SOFTWARE TOOL ARTICLE

RNA-seq analysis is easy as 1-2-3 with limma, Glimma and edgeR [version 1; referees: 3 approved]

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Abstract
The ability to easily and efficiently analyse RNA-sequencing data is a key strength of the Bioconductor project. Starting with counts summarised at the gene-level, a typical analysis involves pre-processing, exploratory data analysis, differential expression testing and pathway analysis with the results obtained informing future experiments and validation studies. In this workflow article, we analyse RNA-sequencing data from the mouse mammary gland, demonstrating use of the popular edgeR package to import, organise, filter and normalise the data, followed by the limma package with its voom method, linear modelling and empirical Bayes moderation to assess differential expression and perform gene set testing. This pipeline is further enhanced by the Glimma package which enables interactive exploration of the results so that individual samples and genes can be examined by the user. The complete analysis offered by these three packages highlights the ease with which researchers can turn the raw counts from an RNA-sequencing experiment into biological insights using Bioconductor.

Keywords
RNA sequencing, data analysis, gene expression

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Introduction

RNA-sequencing (RNA-seq) has become the primary technology for gene expression profiling and the detection of differentially expressed genes between two or more conditions is one of the most commonly asked questions using this approach. The \texttt{edgeR} and \texttt{limma} packages available from the Bioconductor project offer a well-developed suite of statistical methods for dealing with this type of analysis. In this article, we describe an \texttt{edgeR - limma} workflow for analysing RNA-seq data that takes gene-level counts as its input, and moves through pre-processing and exploratory data analysis before obtaining lists of differentially expressed (DE) genes and gene signatures. This analysis is enhanced through the use of interactive graphics from the \texttt{Glimma} package, that allows for a more detailed exploration of the data at both the sample and gene-level than is possible using static R plots.

The experiment analysed in this workflow is from Sheridan et al. (2015) and consists of three cell populations (basal, luminal progenitor (LP) and mature luminal (ML)) sorted from the mammary glands of female virgin mice, each profiled in triplicate. RNA samples were sequenced across three batches on an Illumina HiSeq 2000 to obtain 100 base-pair single-end reads. The analysis outlined in this article assumes that reads obtained from an RNA-seq experiment have been aligned to an appropriate reference genome and summarised into counts associated with gene-specific regions. In this instance, reads were aligned to the mouse reference genome (mm10) using the R based pipeline available in the \texttt{Rsubread} package (specifically the \texttt{align} function followed by \texttt{featureCounts} for gene-level summarisation based on the in-built mm10 RefSeq-based annotation). Count data for these samples can be downloaded from the Gene Expression Omnibus (GEO) \url{http://www.ncbi.nlm.nih.gov/geo} using GEO Series accession number GSE63310. Further information on experimental design and sample preparation is also available from GEO under this accession number.

Data packaging

Reading in count-data

To get started with this analysis, download the file GSE63310_RAW.tar available online from \url{http://www.ncbi.nlm.nih.gov/geo/download?acc=GSE63310&format=file}, and extract the relevant files from this archive. Each of these text files contains the raw gene-level counts for a given sample. Note that our analysis only includes the basal, LP and ML samples from this experiment (see associated file names below).

```r
files <- c("GSM1545535_10_6_5_11.txt", "GSM1545536_9_6_5_11.txt", "GSM1545538_purep53.txt", "GSM1545539_JMS8-2.txt", "GSM1545540_JMS8-3.txt", "GSM1545541_JMS8-4.txt", "GSM1545542_JMS8-5.txt", "GSM1545544_JMS9-P7c.txt", "GSM1545545_JMS9-P8c.txt")
read.delim(files[1], nrow=5)

#  EntrezID GeneLength Count
# 1  497097 3634  1
# 2 100503874 3259  0
# 3 100038431 1634  0
# 4  19888 9747  0
# 5  20671 3130  1
```

Whilst each of the nine text files can be read into \texttt{R} separately and combined into a matrix of counts, \texttt{edgeR} offers a convenient way to do this in one step using the \texttt{readDGE} function. The resulting \texttt{DGEList}-object contains a matrix of counts with 27,179 rows associated with unique Entrez gene identifiers (IDs) and nine columns associated with the individual samples in the experiment.

```r
library(limma)
library(edgeR)
x <- readDGE(files, columns=c(1,3))
class(x)
# [1] "DGEList"
# attr(,"package")
# [1] "edgeR"
dim(x)
# [1] 27179 9
```
If the counts from all samples were stored in a single file, the data can be read into R and then converted into a DGEList-object using the DGEList function.

**Organising sample information**

For downstream analysis, sample-level information related to the experimental design needs to be associated with the columns of the counts matrix. This should include experimental variables, both biological and technical, that could have an effect on expression levels. Examples include cell type (basal, LP and ML in this experiment), genotype (wild-type, knock-out), phenotype (disease status, sex, age), sample treatment (drug, control) and batch information (date experiment was performed if samples were collected and analysed at distinct time points) to name just a few.

Our DGEList-object contains a samples data frame that stores both cell type (or group) and batch (sequencing lane) information, each of which consists of three distinct levels. Note that within x$samples, library sizes are automatically calculated for each sample and normalisation factors are set to 1. For simplicity, we remove the GEO sample IDs (GSM*) from the column names of our DGEList-object x.

```r
samplenames <- substring(colnames(x), 12, nchar(colnames(x)))
samplenames
## [1] "10_6_5_11" "9_6_5_11" "purep53" "JMS8-2" "JMS8-3" "JMS8-4" "JMS8-5"
## [8] "JMS9-P7c" "JMS9-P8c"
```

```r
colnames(x) <- samplenames
```

```r
lane <- as.factor(rep(c("L004", "L006", "L008"), c(3, 4, 2)))
```

**Organising gene annotations**

A second data frame named genes in the DGEList-object is used to store gene-level information associated with rows of the counts matrix. This information can be retrieved using organism specific packages such as Mus.musculus for mouse (or Homo.sapiens for human) or the biomaRt package which interfaces the Ensembl genome databases in order to perform gene annotation. The type of information that can be retrieved includes gene symbols, gene names, chromosome names and locations, Entrez gene IDs, Refseq gene IDs and Ensembl gene IDs to name just a few.

```r
library(Mus.musculus)
geneid <- rownames(x)
genes <- select(Mus.musculus, keys=geneid, columns=c("SYMBOL", "TXCHROM"),
                 keytype="ENTREZID")
```

```r
head(genes)
##     ENTREZID SYMBOL TXCHROM
## 1   497097 Xkr4  chr1
## 2 100503874 Gm19938 <NA>
## 3 100038431 Gm10568 <NA>
```
As with any gene ID, Entrez gene IDs may not map one-to-one to the gene information of interest. It is important to check for duplicated gene IDs and resolve them to ensure the gene order is consistent between our annotation and the counts in the DGEList-object.

```r
dup <- genes$ENTREZID[ duplicated(genes$ENTREZID) ]
genes[genes$ENTREZID %in% dup,][1:10,]
```

```
## ENTREZID SYMBOL TXCHROM
##  5360 100316809 Mir1906-1 chr12
##  5361 100316809 Mir1906-1 chrX
##  7128 218963 Gm1821 chr11
##  7129 218963 Gm1821 chr14
##  9564 12228 Btg3 chr16
##  9565 12228 Btg3 chr17
## 11351 433182 Enolb chr4
## 11352 433182 Enolb chr18
## 11544 100217457 Snord58b chr14
## 11545 100217457 Snord58b chr18
```

```r
mat <- match(geneid, genes$ENTREZID)
genes <- genes[mat,,]
genes[genes$ENTREZID %in% dup,][1:5,]
```

```
## ENTREZID SYMBOL TXCHROM
##  5360 100316809 Mir1906-1 chr12
##  7128 218963 Gm1821 chr11
##  9564 12228 Btg3 chr16
## 11351 433182 Enolb chr4
## 11544 100217457 Snord58b chr14
```

