

Class12

AUTHOR

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2.Import count and col data

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

	SRR1039508	SRR1039509	SRR1039512	SRR1039513	SRR1039516
ENSG00000000003	723	486	904	445	1170
ENSG00000000005	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
ENSG00000000003	1097	806	604
ENSG00000000005	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
```

There are 38,694 genes in the dataset!

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

```
dim(metadata)
```

```
[1] 8 4
```

There are 4 control cell lines.

3. Toy differential gene expression

Mean counts per gene across these samples:

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

```
ENSG00000000003 ENSG00000000005 ENSG000000000419 ENSG000000000457 ENSG000000000460
          900.75           0.00           520.50           339.75           97.25
ENSG000000000938
          0.75
```

Another way of calculating it:

```
library(dplyr)
```

Warning: package 'dplyr' was built under R version 4.1.3

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

```
filter, lag
```

The following objects are masked from 'package:base':

```
intersect, setdiff, setequal, union
```

```
control <- metadata %>% filter(dex=="control")
control.counts <- counts %>% select(control$id)
control.mean <- rowSums(control.counts)/4
head(control.mean)
```

```
ENSG00000000003 ENSG00000000005 ENSG000000000419 ENSG000000000457 ENSG000000000460
          900.75           0.00           520.50           339.75           97.25
ENSG000000000938
          0.75
```

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

I could turn it into a function.

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)

```
library(dplyr)
treated <- metadata %>% filter(dex=="treated")
treated.counts <- counts %>% select(treated$id)
treated.mean <- rowSums(treated.counts)/4
head(treated.mean)
```

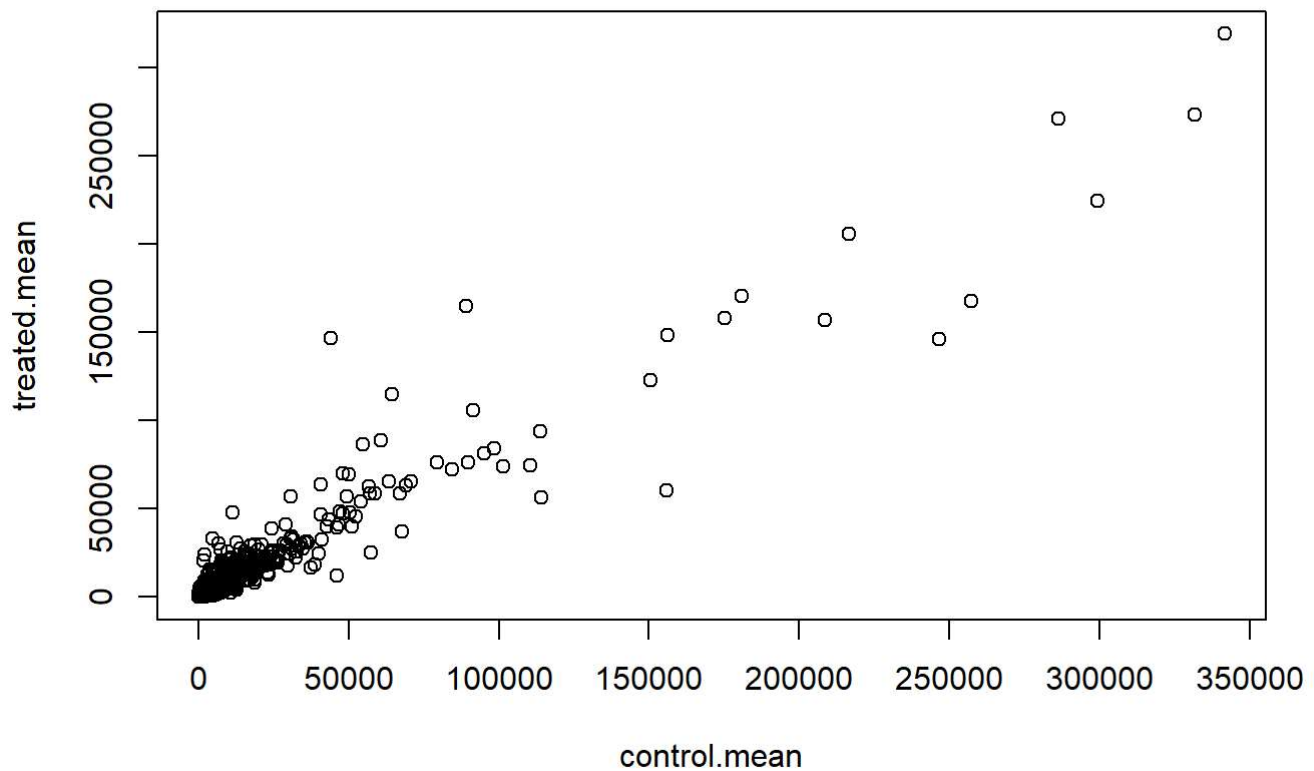
```
ENSG00000000003 ENSG00000000005 ENSG000000000419 ENSG000000000457 ENSG000000000460
           658.00           0.00           546.00           316.50           78.75
ENSG000000000938
           0.00
```

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.

