", row.names="filename")
> targets
```

	filename	estrogen	time.h
low10-1	low10-1.cel	absent	10
low10-2	low10-2.cel	absent	10
high10-1	high10-1.cel	present	10
high10-2	high10-2.cel	present	10
low48-1	low48-1.cel	absent	48
low48-2	low48-2.cel	absent	48
high48-1	high48-1.cel	present	48
high48-2	high48-2.cel	present	48

Now read the cel files into an `AffyBatch` object and normalize using the `rma()` function from the `affy` package:

```
> ab <- ReadAffy(filename=targets$filename, celfile.path=datadir)
> eset <- rma(ab)
Background correcting
Normalizing
Calculating Expression
```

By default, the only probe-set annotation contained in `eset` is the Affymetrix ID number. We will add gene symbols to the data object now, so that they will be automatically included in limma results tables later on.

```
> library(annotate)
Loading required package: AnnotationDbi
> library(hgu95av2.db)
Loading required package: org.Hs.eg.db
Loading required package: DBI
> ID <- featureNames(eset)
> Symbol <- getSYMBOL(ID,"hgu95av2.db")
> fData(eset) <- data.frame(Symbol=Symbol)
```

There are many ways to construct a design matrix for this experiment. Given that we are interested in the early and late estrogen responders, we can choose a parametrization which includes these two contrasts.

```
> treatments <- factor(c(1,1,2,2,3,3,4,4),labels=c("e10","E10","e48","E48"))
> contrasts(treatments) <- cbind(Time=c(0,0,1,1),E10=c(0,1,0,0),E48=c(0,0,0,1))
> design <- model.matrix(~treatments)
> colnames(design) <- c("Intercept","Time","E10","E48")
```

The second coefficient picks up the effect of time in the absence of estrogen. The third and fourth coefficients estimate the log<sub>2</sub>-fold change for estrogen at 10 hours and 48 hours respectively.

```
> fit <- lmFit(eset,design)
```

We are only interested in the estrogen effects, so we choose a contrast matrix which picks these two coefficients out:

```
> cont.matrix <- cbind(E10=c(0,0,1,0),E48=c(0,0,0,1))
> fit2 <- contrasts.fit(fit, cont.matrix)
> fit2 <- eBayes(fit2)
```

We can examine which genes respond to estrogen at either time using the moderated  $F$ -statistics on 2 degrees of freedom. The moderated  $F$   $p$ -value is stored in the component `fit2$F.p.value`.

What  $p$ -value cutoff should be used? One way to decide which changes are significant for each gene would be to use Benjamini and Hochberg's method to control the false discovery rate across all the genes and both tests:

```
> results <- decideTests(fit2, method="global")
```

Another method would be to adjust the  $F$ -test  $p$ -values rather than the  $t$ -test  $p$ -values:

```
> results <- decideTests(fit2, method="nestedF")
```

Here we use a more conservative method which depends far less on distributional assumptions, which is to make use of control and spike-in probe-sets which theoretically should not be differentially-expressed. The smallest  $p$ -value amongst these controls turns out to be about 0.00014:

```
> i <- grep("AFFX",featureNames(eset))
> summary(fit2$F.p.value[i])
      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
0.0001391 0.1727000 0.3562000 0.4206000 0.6825000 0.9925000
```

So a cutoff  $p$ -value of 0.0001, say, would conservatively avoid selecting any of the control probe-sets as differentially expressed:

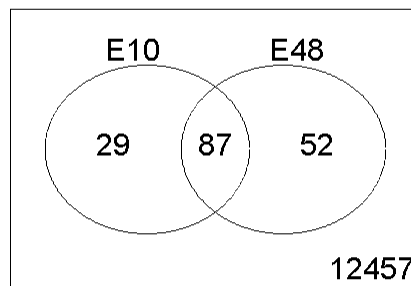
```
> results <- classifyTestsF(fit2, p.value=0.0001)
> summary(results)
```

	E10	E48
-1	40	76
0	12469	12410
1	116	139

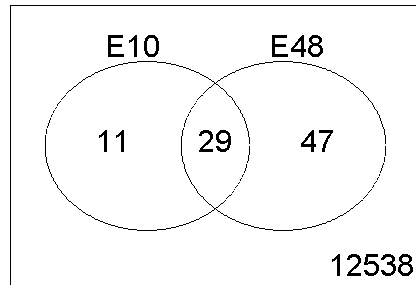
```
> table(E10=results[,1],E48=results[,2])
```

	E48		
E10	-1	0	1
-1	29	11	0
0	47	12370	52
1	0	29	87

```
> vennDiagram(results,include="up")
```



```
> vennDiagram(results,include="down")
```



We see that 87 genes were up regulated at both 10 and 48 hours, 29 only at 10 hours and 52 only at 48 hours. Also, 29 genes were down-regulated throughout, 11 only at 10 hours and 47 only at 48 hours. No genes were up at one time and down at the other.

`topTable` gives a detailed look at individual genes. Estrogen effect at 10 hours:

```
> options(digits=3)
> topTable(fit2,coef="E10",n=20)
```

	Symbol	logFC	AveExpr	t	P.Value	adj.P.Val	B
39642_at	ELOVL2	2.94	7.88	23.7	4.74e-09	3.13e-05	9.97
910_at	TK1	3.11	9.66	23.6	4.96e-09	3.13e-05	9.94
31798_at	TFF1	2.80	12.12	16.4	1.03e-07	3.51e-04	7.98
41400_at	TK1	2.38	10.04	16.2	1.11e-07	3.51e-04	7.92
40117_at	MCM6	2.56	9.68	15.7	1.47e-07	3.58e-04	7.71
1854_at	MYBL2	2.51	8.53	15.2	1.95e-07	3.58e-04	7.49
39755_at	XBP1	1.68	12.13	15.1	2.05e-07	3.58e-04	7.45
1824_s_at	PCNA	1.91	9.24	14.9	2.27e-07	3.58e-04	7.37
1126_s_at	CD44	1.78	6.88	13.8	4.12e-07	5.78e-04	6.89
1536_at	CDC6	2.66	5.94	13.3	5.80e-07	7.32e-04	6.61
981_at	MCM4	1.82	7.78	13.1	6.46e-07	7.42e-04	6.52
33252_at	MCM3	1.74	8.00	12.6	8.86e-07	9.20e-04	6.25
1505_at	TYMS	2.40	8.76	12.5	9.48e-07	9.20e-04	6.19
34363_at	SEPP1	-1.75	5.55	-12.2	1.14e-06	1.03e-03	6.03
1884_s_at	PCNA	2.80	9.03	12.1	1.26e-06	1.06e-03	5.95
36134_at	OLFM1	2.49	8.28	11.8	1.50e-06	1.19e-03	5.79
37485_at	SLC27A2	1.61	6.67	11.4	1.99e-06	1.48e-03	5.55
239_at	CTSD	1.57	11.25	10.4	4.07e-06	2.66e-03	4.90
38116_at	KIAA0101	2.32	9.51	10.4	4.09e-06	2.66e-03	4.90
40533_at	BIRC5	1.26	8.47	10.4	4.21e-06	2.66e-03	4.87

Estrogen effect at 48 hours:

```
> topTable(fit2,coef="E48",n=20)
```

	Symbol	logFC	AveExpr	t	P.Value	adj.P.Val	B
910_at	TK1	3.86	9.66	29.2	8.27e-10	1.04e-05	11.61

31798_at	TFF1	3.60	12.12	21.0	1.28e-08	7.63e-05	9.89
1854_at	MYBL2	3.34	8.53	20.2	1.81e-08	7.63e-05	9.64
38116_at	KIAA0101	3.76	9.51	16.9	8.12e-08	2.51e-04	8.48
38065_at	HMGB2	2.99	9.10	16.2	1.12e-07	2.51e-04	8.21
39755_at	XBP1	1.77	12.13	15.8	1.36e-07	2.51e-04	8.05
1592_at	TOP2A	2.30	8.31	15.8	1.39e-07	2.51e-04	8.03
41400_at	TK1	2.24	10.04	15.3	1.81e-07	2.75e-04	7.81
33730_at	GPRC5A	-2.04	8.57	-15.1	1.96e-07	2.75e-04	7.74
1651_at	UBE2C	2.97	10.50	14.8	2.39e-07	3.02e-04	7.57
38414_at	CDC20	2.02	9.46	14.6	2.66e-07	3.05e-04	7.48
1943_at	CCNA2	2.19	7.60	14.0	3.72e-07	3.69e-04	7.18
40117_at	MCM6	2.28	9.68	14.0	3.80e-07	3.69e-04	7.17
40533_at	BIRC5	1.64	8.47	13.5	4.94e-07	4.45e-04	6.93
39642_at	ELOVL2	1.61	7.88	13.0	6.71e-07	5.18e-04	6.65
34851_at	AURKA	1.96	9.96	12.8	7.51e-07	5.18e-04	6.55
1824_s_at	PCNA	1.64	9.24	12.8	7.95e-07	5.18e-04	6.50
35995_at	ZWINT	2.76	8.87	12.7	8.32e-07	5.18e-04	6.46
893_at	UBE2S	1.54	10.95	12.7	8.43e-07	5.18e-04	6.45
40079_at	GPRC5A	-2.41	8.23	-12.6	8.62e-07	5.18e-04	6.42

```
> sessionInfo()
```

```
R version 3.0.0 (2013-04-03)
```

```
Platform: i386-w64-mingw32/i386 (32-bit)
```

```
locale:
```

```
[1] LC_COLLATE=English_Australia.1252 LC_CTYPE=English_Australia.1252
```

```
[3] LC_MONETARY=English_Australia.1252 LC_NUMERIC=C
```

```
[5] LC_TIME=English_Australia.1252
```

```
attached base packages:
```

```
[1] parallel stats graphics grDevices utils datasets methods base
```

```
other attached packages:
```

```
[1] hgu95av2.db_2.9.0 org.Hs.eg.db_2.9.0 RSQLite_0.11.3
```

```
[4] DBI_0.2-6 annotate_1.38.0 hgu95av2cdf_2.12.0
```

```
[7] AnnotationDbi_1.22.2 affy_1.38.1 Biobase_2.20.0
```

```
[10] BiocGenerics_0.6.0 limma_3.17.7 BiocInstaller_1.10.0
```

```
loaded via a namespace (and not attached):
```

```
[1] affyio_1.28.0 IRanges_1.18.0 preprocessCore_1.22.0
```

```
[4] stats4_3.0.0 tools_3.0.0 XML_3.96-1.1
```

```
[7] xtable_1.7-1 zlibbioc_1.6.0
```

## 17.3 Comparing Mammary Progenitor Cell Populations with Illumina BeadChips

### 17.3.1 Introduction

This case study examines the expression profiles of adult mammary stem cells and of progenitor and mature mammary lumina cells. The data was first published by Lim et al [19], who used

the expression profiles to show that lumina progenitor cells are the likely cell of origin for basal-like breast cancer.

The data files used in this case study can be downloaded from <http://bioinf.wehi.edu.au/marray/IlluminaCaseStudy>. The expression data files are provided as gzip files and will need to be uncompressed before they can be used for a limma analysis. To run the analysis described here, download and unzip the data files and set the working directory of R to the folder containing the files.

### 17.3.2 The target RNA samples

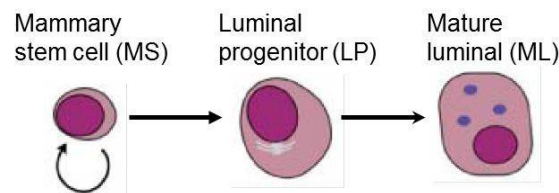
The data consists of three files:

```
> dir()
[1] "control probe profile.txt"
[2] "probe profile.txt"
[3] "Targets.txt"
```

First read the targets file describing the target RNA samples.