The matching process above takes care of the duplication by keeping the first occurrence of each gene ID. Now that non-unique gene IDs have been resolved, the data frame of gene annotations is added to the data object:

```r
x$genes <- genes
```

Now our data is packaged neatly in a DGEList-object containing raw count data with associated sample information and gene annotations.

```r
x
```

```
## An object of class "DGEList"
## $samples
## # An object of class "data.frame"
## # samples
## # An object of class "data.frame"
## # An object of class "data.frame"
## # An object of class "data.frame"
## # An object of class "data.frame"
```
##    Samples
## Tags  10_6_5_11 9_6_5_11 purep53 JMS8-2 JMS8-3 JMS8-4 JMS8-5 JMS9-P7c JMS9-P8c
## 497097 1     2   342   526    3    3   535     2     0
## 100503874 0    0    5    6    0    0    5     0     0
## 10038431 0    0    0    0    0    0    1     0     0
## 19888   0    1    0    0    17   2    0     1     0
## 20671   1    1   76    40   33    14   98    18    8
## 27174 more rows ...

## $genes
## ENTREZID  SYMBOL TXCHROM
## 1    497097    Xkr4    chr1
## 2 100503874 Gm19938 <NA>
## 3 100038431 Gm10568 <NA>
## 4     19888     Rp1    chr1
## 5     20671   Sox17    chr1
## 27174 more rows ...

### Data pre-processing

#### Transformations from the raw-scale

For differential expression and related analyses, gene expression is rarely considered at the level of raw counts since libraries sequenced at a greater depth will result in higher counts. Rather, it is common practice to transform raw counts onto a scale that accounts for such library size differences. Popular transformations include counts per million (CPM), log$_2$-counts per million (log-CPM), reads per kilobase of transcript per million (RPKM), and fragments per kilobase of transcript per million (FPKM).

In our analyses, CPM and log-CPM transformations are used regularly although they do not account for feature length differences which RPKM and FPKM values do. Whilst RPKM and FPKM values can just as well be used, CPM and log-CPM values can be calculated using a counts matrix alone and will suffice for the type of comparisons we are interested in. Differential expression analyses look at gene expression differences between conditions, rather than comparing expression across multiple genes or drawing conclusions on absolute levels of expression. In other words, gene lengths remain constant for comparisons of interest and any observed differences are a result of changes in condition rather than changes in gene length.

Here raw counts are converted to CPM and log-CPM values using the \texttt{cpm} function in \texttt{edgeR}, where log-transformations use a prior count of 0.25 to avoid taking the log of zero. RPKM values are just as easily calculated as CPM values using the \texttt{rpkm} function in \texttt{edgeR} if gene lengths are available.

```r

cpm <- cpm(x)
lcpm <- cpm(x, log=TRUE)
```

### Removing genes that are not expressed

All datasets will include a mix of genes that are expressed and those that are not expressed. Whilst it is of interest to examine genes that are expressed in one condition but not in another, some genes are unexpressed throughout all samples. In fact, 19% of genes in this dataset have zero counts across all nine samples.

```r

table(rowSums(x$counts==0)==9)
```

```
##       FALSE TRUE
## 22026   5153
```

Genes that are not expressed at a biologically meaningful level in any condition should be discarded to reduce the subset of genes to those that are of interest, and to reduce the number of tests carried out downstream when looking at differential expression. Upon examination of log-CPM values, it can be seen that a large proportion of genes within each sample is unexpressed or lowly-expressed (Figure 1A). Using a nominal CPM value of 1 (which is equivalent to a log-CPM value of 0) a gene is deemed to be expressed in a given sample if its transformed count is above this threshold, and unexpressed otherwise. Genes must be expressed in at least one group (or roughly any three samples across the entire experiment) to be kept for downstream analysis.
Using this criterion, the number of genes is reduced to approximately half the number that we started with (14,165 genes, Figure 1B). Note that subsetting the entire DGEList-object removes both the counts as well as the associated gene information. Code to produce Figure 1 is given below.

```r
library(RColorBrewer)
samples <- ncol(x)
col <- brewer.pal(samples, "Paired")
par(mfrow=c(1,2))
plot(density(lcpm[,1]), col=col[1], lwd=2, ylim=c(0,0.21), las=2, main="", xlab="")
title(main="A. Raw data", xlab="Log-cpm")
abline(v=0, lty=3)
for (i in 2:samples){
den <- density(lcpm[,i])
lines(den$x, den$y, col=col[i], lwd=2)
}
legend("topright", samplenames, text.col=col, bty="n")
lcpm <- cpm(x, log=TRUE)
plot(density(lcpm[,1]), col=col[1], lwd=2, ylim=c(0,0.21), las=2, main="", xlab="")
title(main="B. Filtered data", xlab="Log-cpm")
abline(v=0, lty=3)
for (i in 2:samples){
den <- density(lcpm[,i])
lines(den$x, den$y, col=col[i], lwd=2)
}
legend("topright", samplenames, text.col=col, bty="n")
```

**Figure 1.** The density of log-CPM values for raw pre-filtered data (A) and post-filtered data (B) are shown for each sample. Dotted vertical lines mark the log-CPM of zero threshold (equivalent to a CPM value of 1) used in the filtering step.
Normalising gene expression distributions
During the sample preparation or sequencing process, external factors that are not of biological interest can affect the
gene expression levels of individual samples. For example, samples processed in the first batch of an experiment may
have been sequenced more deeply than samples processed in a second batch. It is assumed that all samples should have
a similar range and distribution of expression values. Normalisation is generally required to ensure that the expression
distributions of each sample are similar across the entire experiment.

Any plot showing the per sample expression distributions, such as a density or boxplot, is useful in determining
whether any samples are dissimilar to others. Distributions of log-CPM values are similar throughout all samples
within this dataset (Figure 1B).