```
plot(meancounts)
```

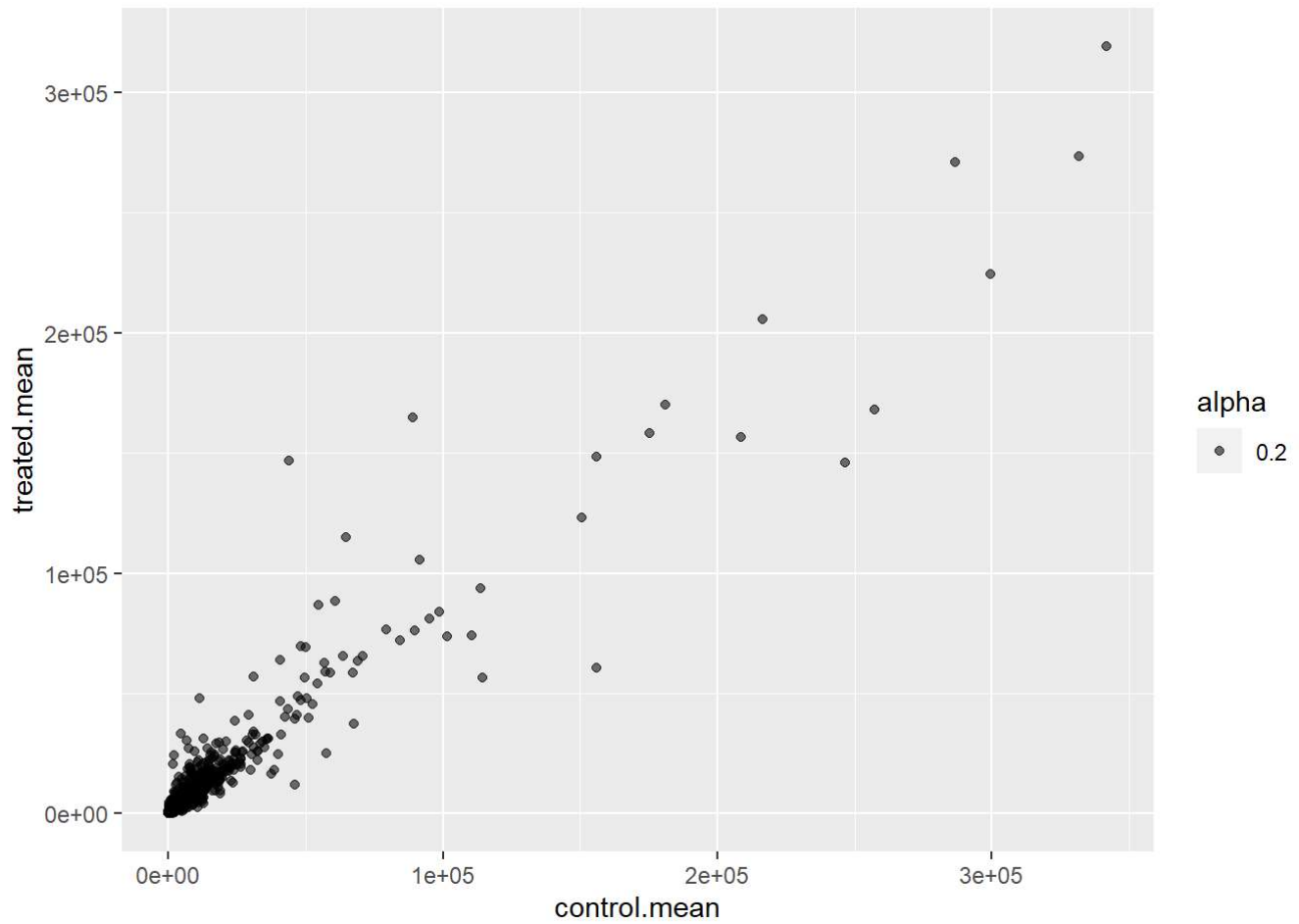


Q5 (b). You could also use the ggplot2 package to make this figure producing the plot below.

