

Class 15: Transcriptomics and RNA Seq Analysis

Jasmine Lee (PID: A15583527)

11/16/2021

Background

Our data for today comes from Himes et al. RNASeq analysis of the drug dexamethasone, a synthetic glucocorticoid steroid with anti-inflammatory effects (Himes et al. 2014).

Read the countData and colData.

```
counts <- read.csv("airway_scaledcounts.csv", row.names=1)
metadata <- read.csv("airway_metadata.csv")
```

Now take a look at each.

```
head(counts)
```

```
##          SRR1039508 SRR1039509 SRR1039512 SRR1039513 SRR1039516
## ENSG000000000003      723        486       904       445      1170
## ENSG000000000005       0         0         0         0         0
## ENSG000000000419     467       523       616       371      582
## ENSG000000000457     347       258       364       237      318
## ENSG000000000460      96        81        73        66      118
## ENSG000000000938      0         0         1         0         2
##          SRR1039517 SRR1039520 SRR1039521
## ENSG000000000003    1097       806       604
## ENSG000000000005       0         0         0
## ENSG000000000419     781       417       509
## ENSG000000000457     447       330       324
## ENSG000000000460      94       102       74
## ENSG000000000938      0         0         0
```

```
head(metadata)
```

```
##      id   dex celltype geo_id
## 1 SRR1039508 control N61311 GSM1275862
## 2 SRR1039509 treated N61311 GSM1275863
## 3 SRR1039512 control N052611 GSM1275866
## 4 SRR1039513 treated N052611 GSM1275867
## 5 SRR1039516 control N080611 GSM1275870
## 6 SRR1039517 treated N080611 GSM1275871
```

Q1. How many genes are in this dataset?

```
nrow(counts)
```

```
## [1] 38694
```

Answer: There are 38,694 genes in this dataset.

Q2. How many ‘control’ cell lines do we have?

```
sum(metadata$dex == "control")
```

```
## [1] 4
```

Answer: There are 4 ‘control’ cell lines.

Toy Differential Gene Expression

First I need to extract all the ‘control’ columns. Then I will take the row-wise mean to get the average count values for all genes in these four experiments.

```
control inds <- metadata$dex=="control"  
control.counts <- counts[ ,control inds]  
head(control.counts)
```

```
##          SRR1039508 SRR1039512 SRR1039516 SRR1039520  
## ENSG00000000003     723      904     1170      806  
## ENSG00000000005      0        0        0        0  
## ENSG00000000419     467      616      582      417  
## ENSG00000000457     347      364      318      330  
## ENSG00000000460      96       73      118      102  
## ENSG00000000938      0        1        2        0
```

```
control.mean <- rowMeans(control.counts)
```

Q3. How would you make the above code (in the hands-on worksheet) in either approach more robust?

Answer: I would make the above code in either approach shown in the hands-on section worksheet more robust by using the rowMeans function instead of finding the mean by dividing rowSums by the number of rows. This would allow for me to easily use this code on datasets with more or less samples.

Q4. Follow the same procedure for the treated samples (i.e. calculate the mean per gene across drug treated samples and assign to a labeled vector called treated.mean).

Answer:

Now do the same for all the ‘treated’ columns.

```

treated inds <- metadata$dex=="treated"
treated.counts <- counts[, treated inds]
head(treated.counts)

##          SRR1039509 SRR1039513 SRR1039517 SRR1039521
## ENSG000000000003     486        445      1097       604
## ENSG000000000005      0          0         0         0
## ENSG000000000419     523        371      781       509
## ENSG000000000457     258        237      447       324
## ENSG000000000460      81         66       94        74
## ENSG000000000938      0          0         0         0

treated.mean <- rowMeans(treated.counts)

```

We will combine our meancount data for bookkeeping purposes.

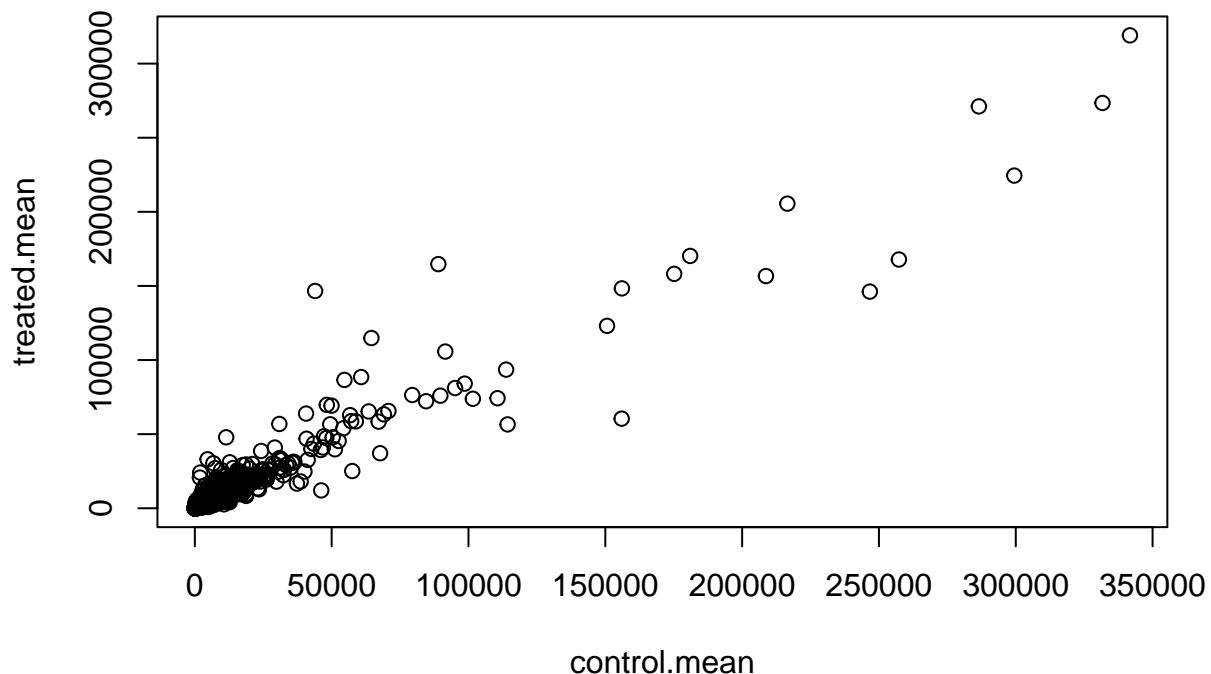
```
meancounts <- data.frame(control.mean, treated.mean)
```

Q5(a). Create a scatter plot showing the mean of the treated samples against the mean of the control samples. Your plot should look something like the following.