```
> library(limma)
> targets <- readTargets()
> targets
  Donor Age CellType
1      1  39      MS
2      1  39   Stroma
3      1  39      ML
4      1  39      LP
5      2  57      MS
6      2  57   Stroma
7      2  57      ML
8      2  57      LP
9      3  21      MS
10     3  21   Stroma
11     3  21      ML
12     3  21      LP
```

Breast tissue was obtained from three healthy human donors who were undergoing reduction mammoplasties. Epithelial cells were sorted into three subpopulations enriched for mammary stem cells (MS), luminal progenitor cells (LP) and mature luminal cells (ML) [19]. The MS, LP and ML cells representative a lineage of luminal cells use to construct the ducts used to transport milk in the breast [44]:



Stromal cells were also profiled as a comparison group. There were therefore four cell populations from each person. RNA was extracted from freshly sorted cells, making twelve RNA samples in total.

### 17.3.3 The expression profiles

The RNA samples were hybridized to two Illumina HumanWG-6 version 3 BeadChips. Each BeadChip is able to accommodate six samples. The BeadChips images were scanned and summarized using BeadStudio. Un-normalized summary probe profiles were exported from BeadStudio to tab-delimited text files.

Separate files were written for regular probes and for control probes. The file `probe profile.txt` contains the expression profiles for regular probes, designed to interrogate the expression levels of genes. `control probe profile.txt` contains the profiles of control probes, including negative control probes. Note that BeadStudio by default writes the profiles for all the samples to the same two files.

We read in the expression profiles for both regular and control probes, telling `read.ilm` that we wish to read the detection  $p$ -values as well as the expression values:

```
> x <- read.ilmn(files="probe profile.txt",ctrlfiles="control probe profile.txt",
+ other.columns="Detection")
Reading file probeprofile.txt ... ...
Reading file controlprobeprofile.txt ... ...
```

This reads a `EListRaw` object. There are about 750 negative probes and about 49,000 regular probes:

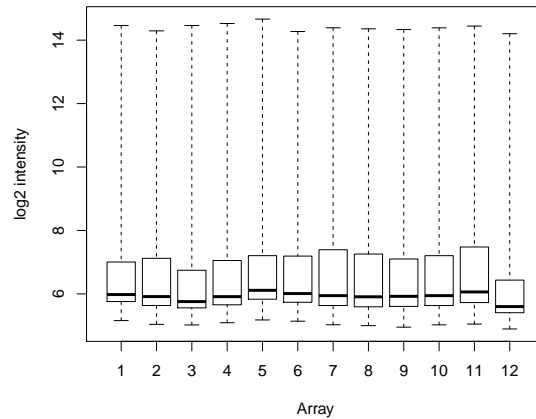
```
> table(x$genes$Status)
      BIOTIN      CY3_HYB      HOUSEKEEPING      LABELING
      2         6         7         2
LOW_STRINGENCY_HYB  NEGATIVE      regular
      8         759      48803
```

The component `E` contains the expression value for each probe

```
> options(digits=3)
> head(x$E)
      1      2      3      4      5      6      7      8      9     10     11     12
ILMN_1762337 52.3 46.1 54.0 47.7 54.8 47.4 67.4 47.9 40.5 44.7 80.6 42.5
ILMN_2055271 69.9 73.9 58.6 72.4 77.1 82.1 69.1 81.3 79.1 82.5 87.0 60.9
ILMN_1736007 57.5 53.7 53.4 49.4 58.6 59.9 56.4 51.6 58.7 51.7 58.4 43.9
ILMN_2383229 53.6 57.5 48.2 48.2 61.8 64.5 52.7 43.5 65.5 49.8 53.9 39.3
ILMN_1806310 58.1 55.1 50.5 60.0 64.2 58.4 58.0 52.3 56.6 55.6 65.3 46.4
ILMN_1779670 64.5 61.2 52.8 61.9 67.9 59.7 68.2 63.1 65.1 65.7 69.6 52.0
```

The intensities vary from about 5 to 14 on the  $\log_2$  scale:

```
> boxplot(log2(x$E),range=0,ylab="log2 intensity")
```



### 17.3.4 How many probes are truly expressed?

The detection values contain  $p$ -values for testing whether each probe is more intense than the negative control probes. Small values are evidence that the probe corresponds to a truly expressed gene:

```
> head(x$other$Detection)
```

	1	2	3	4	5	6	7	8	9	10	11	12
ILMN_1762337	0.5585	0.675	0.1370	0.60139	0.5776	0.782	0.0503	0.4781	0.9082	0.7145	0.0000	0.460
ILMN_2055271	0.0306	0.000	0.0493	0.00278	0.0364	0.000	0.0391	0.0000	0.0000	0.0000	0.0000	0.000
ILMN_1736007	0.2772	0.292	0.1534	0.48611	0.4112	0.220	0.2318	0.3145	0.1554	0.3774	0.2539	0.360
ILMN_2383229	0.4735	0.187	0.3658	0.56389	0.2951	0.124	0.3408	0.7447	0.0537	0.4680	0.3986	0.747
ILMN_1806310	0.2618	0.248	0.2589	0.12778	0.2196	0.264	0.1955	0.2920	0.1963	0.2382	0.1220	0.203
ILMN_1779670	0.0850	0.113	0.1644	0.10417	0.1469	0.224	0.0461	0.0691	0.0621	0.0655	0.0709	0.058

We can go further than this and estimate the overall proportion of the regular probes that correspond to expressed transcript, using the method of Shi et al [34].

```
> pe <- propexpr(x)
> dim(pe) <- c(4,3)
> dimnames(pe) <- list(CellType=c("MS","Stroma","ML","LP"),Donor=c(1,2,3))
> pe
```

	Donor		
CellType	1	2	3
MS	0.557	0.504	0.529
Stroma	0.518	0.514	0.514
ML	0.549	0.495	0.535
LP	0.555	0.518	0.517

The proportion of probes that are expressed varies from 50–56%. The average is 52.5%.

### 17.3.5 Normalization and filtering

Background correction and normalize:



```
> y <- neqc(x)
```

The `neqc` functions performs normexp background correction using negative controls, then quantile normalizes and finally  $\log_2$  transforms [35]. It also automatically removes the control probes, leaving only the regular probes in `y`:

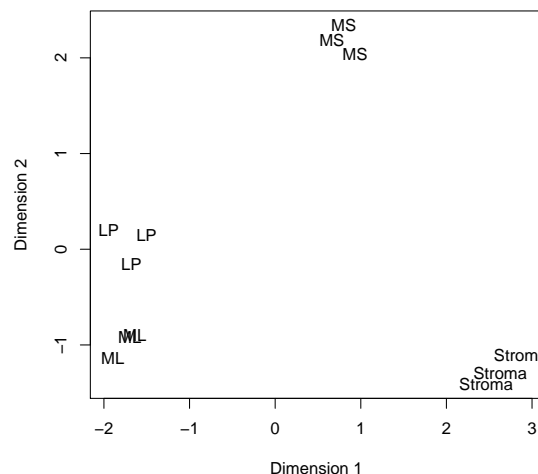
```
> dim(y)
[1] 48803    12
```

Filter out probes that are not expressed. We keep probes that are expressed in at least three arrays according to a detection  $p$ -values of 5%:

```
> expressed <- rowSums(y$other$Detection < 0.05) >= 3
> y <- y[expressed,]
> dim(y)
[1] 24691    12
```

A multi-dimensional scaling plot shows that the cell types are cell separated:

```
> plotMDS(y, labels=targets$CellType)
```



### 17.3.6 Within-patient correlations

The study involves multiple cell types from the same patient. Arrays from the same donor are not independent, so we need to estimate the within-donor correlation:

```
> ct <- factor(targets$CellType)
> design <- model.matrix(~0+ct)
> colnames(design) <- levels(ct)
> dupcor <- duplicateCorrelation(y, design, block=targets$Donor)
> dupcor$consensus.correlation
[1] 0.134
```

As expected, the within-donor correlation is small but positive.

### 17.3.7 Differential expression between cell types

Now we look for differentially expressed genes. We make all possible pairwise comparisons between the epithelial cell types, allowing for the correlation within donors:

```
> fit <- lmFit(y,design,block=targets$Donor,correlation=dupcor$consensus.correlation)
> contrasts <- makeContrasts(ML-MS, LP-MS, ML-LP, levels=design)
> fit2 <- contrasts.fit(fit, contrasts)
> fit2 <- eBayes(fit2, trend=TRUE)
> summary(decideTests(fit2, method="global"))
```

	ML - MS	LP - MS	ML - LP
-1	3074	2836	1631
0	18088	18707	21307
1	3529	3148	1753

Top ten differentially expressed probes between ML and MS:

```
> topTable(fit2, coef=1)
```

	SYMBOL	logFC	AveExpr	t	P.Value	adj.P.Val	B
ILMN_1766707	IL17B	-4.19	5.94	-29.0	2.51e-12	5.19e-08	18.1
ILMN_1706051	PLD5	-4.00	5.67	-27.8	4.20e-12	5.19e-08	17.7
ILMN_1656369	C8orf4	5.24	11.26	25.1	1.36e-11	1.06e-07	16.7
ILMN_2413323	GRP	-6.60	6.82	-24.3	2.01e-11	1.06e-07	16.4
ILMN_1787750	CD200	-5.68	6.30	-23.9	2.43e-11	1.06e-07	16.2
ILMN_1669819	LOC402569	2.52	5.50	23.8	2.57e-11	1.06e-07	16.2
ILMN_1777998	ARHGAP25	-4.78	6.26	-23.1	3.50e-11	1.15e-07	15.9
ILMN_1701933	SNCA	-5.26	6.27	-22.8	4.19e-11	1.15e-07	15.7
ILMN_1777199	GRP	-5.47	6.36	-22.8	4.23e-11	1.15e-07	15.7
ILMN_1708303	CYP4F22	4.09	5.94	22.5	4.76e-11	1.15e-07	15.6

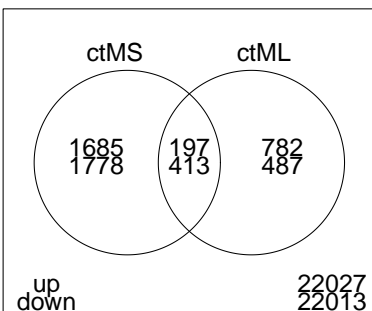
### 17.3.8 Signature genes for luminal progenitor cells

Now we find genes uniquely expressed in LP cells, as compared to MS and ML. We refit the linear model, making LP the reference cell type:

```
> ct <- relevel(ct, ref="LP")
> design <- model.matrix(~ct)
> fit <- lmFit(y,design,block=targets$Donor,correlation=dupcor$consensus.correlation)
> fit2 <- fit[,c("ctMS","ctML")]
> fit2 <- eBayes(fit2, trend=TRUE)
```

The we find all those genes that are up-regulated in LP vs both MS and ML, using a 2-fold-change and 5% FDR:

```
> results <- decideTests(fit2, lfc=1)
> vennDiagram(results, include=c("up","down"))
```



There are 197 positive signature genes and 413 negative. To see the top positive signature genes with their fold-changes:

```
> LP.sig <- rowSums(results>0)==2
> topTable(fit2[LP.sig,])
```

	SYMBOL	ctMS	ctML	AveExpr	F	P.Value	adj.P.Val
ILMN_1716370	TNS4	4.87	1.47	6.81	156.3	3.31e-09	4.81e-07
ILMN_1810054	CNN1	6.41	1.42	8.47	146.0	4.88e-09	4.81e-07
ILMN_1713744	C14orf132	3.85	1.74	7.34	103.5	3.37e-08	2.21e-06
ILMN_1720513	SETBP1	4.17	1.27	8.27	92.5	6.28e-08	3.09e-06
ILMN_1767662	LASS6	2.60	1.98	10.01	85.2	9.88e-08	3.46e-06
ILMN_1681984	GALNT10	3.54	1.23	8.09	84.2	1.06e-07	3.46e-06
ILMN_1731374	CPE	4.23	3.01	9.12	81.9	1.23e-07	3.46e-06
ILMN_1789639	FMOD	3.57	2.24	8.21	75.7	1.89e-07	4.65e-06
ILMN_1743933	TSHZ3	3.94	1.22	8.93	72.6	2.38e-07	5.21e-06
ILMN_1721876	TIMP2	3.57	1.38	10.10	69.0	3.13e-07	6.17e-06

## 17.4 Time Course Effects of Corn Oil on Rat Thymus with Agilent 4x44K Arrays

This case study analyses a time-course experiment using single-channel Agilent Whole Rat Genome Microarray 4x44K v3 arrays.

**Background.** The experiment concerns the effect of corn oil on gene expression in the thymus of rats. The data was submitted by Hong Weiguo to ArrayExpress as series E-GEOD-33005. The description of the experiment reads:

“To investigate the effects of corn oil (CO), common drug vehicle, on the gene expression profiles in rat thymus with microarray technique. Female Wistar Rats were administered daily with normal saline (NS), CO 2, 5, 10 ml/kg for 14 days, respectively. Then, the thymus samples of rats were collected for microarray test and histopathology examination. The microarray data showed that 0, 40, 458 differentially expressed genes (DEGs) in 2, 5, 10 ml/kg CO group compared to NS

group, respectively. The altered genes were associated with immune response, cellular response to organic cyclic substance, regulation of fatty acid beta-oxidation, et al. However, no obvious histopathologic change was observed in the three CO dosage groups. These data show that 10 ml/kg CO, that dosage has been determined as the vehicle in drug safety assessment, can cause obvious influence on gene expression in rat thymus. Our study suggest that the dosage of CO gavage as the vehicle for water-in-soluble agents in drug development should be no more than 5 ml/kg if agents' molecular effects in thymus want to be assessed. Gene expression in thymus from female Wistar rats daily administered with 2, 5, 10 ml/kg of corn oil or 10 ml/kg of saline by gavage for 14 consecutive days were measured using Agilent Rat Whole Genome 8×60K array.”

**Data availability.** All files were downloaded from <http://www.ebi.ac.uk/arrayexpress/experiments/E-GEOD-33005>.

Read the sample and data relationship format (SDRF) file. This is equivalent to what is known as the targets file in limma:

```
> SDRF <- read.delim("E-GEOD-33005.sdrf.txt",check.names=FALSE,stringsAsFactors=FALSE)
```

Read data:

```
> x <- read.maimages(SDRF[, "Array Data File"], source="agilent", green.only=TRUE)
Read GSM819076_US10283824_252828210181_S01_GE1_107_Sep09_1_4.txt
Read GSM819075_US10283824_252828210181_S01_GE1_107_Sep09_1_3.txt
Read GSM819074_US10283824_252828210181_S01_GE1_107_Sep09_1_2.txt
Read GSM819073_US10283824_252828210180_S01_GE1_107_Sep09_1_4.txt
Read GSM819072_US10283824_252828210180_S01_GE1_107_Sep09_1_3.txt
Read GSM819071_US10283824_252828210180_S01_GE1_107_Sep09_1_2.txt
Read GSM819070_US10283824_252828210180_S01_GE1_107_Sep09_1_1.txt
Read GSM819069_US10283824_252828210179_S01_GE1_107_Sep09_1_4.txt
Read GSM819068_US10283824_252828210179_S01_GE1_107_Sep09_1_3.txt
Read GSM819067_US10283824_252828210179_S01_GE1_107_Sep09_1_2.txt
Read GSM819066_US10283824_252828210179_S01_GE1_107_Sep09_1_1.txt
Read GSM819065_US10283824_252828210178_S01_GE1_107_Sep09_1_4.txt
Read GSM819064_US10283824_252828210178_S01_GE1_107_Sep09_1_3.txt
Read GSM819063_US10283824_252828210178_S01_GE1_107_Sep09_1_2.txt
Read GSM819062_US10283824_252828210178_S01_GE1_107_Sep09_1_1.txt
Read GSM819061_US10283824_252828210177_S01_GE1_107_Sep09_1_4.txt
Read GSM819060_US10283824_252828210177_S01_GE1_107_Sep09_1_3.txt
Read GSM819059_US10283824_252828210177_S01_GE1_107_Sep09_1_2.txt
Read GSM819058_US10283824_252828210177_S01_GE1_107_Sep09_1_1.txt
```

Background correct and normalize:

```
> y <- backgroundCorrect(x, method="normexp")
Array 1 corrected
Array 2 corrected
Array 3 corrected
Array 4 corrected
```

```

Array 5 corrected
Array 6 corrected
Array 7 corrected
Array 8 corrected
Array 9 corrected
Array 10 corrected
Array 11 corrected
Array 12 corrected
Array 13 corrected
Array 14 corrected
Array 15 corrected
Array 16 corrected
Array 17 corrected
Array 18 corrected
Array 19 corrected
> y <- normalizeBetweenArrays(y,method="quantile")

```

Now filter out control probes and low expressed probes. To get an idea of how bright expression probes should be, we compute the 95% percentile of the negative control probes on each array. We keep probes that are at least 10% brighter than the negative controls on at least four arrays (because there are four replicates):

```

> neg95 <- apply(y$E[y$genes$ControlType==1,],2,function(x) quantile(x,p=0.95))
> cutoff <- matrix(1.1*neg95,nrow(y),ncol(y),byrow=TRUE)
> isexpr <- rowSums(y$E > cutoff) >= 4
> table(isexpr)
isexpr
FALSE  TRUE
11500 32754

```

Regular probes are code as "0" in the ControlType column:

```

> y0 <- y[y$genes$ControlType==0 & isexpr,]

```

Now we can find genes differentially expressed for the corn oil treatments compared to the saline control:

```

> Treatment <- SDRF[, "Characteristics[treatment]"]
> levels <- c("10 ml/kg saline", "2 ml/kg corn oil", "5 ml/kg corn oil", "10 ml/kg corn oil")
> Treatment <- factor(Treatment, levels=levels)
> design <- model.matrix(~Treatment)
> fit <- lmFit(y0, design)
> fit <- eBayes(fit, trend=TRUE)
> plotSA(fit, main="Probe-level")
> summary(decideTests(fit[, -1]))

```

	Treatment2 ml/kg corn oil	Treatment5 ml/kg corn oil	Treatment10 ml/kg corn oil
-1	0	0	911
0	32723	32723	30063
1	0	0	1749

It appears that only the 10 ml/kg treatment is different from the saline control, however this is quite different.

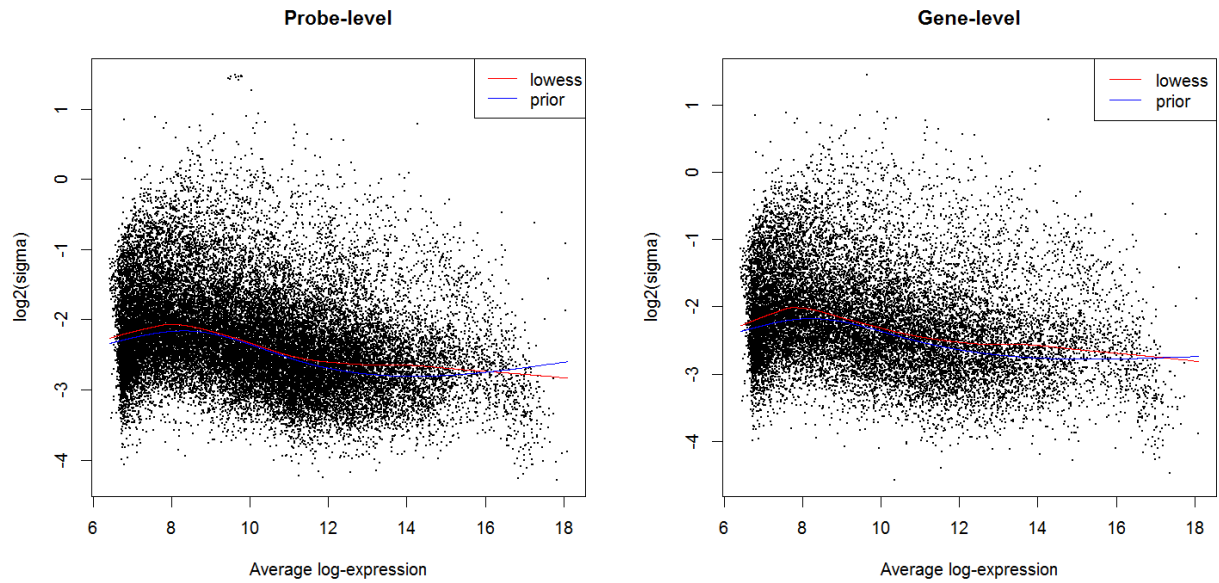
Same analysis, but now averaging probes for each gene:

```

> yave <- avereps(y0,ID=y0$genes[, "SystematicName"])
> fit <- lmFit(yave,design)
> fit <- eBayes(fit,trend=TRUE)
> plotSA(fit, main="Gene-level")
> summary(decideTests(fit[,-1]))

```

	Treatment2 ml/kg corn oil	Treatment5 ml/kg corn oil	Treatment10 ml/kg corn oil
-1	0	0	407
0	19112	19112	17878
1	0	0	827



# Chapter 18

## RNA-Seq Case Studies

### 18.1 Profiles of Unrelated Nigerian Individuals

#### 18.1.1 Background

RNA-Seq profiles were made from lymphoblastoid cell lines generated as part of the International HapMap project from 69 unrelated Nigerian individuals [25]. RNA from each individual was sequenced on at least two lanes of the Illumina Genome Analyser 2 platform, and mapped reads to the human genome using MAQ v0.6.8.

The study group here is essentially an opportunity sample and the individuals are likely to be genetically diverse. In this analysis we look at genes that are differentially expressed between males and females. This case study requires limma 3.9.19 or later.

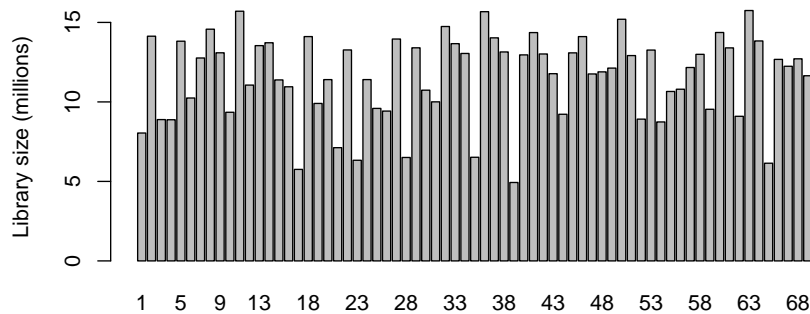
#### 18.1.2 Loading the data

Read counts summarized by Ensembl gene identifiers are available in the `tweedEseqCountData` package:

```
> library(tweedEseqCountData)
> data(pickrell11)
> Counts <- exprs(pickrell11.eset)
> dim(Counts)
[1] 38415      69
> Counts[1:5,1:5]
      NA18486 NA18498 NA18499 NA18501 NA18502
ENSG000000127720      6      32      14      35      14
ENSG000000242018     20      21      24      22      16
ENSG000000224440      0       0       0       0       0
ENSG000000214453      0       0       0       0       0
ENSG000000237787      0       0       1       0       0
```

The library sizes vary from about 5 million to over 15 million:

```
> barplot(colSums(Counts)*1e-6, names=1:69, ylab="Library size (millions)")
```



To demonstrate limma on RNA-Seq data, we will compare female with male individuals.