```
library(ggplot2)
```

Warning: package 'ggplot2' was built under R version 4.1.3

```
ggplot(meancounts, aes(x = control.mean, y = treated.mean, alpha = 0.2)) +  
  geom_point()
```

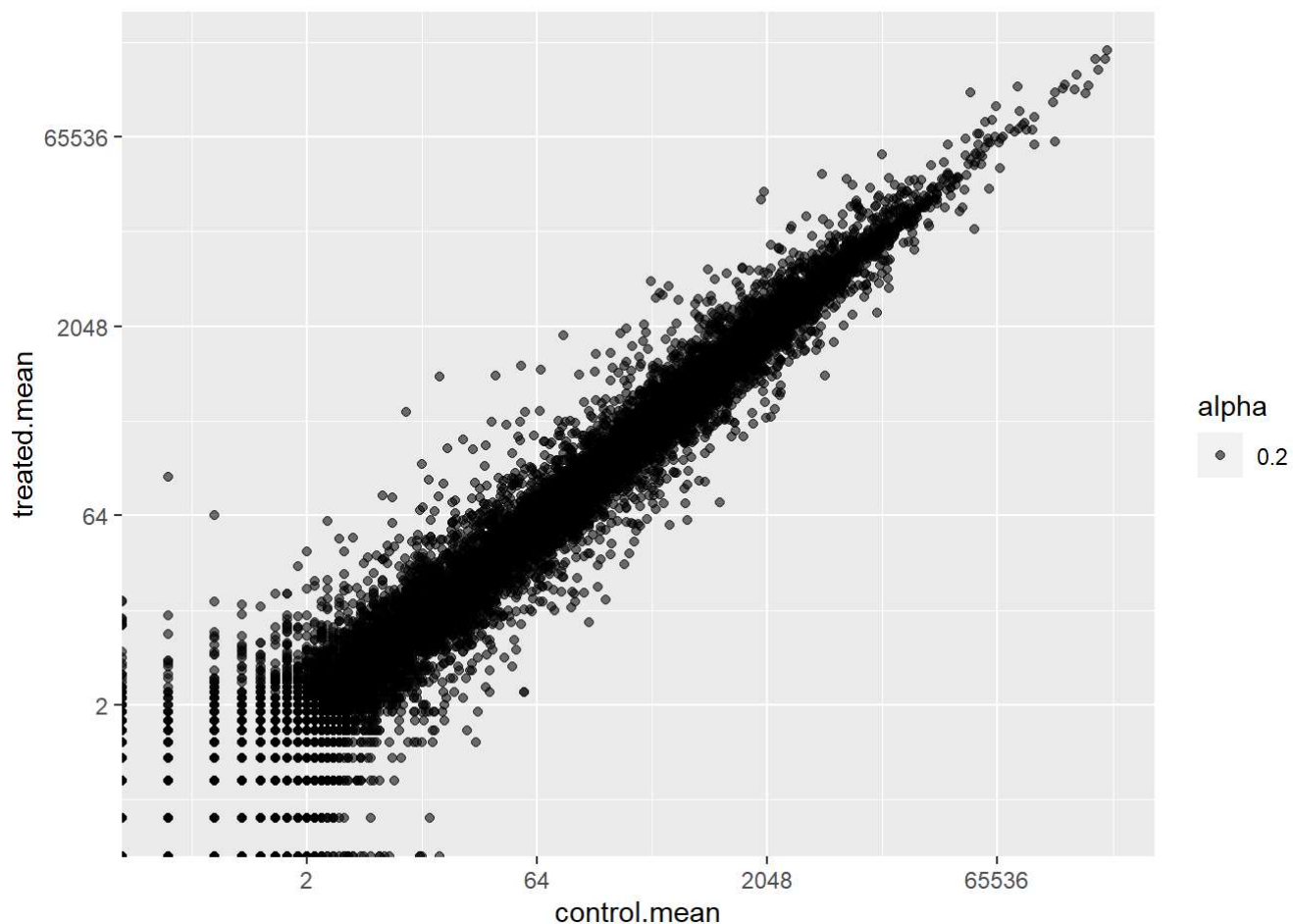


Q6. Try plotting both axes on a log scale.