Answer:

Let's make a quick plot.

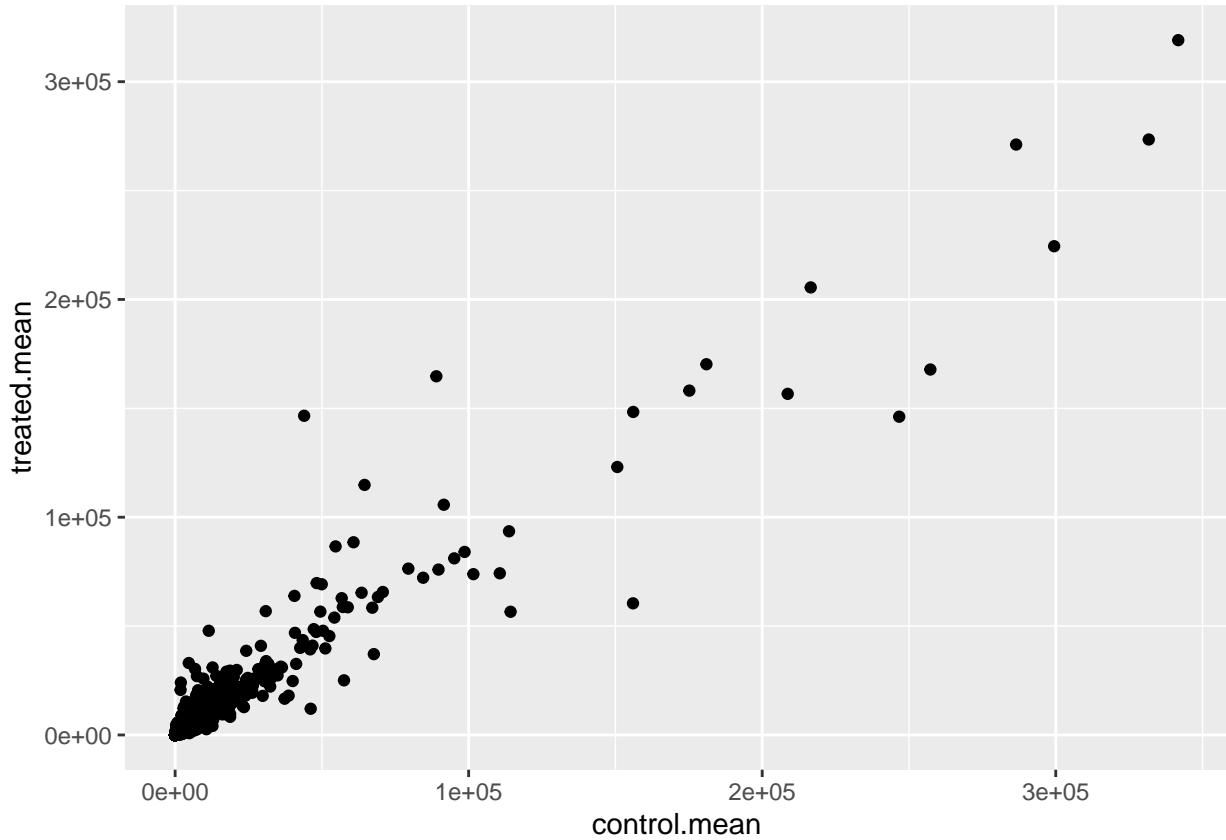
```
plot(meancounts)
```



Q5(b). You could also use the ggplot2 package to make this figure producing the plot below. What geom_?() function would you use for this plot?

Answer: I would use the geom_point() function for this plot.

```
library(ggplot2)
ggplot(meancounts) +
  aes(control.mean,treated.mean) +
  geom_point()
```



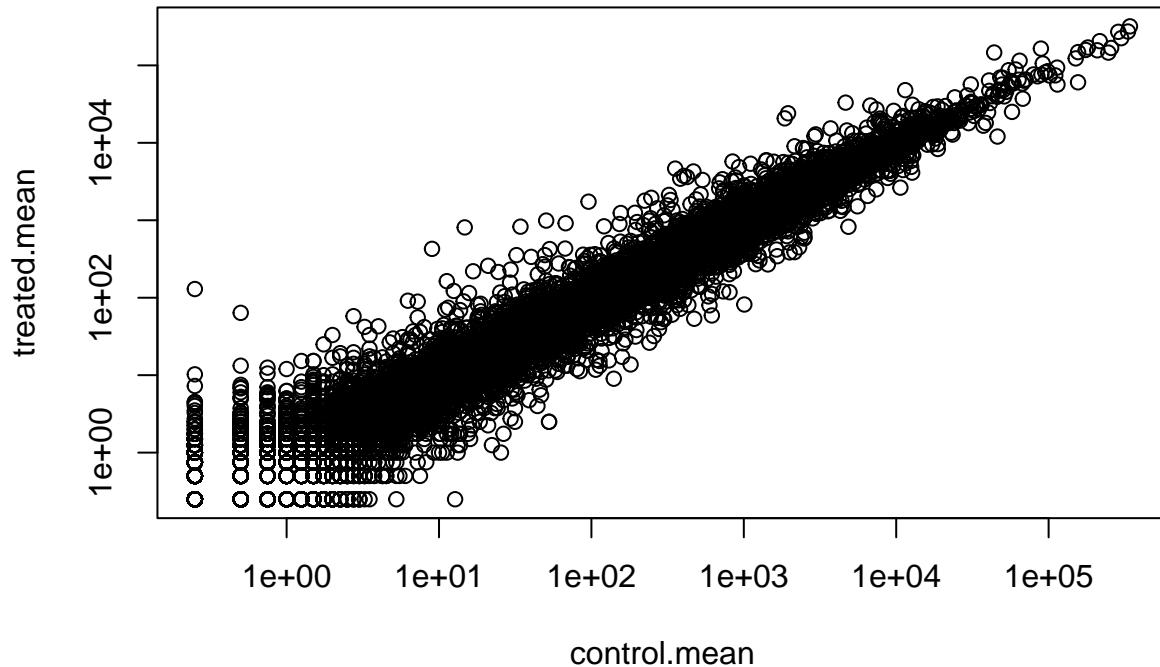
Q6. Try plotting both axes on a log scale. What is the argument to plot() that allows you to do this?