Nonetheless, normalisation by the method of trimmed mean of M-values (TMM)\textsuperscript{12} is performed using the
calcNormFactors function in \texttt{edgeR}. The normalisation factors calculated here are used as a scaling fac-
tor for the library sizes. When working with DGEList-objects, these normalisation factors are automatically stored in \texttt{x$samples$norm.factors}. For this dataset the effect of TMM-normalisation is mild, as evident in the
magnitude of the scaling factors, which are all relatively close to 1.

\begin{verbatim}
x <- calcNormFactors(x, method = "TMM")
x$samples$norm.factors
## [1] 0.896 1.035 1.044 1.041 1.032 0.922 0.984 1.083 0.979
\end{verbatim}

To give a better visual representation of the effects of normalisation, the data was duplicated then adjusted so that the
counts of the first sample are reduced to 5% of their original values, and in the second sample they are inflated to be
5-times larger.

\begin{verbatim}
x2 <- x
x2$samples$norm.factors <- 1
x2$counts[,1] <- ceiling(x2$counts[,1]*0.05)
x2$counts[,2] <- x2$counts[,2]*5
\end{verbatim}

\textbf{Figure 2} shows the expression distribution of samples for unnormalised and normalised data, where distributions are
noticeably different pre-normalisation and are similar post-normalisation. Here the first sample has a small TMM scal-
ing factor of 0.05, whereas the second sample has a large scaling factor of 6.13 – neither values are close to 1.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Example data: Boxplots of log-CPM values showing expression distributions for unnormalised data (A) and
normalised data (B) for each sample in the modified dataset where the counts in samples 1 and 2 have been scaled to
5\% and 500\% of their original values respectively.}
\end{figure}
Unsupervised clustering of samples

In our opinion, one of the most important exploratory plots to examine for gene expression analyses is the multidimensional scaling (MDS) plot, or similar. The plot shows similarities and dissimilarities between samples in an unsupervised manner so that one can have an idea of the extent to which differential expression can be detected before carrying out formal tests. Ideally, samples would cluster well within the primary condition of interest, and any sample straying far from its group could be identified and followed up for sources of error or extra variation. If present, technical replicates should lie very close to one another.

Such a plot can be made in \texttt{limma} using the \texttt{plotMDS} function. The first dimension represents the leading-fold-change that best separates samples and explains the largest proportion of variation in the data, with subsequent dimensions having a smaller effect and being orthogonal to the ones before it. When experimental design involves multiple factors, it is recommended that each factor is examined over several dimensions. If samples cluster by a given factor in any of these dimensions, it suggests that the factor contributes to expression differences and is worth including in the linear modelling. On the other hand, factors that show little or no effect may be left out of downstream analysis.

In this dataset, samples can be seen to cluster well within experimental groups over dimension 1 and 2, and then separate by sequencing lane (sample batch) over dimension 3 (Figure 3). Keeping in mind that the first dimension explains the largest proportion of variation in the data, notice that the range of values over the dimensions become smaller as we move to higher dimensions. Whilst all samples cluster by groups, the largest transcriptional difference is observed between basal and LP, and basal and ML over dimension 1. For this reason, it is expected that pairwise comparisons between cell populations will result in a greater number of DE genes for comparisons involving basal samples.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{mds_plot.png}
\caption{MDS plots of log-CPM values over dimensions 1 and 2 with samples coloured and labeled by sample groups (A) and over dimensions 3 and 4 with samples coloured and labeled by sequencing lane (B). Distances on the plot correspond to the leading fold-change, which is the average (root-mean-square) log$_2$-fold-change for the 500 genes most divergent between each pair of samples by default.}
\end{figure}
and relatively small numbers of DE genes when comparing ML to LP. In other datasets, samples that do not cluster by their groups of interest may also show little or no evidence of differential expression in the downstream analysis.

To create the MDS plots, different colour groupings are assigned to factors of interest. Dimensions 1 and 2 are examined using the color grouping defined by cell types.

```r
lcpm <- cpm(x, log=TRUE)
par(mfrow=c(1,2))
col.group <- group
levels(col.group) <- brewer.pal(nlevels(col.group), "Set1")
col.group <- as.character(col.group)
col.lane <- lane
levels(col.lane) <- brewer.pal(nlevels(col.lane), "Set2")
col.lane <- as.character(col.lane)
plotMDS(lcpm, labels=group, col=col.group)
title(main="A. Sample groups")
```

Dimensions 3 and 4 are examined using the colour grouping defined by sequencing lanes (batch).

```r
plotMDS(lcpm, labels=lane, col=col.lane, dim=c(3,4))
title(main="B. Sequencing lanes")
```

Alternatively, the Glimma package offers the convenience of an interactive MDS plot where multiple dimensions can be explored. The glMDSPlot function generates an html page (that is opened in a browser if launch=TRUE) with an MDS plot in the left panel and a barplot showing the proportion of variation explained by each dimension in the right panel. Clicking on the bars of the bar plot changes the pair of dimensions plotted in the MDS plot, and hovering over the individual points reveals the sample label. The colour scheme can be changed as well to highlight cell population or sequencing lane (batch). An interactive MDS plot of this dataset can be found at http://bioinf.wehi.edu.au/folders/limmaWorkflow/glimma-plots/MDS-Plot.html.

```r
library(Glimma)
glMDSPlot(lcpm, labels=paste(group, lane, sep="_"), groups=x$samples[,c(2,5)], launch=FALSE)
```

### Differential expression analysis

#### Creating a design matrix and contrasts

In this study, it is of interest to see which genes are expressed at different levels between the three cell populations profiled. In our analysis, linear models are fitted to the data with the assumption that the underlying data is normally distributed. To get started, a design matrix is set up with both the cell population and sequencing lane (batch) information.

```r
design <- model.matrix(~0+group+lane)
colnames(design) <- gsub("group", "", colnames(design))
design
```

```r
##   Basal LP ML laneL006 laneL008
## 1     0  1  0        0        0
## 2     0  0  1        0        0
## 3     1  0  0        0        0
## 4     1  0  0        1        0
## 5     0  0  1        1        0
## 6     0  1  0        1        0
## 7     1  0  0        1        0
## 8     0  0  1        0        1
## 9     0  1  0        0        1
## attr("assign")
## [1] 1 1 1 2 2
## attr("contrasts")
## attr("contrasts")$group
```
For a given experiment, there are usually several equivalent ways to set up an appropriate design matrix. For example, 
\(-0+\text{group}+\text{lane}\) removes the intercept from the first factor, \text{group}, but an intercept remains in the second factor \text{lane}. Alternatively, \(-\text{group}+\text{lane}\) could be used to keep the intercepts in both \text{group} and \text{lane}. Understanding how to interpret the coefficients estimated in a given model is key here. We choose the first model for our analysis, as setting up model contrasts is more straightforward in the absence of an intercept for \text{group}. Contrasts for pairwise comparisons between cell populations are set up in \textit{limma} using the \texttt{makeContrasts} function.

```r
contr.matrix <- makeContrasts(
  BasalvsLP = Basal - LP,
  BasalvsML = Basal - ML,
  LPvsML = LP - ML,
  levels = colnames(design))
```

### Levels | Contrasts  
--- | ---  
Basal | 1 | 1 | 0  
LP | -1 | 0 | 1  
ML | 0 | -1 | -1  
laneL006 | 0 | 0 | 0  
laneL008 | 0 | 0 | 0

A key strength of \textit{limma}’s linear modelling approach, is the ability accommodate arbitrary experimental complexity. Simple designs, such as the one in this workflow, with cell type and batch, through to more complicated factorial designs and models with interaction terms can be handled relatively easily. Where experimental or technical effects can be modelled using a random effect, another possibility in \textit{limma} is to estimate correlations using \texttt{duplicateCorrelation} by specifying a \texttt{block} argument for both this function and in the \texttt{lmFit} linear modelling step.

