

Class 12

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2. Import countData and colData

We will start by loading the airway data, we will import count and metadata

```
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

```

```
nrow(counts)
```

```
[1] 38694
```

```
control_cell_lines = table(metadata$dex)['control']
```

- **Q1.** How many genes are in this dataset? In this code there are 38694 genes
- **Q2.** How many 'control' cell lines do we have? We have 4 control cell lines in this data.

3. Toy differential gene expression

Code that was provided

```

control <- metadata[metadata[, "dex"]=="control",]
control.counts <- counts[, control$id]
control.mean <- rowSums( control.counts )/4
head(control.mean)

```

```

ENSG000000000003 ENSG000000000005 ENSG000000000419 ENSG000000000457 ENSG000000000460
          900.75           0.00           520.50           339.75           97.25
ENSG000000000938
          0.75

```

Breaking down the code to understand it

```
metadata[, "dex"]=="control"
```

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

```

control = metadata[metadata[, "dex"]=="control",]
control$id

```

```
[1] "SRR1039508" "SRR1039512" "SRR1039516" "SRR1039520"
```

```
control.counts = counts[,control$id]
control.mean <- rowMeans( control.counts )
```

- **Q3.** How would you make the above code in either approach more robust?

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

```
ENSG00000000003 ENSG00000000005 ENSG00000000419 ENSG00000000457 ENSG00000000460
          900.75           0.00           520.50           339.75           97.25
ENSG000000000938
          0.75
```

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

```
treated = metadata[metadata[, "dex"]=="treated",]
treated.counts = counts[ ,treated$id]
treated.mean = rowMeans( treated.counts)
head(treated.mean)
```

```
ENSG00000000003 ENSG00000000005 ENSG00000000419 ENSG00000000457 ENSG00000000460
          658.00           0.00           546.00           316.50           78.75
ENSG000000000938
          0.00
```

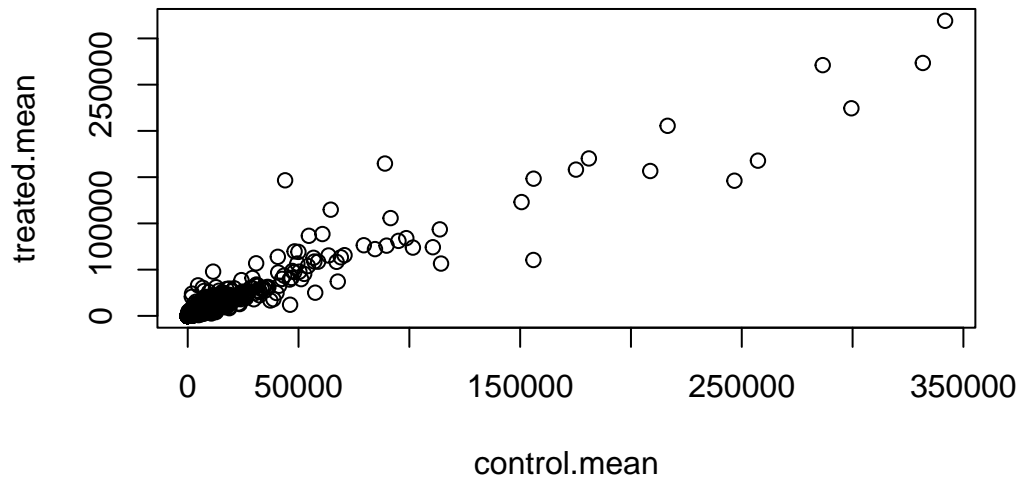
Combining both means

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

```
control.mean treated.mean
      23005324      22196524
```

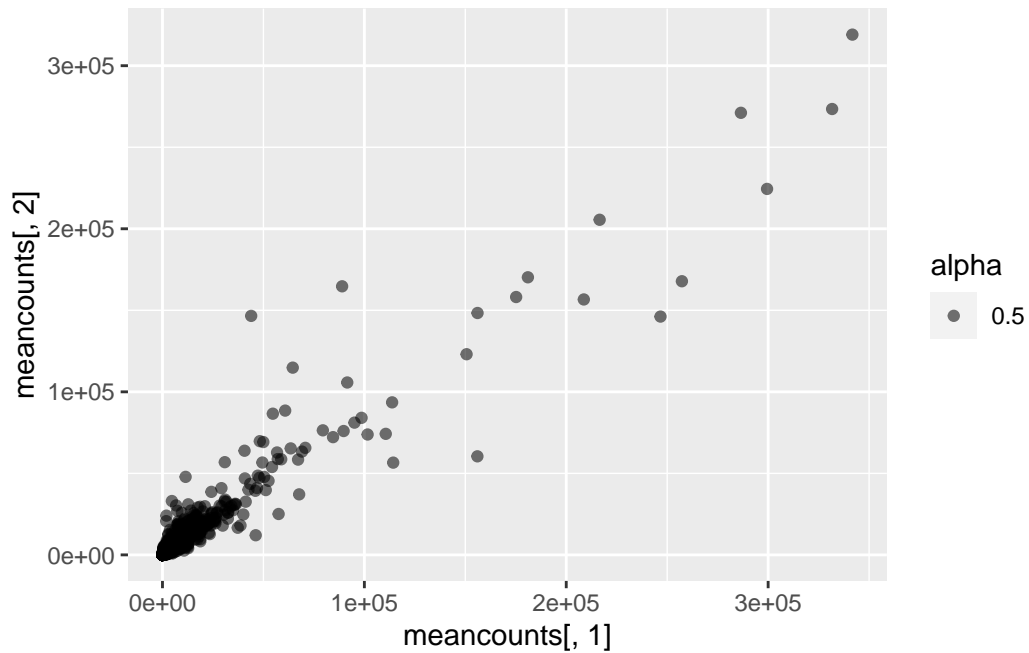
- **Q5 (a).** Create a scatter plot showing the mean of the treated samples against the mean of the control samples. Your plot should look something like the following.

```
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? You would use **geom_point()**