```
> Gender <- pickrell1.eset$gender
> table(Gender)
Gender
female    male
     40      29
> rm(pickrell1.eset)
> data(genderGenes)
```

Annotation for each Ensemble gene is also available from the `tweeDEseqCountData` package:

```
> data(annotEnsembl63)
> annot <- annotEnsembl63[,c("Symbol", "Chr")]
> annot[1:5,]
      Symbol Chr
ENSG000000252775    U7    5
ENSG000000207459    U6    5
ENSG000000252899    U7    5
ENSG000000201298    U6    5
ENSG000000222266    U6    5
> rm(annotEnsembl63)
```

### 18.1.3 DGEList object

Form a `DGEList` object combining the counts and associated annotation:

```
> library(edgeR)
> y <- DGEList(counts=Counts, genes=annot[rownames(Counts),])
```

### 18.1.4 Filtering

Keep genes with least 1 count-per-million reads (cpm) in at least 20 samples:

```
> isexpr <- rowSums(cpm(y)>1) >= 20
```



Keep only genes with defined annotation:

```
> hasannot <- rowSums(is.na(y$genes))==0
> y <- y[isexpr & hasannot,,keep.lib.sizes=FALSE]
> dim(y)
[1] 17310    69
```

### 18.1.5 Scale normalization

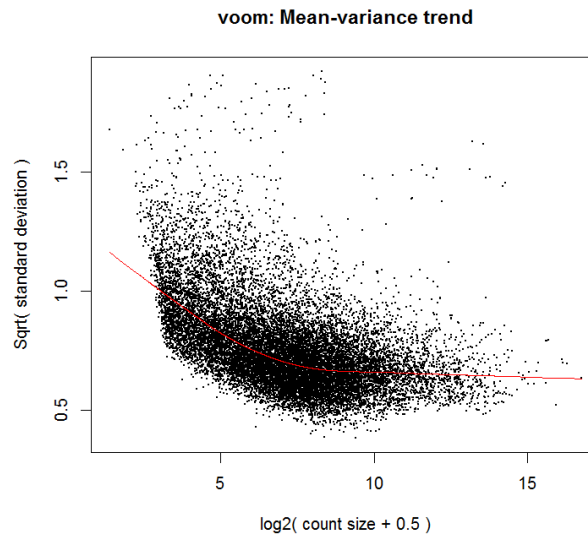
Apply scale normalization:

```
> y <- calcNormFactors(y)
```

### 18.1.6 Linear modeling

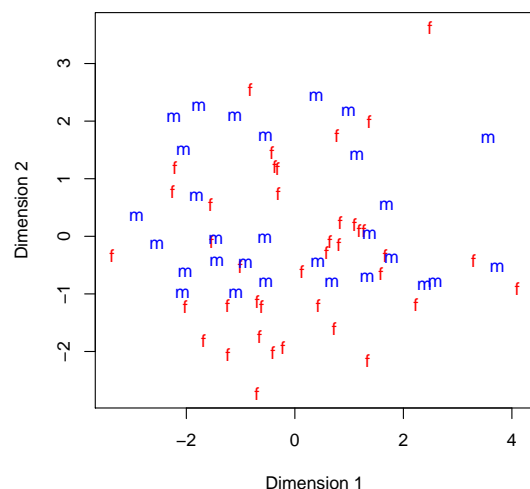
Use `voom()` [15] to convert the read counts to  $\log_2$ -cpm, with associated weights, ready for linear modelling:

```
> library(limma)
> design <- model.matrix(~Gender)
> v <- voom(y,design,plot=TRUE)
```



Some separation of female and male profiles is evident from an MDS plot, although clear differences seem to rely on only a few score genes.

```
> plotMDS(v,top=50,labels=substring(Gender,1,1),
+         col=ifelse(Gender=="male","blue","red"),gene.selection="common")
```



Now find genes differentially expression between male and females. Positive log-fold-changes mean higher in males. The highly ranked genes are mostly on the X or Y chromosomes.

```
> fit <- lmFit(v,design)
> fit <- eBayes(fit)
> options(digits=3)
> topTable(fit,coef=2,n=16,sort="p")
```

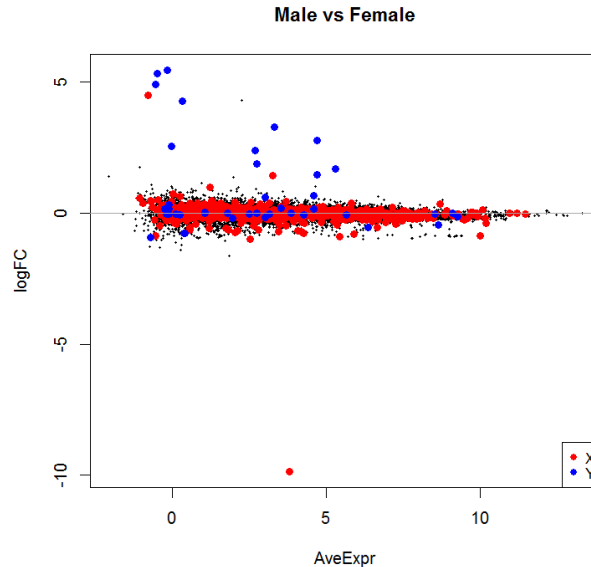
	Symbol	Chr	logFC	AveExpr	t	P.Value	adj.P.Val	B
ENSG00000229807	XIST	X	-9.857	3.8076	-32.5	1.21e-44	2.10e-40	66.5
ENSG00000099749	CYorf15A	Y	4.260	0.3139	27.1	2.40e-39	2.08e-35	64.8
ENSG00000157828	RPS4Y2	Y	3.280	3.3074	26.7	5.88e-39	3.39e-35	73.8
ENSG00000233864	TTY15	Y	4.896	-0.5546	25.4	1.62e-37	7.00e-34	59.6
ENSG00000198692	EIF1AY	Y	2.397	2.6799	20.5	1.04e-31	3.60e-28	59.1
ENSG00000131002	CYorf15B	Y	5.439	-0.1717	20.2	2.46e-31	7.09e-28	51.1
ENSG00000213318	RP11-331F4.1	16	4.295	2.2647	19.4	3.04e-30	7.51e-27	55.0
ENSG00000165246	NLGN4Y	Y	5.330	-0.4924	17.9	3.59e-28	7.78e-25	45.9
ENSG00000129824	RPS4Y1	Y	2.779	4.7110	17.8	6.17e-28	1.19e-24	52.2
ENSG00000183878	UTY	Y	1.877	2.7422	16.6	3.35e-26	5.81e-23	47.9
ENSG00000012817	KDM5D	Y	1.470	4.7039	14.7	2.33e-23	3.67e-20	42.3
ENSG00000243209	AC010889.1	Y	2.536	-0.0186	14.0	2.97e-22	4.28e-19	36.5
ENSG00000146938	NLGN4X	X	4.472	-0.7808	13.8	6.47e-22	8.62e-19	34.8
ENSG00000067048	DDX3Y	Y	1.670	5.3070	13.3	4.54e-21	5.61e-18	37.3
ENSG00000006757	PNPLA4	X	-0.989	2.5333	-10.4	5.09e-16	5.87e-13	25.8
ENSG00000232928	RP13-204A15.4	X	1.434	3.2499	10.2	1.43e-15	1.54e-12	25.0

```
> fit$df.prior
[1] 4.6
> summary(decideTests(fit))
      (Intercept) Gendermale
-1             292         43
0              913        17251
1             16105         16
```

```

> chrom <- fit$genes$Chr
> plot(fit,coef=2,status=chrom,values=c("X","Y"),col=c("red","blue"),
+      main="Male vs Female",legend="bottomright")
> abline(h=0,col="darkgrey")

```



### 18.1.7 Gene set testing

The `tweeDeseqCountData` package includes a list of genes belonging to the male-specific region of chromosome Y, and a list of genes located in the X chromosome that have been reported to escape X-inactivation. We expect genes in the first list to be up-regulated in males, whereas genes in the second list should be up-regulated in females.

```

> Ymale <- rownames(v) %in% msYgenes
> Xescape <- rownames(v) %in% XiEgenes

```

Roast gene set tests confirm that the male-specific genes are significantly up as a group in our comparison of males with females, whereas the X genes are significantly down as a group [49]:

```

> index <- list(Y=Ymale,X=Xescape)
> mroast(v,index,design,nrot=9999)

```

	NGenes	PropDown	PropUp	Direction	PValue	FDR	PValue.Mixed	FDR.Mixed
Y	12	0.0833	0.9167	Up	2e-04	1e-04	1e-04	5e-05
X	46	0.5217	0.0435	Down	2e-04	1e-04	1e-04	5e-05

The results from competitive camera gene sets tests are even more convincing [50]:

```

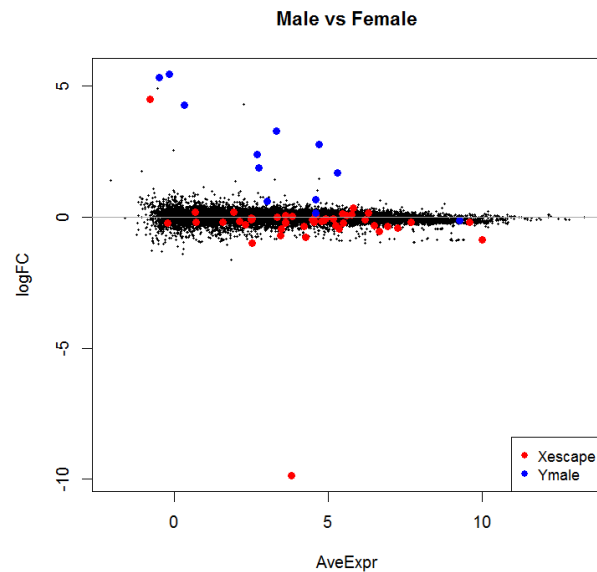
> camera(v,index,design)

```

	NGenes	Correlation	Direction	PValue	FDR
Y	12	0.0836	Up	2.12e-28	4.23e-28
X	46	0.0206	Down	1.14e-10	1.14e-10

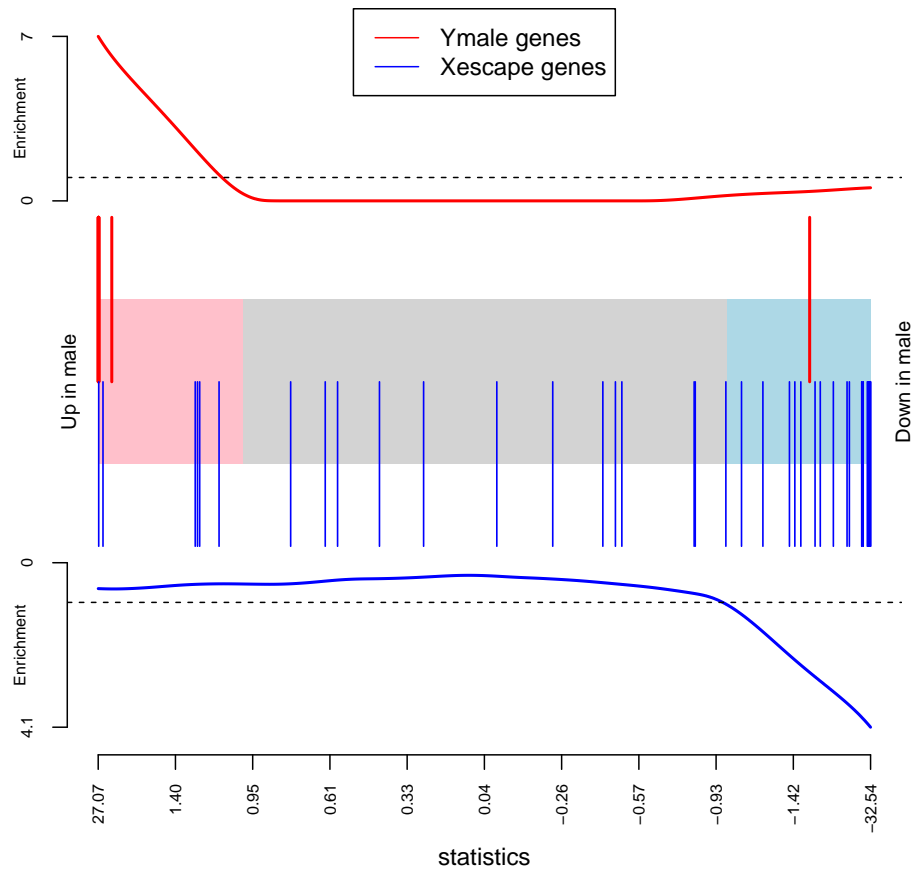
We can highlight the male-specific and X-escape genes on the MA-plot:

```
> status <- rep("Other",nrow(fit))
> status[Ymale] <- "Ymale"
> status[Xescape] <- "Xescape"
> plot(fit,coef=2,status=status,values=c("Xescape","Ymale"),col=c("red","blue"),
+      main="Male vs Female",legend="bottomright")
> abline(h=0,col="darkgrey")
```



Another way to view the gene sets is to view the ranking of the Y and X specific genes in the differential expression results. This shows that, with a couple of exceptions, the Y specific genes are highly ranked (positive) while the X specific genes are low ranked (negative):

```
> barcodeplot(fit$t[,2],Ymale,Xescape, labels=c("Up in male","Down in male"))
> legend("top",legend=c("Ymale genes","Xescape genes"),lty=1,col=c("red","blue"))
```