### Removing heteroscedasticity from count data

It has been shown that for RNA-seq count data, the variance is not independent of the mean\(^{13}\) – this is true of raw counts or when transformed to log-CPM values. Methods that model counts using a Negative Binomial distribution assume a quadratic mean-variance relationship. In \textit{limma}, linear modelling is carried out on the log-CPM values which are assumed to be normally distributed and the mean-variance relationship is accommodated using precision weights calculated by the \texttt{voom} function.

When operating on a \texttt{DGEList}-object, \texttt{voom} converts raw counts to log-CPM values by automatically extracting library sizes and normalisation factors stored in the object. For a matrix of counts, the method of normalisation can be specified within \texttt{voom} using the \texttt{normalize.method} (by default no normalisation is performed).

The mean-variance relationship of log-CPM values for this dataset is shown in Figure 4A. Typically, the “voom-plot” shows a decreasing trend between the means and variances resulting from a combination of technical variation in the sequencing experiment and biological variation amongst the replicate samples from different cell populations. Experiments with high biological variation usually result in flatter trends, where variance values plateau at high expression values. Experiments with low biological variation tend to result in sharp decreasing trends.

Moreover, the voom-plot provides a visual check on the level of filtering performed upstream. If filtering of lowly-expressed genes is insufficient, a drop in variance levels can be observed at the low end of the expression scale due to very small counts. If this is observed, one should return to the earlier filtering step and increase the expression threshold applied to the dataset.
Where sample-level variation is evident from earlier inspections of the MDS plot, the `voomWithQualityWeights` function can be used to simultaneously incorporate sample-level weights together with the abundance dependent weights estimated by `voom`. For an example of this, see Liu et al. (2016).

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

Figure 4. Means (x-axis) and variances (y-axis) of each gene are plotted to show the dependence between the two before `voom` is applied to the data (A) and how the trend is removed after `voom` precision weights are applied to the data (B). The plot on the left is created within the `voom` function which extracts residual variances from fitting linear models to log-CPM transformed data. Variances are then rescaled to quarter-root variances (or square-root of standard deviations) and plotted against the mean expression of each gene. The means are log₂-transformed mean-counts with an offset of 0.5. The plot on the right is created using `plotSA` which plots log residual standard deviations against mean log-CPM values. The average log₂ residual standard deviation is marked by a horizontal blue line. In both plots, each black dot represents a gene and a red curve is fitted to these points.
Note that the other data frames stored within the DGEList-object that contain gene- and sample-level information, are retained in the EList-object v created by voom. The v$genes data frame is equivalent to x$genes, v$targets is equivalent to x$samples, and the expression values stored in v$E is analogous to x$counts, albeit on a transformed scale. In addition to this, the voom EList-object has a matrix of precision weights v$weights and stores the design matrix in v$design.

Fitting linear models for comparisons of interest
Linear modelling in limma is carried out using the lmFit and contrasts.fit functions which can be used for both microarray and RNA-seq data and fit a separate model to the expression values for each gene. Next, empirical Bayes moderation is carried out by the eBayes function which borrows information across all the genes to obtain more precise estimates of gene-wise variability. The model’s residual variances are plotted against average expression values in Figure 4B. It can be seen from this plot that the variance is no longer dependent on the mean expression level.

vfit <- lmFit(v, design)
vfit <- contrasts.fit(vfit, contrasts=contr.matrix)
efit <- eBayes(vfit)
plotSA(efit)

Examining the number of DE genes
For a quick look at differential expression levels, the number of significantly up- and down-regulated genes can be summarised in a table. Significance is defined using an adjusted p-value cutoff that is set at 5% by default. For the

```r
# Tags  10_6_5_11 9_6_5_11 purep53 JMS8-2 JMS8-3 JMS8-4 JMS8-5 JMS9-P7c JMS9-P8c
# 497097 -4.29 -3.87 2.52 3.30 -4.48 3.90 3.30 -3.20 -5.29
# 27395  3.88  4.40  4.52  4.32  3.79  3.92  4.35  4.13
# 18777  4.71  5.56  5.40  5.17  5.63  5.08  5.08  5.76  5.15
# 21399  4.78  4.74  5.37  5.13  4.85  4.94  5.16  4.99
# 58175  3.94  3.29 -1.77 -1.88  2.99  3.36 -2.11  3.14  3.52
# 14160 more rows ...
```

```r
## $weights
## [1,]  1.18  1.18 20.53 20.98  1.77  1.22 21.13  1.18  1.18
## [2,] 20.88 26.56 31.60 29.66 32.56 26.75 29.79 21.90 17.15
## [3,] 28.00 33.70 34.85 34.46 35.15 33.55 34.52 31.44 25.23
## [4,] 27.67 29.60 34.90 34.43 34.84 33.16 34.49 26.14 24.50
## [5,] 19.74 18.66 3.18  2.63 24.19 24.01  2.65 13.15 14.35
# 14160 more rows ...
```

```r
## $design
##   Basal LP ML laneL006 laneL008
## 1     0  1  0        0        0
## 2     0  0  1        0        0
## 3     1  0  0        0        0
## 4     1  0  0        1        0
## 5     0  0  1        1        0
## 6     0  1  0        1        0
## 7     1  0  0        1        0
## 8     0  0  1        0        1
## 9     0  1  0        0        1
## attr(, "assign")
## [1] 1 1 1 2 2
## attr(, "contrasts")
## attr("contrasts")$group
## [1] "contr.treatment"
## attr(, "contrasts")$lane
## [1] "contr.treatment"
```
comparison between expression levels in basal and LP, 4,127 genes are found to be down-regulated in basal relative
to LP and 4,298 genes are up-regulated in basal relative to LP – a total of 8,425 DE genes. A total of 8,510 DE genes
are found between basal and ML (4,338 down- and 4,172 up-regulated genes), and a total of 5,340 DE genes are found
between LP and ML (2,895 down- and 2,445 up-regulated). The larger numbers of DE genes observed for comparisons
involving the basal population are consistent with our observations from the MDS plots.

```
summary(decideTests(efit))
```