```
library(ggplot2)
ggplot(meancounts) + geom_point(aes(meancounts[,1], meancounts[,2], alpha = 0.5))
```

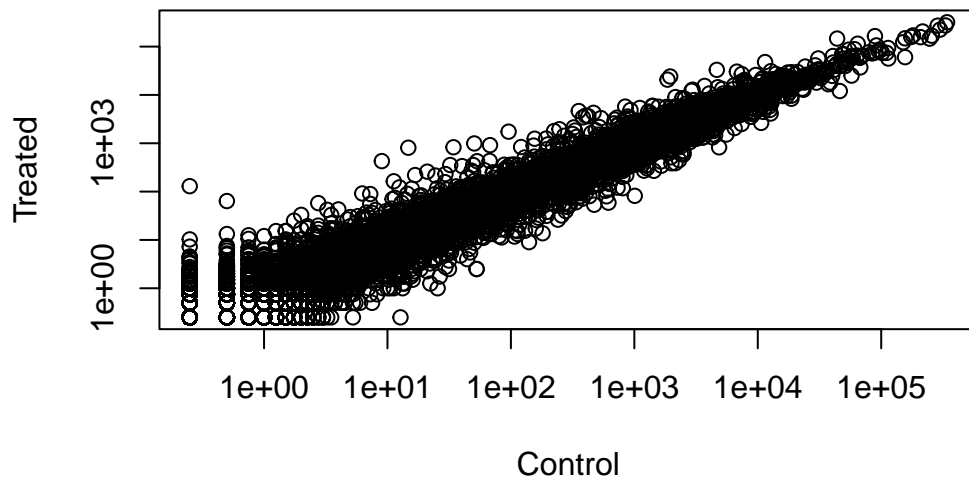


Q6. Try plotting both axes on a log scale. What is the argument to **plot()** that allows you to do this?

```
plot(meancounts, log = "xy", xlab = "Control", ylab = "Treated")
```

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 will begin to take log2 of the data in order to find larger mathematical differences between control and treated. Log2 of the fold change between both.

```

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

We will try to remove and filter out zeros so that we do not get the same errors

```

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

to.rm <- unique(zero.vals[, 1])
mycounts <- meancounts[-to.rm,]
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

- **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?

Overexpressed and underexpressed genes

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

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

```
table(up.ind)
```

```
up.ind
FALSE  TRUE
21567   250
```

There are 250 up regulated genes

Q9. Using the `down.ind` vector above can you determine how many down regulated genes we have at the greater than 2 fc level?

```
table(down.ind)
```

```
down.ind
FALSE  TRUE
21450   367
```

There are 367 down regulated genes

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

No there are many other factors that need to be included into having statistical significance. We need to bring the statistics that represent why the difference matters.

4. DESeq2 analysis

first step, loading the library

```
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, aperm, 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

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,
colDiffs, colIQRDiffs, colIQRs, colLogSumExps, colMadDiffs,
colMads, colMaxs, colMeans2, colMedians, colMins, colOrderStats,
colProds, colQuantiles, colRanges, colRanks, colSdDiffs, colSds,
colSums2, colTabulates, colVarDiffs, colVars, colWeightedMads,
colWeightedMeans, colWeightedMedians, colWeightedSds,
colWeightedVars, rowAlls, rowAnyNAs, rowAnys, rowAvgsPerColSet,
rowCollapse, rowCounts, rowCummaxs, rowCummins, rowCumprods,
rowCumsums, rowDiffs, rowIQRDiffs, rowIQRs, rowLogSumExps,
rowMadDiffs, rowMads, rowMaxs, rowMeans2, rowMedians, rowMins,
rowOrderStats, rowProds, rowQuantiles, rowRanges, rowRanks,
rowSdDiffs, rowSds, rowSums2, rowTabulates, rowVarDiffs, 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
```

```
citation('DESeq2')
```

To cite package 'DESeq2' in publications use:

Love, M.I., Huber, W., Anders, S. Moderated estimation of fold change and dispersion for RNA-seq data with DESeq2 Genome Biology 15(12):550 (2014)

A BibTeX entry for LaTeX users is

```
@Article{,
  title = {Moderated estimation of fold change and dispersion for RNA-seq data with DESeq2},
  author = {Michael I. Love and Wolfgang Huber and Simon Anders},
  year = {2014},
  journal = {Genome Biology},
  doi = {10.1186/s13059-014-0550-8},
  volume = {15},
  issue = {12},
  pages = {550},
}
```

Let's generate the specific object that DESeq2 needs:

```
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

DESeq(dds)

estimating size factors

estimating dispersions

gene-wise dispersion estimates

mean-dispersion relationship

final dispersion estimates

fitting model and testing

class: DESeqDataSet

dim: 38694 8

metadata(1): version

assays(4): counts mu H cooks

rownames(38694): ENSG000000000003 ENSG000000000005 ... ENSG00000283120
ENSG00000283123

rowData names(22): baseMean baseVar ... deviance maxCooks

colnames(8): SRR1039508 SRR1039509 ... SRR1039520 SRR1039521

colData names(5): id dex celltype geo_id sizeFactor