

Class 13

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```
library(BiocManager)
```

Warning: package 'BiocManager' was built under R version 4.2.3

Bioconductor version '3.15' is out-of-date; the current release version '3.18' is available with R version '4.3'; see <https://bioconductor.org/install>

```
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

Warning: package 'matrixStats' was built under R version 4.2.3

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, 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
```

```
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

ENSG00000000460	96	81	73	66	118
ENSG00000000938	0	0	1	0	2
	SRR1039517	SRR1039520	SRR1039521		
ENSG00000000003	1097	806	604		
ENSG00000000005	0	0	0		
ENSG00000000419	781	417	509		
ENSG00000000457	447	330	324		
ENSG00000000460	94	102	74		
ENSG00000000938	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?

38694 genes in the data set

```
nrow(counts)
```

```
[1] 38694
```

Q how many samples are there

8 differnt samples

```
ncol(counts)
```

```
[1] 8
```

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

4 control cell lines were used

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

```
[1] 4
```

make sure the the id's in the metadata match those in the counts

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

```
[1] TRUE
```

control mean

```
control.inds <- metadata$dex == 'control'
control.counts <- counts[,control.inds]
control.mean<- apply(control.counts,1,mean)
head(control.mean)
```

```
ENSG000000000003 ENSG000000000005 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? Is there a function that could help here?

Writing this process into a function would be more robust as opposed to copying where there is more room for error. if there were more treatmets it would save time and leave less space for mistakes.

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 mean

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

```
ENSG000000000003 ENSG000000000005 ENSG000000000419 ENSG000000000457 ENSG000000000460
          658.00           0.00           546.00           316.50           78.75
ENSG000000000938
          0.00
```

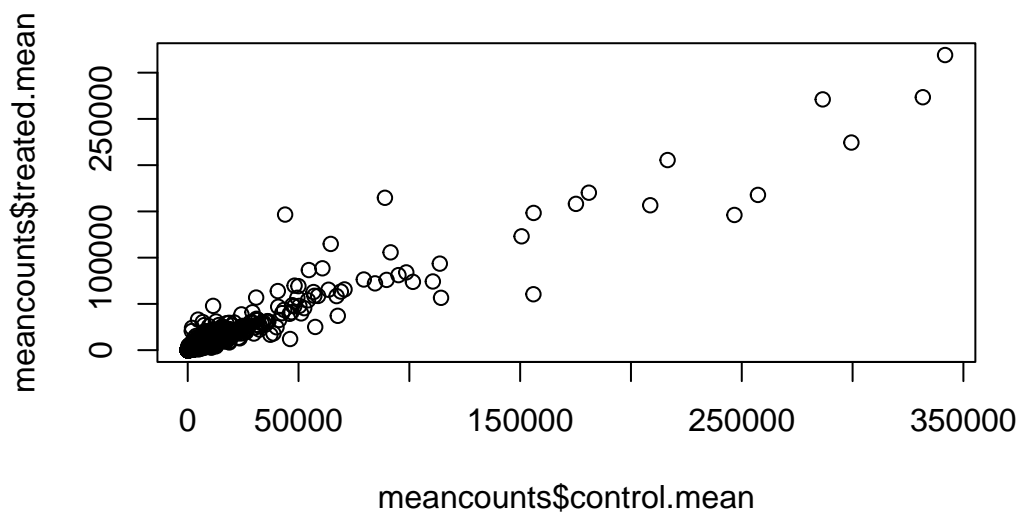
combining the treated and control means into one data frame

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

	control.mean	treated.mean
ENSG000000000003	900.75	658.00
ENSG000000000005	0.00	0.00
ENSG0000000000419	520.50	546.00
ENSG0000000000457	339.75	316.50
ENSG0000000000460	97.25	78.75
ENSG0000000000938	0.75	0.00

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$control.mean, meancounts$treated.mean)
```