##    BasalvsLP BasalvsML LPvsML
## -1      4127      4338   2895
## 0       5740      5655   8825
## 1       4298      4172   2445

Some studies require more than an adjusted \( p \)-value cut-off. For a stricter definition on significance, one may require
log-fold-changes (log-FCs) to be above a minimum value. The \texttt{treat} method\(^1\) can be used to calculate \( p \)-values from
empirical Bayes moderated \( t \)-statistics with a minimum log-FC requirement. The number of differentially expressed
genes are reduced to a total of 3,135 DE genes for basal versus LP, 3,270 DE genes for basal versus ML, and 385 DE
genes for LP versus ML when testing requires genes to have a log-FC that is significantly greater than 1 (equivalent to
a 2-fold difference between cell types on the original scale).

```
tfit <- treat(vfit, lfc=1)
dt <- decideTests(tfit)
summary(dt)
```

##    BasalvsLP BasalvsML LPvsML
## -1    1417    1512    203
## 0   11030   10895  13780
## 1     1718    1758    182

Genes that are DE in multiple comparisons can be extracted using the results from \texttt{decideTests}, where 0s represent
genes that are not DE, 1s represent genes that are up-regulated, and -1s represent genes that are down-regulated. A total
of 2,409 genes are DE in both basal versus LP and basal versus ML (Figure 5), twenty of which are listed below. The
\texttt{write.fit} function can be used to extract and write results for all three comparisons to a single output file.

```
de.common <- which(dt[,1]!=0 & dt[,2]!=0)
length(de.common)
```

## [1] 2409

![Figure 5](image_url)

**Figure 5.** Venn diagram showing the number of genes DE in the comparison between basal versus LP only (left),
basal versus ML only (right), and the number of genes that are DE in both comparisons (center). The number of
genes that are not DE in either comparison are marked in the bottom-right.
Examining individual DE genes from top to bottom
The top DE genes can be listed using `topTreat` for results using `treat` (or `topTable` for results using `eBayes`). By default `topTreat` arranges genes from smallest to largest adjusted \( p \)-value with associated gene information, log-FC, average log-CPM, moderated \( t \)-statistic, raw and adjusted \( p \)-value for each gene. The number of top genes displayed can be specified, where `n=Inf` includes all genes. Genes `Cldn7` and `Rasef` are amongst the top DE genes for both basal versus LP and basal versus ML.

```r
basal.vs.lp <- topTreat(tfit, coef=1, n=Inf)
basal.vs.ml <- topTreat(tfit, coef=2, n=Inf)
head(basal.vs.lp)
```

<table>
<thead>
<tr>
<th>ENTREZID</th>
<th>SYMBOL</th>
<th>TXCHROM</th>
<th>logFC</th>
<th>AveExpr</th>
<th>t</th>
<th>P.Value</th>
<th>adj.P.Val</th>
</tr>
</thead>
<tbody>
<tr>
<td>12759</td>
<td>Clu</td>
<td>chr14</td>
<td>-5.44</td>
<td>8.86</td>
<td>-33.4</td>
<td>3.99e-10</td>
<td>2.7e-06</td>
</tr>
<tr>
<td>53624</td>
<td>Cldn7</td>
<td>chr11</td>
<td>-5.51</td>
<td>6.30</td>
<td>-32.9</td>
<td>4.50e-10</td>
<td>2.7e-06</td>
</tr>
<tr>
<td>242505</td>
<td>Rasef</td>
<td>chr4</td>
<td>-5.92</td>
<td>5.42</td>
<td>-30.7</td>
<td>8.11e-10</td>
<td>2.7e-06</td>
</tr>
<tr>
<td>70350</td>
<td>Baspl</td>
<td>chr15</td>
<td>-6.07</td>
<td>5.25</td>
<td>-28.6</td>
<td>1.38e-09</td>
<td>2.7e-06</td>
</tr>
</tbody>
</table>

```r
head(basal.vs.ml)
```

<table>
<thead>
<tr>
<th>ENTREZID</th>
<th>SYMBOL</th>
<th>TXCHROM</th>
<th>logFC</th>
<th>AveExpr</th>
<th>t</th>
<th>P.Value</th>
<th>adj.P.Val</th>
</tr>
</thead>
<tbody>
<tr>
<td>242505</td>
<td>Rasef</td>
<td>chr4</td>
<td>-6.51</td>
<td>5.12</td>
<td>-35.5</td>
<td>2.57e-10</td>
<td>1.92e-06</td>
</tr>
<tr>
<td>53624</td>
<td>Cldn7</td>
<td>chr11</td>
<td>-5.47</td>
<td>6.30</td>
<td>-32.5</td>
<td>4.98e-10</td>
<td>1.92e-06</td>
</tr>
<tr>
<td>12521</td>
<td>Cldn7</td>
<td>chr11</td>
<td>-4.67</td>
<td>7.07</td>
<td>-31.8</td>
<td>8.01e-10</td>
<td>1.92e-06</td>
</tr>
<tr>
<td>71740</td>
<td>Fvr14</td>
<td>chr1</td>
<td>-5.56</td>
<td>5.17</td>
<td>-31.3</td>
<td>6.76e-10</td>
<td>1.92e-06</td>
</tr>
<tr>
<td>20661</td>
<td>Sort1</td>
<td>chr3</td>
<td>-4.91</td>
<td>6.71</td>
<td>-31.2</td>
<td>7.66e-10</td>
<td>1.92e-06</td>
</tr>
<tr>
<td>15375</td>
<td>Foxal</td>
<td>chr12</td>
<td>-5.75</td>
<td>5.63</td>
<td>-28.3</td>
<td>1.49e-09</td>
<td>2.28e-06</td>
</tr>
</tbody>
</table>

Useful graphical representations of differential expression results
To summarise results for all genes visually, mean-difference plots, which display log-FCs from the linear model fit against the average log-CPM values can be generated using the `plotMD` function, with the differentially expressed genes highlighted.

```r
plotMD(tfit, column=1, status=dt[,1], main=colnames(tfit)[1],
       xlim=c(-8,13))
```

Glimma extends this functionality by providing an interactive mean-difference plot via the `glMDPlot` function. The output of this function is an html page, with summarised results in the left panel (similar to what is output by `plotMD`), and the log-CPM values from individual samples in the right panel, with a table of results below the plots (Figure 6). This interactive display allows the user to search for particular genes based on their Gene symbol, which is not possible in a static R plot. The `glMDPlot` function is not limited to mean-difference plots, with a default version allowing a data frame to be passed with the user able to select the columns of interest to plot in the left panel.

```r
glMDPlot(tfit, coef=1, status=dt[,1], main=colnames(tfit)[1],
          counts=x$counts, samples=colnames(x), anno=x$genes, groups=group,
          id.column="ENTREZID", display.columns=c("SYMBOL", "ENTREZID"),
          search.by="SYMBOL", launch=FALSE)
```
The mean-difference plot generated by the command above is available online (see http://bioinf.wehi.edu.au/folders/limmaWorkflow/glimma-plots/MD-Plot.htm). The interactivity provided by the Glimma package allows additional information to be presented in a single graphical window. Glimma is implemented in R and Javascript, with the R code generating the data which is converted into graphics using the Javascript library D3 (https://d3js.org), with the Bootstrap library handling layouts and Datatables generating the interactive searchable tables. This allows plots to be viewed in any modern browser, which is convenient for including them as linked files from an Rmarkdown report of the analysis.