```
library(ggplot2)
ggplot(meancounts, aes(x = control.mean, y = treated.mean, alpha = 0.2)) +
  geom_point()+
  scale_x_continuous(trans="log2")+
  scale_y_continuous(trans="log2")
```

Warning: Transformation introduced infinite values in continuous x-axis

Warning: Transformation introduced infinite values in continuous y-axis



Lets look at genes with a large change between control and treated samples.

```
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
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 weird NaN results and -Inf results. Lets change our zero values to fix this.

```
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
ENSG00000000003	900.75	658.00	-0.45303916
ENSG000000000419	520.50	546.00	0.06900279

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

Better.

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?

The purpose of the argument is to eliminate the problem of having zeros come up as "weird"

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

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

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

[1] 250

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

[1] 367

The answers to 8 and 9 are 250 and 367 respectively.

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

I want to run a significance test before I trust the results.

4. DESeq2 analysis

DESeq2 will do all the stats for us.

```
library(DESeq2)
```

Loading required package: S4Vectors

Warning: package 'S4Vectors' was built under R version 4.1.3

Loading required package: stats4

Loading required package: BiocGenerics

Attaching package: 'BiocGenerics'

The following objects are masked from 'package:dplyr':

combine, intersect, setdiff, union

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:dplyr':

first, rename

The following objects are masked from 'package:base':

expand.grid, I, unname

Loading required package: IRanges

Attaching package: 'IRanges'

The following objects are masked from 'package:dplyr':

collapse, desc, slice

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

windows

Loading required package: GenomicRanges

Warning: package 'GenomicRanges' was built under R version 4.1.2

Loading required package: GenomeInfoDb

Warning: package 'GenomeInfoDb' was built under R version 4.1.2

Loading required package: SummarizedExperiment

Loading required package: MatrixGenerics

Loading required package: matrixStats

Warning: package 'matrixStats' was built under R version 4.1.3

Attaching package: 'matrixStats'

The following object is masked from 'package:dplyr':

count

Attaching package: 'MatrixGenerics'

The following objects are masked from 'package:matrixStats':

colAlls, colAnyNAs, colAnys, colAvgPerRowSet, 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, rowAvgPerColSet,
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")
```

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},
}
```

```
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
```

```
dds <- DESeq(dds)
```

estimating size factors

estimating dispersions

gene-wise dispersion estimates

mean-dispersion relationship

final dispersion estimates

fitting model and testing