```
> sessionInfo()
```

```
R Under development (unstable) (2014-03-07 r65143)
```

```
Platform: x86_64-w64-mingw32/x64 (64-bit)
```

```
locale:
```

```
[1] LC_COLLATE=English_Australia.1252 LC_CTYPE=English_Australia.1252
```

```
[3] LC_MONETARY=English_Australia.1252 LC_NUMERIC=C
```

```
[5] LC_TIME=English_Australia.1252
```

```
attached base packages:
```

```
[1] parallel stats graphics grDevices utils datasets methods base
```

```
other attached packages:
```

```
[1] edgeR_3.5.27
```

```
limma_3.19.27
```

```
tweedEseqCountData_1.0.11
```

```
[4] Biobase_2.23.6
```

```
BiocGenerics_0.9.3
```

```
loaded via a namespace (and not attached):
```

```
[1] tools_3.1.0
```

## 18.2 Differential Splicing after Pasilla Knockdown

### 18.2.1 Background

This case study re-analyzes data produced by Brooks et al [3].

The proteins NOVA1 and NOVA2 are known to regulate splicing in mammals. Brooks et al used *Drosophila melanogaster* as a model system, and used an RNA interference system (RNAi) to knock down the expression of the *D. melanogaster* ortholog of NOVA1 and NOVA2, which is Pasilla (ps). The experiment compared treated and untreated cells from the S2-DRSC cell line.

In this case study we find exons and genes that are differentially expressed after ps knock-down, and we find genes that are differentially spliced in the knockdown samples as compared to wild-type.

For completeness, we will describe all the steps in the analysis from raw data files including mapping and alignment. If you want to skip the mapping and read counting steps, go straight to Section 18.2.6 where the statistical analysis begins.

### 18.2.2 GEO samples and SRA Files

Brooks et al [3] deposited data for six RNA samples to GEO <http://www.ncbi.nlm.nih.gov/geo>. We have prepared the GEO accession numbers and titles in a csv file:

```
> library(limma)
> GEO <- readTargets("GEO-Samples.csv", sep=",")
> GEO
```

	GEO	Title	Pasilla
1	GSM461176	S2_DRSC_Untreated-1	Normal
2	GSM461177	S2_DRSC_Untreated-3	Normal
3	GSM461178	S2_DRSC_Untreated-4	Normal
4	GSM461179	S2_DRSC_CG8144_RNAi-1	Down
5	GSM461180	S2_DRSC_CG8144_RNAi-3	Down
6	GSM461181	S2_DRSC_CG8144_RNAi-4	Down

There are three untreated biological samples, in which ps should be expressed at normal levels, and three treated biological samples, in which ps should be expressed at reduced levels.

While GEO records the sample information, the sequencing data files are actually held on the NCBI Short Read Archive (SRA). The RNA samples were sequenced on an Illumina Genome Analyzer II. Multiple sequencing runs were used for several of the samples, resulting in a total of 20 SRA files:

```
> SRA <- readTargets("SRA-Files.csv", sep=",")
> SRA
```

	SRA	GEO	Title	RunDate	FlowCellID	Type	ReadLength
1	SRR031708	GSM461176	S2_DRSC_Untreated-1	7/15/08	308T2AAXX	SE	45
2	SRR031709	GSM461176	S2_DRSC_Untreated-1	7/15/08	308T2AAXX	SE	45
3	SRR031710	GSM461176	S2_DRSC_Untreated-1	8/15/08	30AYWAAXX	SE	45

4	SRR031711	GSM461176	S2_DRSC_Untreated-1	8/15/08	30AYWAAXX	SE	45
5	SRR031712	GSM461176	S2_DRSC_Untreated-1	8/15/08	30AYWAAXX	SE	45
6	SRR031713	GSM461176	S2_DRSC_Untreated-1	8/15/08	30AYWAAXX	SE	45
7	SRR031714	GSM461177	S2_DRSC_Untreated-3	11/14/08	30MNEAAXX	PE	37
8	SRR031715	GSM461177	S2_DRSC_Untreated-3	12/23/08	30M2BAAXX	PE	37
9	SRR031716	GSM461178	S2_DRSC_Untreated-4	12/23/08	30M2BAAXX	PE	37
10	SRR031717	GSM461178	S2_DRSC_Untreated-4	12/23/08	30M2BAAXX	PE	37
11	SRR031718	GSM461179	S2_DRSC_CG8144_RNAi-1	7/15/08	308T2AAXX	SE	45
12	SRR031719	GSM461179	S2_DRSC_CG8144_RNAi-1	7/18/08	308UEAAXX	SE	45
13	SRR031720	GSM461179	S2_DRSC_CG8144_RNAi-1	8/15/08	30AYWAAXX	SE	45
14	SRR031721	GSM461179	S2_DRSC_CG8144_RNAi-1	8/15/08	30AYWAAXX	SE	45
15	SRR031722	GSM461179	S2_DRSC_CG8144_RNAi-1	8/15/08	30AYWAAXX	SE	45
16	SRR031723	GSM461179	S2_DRSC_CG8144_RNAi-1	8/21/08	308A0AAXX	SE	45
17	SRR031724	GSM461180	S2_DRSC_CG8144_RNAi-3	12/23/08	30M2BAAXX	PE	37
18	SRR031725	GSM461180	S2_DRSC_CG8144_RNAi-3	12/23/08	30M2BAAXX	PE	37
19	SRR031726	GSM461181	S2_DRSC_CG8144_RNAi-4	12/23/08	30M2BAAXX	PE	37
20	SRR031727	GSM461181	S2_DRSC_CG8144_RNAi-4	12/23/08	30M2BAAXX	PE	37

Run dates are in American format, so that 7/15/08 denotes 15 July 2008. All runs in July and August 2008 used single end (SE) sequencing with 45 base-pair reads, while the later runs used paired end (PE) sequencing with 37 bp reads.

### 18.2.3 Mapping reads to the reference genome

The reads were mapped to the reference *D. melanogaster* genome using subread [17].

First the SRA format files need to be converted to FASTQ format, which is the *de facto* standard for representing high-throughput sequencing data. This was done using the SRA Toolkit version 2.3.4. Specifically the Unix SRA toolkit command `fastq-dump --split-spot --split-files` was used to produce one FASTQ file for each single-end SRA file and two FASTQ files for each paired-end SRA file.

Second, FASTA files representing the *D. melanogaster* genome were downloaded from `ftp://ftp.ncbi.nlm.nih.gov/genomes/Drosophila_melanogaster/RELEASE_5_48`. There are five FASTA files corresponding to chromosome arms:

```
> DM <- readTargets("FASTA-GFF-files.csv",sep=",")
> DM
```

	FASTA	GFF	Chromosome
1	CHR_2/NT_033778.fna	CHR_2/NT_033778.gff	Chr2R
2	CHR_2/NT_033779.fna	CHR_2/NT_033779.gff	Chr2L
3	CHR_3/NT_033777.fna	CHR_3/NT_033777.gff	Chr3R
4	CHR_3/NT_037436.fna	CHR_3/NT_037436.gff	Chr3L
5	CHR_4/NC_004353.fna	CHR_4/NC_004353.gff	Chr4
6	CHR_X/NC_004354.fna	CHR_X/NC_004354.gff	ChrX

The five \*.fna files were concatenated into a single FASTA-format file `Drosophila_ref.fasta`, and an index file was built using Rsubread

```
> library(Rsubread)
> buildindex(basename="index",reference="Drosophila_ref.fasta")
```

Third, reads were aligned to the genome. The SE reads were mapped using:

```
> align("index",SE_fastq_files,input_format="FASTQ")
```

where `SE_fastq_files` is a character vector containing the names of the SE FASTQ files. The PE reads were mapped using:

```
> align("index",PE_fastq_files1,PE_fastq_files2,input_format="FASTQ")
```

where `PE_fastq_files1` and `PE_fastq_files2` are vectors containing the names of the PE FASTQ files. These commands produce BAM files containing aligned reads (SE) or fragments (PE).

## 18.2.4 Read counts for exons

Next we counted the number of reads or fragments overlapping each annotated exon of each gene. GFF files containing gene and exon annotation were downloaded from `ftp://ftp.ncbi.nlm.nih.gov/genomes/Drosophila_melanogaster/RELEASE_5_48`. There is one GFF file for each chromosome arm as shown above.

Now we need to assign mapped reads to exons. The five `*.gff` files were concatenated into one file, and repeated exons instances of the same exon (same start and stop position) were removed, to create a data.frame of start/stop positions called `unique.gff`. SE reads were counted by:

```
> fc_SE <- featureCounts(SE_bam_files, annot.ext="unique.gff",
+                         isGTFAnnotationFile=TRUE,
+                         GTF.featureType="exon", GTF.attrType="ID",
+                         useMetaFeatures=FALSE, allowMultiOverlap=TRUE)
```

where `SE_bam_files` is a vector of BAM file names for the SE reads. PE reads were counted by

```
> fc_SE <- featureCounts(PE_bam_files, annot.ext="unique.gff",
+                         isGTFAnnotationFile=TRUE,
+                         GTF.featureType="exon", GTF.attrType="ID",
+                         useMetaFeatures=FALSE, allowMultiOverlap=TRUE,
+                         isPairedEnd=TRUE)
```

where `PE_bam_files` is a vector of BAM file names for the PE reads.

## 18.2.5 Assemble DGEList and sum counts for technical replicates

We assemble all the counts into an edgeR DGEList object:

```
> library(edgeR)
> y.all <- DGEList(counts=cbind(fc_SE$counts,fc_PE$counts), genes=fc_SE$annotation)
> dim(y.all)
```

```
[1] 72687    20
```



```
> head(y.all$genes)
```

	GeneID	Chr	Start	End	Strand	Length
1	3355011	NT_033778.3	18479	18629	+	151
2	3355011	NT_033778.3	18681	19484	+	804
3	3355011	NT_033778.3	19542	20989	+	1448
5	3355011	NT_033778.3	18852	19484	+	633
8	3355011	NT_033778.3	18693	18773	+	81
9	3355011	NT_033778.3	18827	19484	+	658

The annotation includes Entrez ID and the length, chromosome and start and stop position of each exon.

Resort back to original SRA order:

```
> y.all <- y.all[,SRA$SRA]
```

Then we collapse the data so that there is a single column for each GEO sample by summing the counts over the technical replicates:

```
> y <- sumTechReps(y.all, ID=SRA$GEO)
> y$samples
```

	group	lib.size	norm.factors
GSM461176	1	28726876	1
GSM461177	1	12204569	1
GSM461178	1	14104800	1
GSM461179	1	26041043	1
GSM461180	1	13898076	1
GSM461181	1	15189911	1

```
> colnames(y) <- c("N1","N3","N4","D1","D3","D4")
```

## 18.2.6 Gene annotation

Annotation for *D. melanogaster* genes was downloaded from [ftp://ftp.ncbi.nlm.nih.gov/gene/DATA/GENE\\_INFO/Invertebrates](ftp://ftp.ncbi.nlm.nih.gov/gene/DATA/GENE_INFO/Invertebrates). We now add selected annotation columns to the DGEList object:

```
> ncbi.L1 <- readLines("Drosophila_melanogaster.gene_info", n = 1)
> ncbi.colname <- unlist(strsplit(substring(ncbi.L1, 10, 234), ' '))
> ncbi <- read.delim("Drosophila_melanogaster.gene_info",
+ skip=1, header=FALSE, stringsAsFactors=FALSE)
> colnames(ncbi) <- ncbi.colname
> m <- match(y$genes$GeneID, ncbi$GeneID)
> y$genes$Chr <- ncbi$chromosome[m]
> y$genes$Symbol <- ncbi$Symbol[m]
> y$genes$Strand <- NULL
> head(y$genes)
```

	GeneID	Chr	Start	End	Length	Symbol
1	3355011	2R	18479	18629	151	CG17683
2	3355011	2R	18681	19484	804	CG17683
3	3355011	2R	19542	20989	1448	CG17683
5	3355011	2R	18852	19484	633	CG17683
8	3355011	2R	18693	18773	81	CG17683
9	3355011	2R	18827	19484	658	CG17683

## 18.2.7 Filtering

Keep exons that have more than 1 cpm in at least 3 samples.