Plots shown previously include either all of the genes that are expressed in any one condition (such as the Venn diagram of common DE genes or mean-difference plot) or look at genes individually (log-CPM values shown in right panel of the interactive mean-difference plot). Heatmaps allow users to look at the expression of a subset of genes. This can give useful insight into the expression of individual groups and samples without losing perspective of the overall study when focusing on individual genes, or losing resolution when examining patterns averaged over thousands of genes at the same time.

A heatmap is created for the top 100 DE genes (as ranked by adjusted p-value) from the basal versus LP contrast using the heatmap.2 function from the gplots package (Figure 7). The heatmap correctly clusters samples into cell type and rearranges the order of genes to form blocks of similar expression. From the heatmap, we observe that the expression of ML and LP samples are very similar for the top 100 DE genes between basal and LP.

```r
library(gplots)
basal.vs.lp.topgenes <- basal.vs.lp$ENTREZID[1:100]
i <- which(v$genes$ENTREZID %in% basal.vs.lp.topgenes)
mycol <- colorpanel(1000,"blue","white","red")
heatmap.2(v$E[i,], scale="row",
  labRow=v$genes$SYMBOL[i], labCol=group,
  col=mycol, trace="none", density.info="none",
  margin=c(8,6), lhei=c(2,10), dendrogram="column")
```

Figure 6. Interactive mean-difference plot generated using Glimma. Summary data (log-FCs versus log-CPM values) are shown in the left panel which is linked to the individual values per sample for a selected gene in the right panel. A table of results is also displayed below these figures, along with a search bar to allow users to look up a particular gene using its Gene symbol identifier, e.g. Clu.
Figure 7. Heatmap of log-CPM values for top 100 genes DE in basal versus LP. Expression across each gene (or row) have been scaled so that mean expression is zero and standard deviation is one. Samples with relatively high expression within a gene are marked in red, samples with relatively low expression are marked in blue. Lighter shades and white represent genes with intermediate expression levels. Samples and genes have been reordered by the method of hierarchical clustering. A dendrogram is shown for the clustering of samples.
Gene set testing with camera

We finish this analysis with gene set testing by applying the *camera* method\(^1\) to the \(c2\) gene signatures from the Broad Institute’s MSigDB \(c2\) collection\(^2\) that have been adapted for mouse and are available as Rdata objects from http://bioinf.wehi.edu.au/software/MSigDB/.

```r
load(url("http://bioinf.wehi.edu.au/software/MSigDB/mouse_c2_v5p1.rdata"))
idx <- ids2indices(Mm.c2, id=rownames(v))
cam.BasalvsLP <- camera(v,idx,design,contrast=contr.matrix[,1],
                        inter.gene.cor=0.01)
```

Figure 8. Barcode plot of LIM,MAMMARY,LUMINAL,MATURE,UP (red bars, top of plot) and LIM,MAMMARY,LUMINAL,MATURE,DN (blue bars, bottom of plot) gene sets in the LP versus ML contrast with an enrichment line for each set that shows the relative enrichment of the vertical bars in each part of the plot. The experiment of Lim *et al.* (2010) is very similar to the current one, with the same sorting strategy used to obtain the different cell populations, except that microarrays were used instead of RNA-seq to profile gene expression. Note that the inverse correlation (the up gene set is down and the down gene set is up) is a result of the way the contrast has been set up (LP versus ML) – if reversed, the directionality would agree.
head(cam.BasalvsLP,5)
## NGenes Correlation Direction PValue
## LIM_MAMMARY_STEM_CELL_UP              739 0.01 Up 1.13e-18
## LIM_MAMMARY_STEM_CELL_DN               630 0.01 Down 1.57e-15
## ROSTY_CERVICAL_CANCER_PROLIFERATION_CLUSTER 163 0.01 Up 1.44e-13
## SOTIRIOU_BREAST_CANCER_GRADE_1_VS_3_UP  183 0.01 Down 2.18e-13
## LIM_MAMMARY_LUMINAL_PROGENITOR_UP       87  0.01 Down 6.73e-13
## FDR
## LIM_MAMMARY_STEM_CELL_UP                 5.36e-15
## LIM_MAMMARY_STEM_CELL_DN                 3.71e-12
## ROSTY_CERVICAL_CANCER_PROLIFERATION_CLUSTER 2.26e-10
## SOTIRIOU_BREAST_CANCER_GRADE_1_VS_3_UP  2.58e-10
## LIM_MAMMARY_LUMINAL_PROGENITOR_UP        6.36e-10

head(cam.BasalvsML,5)
## NGenes Correlation Direction PValue
## LIM_MAMMARY_STEM_CELL_UP                  779 0.01 Up 5.09e-23
## LIM_MAMMARY_STEM_CELL_DN                  630 0.01 Down 5.13e-19
## LIM_MAMMARY_LUMINAL_MATURE_DN             166 0.01 Up 1.44e-13
## LIM_MAMMARY_LUMINAL_MATURE_UP             180 0.01 Down 6.29e-13
## ROSTY_CERVICAL_CANCER_PROLIFERATION_CLUSTER 163 0.01 Up 1.68e-13
## FDR
## LIM_MAMMARY_STEM_CELL_UP                  2.40e-19
## LIM_MAMMARY_STEM_CELL_DN                  1.21e-15
## LIM_MAMMARY_LUMINAL_MATURE_DN             1.40e-12
## LIM_MAMMARY_LUMINAL_MATURE_UP             7.43e-10
## ROSTY_CERVICAL_CANCER_PROLIFERATION_CLUSTER 1.59e-09

cam.LPvsML <- camera(v,idx,design,contrast=contr.matrix[,2],
                     inter.gene.cor=0.01)

cam.LPvsML <- camera(v,idx,design,contrast=contr.matrix[,3],
                     inter.gene.cor=0.01)

barcodeplot(efit$t[,3], index=idx$LIM_MAMMARY_LUMINAL_MATURE_UP,
             index2=idx$LIM_MAMMARY_LUMINAL_MATURE_DN, main="LPvsML")
Software availability