Answer: The argument to plot() is log.

```
plot(meancounts, log="xy")
```

```
## Warning in xy.coords(x, y, xlabel, ylabel, log): 15032 x values <= 0 omitted
## from logarithmic plot
```

```
## Warning in xy.coords(x, y, xlabel, ylabel, log): 15281 y values <= 0 omitted
## from logarithmic plot
```



We often use `log2` in this field because it has nice math properties that make interpretation easier.

```
# No change in gene expression
log2(10/10)
```

```
## [1] 0
```

```
# Doubled increase in gene expression
log2(20/10)
```

```
## [1] 1
```

```
log2(40/10)
```

```
## [1] 2
```

```
log2(5/10)
```

```
## [1] -1
```

Cool, we see 0 values for no change, + values for upregulation, and - values for decreases. This nice property leads us to work with `log2(fold-change)` all the time in the genomics and proteomics field.

Let's add the `log2(fold-change)` values to our 'meancounts' data.

```

meancounts$log2fc <- log2(meancounts[, "treated.mean"]/
                           meancounts[, "control.mean"])
head(meancounts)

```

	control.mean	treated.mean	log2fc
## ENSG00000000003	900.75	658.00	-0.45303916
## ENSG00000000005	0.00	0.00	NaN
## ENSG00000000419	520.50	546.00	0.06900279
## ENSG00000000457	339.75	316.50	-0.10226805
## ENSG00000000460	97.25	78.75	-0.30441833
## ENSG00000000938	0.75	0.00	-Inf

NaN is returned when you divide by zero and try to take the log. The -Inf is returned when you try to take the log of zero. Let's filter our data to remove these genes because we can't say anything about these as we have no data for them.

```

zero.vals <- which(meancounts[, 1:2]==0, arr.ind=TRUE)
to.rm <- unique(zero.vals[, 1])
head(zero.vals)

```

	row	col
## ENSG00000000005	2	1
## ENSG00000004848	65	1
## ENSG00000004948	70	1
## ENSG00000005001	73	1
## ENSG00000006059	121	1
## ENSG00000006071	123	1

```

mycounts <- meancounts[-to.rm,]
head(mycounts)

```

	control.mean	treated.mean	log2fc
## ENSG00000000003	900.75	658.00	-0.45303916
## ENSG00000000419	520.50	546.00	0.06900279
## ENSG00000000457	339.75	316.50	-0.10226805
## ENSG00000000460	97.25	78.75	-0.30441833
## ENSG00000000971	5219.00	6687.50	0.35769358
## ENSG00000001036	2327.00	1785.75	-0.38194109

How many do we have left?

```
nrow(mycounts)
```

```
## [1] 21817
```

Q7. What is the purpose of the arr.ind argument in the which() function call above? Why would we then take the first column of the output and need to call the unique() function?

Answer: The arr.ind argument provides the columns and rows for any object in the array that is TRUE for being equal to 0. The purpose of taking the first column of the output and calling the unique() function is to make sure that rows that have two zeroes are not counted twice.

```
up.ind <- mycounts$log2fc > 2  
down.ind <- mycounts$log2fc < (-2)
```

Q8. Using the up.ind vector above, can you determine how many upregulated genes we have at the greater than 2 fc level?

```
sum(up.ind)
```

```
## [1] 250
```

Answer: There are 250 upregulated genes at the greater than 2 fc level.

Q9. Using the down.ind vector above, can you determine how many downregulated genes we have at the less than -2 fc level?

```
sum(down.ind)
```

```
## [1] 367
```

Answer: There are 367 downregulated genes at the less than -2 fc level.

Q10. Do you trust these results? Why or why not?

Answer: No, I do not trust these results. We have not normalized the fold changes or analyzed them to determine statistical significance yet.

DESeq2 Analysis

Let's do this the right way. DESeq2 is an R package specifically for analyzing count-based NGS data like RNA-seq. It is available from Bioconductor.

```
library(DESeq2)  
  
## Loading required package: S4Vectors  
  
## Loading required package: stats4  
  
## Loading required package: BiocGenerics  
  
##  
## Attaching package: 'BiocGenerics'  
  
## The following objects are masked from 'package:stats':  
##  
##     IQR, mad, sd, var, xtabs
```

```

## The following objects are masked from 'package:base':
##
##   anyDuplicated, append, as.data.frame, basename, cbind, colnames,
##   dirname, do.call, duplicated, eval, evalq, Filter, Find, get, grep,
##   grepl, intersect, is.unsorted, lapply, Map, mapply, match, mget,
##   order, paste, pmax, pmax.int, pmin, pmin.int, Position, rank,
##   rbind, Reduce, rownames, sapply, setdiff, sort, table, tapply,
##   union, unique, unsplit, which.max, which.min

##
## Attaching package: 'S4Vectors'

## The following objects are masked from 'package:base':
##
##   expand.grid, I, unname

## Loading required package: IRanges

##
## Attaching package: 'IRanges'

## The following object is masked from 'package:grDevices':
##
##   windows

## Loading required package: GenomicRanges

## Loading required package: GenomeInfoDb

## Loading required package: SummarizedExperiment

## Loading required package: MatrixGenerics

## Loading required package: matrixStats

##
## Attaching package: 'MatrixGenerics'

## The following objects are masked from 'package:matrixStats':
##
##   colAlls, colAnyNAs, colAnys, colAvgsPerRowSet, colCollapse,
##   colCounts, colCummaxs, colCummins, colCumprods, colCumsums,
##   colDiffss, colIQRDiffss, colIQRs, colLogSumExps, colMadDiffss,
##   colMads, colMaxs, colMeans2, colMedians, colMins, colOrderStats,
##   colProds, colQuantiles, colRanges, colRanks, colSdDiffss, colSds,
##   colSums2, colTabulates, colVarDiffss, colVars, colWeightedMads,
##   colWeightedMeans, colWeightedMedians, colWeightedSds,
##   colWeightedVars, rowAlls, rowAnyNAs, rowAnys, rowAvgsPerColSet,
##   rowCollapse, rowCounts, rowCummaxs, rowCummins, rowCumprods,
##   rowCumsums, rowDiffss, rowIQRDiffss, rowIQRs, rowLogSumExps,
##   rowMadDiffss, rowMads, rowMaxs, rowMeans2, rowMedians, rowMins,
##   rowOrderStats, rowProds, rowQuantiles, rowRanges, rowRanks,
##   rowSdDiffss, rowSds, rowSums2, rowTabulates, rowVarDiffss, rowVars,
##   rowWeightedMads, rowWeightedMeans, rowWeightedMedians,
##   rowWeightedSds, rowWeightedVars