```
> isexpr <- rowSums(cpm(y) > 1) >=3
> y <- y[isexpr,,keep.lib.sizes=FALSE]
```

## 18.2.8 Scale normalization

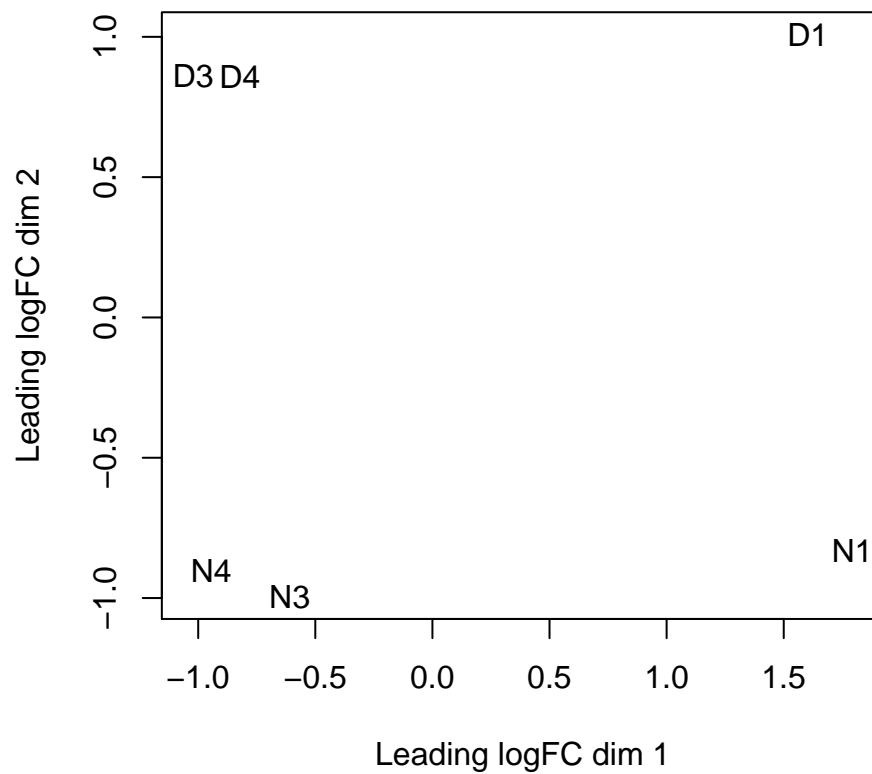
Apply TMM normalization.

```
> y <- calcNormFactors(y)
> y$sample
```

	group	lib.size	norm.factors
N1	1	28604956	0.954
N3	1	12132492	1.028
N4	1	13991699	0.975
D1	1	25901171	1.009
D3	1	13768063	1.022
D4	1	15105975	1.014

An MDS plot shows clear separation of the Pasilla down vs normal samples, but also a batch effect associated with sequencing type and date:

```
> plotMDS(y)
```



### 18.2.9 Linear modelling

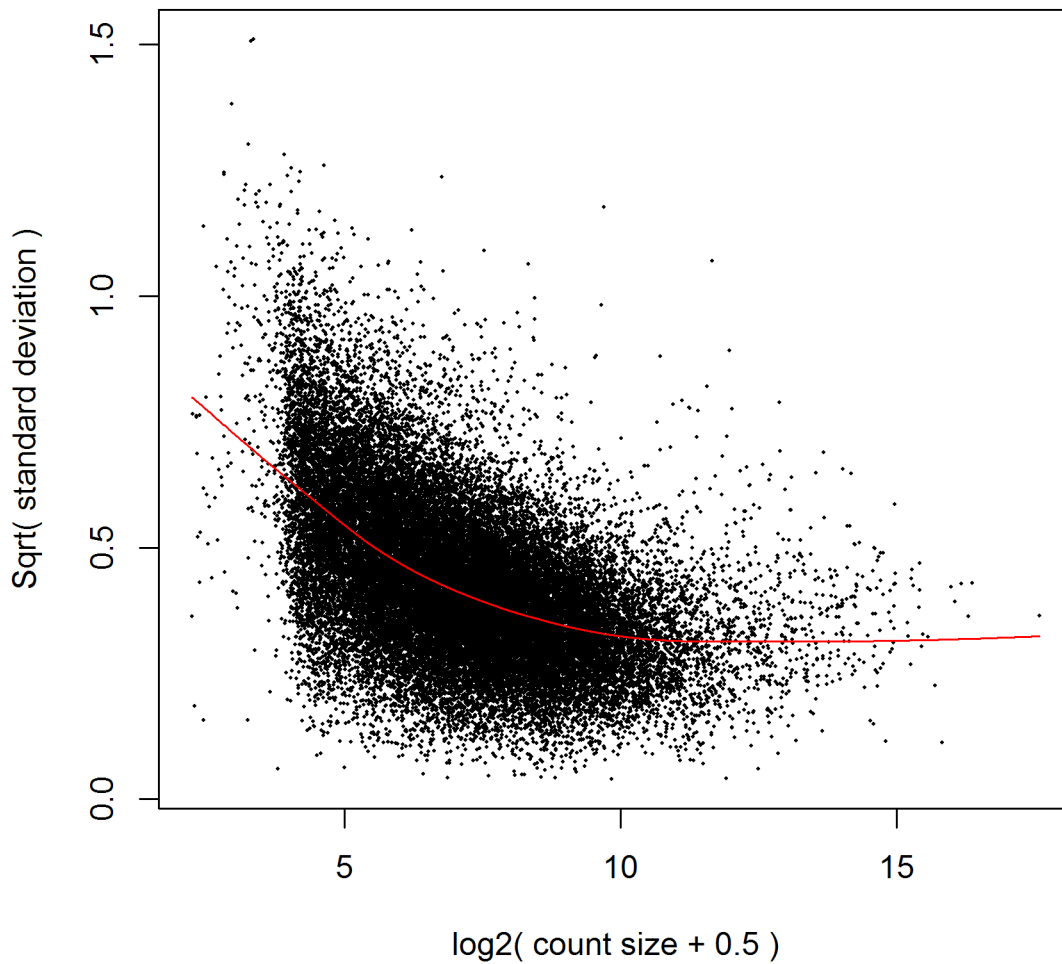
Create design matrix:

```
> Batch <- factor(c(1,3,4,1,3,4))
> Pasilla <- factor(GEO$Pasilla,levels=c("Normal","Down"))
> design <- model.matrix(~ Batch + Pasilla)
```

Apply voom to convert the read counts to log2-cpm with associated weights:

```
> v <- voom(y,design,plot=TRUE)
```

## voom: Mean-variance trend



Linear modelling:

```
> fit <- lmFit(v, design)
```

Test for differentially expressed exons:

```
> fit.de <- eBayes(fit, robust=TRUE)
> topTable(fit.de, coef="PasillaDown")
```

	GeneID	Chr	Start	End	Length	Symbol	logFC	AveExpr	t	P.Value	adj.P.Val	B
150709	32007	X	10674926	10676128	1203	sesB	-3.26	6.51	-31.7	1.31e-14	2.39e-10	23.5
150713	32007	X	10675026	10676128	1103	sesB	-3.26	6.51	-31.6	1.31e-14	2.39e-10	23.5
96435	43230	3R	22694960	22695852	893	BM-40-SPARC	-2.47	10.60	-27.7	8.61e-14	8.83e-10	21.9
150697	32008	X	10672987	10673728	742	Ant2	2.85	5.63	27.4	9.72e-14	8.83e-10	21.6
96434	43230	3R	22695915	22696094	180	BM-40-SPARC	-2.27	8.21	-26.3	1.78e-13	1.29e-09	21.3
96433	43230	3R	22697648	22697717	70	BM-40-SPARC	-2.17	6.37	-23.0	1.11e-12	5.75e-09	19.5

107856	44030	3L	2561932	2562843	912	msn	-2.46	5.22	-23.1	1.08e-12	5.75e-09	19.4
11333	44548	2R	6407125	6408782	1658	lola	2.25	5.83	22.6	1.43e-12	6.49e-09	19.2
52822	34652	2L	12403270	12404177	908	vir-1	2.15	5.55	21.3	3.40e-12	1.16e-08	18.4
150695	32008	X	10674230	10674559	330	Ant2	2.96	3.98	21.7	2.59e-12	1.05e-08	18.3

```
> summary(decideTests(fit.de))
```

	(Intercept)	Batch3	Batch4	PasillaDown
-1	422	5104	5791	1983
0	3237	25887	24787	32603
1	32712	5380	5793	1785

## 18.2.10 Alternate splicing

Test for differences in exon retention between Pasilla down vs normal:

```
> ex <- diffSplice(fit[, "PasillaDown"], geneid = "GeneID", exonid = "Start")
```

```
Total number of exons: 36371
Total number of genes: 8272
Number of genes with 1 exon: 1715
Mean number of exons in a gene: 4
Max number of exons in a gene: 57
```

```
> summary(decideTests(ex))
```

	PasillaDown
-1	127
0	34341
1	188

Show top exons that don't follow the pattern of the other exons in the same gene:

```
> topSplice(ex, level="exon")
```

	GeneID	Chr	Start	End	Length	Symbol	logFC	t	P.Value	FDR
11333	44548	2R	6407125	6408782	1658	lola	2.49	22.9	2.29e-33	7.95e-29
11314	44548	2R	6403340	6403556	217	lola	-2.29	-14.8	8.85e-23	1.53e-18
141286	45320	X	2388437	2388670	234	trol	3.56	12.6	4.73e-22	5.47e-18
95854	44448	3R	22426969	22429773	2805	scrib	-2.15	-13.3	1.04e-20	8.99e-17
141328	45320	X	2390494	2390626	133	trol	5.88	11.8	2.25e-20	1.56e-16
16382	36542	2R	9771600	9782097	10498	shot	-1.61	-11.7	2.12e-19	1.23e-15
41964	3771968	2L	5158455	5185964	27510	Msp-300	-1.46	-12.5	3.31e-19	1.64e-15
141285	45320	X	2389074	2389271	198	trol	4.01	11.1	6.73e-19	2.92e-15
141327	45320	X	2390809	2390958	150	trol	5.49	10.9	1.39e-18	5.34e-15
141246	45320	X	2393244	2393711	468	trol	2.73	10.8	2.09e-18	7.24e-15

Show top genes that show differential splicing:

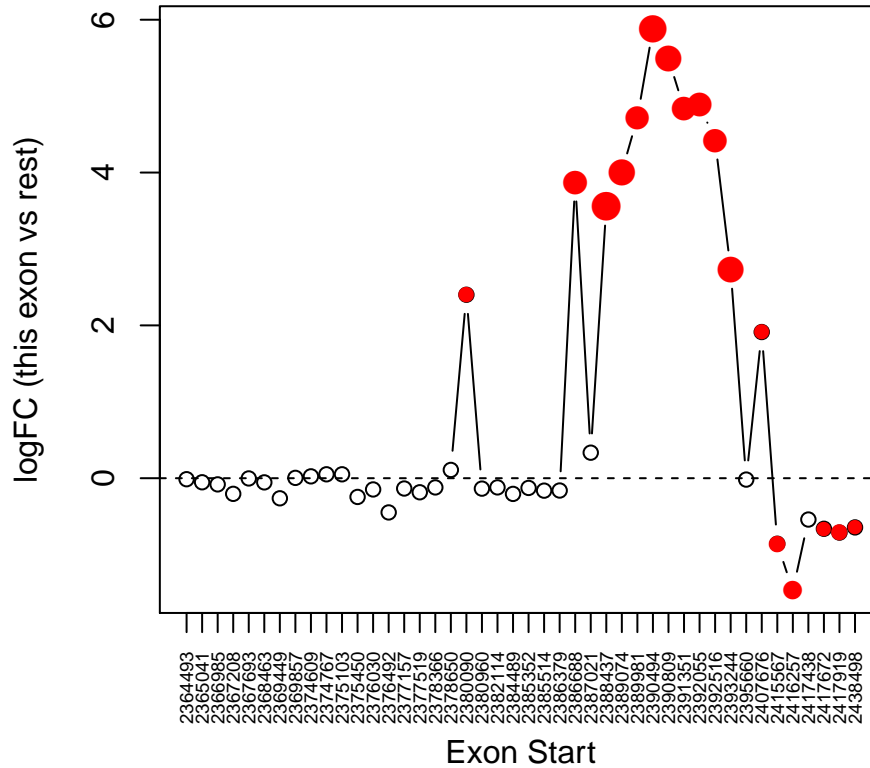
```
> topSplice(ex, level="gene", n=20)
```

	GeneID	Chr	Symbol	NExons	F	P.Value	FDR
141235	45320	X	trol	44	30.71	1.63e-40	1.07e-36
11214	44548	2R	lola	29	42.31	1.87e-32	6.12e-29
32242	37893	2R	slik	19	26.42	1.35e-18	2.94e-15
16060	36542	2R	shot	38	9.39	1.49e-17	2.43e-14
95956	44448	3R	scrib	30	11.50	1.08e-16	1.42e-13
19880	36773	2R	Dg	15	18.75	4.93e-13	5.38e-10
41795	3771968	2L	Msp-300	29	8.00	2.04e-12	1.91e-09
107883	44030	3L	msn	23	9.77	4.90e-12	4.01e-09
150694	32008	X	Ant2	4	135.61	5.86e-12	4.27e-09
82117	42130	3R	osa	18	12.10	1.52e-11	9.96e-09
150710	32007	X	sesB	7	44.73	1.80e-11	1.07e-08
166083	33098	X	CG32521	6	53.49	3.71e-11	2.03e-08
52817	34652	2L	vir-1	9	23.69	3.01e-10	1.52e-07
115767	38879	3L	pbl	12	15.02	8.21e-10	3.85e-07
11040	36104	2R	G-oalpha47A	12	14.27	1.59e-09	6.96e-07
2032	2768716	2R	mim	24	6.81	2.14e-09	8.78e-07
134207	40464	3L	Ten-m	12	13.65	2.82e-09	1.09e-06
47338	34170	2L	Akap200	8	21.75	4.22e-09	1.54e-06
36154	33367	2L	CG7337	23	6.70	5.59e-09	1.93e-06
118209	39048	3L	Tequila	20	7.47	7.55e-09	2.48e-06

We can plot all the exons for the most differentially spliced gene:

```
> plotSplice(ex)
```

## 45320.trol



The plot highlights exons that are individually significant. We can see that a block of five or six exons at the end of the gene are relatively lost when Pasilla is down, at the expense of an earlier block of twelve exons which become relatively more highly expressed when Pasilla is down. Most exons in the first half of the gene behave similarly to each other. This gene is on the negative strand, so transcription is from right to left.

By going back to the absolute fold changes for the top gene, we can confirm that the early exons are not differentially expressed, whereas the second block is up-regulated and the last block is down-regulated:

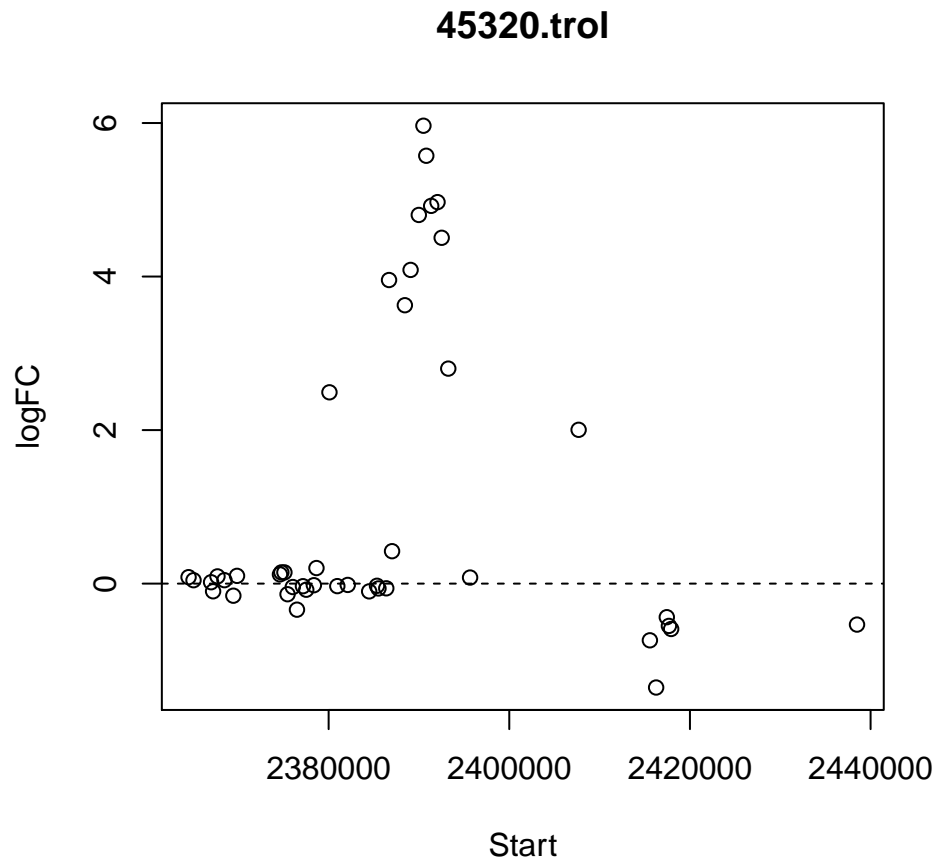
```
> trol <- fit.de$genes$Symbol=="trol"
> tab <- topTable(fit.de[trol,], coef="PasillaDown", n=Inf)
> o <- order(tab$Start)
> tab[o,]
```

	GeneID	Chr	Start	End	Length	Symbol	logFC	AveExpr	t	P.Value	adj.P.Val	B
141270	45320	X	2364493	2365227	735	trol	0.0845	4.3283	0.724	4.81e-01	6.80e-01	-7.033
141600	45320	X	2365041	2365227	187	trol	0.0449	2.7849	0.286	7.79e-01	8.65e-01	-6.965
141269	45320	X	2366985	2367132	148	trol	0.0183	3.5476	0.135	8.95e-01	8.95e-01	-7.153
141268	45320	X	2367208	2367624	417	trol	-0.0996	5.0373	-0.846	4.12e-01	6.25e-01	-7.039
141267	45320	X	2367693	2368393	701	trol	0.0944	5.4923	0.940	3.63e-01	5.80e-01	-7.010
141266	45320	X	2368463	2369388	926	trol	0.0452	5.6816	0.478	6.40e-01	8.28e-01	-7.368

141265	45320	X	2369449	2369721	273	trol	-0.1571	4.5131	-1.262	2.27e-01	4.55e-01	-6.531
141264	45320	X	2369857	2370062	206	trol	0.1013	4.0798	0.809	4.32e-01	6.33e-01	-6.919
141958	45320	X	2374609	2374941	333	trol	0.1207	4.3153	0.988	3.40e-01	5.80e-01	-6.798
141263	45320	X	2374767	2374941	175	trol	0.1467	4.2557	1.195	2.52e-01	4.81e-01	-6.566
141262	45320	X	2375103	2375352	250	trol	0.1466	4.4477	1.059	3.09e-01	5.67e-01	-6.747
141261	45320	X	2375450	2375909	460	trol	-0.1379	5.1931	-0.939	3.69e-01	5.80e-01	-6.972
141260	45320	X	2376030	2376424	395	trol	-0.0441	5.1535	-0.384	7.07e-01	8.49e-01	-7.351
141259	45320	X	2376492	2376669	178	trol	-0.3391	3.7965	-1.962	7.48e-02	1.65e-01	-5.415
141258	45320	X	2377157	2377419	263	trol	-0.0333	4.5543	-0.277	7.86e-01	8.65e-01	-7.301
141257	45320	X	2377519	2378122	604	trol	-0.0792	5.3762	-0.701	4.95e-01	6.80e-01	-7.198
141256	45320	X	2378366	2378546	181	trol	-0.0207	3.5837	-0.153	8.81e-01	8.95e-01	-7.157
141255	45320	X	2378650	2378792	143	trol	0.2030	3.5462	1.433	1.74e-01	3.64e-01	-6.139
141779	45320	X	2380090	2380275	186	trol	2.4925	-0.8566	5.273	1.13e-04	3.83e-04	1.410
141254	45320	X	2380960	2382046	1087	trol	-0.0325	6.0676	-0.348	7.33e-01	8.49e-01	-7.458
141253	45320	X	2382114	2384350	2237	trol	-0.0167	6.9637	-0.188	8.54e-01	8.95e-01	-7.549
141252	45320	X	2384489	2384875	387	trol	-0.1009	4.6787	-0.934	3.66e-01	5.80e-01	-6.909
141250	45320	X	2385352	2385445	94	trol	-0.0279	2.8850	-0.179	8.61e-01	8.95e-01	-7.003
141249	45320	X	2385514	2385647	134	trol	-0.0627	3.0326	-0.366	7.20e-01	8.49e-01	-6.982
141248	45320	X	2386379	2386453	75	trol	-0.0610	2.9856	-0.397	6.97e-01	8.49e-01	-6.961
141546	45320	X	2386688	2386918	231	trol	3.9552	1.0867	12.108	6.83e-09	5.01e-08	9.836
141247	45320	X	2387021	2387248	228	trol	0.4228	3.8149	3.066	8.23e-03	2.01e-02	-3.371
141286	45320	X	2388437	2388670	234	trol	3.6270	2.2685	14.423	6.74e-10	1.48e-08	12.572
141285	45320	X	2389074	2389271	198	trol	4.0867	1.5596	12.791	3.32e-09	2.92e-08	10.692
141329	45320	X	2389981	2390066	86	trol	4.8028	0.3276	10.906	2.64e-08	1.45e-07	8.113
141328	45320	X	2390494	2390626	133	trol	5.9650	0.5677	14.704	5.20e-10	1.48e-08	10.607
141327	45320	X	2390809	2390958	150	trol	5.5739	0.3320	12.937	2.86e-09	2.92e-08	9.585
141326	45320	X	2391351	2391521	171	trol	4.9213	0.0219	11.721	1.04e-08	6.56e-08	8.769
141325	45320	X	2392055	2392148	94	trol	4.9700	-0.1280	10.256	7.80e-08	3.81e-07	7.323
141324	45320	X	2392516	2392664	149	trol	4.5055	0.7069	9.276	6.00e-07	2.64e-06	5.888
141246	45320	X	2393244	2393711	468	trol	2.8011	2.3177	13.156	2.29e-09	2.92e-08	11.710
141241	45320	X	2395660	2395770	111	trol	0.0795	3.2446	0.508	6.19e-01	8.26e-01	-6.962
141529	45320	X	2407676	2407835	160	trol	2.0040	0.1555	5.201	1.27e-04	3.99e-04	1.350
141240	45320	X	2415567	2415821	255	trol	-0.7382	3.7962	-5.061	1.72e-04	5.04e-04	0.530
141239	45320	X	2416257	2416454	198	trol	-1.3530	2.4022	-6.711	9.54e-06	3.81e-05	3.704
141238	45320	X	2417438	2417562	125	trol	-0.4370	2.1375	-2.306	3.66e-02	8.48e-02	-4.453
141237	45320	X	2417672	2417849	178	trol	-0.5505	3.3020	-3.678	2.42e-03	6.65e-03	-2.072
141236	45320	X	2417919	2418435	517	trol	-0.5906	4.5478	-5.321	1.02e-04	3.73e-04	0.943
141235	45320	X	2438498	2438795	298	trol	-0.5333	3.2835	-3.309	5.16e-03	1.34e-02	-2.815

```
> with(tab[o,],plot(Start,logFC,main="45320.trol"))
> abline(h=0,lty=2)
```





### 18.2.11 Session information

```
> sessionInfo()

R version 3.1.0 alpha (2014-03-24 r65271)
Platform: x86_64-w64-mingw32/x64 (64-bit)

locale:
[1] LC_COLLATE=English_Australia.1252 LC_CTYPE=English_Australia.1252
[3] LC_MONETARY=English_Australia.1252 LC_NUMERIC=C
[5] LC_TIME=English_Australia.1252