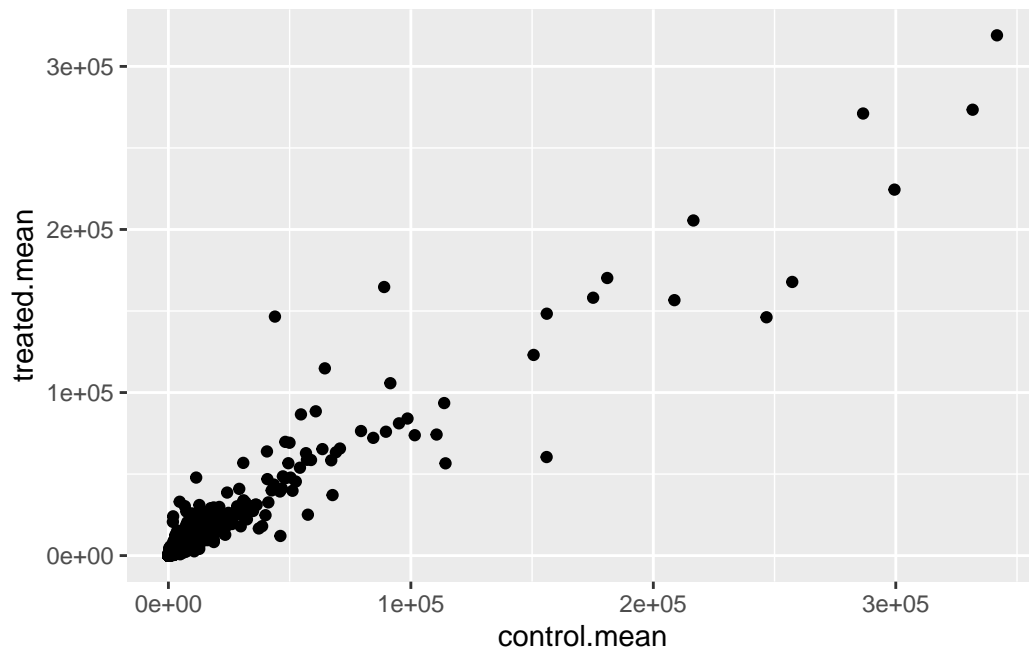


Q5 (b). You could also use the ggplot2 package to make this figure producing the plot below. What geom_?() function would you use for this plot?

```
library(ggplot2)
```

Warning: package 'ggplot2' was built under R version 4.2.3

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

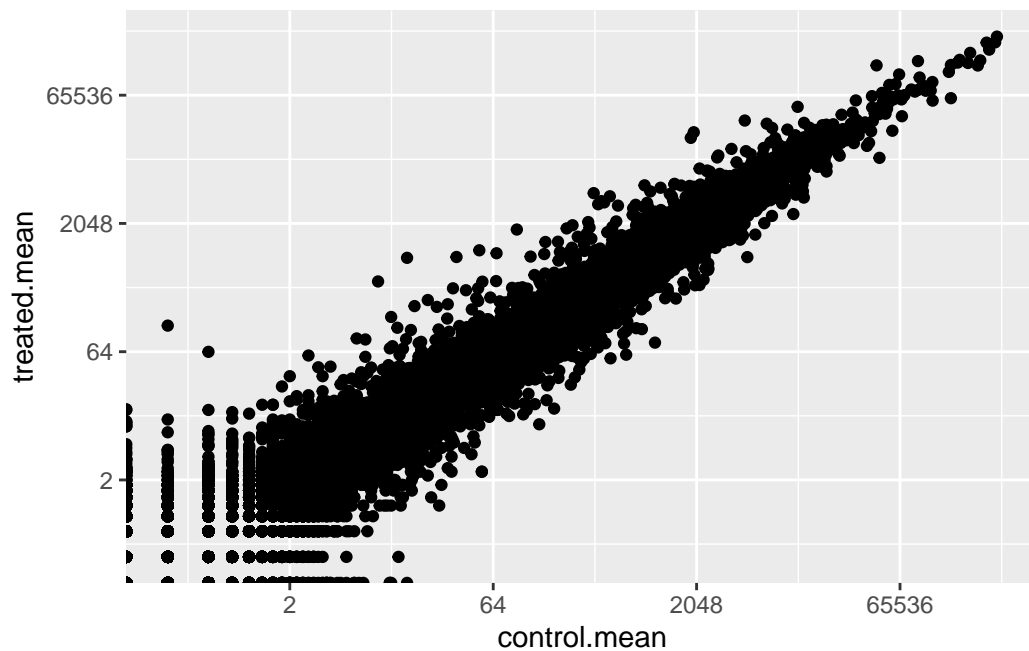


Q6. Try plotting both axes on a log scale. What is the argument to plot() that allows you to do this?