```

```

## Loading required package: Biobase

## Welcome to Bioconductor
##
##   Vignettes contain introductory material; view with
##   'browseVignettes()'. To cite Bioconductor, see
##   'citation("Biobase")', and for packages 'citation("pkgname")'.

##
## Attaching package: 'Biobase'

## The following object is masked from 'package:MatrixGenerics':
##   rowMedians

## The following objects are masked from 'package:matrixStats':
##   anyMissing, rowMedians

```

We will use the DESeqDataSetFromMatrix() function to built the required DESeqDataSet object and call it dds.

```

dds <- DESeqDataSetFromMatrix(countData=counts,
                               colData=metadata,
                               design=~dex)

## converting counts to integer mode

## Warning in DESeqDataSet(se, design = design, ignoreRank): some variables in
## design formula are characters, converting to factors

dds

## class: DESeqDataSet
## dim: 38694 8
## metadata(1): version
## assays(1): counts
## rownames(38694): ENSG00000000003 ENSG00000000005 ... ENSG00000283120
##   ENSG00000283123
## rowData names(0):
## colnames(8): SRR1039508 SRR1039509 ... SRR1039520 SRR1039521
## colData names(4): id dex celltype geo_id

```

Now we can run DESeq analysis.

```

dds <- DESeq(dds)

## estimating size factors

## estimating dispersions

```

```
## gene-wise dispersion estimates  
## mean-dispersion relationship  
## final dispersion estimates  
## fitting model and testing
```

To get the results here, we use the DESeq ‘results()’ function:

```
res <- results(dds)
res

## log2 fold change (MLE): dex treated vs control
## Wald test p-value: dex treated vs control
## DataFrame with 38694 rows and 6 columns
##           baseMean log2FoldChange      lfcSE      stat     pvalue
##          <numeric>      <numeric> <numeric> <numeric> <numeric>
## ENSG000000000003    747.1942    -0.3507030  0.168246 -2.084470 0.0371175
## ENSG000000000005     0.0000       NA        NA        NA        NA
## ENSG000000000419    520.1342    0.2061078  0.101059  2.039475 0.0414026
## ENSG000000000457    322.6648    0.0245269  0.145145  0.168982 0.8658106
## ENSG000000000460    87.6826   -0.1471420  0.257007 -0.572521 0.5669691
## ...
##           ...       ...
## ENSG0000283115    0.000000       NA        NA        NA        NA
## ENSG0000283116    0.000000       NA        NA        NA        NA
## ENSG0000283119    0.000000       NA        NA        NA        NA
## ENSG0000283120    0.974916   -0.668258  1.69456 -0.394354 0.693319
## ENSG0000283123    0.000000       NA        NA        NA        NA
##           padj
##          <numeric>
## ENSG000000000003  0.163035
## ENSG000000000005    NA
## ENSG000000000419  0.176032
## ENSG000000000457  0.961694
## ENSG000000000460  0.815849
## ...
##           ...
## ENSG0000283115    NA
## ENSG0000283116    NA
## ENSG0000283119    NA
## ENSG0000283120    NA
## ENSG0000283123    NA
```

Save Our Results

Write out whole results dataset (including genes that don't change significantly).

```
write.csv(res, file="allmyresults.csv")
```

Focus in on those genes with a small p-value (i.e. show a significant change).

```

res05 <- results(dds, alpha=0.05)

summary(res05)

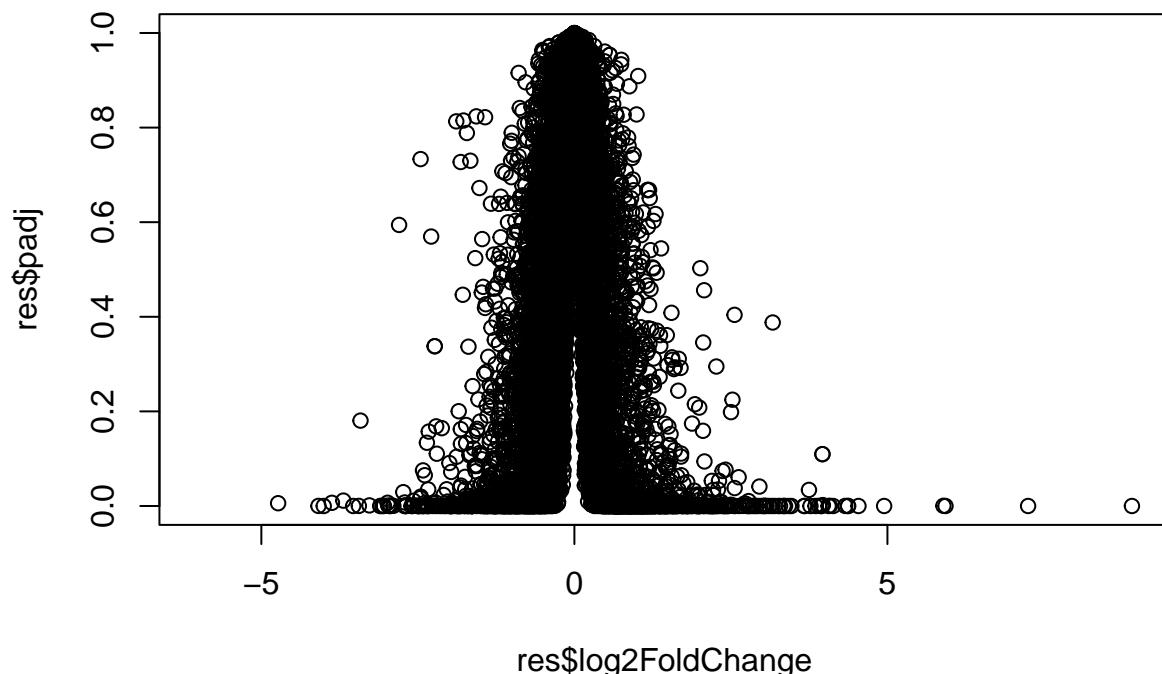
##
## out of 25258 with nonzero total read count
## adjusted p-value < 0.05
## LFC > 0 (up)      : 1236, 4.9%
## LFC < 0 (down)    : 933, 3.7%
## outliers [1]       : 142, 0.56%
## low counts [2]     : 9033, 36%
## (mean count < 6)
## [1] see 'cooksCutoff' argument of ?results
## [2] see 'independentFiltering' argument of ?results

