

class 13: RNASeq Analysis

Vidisha Marwaha (PID: A16677246)

The data for this hands-on session comes from a published RNA-seq experiment where airway smooth muscle cells were treated with dexamethasone, a synthetic glucocorticoid steroid with anti-inflammatory effects (Himes et al. 2014).

Import Data

We need two things for this analysis: counts and metadata these are called “countData” and “colData” in the DESeq2 world.

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

```
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

Examine Data

Q1. How many genes are in this dataset?

```
nrow(counts)
```

```
[1] 38694
```

Q2. How many 'control' cell lines do we have?

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

```
[1] 4
```

```
table(metadata$dex)
```

control	treated
4	4

Check on the match of metadata with the counts data

```
colnames(counts)
```

```
[1] "SRR1039508" "SRR1039509" "SRR1039512" "SRR1039513" "SRR1039516"  
[6] "SRR1039517" "SRR1039520" "SRR1039521"
```

```
metadata$id
```

```
[1] "SRR1039508" "SRR1039509" "SRR1039512" "SRR1039513" "SRR1039516"  
[6] "SRR1039517" "SRR1039520" "SRR1039521"
```

```
colnames(counts) == metadata$id
```

```
[1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
```

If you want to know all the elements of a vector are TRUE we can use the `all()` function.

```
all(c(T,T,T, F))
```

```
[1] FALSE
```

```
all(colnames(counts) == metadata$id)
```

```
[1] TRUE
```

Analysis

I want to start by comparing “control” and “treated” columns. To this I will first find the average for each gene (row) in all “control” columns. Then I will find the average in the “treated” columns. Then I will compare them.

Lets extract the “control” columns first

```
control.inds <- metadata$dex == "control"
```

```
control.counts <- counts[,control.inds]
```

Now find the mean value per gene using the `apply()` function.

```
control.mean <- apply(control.counts, 1, mean)
```

Now do the same for the “treated” columns ie find the `treated.mean` values

```
treated.mean <- apply(counts[,metadata$dex == "treated"], 1, mean)
```

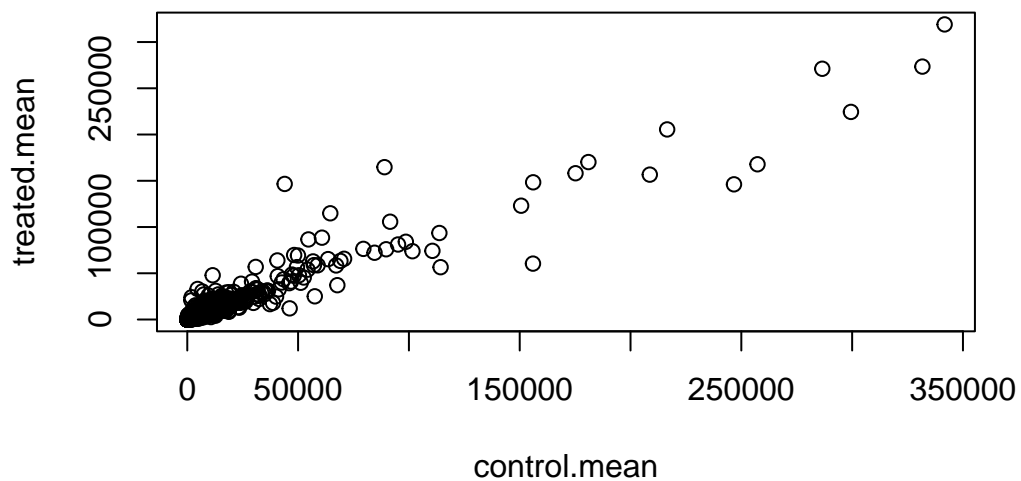
Put these two vectors together for ease of book-keeping

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

	control.mean	treated.mean
ENSG000000000003	900.75	658.00
ENSG000000000005	0.00	0.00
ENSG000000000419	520.50	546.00
ENSG000000000457	339.75	316.50
ENSG000000000460	97.25	78.75
ENSG000000000938	0.75	0.00

Lets have a wee look with a quick plot

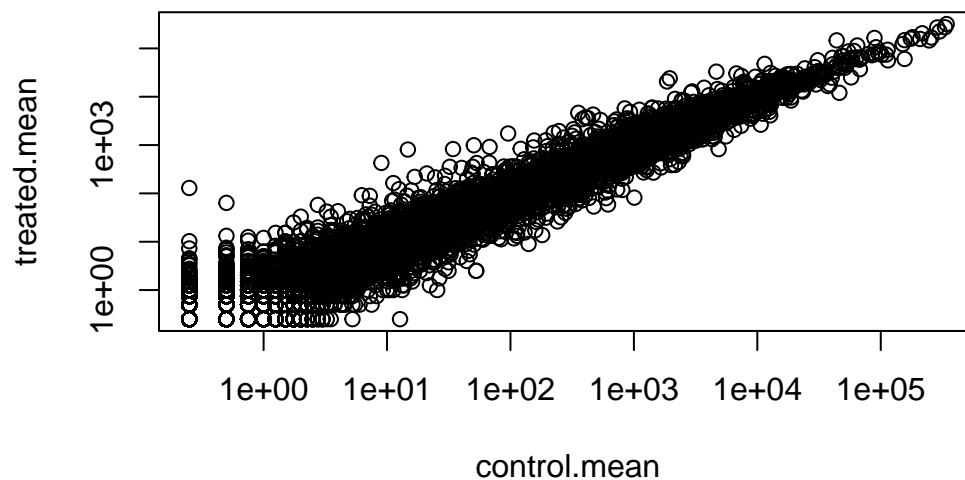
```
plot(meancounts)
```