```
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>
ENSG00000000003	747.1942	-0.3507030	0.168246	-2.084470	0.0371175
ENSG00000000005	0.0000	NA	NA	NA	NA
ENSG00000000049	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
...
ENSG00000283115	0.000000	NA	NA	NA	NA
ENSG00000283116	0.000000	NA	NA	NA	NA
ENSG00000283119	0.000000	NA	NA	NA	NA
ENSG00000283120	0.974916	-0.668258	1.69456	-0.394354	0.693319
ENSG00000283123	0.000000	NA	NA	NA	NA
	padj				
	<numeric>				
ENSG00000000003	0.163035				
ENSG00000000005	NA				
ENSG00000000049	0.176032				
ENSG000000000457	0.961694				
ENSG000000000460	0.815849				
...	...				
ENSG00000283115	NA				
ENSG00000283116	NA				
ENSG00000283119	NA				
ENSG00000283120	NA				
ENSG00000283123	NA				

```
summary(res)
```

```

out of 25258 with nonzero total read count
adjusted p-value < 0.1
LFC > 0 (up)      : 1563, 6.2%
LFC < 0 (down)    : 1188, 4.7%
outliers [1]      : 142, 0.56%
low counts [2]    : 9971, 39%
(mean count < 10)
[1] see 'cooksCutoff' argument of ?results
[2] see 'independentFiltering' argument of ?results

```

```
head(res)
```

log2 fold change (MLE): dex treated vs control

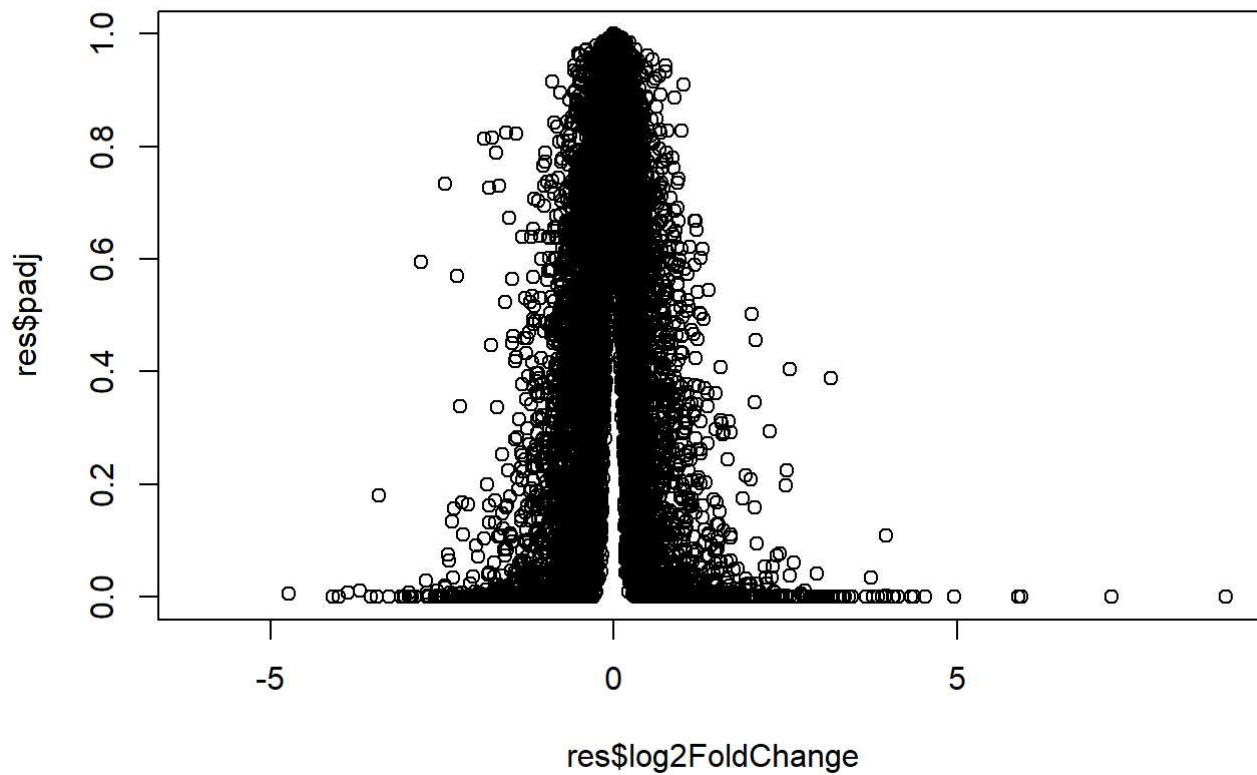
Wald test p-value: dex treated vs control