```

Volcano Plots

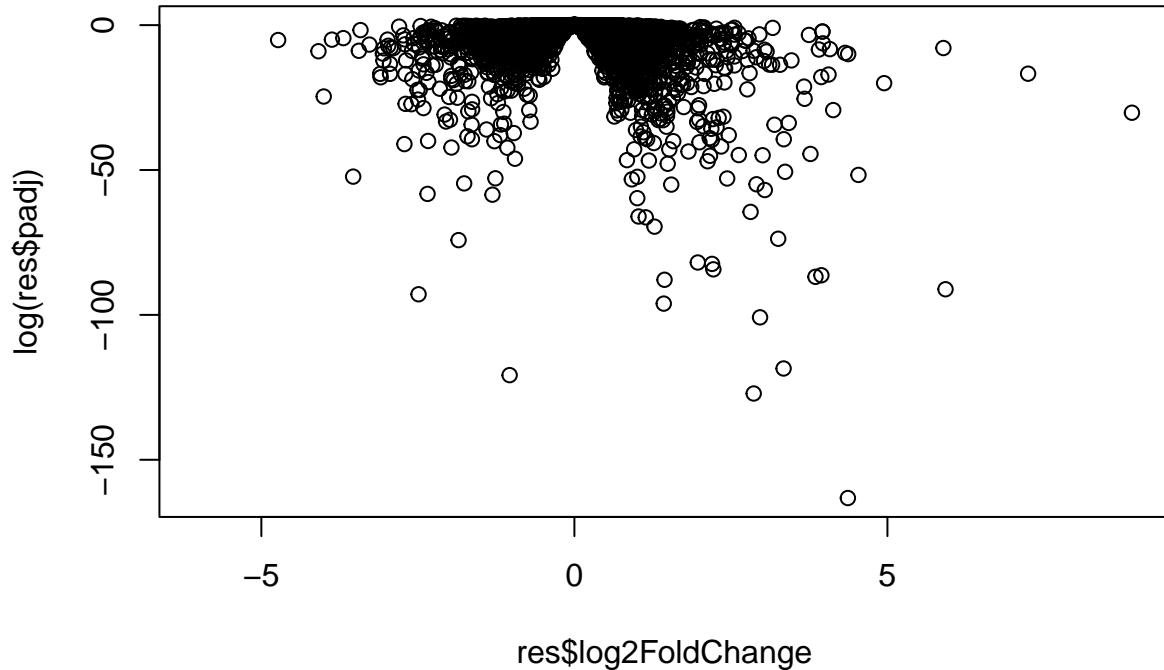
Let's make a commonly produced visualization from this data, namely a so-called Volcano plot. These summary figures are frequently used to highlight the proportion of genes that are both significantly regulated and display a high fold change.

```
plot(res$log2FoldChange, res$padj)
```

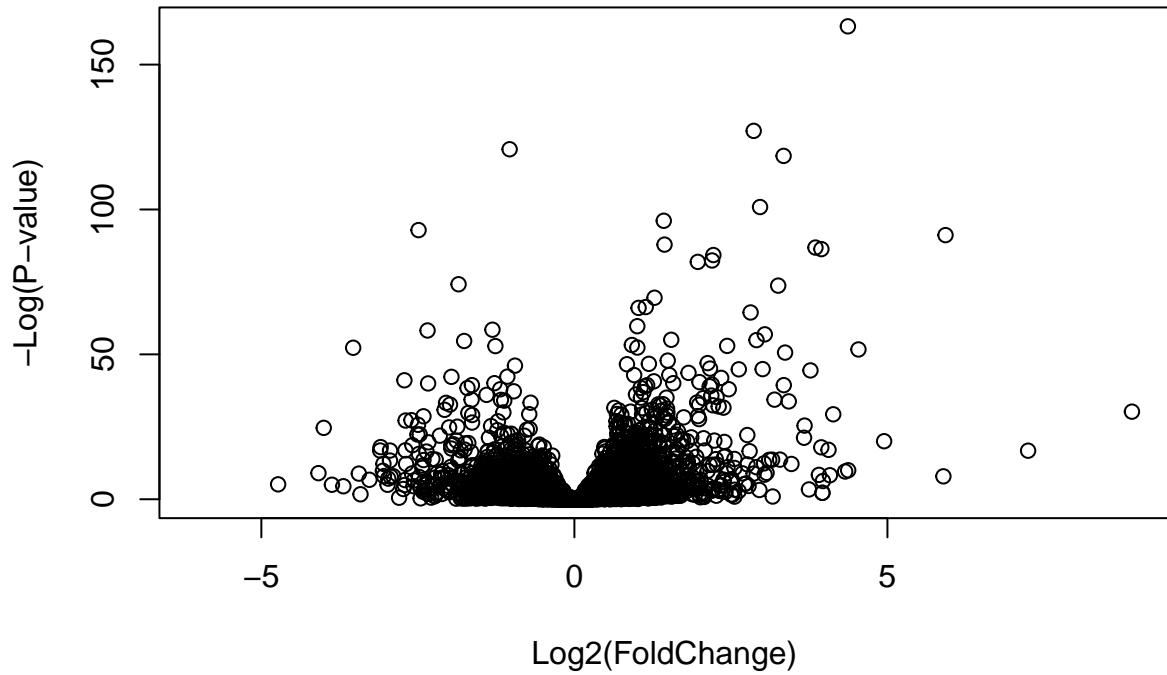


That is not a useful plot because all the small p-values are hidden at the bottom of the plot, and we can't really see them. `log` will help.

```
plot(res$log2FoldChange, log(res$padj))
```