This RNA-seq workflow makes use of various packages available from version 3.4 of the Bioconductor project, running on R version 3.3.0 or higher. Besides the packages highlighted in this article (limma, Glimma and edgeR) it requires a number of other software packages, including gplots and RColorBrewer and the gene annotation package Mus.musculus. This document was compiled using knitr. Version numbers for all packages used are shown below.


sessionInfo()

## R version 3.3.0 (2016-05-03)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: CentOS release 6.4 (Final)
##
## locale:
## [1] LC_CTYPE=en_AU.UTF-8 LC_NUMERIC=C LC_TIME=en_AU.UTF-8
## [4] LC_COLLATE=en_AU.UTF-8 LC_MONETARY=en_AU.UTF-8 LC_MESSAGES=en_AU.UTF-8
## [7] LC_PAPER=en_AU.UTF-8 LC_NAME=C LC_ADDRESS=C
##[10] LC_TELEPHONE=C LC_MEASUREMENT=en_AU.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] parallel stats graphics grDevices utils datasets methods
## [9] base
##
## other attached packages:
## [1] gplots_3.0.1                     Glimma_1.1.1
## [3] RColorBrewer_1.1-2               Mus.musculus_1.3.1
## [5] TxDb.Mmuculus.UCSC.mm10.knownGene_3.2.2 org.Mm.eu.db_3.3.0
## [7] GO.db_3.3.0                      OrganismDbi_1.14.0
## [9] GenomicFeatures_1.24.0           GenomicRanges_1.24.0
## [11] GenomeInfoDb_1.8.1               AnnotationDbi_1.34.3
## [13] IRanges_2.6.0                    S4Vectors_0.10.1
## [15] Biobase_2.32.0                    BiocGenerics_0.18.0
## [17] edgeR_3.14.0                     limma_3.28.5
##
## loaded via a namespace (and not attached):
## [1] locfit_1.5-9.1                     Rcpp_0.12.5
## [4] gtools_3.5.0                        lattice_0.20-33
## [7] plyr_1.8.3                           Rsamtools_2.4.01
## [10] RSQLite_1.0.0                        acepack_1.3-3.3
## [13] highr_0.5.1                         evaluate_0.9
## [15] BiocInstaller_1.23.4               ggplot2_2.1.0
## [16] gdata_2.17.0                        annotate_1.50.0
## [19] R.utils_2.3.0                       data.table_1.9.6
## [22] Matrix_1.2-6                         R.oo_1.20.0
## [25] geneplotter_1.50.0                   rpart_4.1-10
## [28] RCurl_1.95-4.8                       splines_3.3.0
## [31] rtracklayer_1.32.0                   BiocParallel_1.6.2
## [34] gridExtra_2.2.1                      stringr_1.0.0
## [37] GenomicAlignments_1.8.0             foreign_0.8-66
## [40] grid_3.3.0                           nnet_7.3-12
## [43] gtable_0.2.0                         SummarizedExperiment_1.2.2
## [46] formatR_1.3                          biOps_1.0-6
## [49] graph_1.50.0                         R.methodsS3_3.7.1
## [52] gtable_0.2.0                         xtable_1.8-2
## [55] tools_3.3.0                          DBI_0.4-1
## [58] colorspace_1.2-6                     magrittr_1.5
## [61] knitr_1.12.3                         scales_0.4.0
##
F1000Research 2016, 5:1408 Last updated: 30 JAN 2019
Author contributions
All authors were involved in writing and contributing code for the article.

Competing interests
The authors declare that they have no competing interests.

Grant information
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References
Open Peer Review

Current Referee Status: ✅ ✅ ✅

Version 1

Referee Report 06 July 2016

https://doi.org/10.5256/f1000research.9688.r14437

Jovana Maksimovic
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This workflow outlines a step-by-step differential expression analysis of a publicly available RNA-seq dataset using several well-established Bioconductor packages such as limma and edgeR and the novel Glimma package. The workflow describes in detail the key steps that are generally performed as part of most standard, count-based RNAseq analyses: pre-processing, exploratory data analysis, differential expression testing and pathway analysis. Each of the steps is carefully explained and broken down into a series of logical substeps, which also include R code and example output. Furthermore, this workflow is a good example of how multiple Bioconductor packages can be applied in a real-world RNAseq analysis.

Overall, I think this is a very clearly written and well-explained workflow that not only highlights the utility of combining Bioconductor packages for RNAseq analysis but also demystifies the process for those who may be interested in learning what an RNAseq analysis involves. Although some familiarity with R and statistical concepts would be advantageous, they are not necessary to be able to follow the logic behind the steps and what each step is trying to achieve.

I have tested the R code under R 3.3.0 and Bioconductor 3.0 and it ran without errors.

Minor comments:
- As this workflow will be of particular use for those who are very new to RNAseq analysis, I think it should be explained why 1 CPM is chosen as the cutoff for lowly expressed genes. In addition, it may be useful to show the relationship between CPM and raw counts and how the selected cutoff relates to numbers of reads.
- In the gene set testing section, it is worth mentioning that the Hallmark gene sets (also available from the Broad MSigDB) may be a good starting point for pathway analysis as they "summarise and represent specific well-defined, states or processes".
- Also, for those who are new to RNAseq analysis, it may be worth mentioning that there are other gene set testing methods available in limma e.g. roast etc. and a very brief explanation of when the different methods are appropriate.
- General comment regarding Glimma plots: it would be handy to see the gene symbol (if available) as well as EntrezID in the title of the scatter plot next to the MD plot.

Competing Interests: Matthew E. Ritchie and I are both organisers of the Bioconductor Asia-Pacific Developer meeting, which is to be held in Brisbane in November 2016.
I have read this submission. I believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Charity Law, The Walter and Eliza Hall Institute of Medical Research, Australia

Dear Jovana, thank-you for the helpful suggestions. We have added extra text to explain why a CPM value of 1 was chosen and how this value relates to raw counts. We have also given more detail on c2 and Hallmark gene sets, as well as mentioning roast and when one might choose to use roast over camera.

Competing Interests: None

Referee Report 06 July 2016

https://doi.org/10.5256/f1000research.9688.r14439

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Editorial Note from F1000Research - 7th July 2016:

the status of this review was changed after publication from "Approved with Reservations" to "Approved". The referee’s reservation was caused by using the current release (Bioconductor 3.3) as opposed to the development release (Bioconductor 3.4) as used in the article.