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
ENSG0000000000419	520.134160	0.2061078	0.101059	2.039475	0.0414026
ENSG0000000000457	322.664844	0.0245269	0.145145	0.168982	0.8658106
ENSG0000000000460	87.682625	-0.1471420	0.257007	-0.572521	0.5669691
ENSG0000000000938	0.319167	-1.7322890	3.493601	-0.495846	0.6200029
	padj				
	<numeric>				
ENSG000000000003	0.163035				
ENSG000000000005	NA				
ENSG0000000000419	0.176032				
ENSG0000000000457	0.961694				
ENSG0000000000460	0.815849				
ENSG0000000000938	NA				

6. Data Visualization

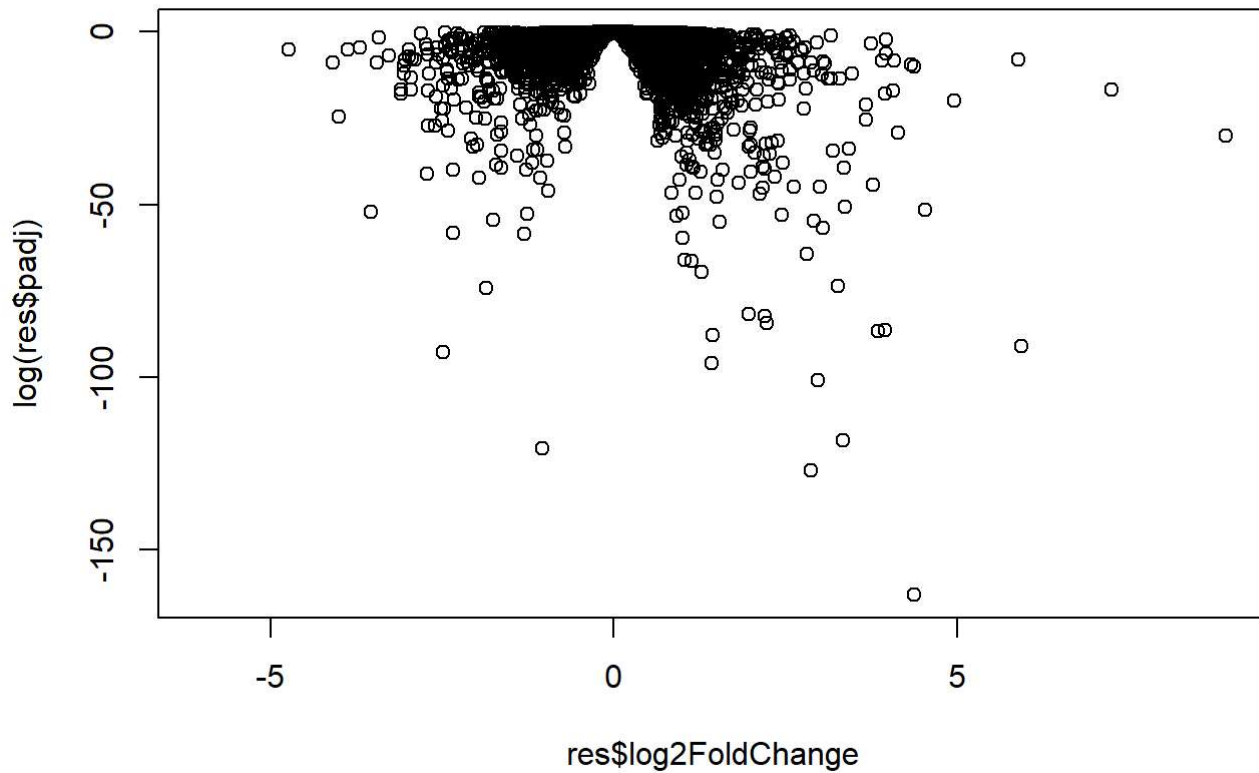
```
plot(res$log2FoldChange, res$padj)
```



Well that plot sucked. All the interesting p-values are down below 0.