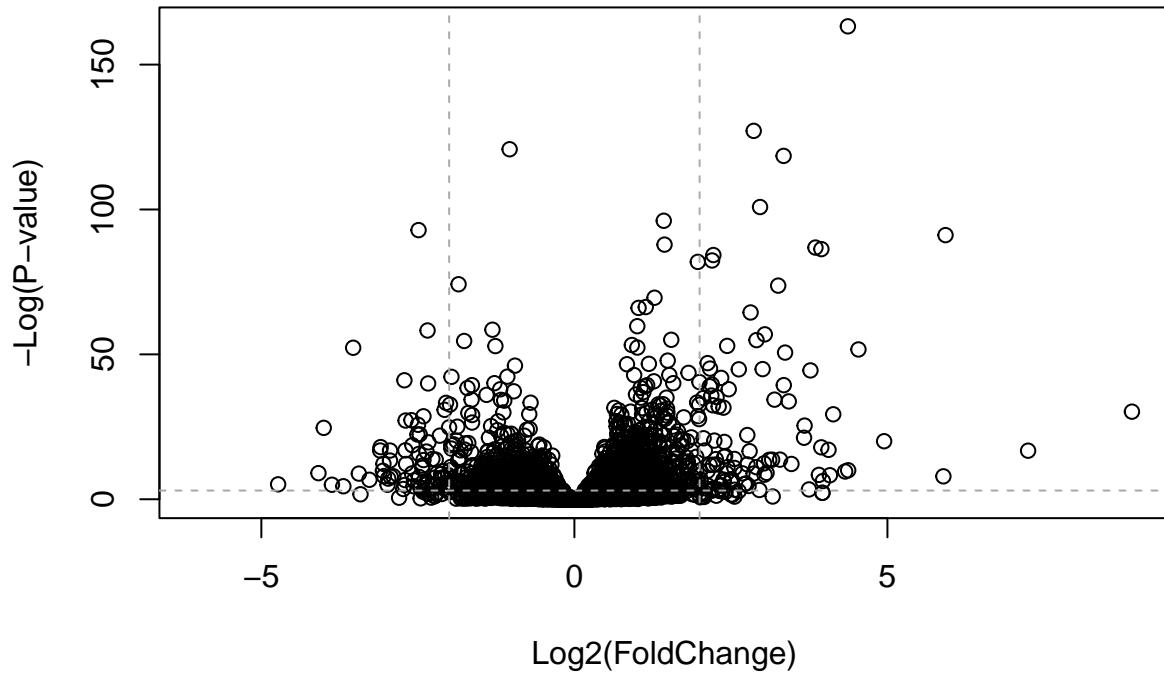
```
plot(res$log2FoldChange, -log(res$padj),
     xlab="Log2(FoldChange)",
     ylab="-Log(P-value)")
```



Finally let's add some color to this plot to draw attention to the genes (i.e. points) we care about— that is those with large fold-change and low p-values (i.e. high $-\log(p\text{values})$).

```
plot( res$log2FoldChange, -log(res$padj),
      ylab="-Log(P-value)", xlab="Log2(FoldChange)")

# Add some cut-off lines
abline(v=c(-2,2), col="darkgray", lty=2)
abline(h=-log(0.05), col="darkgray", lty=2)
```



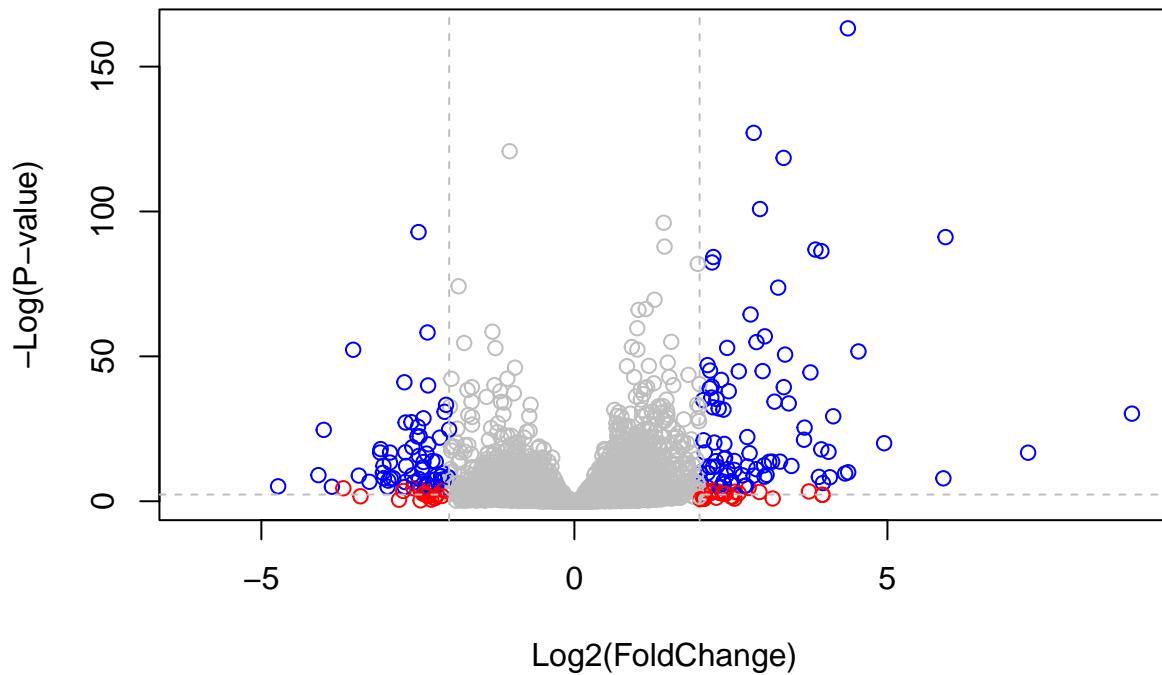
We will now add some color to the points:

```
# Setup our custom point color vector
mycols <- rep("gray", nrow(res))
mycols[abs(res$log2FoldChange) > 2] <- "red"

inds <- (res$padj < 0.01) & (abs(res$log2FoldChange) > 2)
mycols[inds] <- "blue"

# Volcano plot with custom colors
plot(res$log2FoldChange, -log(res$padj),
 col=mycols, ylab="-Log(P-value)", xlab="Log2(FoldChange)")

# Cut-off lines
abline(v=c(-2,2), col="gray", lty=2)
abline(h=-log(0.1), col="gray", lty=2)
```