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



Determining fold change between control and treated

```

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
ENSG0000000000419	520.50	546.00	0.06900279
ENSG0000000000457	339.75	316.50	-0.10226805
ENSG0000000000460	97.25	78.75	-0.30441833
ENSG0000000000938	0.75	0.00	-Inf

removing the zero values from the data set

```

zero.sum <- rowSums(meancounts[,1:2] == 0)
to.rm.idn <- zero.sum>0
mycounts <- meancounts[!to.rm.idn,]
nrow(mycounts)

```

```
[1] 21817
```


a common threshold for calling something differently expressed is a log2FC of +2 or -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? how many of the genes are “up regulated”

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

[1] 314

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

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

[1] 485

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

this is only looking at the difference of the means, so we are only looking at the change between two values without knowing if there is variance in the values put into the means and we don't know the expression change is significant

Doing the analysis with DESeq2

```
library(DESeq2)
```

setup for DESeq analysis

```
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<-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

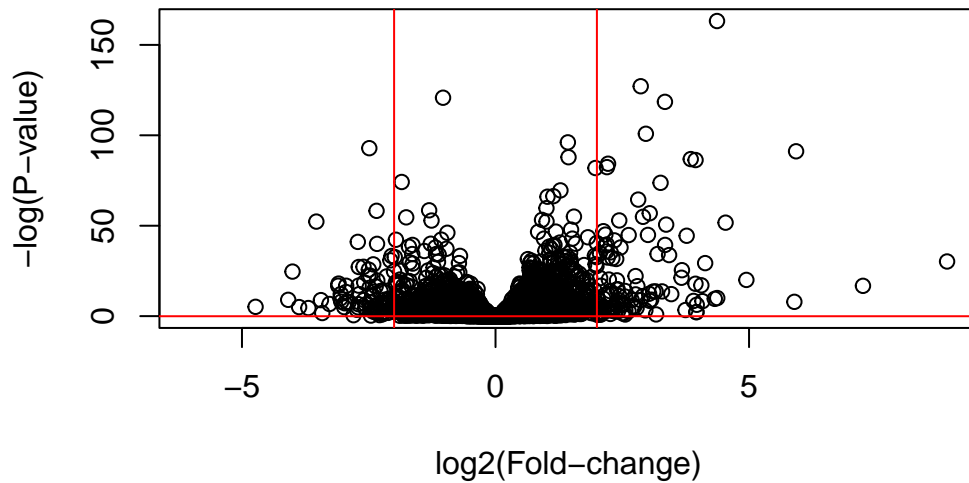
Wald test p-value: dex treated vs control

DataFrame with 38694 rows and 6 columns

	baseMean	log2FoldChange	lfcSE	stat	pvalue
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
ENSG000000000003	747.1942	-0.3507030	0.168246	-2.084470	0.0371175
ENSG000000000005	0.0000	NA	NA	NA	NA
ENSG0000000000419	520.1342	0.2061078	0.101059	2.039475	0.0414026
ENSG0000000000457	322.6648	0.0245269	0.145145	0.168982	0.8658106
ENSG0000000000460	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>				
ENSG000000000003	0.163035				
ENSG000000000005	NA				
ENSG0000000000419	0.176032				
ENSG0000000000457	0.961694				
ENSG0000000000460	0.815849				
...	...				
ENSG00000283115	NA				
ENSG00000283116	NA				
ENSG00000283119	NA				
ENSG00000283120	NA				
ENSG00000283123	NA				

visualization of differential expression is a volcano plot, plotting fold change by pvalue

```
plot(res$log2FoldChange, -log(res$padj),  
      ylab="-log(P-value)",  
      xlab='log2(Fold-change)')  
abline(v=c(-2,2), col='red')  
abline(h=-0.05, col='red')
```



Save the results

```
write.csv(res, file='myresults.csv')
```

Adding annotation data

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

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

```

[1] "ACCNUM"      "ALIAS"      "ENSEMBL"    "ENSEMBLPROT" "ENSEMBLTRANS"
[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"

```

The results has ensemble gene ids but we want to convert them to gene symbol names

```

res$symbol <- mapIds(org.Hs.eg.db,
  keys=row.names(res),
  keytype="ENSEMBL",
  column="SYMBOL",
  multiVals="first")

```

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

```

res$entrez <-mapIds(org.Hs.eg.db,
  keys=row.names(res),
  keytype="ENSEMBL",
  column="ENTREZID",
  multiVals="first")

```

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

multivals=first is the default value, maps to only the first hit(most common)

```

head(res)

```

log2 fold change (MLE): dex treated vs control

Wald test p-value: dex treated vs control

DataFrame with 6 rows and 8 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	symbol	entrez		
	<numeric>	<character>	<character>		
ENSG000000000003	0.163035	TSPAN6	7105		
ENSG000000000005	NA	TNMD	64102		
ENSG000000000419	0.176032	DPM1	8813		
ENSG000000000457	0.961694	SCYL3	57147		
ENSG000000000460	0.815849	C1orf112	55732		
ENSG000000000938	NA	FGR	2268		

overwriting the csv file to include the new id columns

```
write.csv(res, file='myresults.csv')
```