The following text has been removed:

My only reservation to approving the article is that I encountered these two errors when running the Glimma code in the article. I used R 3.3.0 and the most recent version of Glimma from Bioconductor (Glimma 1.0.0) but the sessionInfo() in the article shows Glimma 1.1.1 was used which may account for the errors:

1) With this line of code no plot was produced and it gave the error below:
   glMDSPlot(lcpm, labels=paste(group, lane, sep=" "),
   +   groups=x$samples[,c(2,5)], launch=TRUE)
   Error in glScatter.default(points, xval = "dim1", yval = "dim2", xlab = "Dimension 1", :
   group does not correspond to a column

2) With this line of code the table (shown in Fig 6.) didn't appear, just the 2 plots:
   glMDPlot(tfit, coef=1, status=dt[,1], main=colnames(tfit)[1],
   counts=x$counts, samples=colnames(x), anno=x$genes, groups=group,
   id.column="ENTREZID", display.columns=c("SYMBOL", "ENTREZID"),
   search.by="SYMBOL", launch=FALSE)

This article is a very nice description (nicely written, nicely explained) of an RNA-seq workflow, starting from gene counts and proceeding through a standard differential expression analysis, using 3
complementary Bioconductor packages edgeR, limma & Glimma. It explains clearly how to perform the steps of a differential expression analysis and also how to generate useful plots for visualising the data e.g. MDSplot, MDplot, barcodeplot, heatmap etc.

Two of the packages, edgeR and limma, are well established while Glimma is the new kid on the block. It's a tool along the lines of the web-based Degust (http://www.vicbioinformatics.com/degest/), in that it enables interactive exploration of RNA-seq data. It would seem to be a very useful addition to R RNA-seq workflows as the interactive html plots it can generate (MDS, MD etc) make exploring the results easier (especially by non-R savvy collaborators) and it could help save an analyst's time and effort through not having to reproduce static plots e.g. to highlight different genes. With the Glimma MDplot I like that you can search for a gene and see a plot of the log-cpm counts for that gene in the samples.

It was great to be able to try out the workflow really easily by downloading the data file linked to in the paper (from GEO), with no processing required other than unzipping the files, and the code in the article all worked, giving the same results shown in the paper with the exception of two errors described below.

Minor comments:

The article says the workflow is available from Bioconductor here http://www.bioconductor.org/help/workflows/ but it doesn't seem to be there, however it is available at the other location mentioned http://bioinf.wehi.edu.au/folders/limmaWorkflow/

The section title "Removing genes that are not expressed" suggests only genes with no expression are removed, however the paragraph then explains that genes lowly expressed are also removed so for greater clarity maybe that could be changed to something like "Removing genes that are not sufficiently expressed".

In the section "Organising gene annotations" I think it's good the authors point out to check for duplicated genes, however in this case the duplication appears to be due to extracting the TXCHROM column (as some genes are reported as being present on more than one chromosome) but the TXCHROM information is not used in this workflow and if the TXCHROM column is omitted then there are no duplicates so it might be worth mentioning that.

With this bit "Differential expression analyses look at gene expression differences between conditions, rather than comparing expression across multiple genes or drawing conclusions on absolute levels of expression. In other words, gene lengths remain constant for comparisons of interest and any observed differences are a result of changes in condition rather than changes in gene length." Wouldn't one caveat to this be if there was a significant change in the length of the isoform(s) expressed from a gene (e.g. from expression of a long isoform to a short isoform) as then the assumption of no change in gene length would no longer be valid.

In the online version Fig.7 is in the middle of a code block could it be moved below.

Figs 5-8 have bold headings but Figs 1-4 don't is that an error.

Could perhaps modify title to reflect the order in which the tools are used - edger, limma & Glimma.

It would be nice for consistency if the colours in the Glimma interactive MDS plots matched the colours used in the static MDS plots in Fig 3.
**Competing Interests:** No competing interests were disclosed.

I have read this submission. I believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Referee Response 06 Jul 2016

**Maria A. Doyle,** Peter MacCallum Cancer Centre, Australia

I've just requested that the status of this article be changed to Approved as the code works fine with the development release of Bioconductor 3.4 but could it be made clearer in the article that 3.4 must be used for the code to work as shown.

**Competing Interests:** No competing interests were disclosed.

Author Response 30 Nov 2016

**Charity Law,** The Walter and Eliza Hall Institute of Medical Research, Australia

Dear Maria, we have made changes according to your suggestions, including a change in the section title to “Removing genes that are lowly expressed”, and we have added comments to point out that our analysis assumes no differential isoform usage. We have also simplified our example in the “Organising gene annotations” section.

Thanks for pointing out the inconsistencies in the figure captions. They have now been addressed.

Indeed, it would be nice to make the colours consistent between the interactive and static MDS plots. We like the colours used in the static plot and can have the interactive version of the plot updated once color specification becomes available to the MDS plotting function in Glimma.

**Competing Interests:** None

Referee Report 23 June 2016

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**James W. MacDonald**

Department of Environmental and Occupational Health Sciences, University of Washington, Seattle, WA, USA

In this manuscript the authors perform a step-by-step analysis of a public RNA-Seq data set, using the Bioconductor packages edgeR, limma, and Glimma. The analysis proceeds through four stages (data preparation, preprocessing, univariate analyses, and gene set testing), with each stage broken up into several discrete steps. Each step is clearly explained and is accompanied by R code and output, so the reader can follow along if desired.

The target audience for this paper appears to be someone with passing familiarity with both R and statistics, without requiring expertise in either. Most of the code should be easy to understand, and any
complex sections are clearly explained in the text. Similarly, the authors outline the analytic choices they make (e.g., filtering out unexpressed genes, specifying model coefficients, etc) at a more accessible level.

While both edgeR and limma are well known, popular Bioconductor packages, Glimma is a new package that was released in April 2016. This package uses the d3.js JavaScript library to generate interactive HTML documents that can be viewed locally, rather than needing to be accessed from a server running R (as, say a shiny app requires). This is an exciting development, and is unfortunately not as compelling as it could be, if the Glimma plots were part of the HTML version of the manuscript rather than provided as links.

This is a well written paper, and is a useful contribution to the literature; while each package has either an extensive user's guide or vignette, by necessity these documents pertain only to the package at hand. Most RNA-Seq analyses require a combination of multiple packages to complete, and this paper provides a clear example.

**Major comments**

None.

**Minor comments**

In the section 'Organising gene annotations', the code used to subset the one-to-many mappings is needlessly complex. Simply doing something like

```
genes <- genes[!duplicated(genes[,1]),]
```

will accomplish the same thing, in a more straightforward way.

In the section 'Removing heteroscedasticity from count data', the authors state:

"When operating on a DGEList-object, voom converts raw counts to log-CPM values by automatically extracting library sizes and normalisation factors stored in the object. For a matrix of counts, the method of normalisation can be specified within voom using the normalize.method (by default no normalisation is performed)."

This is confusing; the authors already showed in an earlier section ('Normalising gene expression distributions') that converting to log-CPM using TMM normalization factors will do a shift-normalization (which is what voom will do in this instance). The normalize.method argument to voom specifies additional normalization methods that can be applied to the matrix of TMM normalized log-CPM values.

**Competing Interests:** No competing interests were disclosed.

I have read this submission. I believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.
Dear James, thank-you for your comments. We have considered your suggestions and made changes to simplify the section on ‘Organising gene annotations’ and to clarify that voom offers additional normalisation on top of the TMM-normalisation that is carried out.

**Competing Interests:** None

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