Adding Annotation Data

For this, we need two Bioconductor packages.

```
library(AnnotationDbi)
library(org.Hs.eg.db)
```

```
##
```

Let's have a look at what is in the 'org.Hs.eg.db'.

```
columns(org.Hs.eg.db)
```

```
## [1] "ACNUM"      "ALIAS"       "ENSEMBL"     "ENSEMLPROT"   "ENSEMLTRANS"
## [6] "ENTREZID"    "ENZYME"      "EVIDENCE"    "EVIDENCEALL"  "GENENAME"
## [11] "GENETYPE"    "GO"          "GOALL"       "IPI"          "MAP"
## [16] "OMIM"        "ONTOLOGY"    "ONTOLOGYALL" "PATH"         "PFAM"
## [21] "PMID"        "PROSITE"     "REFSEQ"      "SYMBOL"       "UCSCKG"
## [26] "UNIPROT"
```

We will use the 'mapIDs' function to translate between identifiers from different databases.

```

res$symbol <- mapIds(org.Hs.eg.db,
                      keys=row.names(res), # Our genenames
                      keytype="ENSEMBL",   # Their format
                      column="SYMBOL",     # New format we want
                      multiVals="first")

## 'select()' returned 1:many mapping between keys and columns

head(res)

## log2 fold change (MLE): dex treated vs control
## Wald test p-value: dex treated vs control
## DataFrame with 6 rows and 7 columns
##           baseMean log2FoldChange      lfcSE      stat    pvalue
##           <numeric>      <numeric> <numeric> <numeric>
## ENSG000000000003 747.194195     -0.3507030  0.168246 -2.084470 0.0371175
## ENSG000000000005  0.000000        NA         NA         NA         NA
## ENSG000000000419 520.134160     0.2061078  0.101059  2.039475 0.0414026
## ENSG000000000457 322.664844     0.0245269  0.145145  0.168982 0.8658106
## ENSG000000000460 87.682625     -0.1471420  0.257007 -0.572521 0.5669691
## ENSG000000000938 0.319167     -1.7322890  3.493601 -0.495846 0.6200029
##           padj      symbol
##           <numeric> <character>
## ENSG000000000003 0.163035      TSPAN6
## ENSG000000000005  NA          TMMD
## ENSG000000000419 0.176032      DPM1
## ENSG000000000457 0.961694      SCYL3
## ENSG000000000460 0.815849      C1orf112
## ENSG000000000938  NA          FGR

```

Q11. Run the `mapIds()` function two more times to add the Entrez ID and UniProt accession and GENENAME as new columns called `res$entrez`, `res$uniprot`, and `res$genename`.

Answer:

We need ENTREZ ids for pathway analysis with KEGG.

```

res$entrez <- mapIds(org.Hs.eg.db,
                      keys=row.names(res), # Our genenames
                      keytype="ENSEMBL",   # Their format
                      column="ENTREZID",   # New format we want
                      multiVals="first")

```

```
## 'select()' returned 1:many mapping between keys and columns
```

```

res$uniprot <- mapIds(org.Hs.eg.db,
                      keys=row.names(res), # Our genenames
                      keytype="ENSEMBL",   # Their format
                      column="UNIPROT",     # New format we want
                      multiVals="first")

```

```
## 'select()' returned 1:many mapping between keys and columns
```

```
res$genename <- mapIds(org.Hs.eg.db,
                      keys=row.names(res), # Our genenames
                      keytype="ENSEMBL",   # Their format
                      column="GENENAME",    # New format we want
                      multiVals="first")
```

```
## 'select()' returned 1:many mapping between keys and columns
```

Let's make another volcano plot with some gene labels. For this, we can use the **EnhancedVolcano** package.

```
library(EnhancedVolcano)
```

```
## Loading required package: ggrepel
```

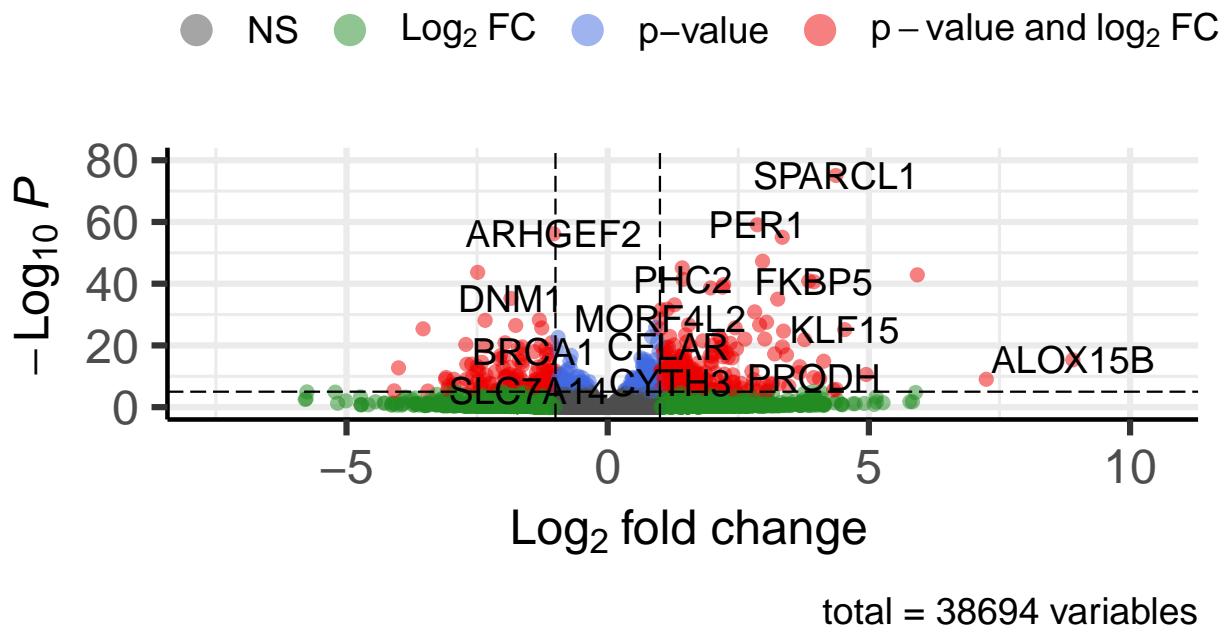
```
## Registered S3 methods overwritten by 'ggalt':
##   method           from
##   grid.draw.absoluteGrob  ggplot2
##   grobHeight.absoluteGrob ggplot2
##   grobWidth.absoluteGrob ggplot2
##   grobX.absoluteGrob    ggplot2
##   grobY.absoluteGrob    ggplot2
```

```
x <- as.data.frame(res)
```

```
EnhancedVolcano(x,
                 lab = x$symbol,
                 x = 'log2FoldChange',
                 y = 'pvalue')
```