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

other attached packages:
[1] statmod_1.4.18 edgeR_3.5.30  limma_3.19.30

loaded via a namespace (and not attached):
[1] tools_3.1.0
```

### **18.2.12 Acknowledgements**

Thanks for Yang Liao for mapping the reads and running featureCounts.

# Notes

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## Conventions

Where possible, **limma** tries to use the convention that class names are in upper *CamelCase*, i.e., the first letter of each word is capitalized, while function names are in lower *camelCase*, i.e., first word is lowercase. When periods appear in function names, the first word should be an action while the second word is the name of a type of object on which the function acts.

## Software Projects Using **limma**

The **limma** package is used as a building block or as the underlying computational engine by a number of software projects designed to provide user-interfaces for microarray data analysis including RMAEML [8], arrayMagic [4], DNMAID [43], GPAP (GenePix Pro Auto-Processor) [45], the KTH Package [33], SKCC WebArray [51], CARMAweb [26] and Pomelo II [22]. The LCBASE project provides a **limma** plug-in for the BASE database [20]. The

Stanford Microarray Database <http://genome-www5.stanford.edu> calls out to `limma` for background correction options.

## Citations

Biological studies using the `limma` package include [10, 32, 28, 2, 24, 42]. Methodological studies using the `limma` package include [13, 14].

# Bibliography

1. Benjamini, Y. and Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B* 57, 289–300.
2. Boutros, P.C., Moffat, I.D., Franc, M.A., Tijet, N., Tuomisto, J., Pohjanvirta, R., and Okey, A.B. (2004). Identification of the DRE-II gene battery by phylogenetic footprinting. *Biochem Biophys Res Commun* 321, 707–715.
3. Brooks, A.N., Yang, L., Duff, M.O., Hansen, K.D., Park, J.W., Dudoit, S., Brenner, S.E., and Graveley, B.R. (2011). Conservation of an RNA regulatory map between *Drosophila* and mammals. *Genome Res* 21, 193–202.
4. Buness, A., Huber, W., Steiner, K., Sultmann, H., and Poustka, A. (2005). arrayMagic: two-colour cDNA microarray quality control and preprocessing. *Bioinformatics* 21, 554–556.
5. Callow, M.J., Dudoit, S., Gong, E.L., Speed, T.P., and Rubin, E.M. (2000). Microarray expression profiling identifies genes with altered expression in HDL deficient mice. *Genome Research* 10, 2022–2029.
6. Dalgaard, P. (2002). *Introductory Statistics with R*. Springer, New York.
7. Diaz, E., Ge, Y., Yang, Y.H., Loh, K.C., Serafini, T.A., Okazaki, Y., Hayashizaki, Y., Speed, T., P., Ngai, J., and Scheiffele, P. (2002). Molecular analysis of gene expression in the developing pontocerebellar projection system. *Neuron* 36, 417–434.
8. Durinck, S., Allemeersch, J., Carey, V.J., Moreau, Y., and De Moor, B. (2004). Importing MAGE-ML format microarray data into BioConductor. *Bioinformatics* 20, 3641–3642.
9. Ellis, L., Pan, Y., Smyth, G., George, D., McCormack, C., Williams-Truax, R., Mita, M., Beck, J., Burris, H., Ryan, G., et al. (2008). Histone deacetylase inhibitor panobinostat induces clinical responses with associated alterations in gene expression profiles in cutaneous T-cell lymphoma. *Clinical Cancer Research* 14, 4500–4510.
10. Golden, T., R. and Melov, S. (2004). Microarray analysis of gene expression with age in individual nematodes. *Aging Cell* 3, 111–124.

11. Hung, S., Baldi, P., and Hatfield, G.W. (2002). Global gene expression profiling in *Escherichia coli* K12: The effects of leucine-responsive regulatory protein. *Journal of Biological Chemistry* 277, 40309–40323.
12. Irizarry, R. (2005). From CEL files to annotated lists of interesting genes. In R. Gentleman, V. Carey, S. Dudoit, R. Irizarry, and W. Huber, editors, *Bioinformatics and Computational Biology Solutions using R and Bioconductor*, pages 431–442. Springer, New York.
13. Kendzierski, C., Irizarry, R.A., Chen, K.S., Haag, J.D., and Gould, M.N. (2005). On the utility of pooling biological samples in microarray experiments. *PNAS* 102, 4252–4257.
14. Kooperberg, C., Aragaki, A., Strand, A.D., and Olson, J.M. (2005). Significance testing for small microarray experiments. *Statistics in Medicine* 24, 2281–2298.
15. Law, C.W., Chen, Y., Shi, W., and Smyth, G.K. (2014). Voom: precision weights unlock linear model analysis tools for RNA-seq read counts. *Genome Biology* 15, R29.
16. Li, B. and Dewey, C. (2011). RSEM: accurate transcript quantification from RNA-Seq data with or without a reference genome. *BMC Bioinformatics* 12, 323.
17. Liao, Y., Smyth, G.K., and Shi, W. (2013). The Subread aligner: fast, accurate and scalable read mapping by seed-and-vote. *Nucleic Acids Research* 41, e108.
18. Liao, Y., Smyth, G.K., and Shi, W. (2014). featureCounts: an efficient general-purpose read summarization program. *Bioinformatics* 30, 923–930.
19. Lim, E., Vaillant, F., Wu, D., Forrest, N., Pal, B., Hart, A., Asselin-Labat, M., Gyorki, D., Ward, T., Partanen, A., et al. (2009). Aberrant luminal progenitors as the candidate target population for basal tumor development in *brca1* mutation carriers. *Nature Medicine* 15, 907–913.
20. Linnaeus Centre for Bioinformatics, Uppsala University, S.
21. Milliken, G.A. and Johnson, D.E. (1992). *Analysis of Messy Data, Volume 1: Designed Experiments*. Chapman & Hall, New York.
22. Morrissey, E.R. and Diaz-Uriarte, R. (2009). Pomelo II: finding differentially expressed genes. *Nucleic Acids Research* 37, W581–W586.
23. Oshlack, A., Emslie, D., Corcoran, L., and Smyth, G. (2007). Normalization of boutique two-color microarrays with a high proportion of differentially expressed probes. *Genome Biology* 8, R2.
24. Peart, M., Smyth, G., Van Laar, R., Bowtell, D., Richon, V., Marks, P., Holloway, A., and Johnstone, R. (2005). Identification and functional significance of genes regulated by structurally different histone deacetylase inhibitors. *Proceedings of the National Academy of Sciences of the United States of America* 102, 3697–3702.

25. Pickrell, J.K., Marioni, J.C., Pai, A.A., Degner, J.F., Engelhardt, B.E., Nkadori, E., Veyrieras, J.B., Stephens, M., Gilad, Y., and Pritchard, J.K. (2010). Understanding mechanisms underlying human gene expression variation with RNA sequencing. *Nature* 464, 768–772.
26. Rainer, J., Sanchez-Cabo, F., Stocker, G., Sturn, A., and Trajanoski, Z. (2006). CARMAweb: comprehensive r- and bioconductor-based web service for microarray data analysis. *Nucleic Acids Res* 34(Web Server issue), W498–503.
27. Reiner, A., Yekutieli, D., and Benjamini, Y. (2003). Identifying differentially expressed genes using false discovery rate controlling procedures. *Bioinformatics* 19, 368–375.
28. Renn, S.C.P., Aubin-Horth, N., and Hofmann, H.A. (2004). Biologically meaningful expression profiling across species using heterologous hybridization to a cDNA microarray. *BMC Genomics* 5.
29. Ritchie, M., Diyagama, D., Neilson, J., Van Laar, R., Dobrovic, A., Holloway, A., and Smyth, G. (2006). Empirical array quality weights in the analysis of microarray data. *BMC bioinformatics* 7, 261.
30. Ritchie, M., Silver, J., Oshlack, A., Holmes, M., Diyagama, D., Holloway, A., and Smyth, G. (2007). A comparison of background correction methods for two-colour microarrays. *Bioinformatics* 23, 2700–2707.
31. Robinson, M.D. and Oshlack, A. (2010). A scaling normalization method for differential expression analysis of RNA-seq data. *Genome Biology* 11, R25.
32. Rodriguez, M.W., Paquet, A.C., Yang, Y.H., and Erle, D.J. (2004). Differential gene expression by integrin  $\beta 7^+$  and  $\beta 7^-$  memory T helper cells. *BMC Immunology* 5.
33. Royal Institute of Technology, Sweden (2005). KTH-package for microarray data analysis. Software package, <http://www.biotech.kth.se/molbio/microarray/pages/kthpackagetransfer.html>.
34. Shi, W., De Graaf, C., Kinkel, S., Achtman, A., Baldwin, T., Schofield, L., Scott, H., Hilton, D., and Smyth, G. (2010). Estimating the proportion of microarray probes expressed in an RNA sample. *Nucleic acids research* 38, 2168–2176.
35. Shi, W., Oshlack, A., and Smyth, G. (2010). Optimizing the noise versus bias trade-off for Illumina whole genome expression beadchips. *Nucleic Acids Research* 38, e204–e204.
36. Smyth, G. (2004). Linear models and empirical Bayes methods for assessing differential expression in microarray experiments. *Statistical applications in genetics and molecular biology* 3, Article 3.
37. Smyth, G. (2005). Individual channel analysis of two-colour microarray data. invited session IPM 11: Computational tools for microarray analysis. In *55th Session of the International Statistics Institute*.

38. Smyth, G., Michaud, J., and Scott, H. (2005). Use of within-array replicate spots for assessing differential expression in microarray experiments. *Bioinformatics* 21, 2067–2075.
39. Smyth, G. and Speed, T. (2003). Normalization of cDNA microarray data. *Methods* 31, 265–273.
40. Smyth, G., Yang, Y., and Speed, T. (2003). Statistical issues in cDNA microarray data analysis. *Methods in Molecular Biology* 224, 111–136.
41. Smyth, G.K. and Altman, N.S. (2013). Separate-channel analysis of two-channel microarrays: recovering inter-spot information. *BMC Bioinformatics* 14, 165.
42. Uppalapati, S.R., Ayoubi, P., Weng, H., Palmer, D.A., Mitchell, R.E., Jones, W., and Bender, C.L. (2005). The phytotoxin coronatine and methyl jasmonate impact multiple phytohormone pathways in tomato. *The Plant Journal* 42, 201–217.
43. Vaquerizas, J.M., Dopazo, J., and Díaz-Uriarte, R. (2004). DNMAID: web-based diagnosis and normalization for microarray data. *Bioinformatics* 20, 3656–3658.
44. Visvader, J.E. (2009). Keeping abreast of the mammary epithelial hierarchy and breast tumorigenesis. *Genes & development* 23, 2563–2577.
45. Weng, H. and Ayoubi, P. (2004). GPAP (GenePix Pro Auto-Processor) for online pre-processing, normalization and statistical analysis of primary microarray data. Software package, Microarray Core Facility, Oklahoma State University, <http://darwin.biochem.okstate.edu/gpap3>.
46. Wettenhall, J.M., Simpson, K.M., Satterley, K., and Smyth, G.K. (2006). affyGUI: a graphical user interface for linear modeling of single channel microarray data. *Bioinformatics* 22, 897–899.
47. Wettenhall, J.M. and Smyth, G.K. (2004). limmaGUI: a graphical user interface for linear modeling of microarray data. *Bioinformatics* 20, 3705–3706.
48. Wolfinger, R.D., Gibson, G., Wolfinger, E.D., Bennett, L., Hamadeh, H., Bushel, P., Afshari, C., and Paules, R.S. (2001). Assessing gene significance from cDNA microarray expression data via mixed models. *Journal of Computational Biology* 8, 625–637.
49. Wu, D., Lim, E., Vaillant, F., Asselin-Labat, M., Visvader, J., and Smyth, G. (2010). ROAST: rotation gene set tests for complex microarray experiments. *Bioinformatics* 26, 2176–2182.
50. Wu, D. and Smyth, G. (2012). Camera: a competitive gene set test accounting for inter-gene correlation. *Nucleic Acids Research* 40, e133.
51. Xia, X., McClelland, M., and Wang, Y. (2005). Webarray: an online platform for microarray data analysis. *BMC Bioinformatics* 6, 306.



52. Yang, Y.H., Dudoit, S., Luu, P., Lin, D.M., Peng, V., Ngai, J., and Speed, T.P. (2002). Normalization for cDNA microarray data: a robust composite method addressing single and multiple slide systematic variation. *Nucleic Acids Research* 30, e15.
53. Yang, Y.H., Dudoit, S., Luu, P., and Speed, T.P. (2001). Normalization for cDNA microarray data. In M.L. Bittner, Y. Chen, A.N. Dorsel, and E.R. Dougherty, editors, *Microarrays: Optical Technologies and Informatics*, pages 141–152. Proceedings of SPIE, Volume 4266.
54. Yang, Y.H. and Speed, T.P. (2003). Design and analysis of comparative microarray experiments. In T.P. Speed, editor, *Statistical Analysis of Gene Expression Microarray Data*, pages 35–91. Chapman & Hall/CRC Press.
55. Yang, Y.H. and Thorne, N.P. (2003). Normalization for two-color cDNA microarray data. In D.R. Goldstein, editor, *Science and Statistics: A Festschrift for Terry Speed*, pages 403–418. Institute of Mathematical Statistics Lecture Notes – Monograph Series, Volume 40.