Lets take the log of p-value

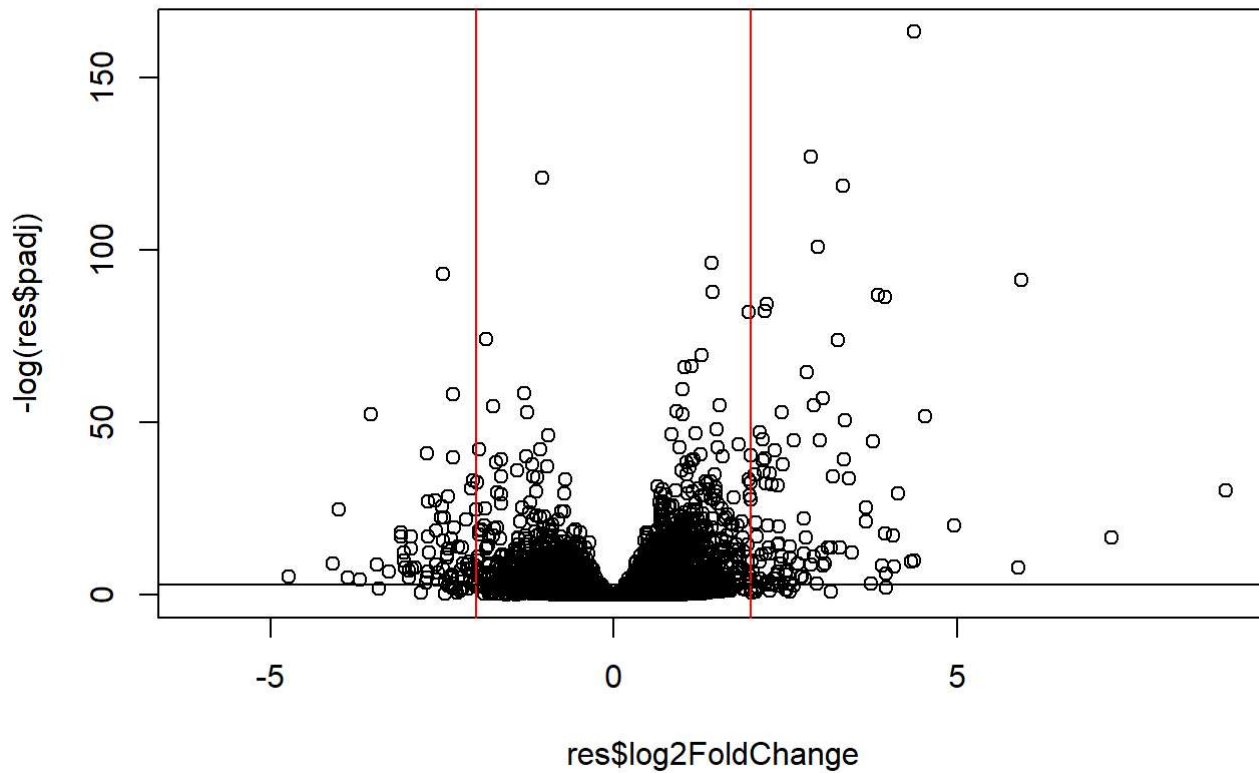
```
plot(res$log2FoldChange, log(res$padj))
```



much better but still weird

lets flip the y axis so its not upside down.

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



```
mycols <- rep("gray", nrow(res))
mycols[ abs(res$log2FoldChange) > 2 ] <- "red"
inds <- (res$padj < 0.01) & (abs(res$log2FoldChange) > 2 )
mycols[ inds ] <- "blue"
```

```
plot( res$log2FoldChange, -log(res$padj),
      col=mycols, ylab="-Log(P-value)", xlab="Log2(FoldChange)" )
abline(v=c(-2,2), col="gray", lty=2)
abline(h=-log(0.1), col="gray", lty=2)
```