Volcano plot

EnhancedVolcano



Pathway Analysis/Geneset Annotation

```
library(pathview)

## #####
## Pathview is an open source software package distributed under GNU General
## Public License version 3 (GPLv3). Details of GPLv3 is available at
## http://www.gnu.org/licenses/gpl-3.0.html. Particullary, users are required to
## formally cite the original Pathview paper (not just mention it) in publications
## or products. For details, do citation("pathview") within R.
##
## The pathview downloads and uses KEGG data. Non-academic uses may require a KEGG
## license agreement (details at http://www.kegg.jp/kegg/legal.html).
## #####
```

```
library(gage)
```

```
##
```

```
library(gageData)
```

```

data(kegg.sets.hs)

# Examine the first 2 pathways in this kegg set for humans
head(kegg.sets.hs, 2)

## $`hsa00232 Caffeine metabolism`
## [1] "10"    "1544"  "1548"  "1549"  "1553"  "7498"  "9"
##
## $`hsa00983 Drug metabolism - other enzymes`
## [1] "10"    "1066"  "10720" "10941" "151531" "1548"  "1549"  "1551"
## [9] "1553"  "1576"  "1577"  "1806"  "1807"  "1890"  "221223" "2990"
## [17] "3251"  "3614"  "3615"  "3704"  "51733"  "54490" "54575"  "54576"
## [25] "54577" "54578" "54579" "54600" "54657"  "54658" "54659"  "54963"
## [33] "574537" "64816" "7083"  "7084"  "7172"  "7363"  "7364"  "7365"
## [41] "7366"  "7367"  "7371"  "7372"  "7378"  "7498"  "79799" "83549"
## [49] "8824"  "8833"  "9"     "978"

```

The main `gage()` function requires a named vector of fold changes, where the names of the values are the Entrez gene IDs.

```

foldchanges <- res$log2FoldChange
names(foldchanges) <- res$entrez
head(foldchanges)

##          7105      64102      8813      57147      55732      2268
## -0.35070302        NA  0.20610777  0.02452695 -0.14714205 -1.73228897

# Get the results
keggres = gage(foldchanges, gsets=kegg.sets.hs)

attributes(keggres)

```

```

## $names
## [1] "greater" "less"     "stats"

```

This separates out results by “greater” and “less” (i.e. those that are upregulated and those that are down-regulated).

```

# Look at the first three down (less) pathways
head(keggres$less, 3)

##                               p.geomean stat.mean      p.val
## hsa05332 Graft-versus-host disease 0.0004250461 -3.473346 0.0004250461
## hsa04940 Type I diabetes mellitus 0.0017820293 -3.002352 0.0017820293
## hsa05310 Asthma                  0.0020045888 -3.009050 0.0020045888
##                               q.val set.size      exp1
## hsa05332 Graft-versus-host disease 0.09053483      40 0.0004250461
## hsa04940 Type I diabetes mellitus 0.14232581      42 0.0017820293
## hsa05310 Asthma                  0.14232581      29 0.0020045888

```

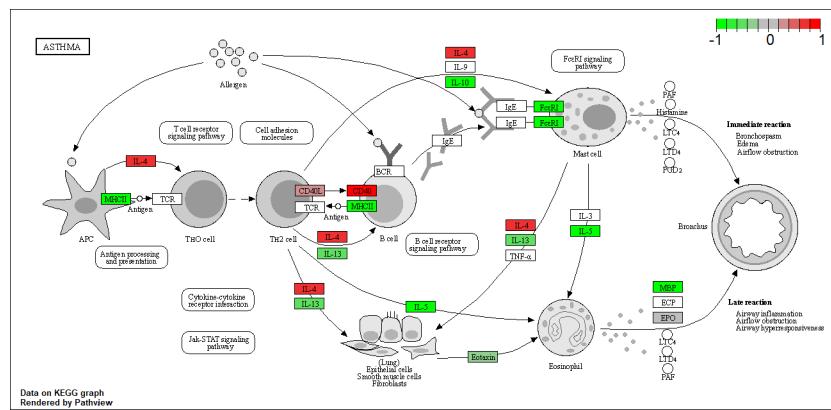
Now, let's try out the 'pathview()' function from the **pathview** package to make a pathway plot with our RNA-Seq expression results shown in color.

```
pathview(gene.data=foldchanges, pathway.id="hsa05310")
```

'select()' returned 1:1 mapping between keys and columns

Info: Working in directory C:/Users/jasmi/OneDrive/Documents/UCSD Fall 2021/BIMM 143/BIMM143_github/

Info: Writing image file hsa05310.pathview.png



Q12. Can you do the same procedure as above to plot the pathview figures for the top 2 downregulated pathways?

Answer:

```
pathview(gene.data=foldchanges, pathway.id="hsa05332")
```

'select()' returned 1:1 mapping between keys and columns

Info: Working in directory C:/Users/jasmi/OneDrive/Documents/UCSD Fall 2021/BIMM 143/BIMM143_github/

Info: Writing image file hsa05332.pathview.png

```
pathview(gene.data=foldchanges, pathway.id="hsa04940")
```

`select()` returned 1:1 mapping between rows and columns

Tafel: Verhältnis von direkten zu Gruppen-/Intra-/Cross-Devices/Documenten (HCSB_E11_2001/BIMM_143/BIMM143_mitbl/)

To save this image as a file, type: ggsave("myplot.png")