```
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



```
log(10, base=2)
```

```
[1] 3.321928
```

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

```
[1] 0
```

```
log2(20/10)
```

```
[1] 1
```

```
log2(10/20)
```

```
[1] -1
```

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

```
[1] 2
```

We most often work in log2 units because they have a more simple interpretation.

Here we calculate the log2 fold change of treated/control values add it to our wee data frame of results.

```
meancounts$log2fc <- log2(meancounts$treated.mean/meancounts$control.mean)
head(meancounts)
```

	control.mean	treated.mean	log2fc
ENSG000000000003	900.75	658.00	-0.45303916
ENSG000000000005	0.00	0.00	NaN
ENSG000000000419	520.50	546.00	0.06900279
ENSG000000000457	339.75	316.50	-0.10226805
ENSG000000000460	97.25	78.75	-0.30441833
ENSG000000000938	0.75	0.00	-Inf

There are some funky answers in there like NaN (Not a Number) and -Inf (minus infinity) that all come because I have zero count genes in my dataset.

It is common practice to filter these zero count genes out before we go too deep.

```
to.keep.inds <- (rowSums(meancounts[,1:2] == 0) == 0)
mycounts <- meancounts[to.keep.inds,]
head(mycounts)
```

	control.mean	treated.mean	log2fc
ENSG000000000003	900.75	658.00	-0.45303916
ENSG000000000419	520.50	546.00	0.06900279
ENSG000000000457	339.75	316.50	-0.10226805
ENSG000000000460	97.25	78.75	-0.30441833
ENSG000000000971	5219.00	6687.50	0.35769358
ENSG000000001036	2327.00	1785.75	-0.38194109

Q. How many genes do we have left after zero count genes filtering?

```
nrow(mycounts)
```

```
[1] 21817
```

A common threshold for calling a gene “up” or “down” is a log2 fold change of +2 or -2.

Q. How many “up” regulated genes do we have?

```
sum(mycounts$log2fc >= +2)
```

```
[1] 314
```

Q. How many “down” regulated genes do we have?

```
sum(mycounts$log2fc <= -2)
```

```
[1] 485
```

DESeq2 Analysis

We need to do this analysis properly with our inner stats person kept happy.

```
library(DESeq2)
```

To use DESeq we need to get our input data in very particular format.

```
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

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

Get the results

```
res <- results(dds)
head(res)
```

log2 fold change (MLE): dex treated vs control

Wald test p-value: dex treated vs control

DataFrame with 6 rows and 6 columns

	baseMean	log2FoldChange	lfcSE	stat	pvalue
	<numeric>	<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				
	<numeric>				
ENSG000000000003	0.163035				
ENSG000000000005	NA				
ENSG000000000419	0.176032				
ENSG000000000457	0.961694				
ENSG000000000460	0.815849				
ENSG000000000938	NA				

I want to make a figure showing an overview of all my results to date. A plot of **log2 fold change** vs the **p-value** (adjusted p-value)

```
plot(res$log2FoldChange, -log(res$padj))
abline(v=-2, col="gray")
abline(v=+2, col="gray")
abline(h=-log(0.05), col="gray")
```

