

Class 14: RNASeq mini project

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Background

Here we work through a complete RNASeq analysis project. The input data comes from a knock-down experiment of a HOX gene

Data Import

Reading the `counts` and `metadata` CSV files

```
counts <- read.csv("GSE37704_featurecounts.csv", row.names = 1)
metadata <- read.csv("GSE37704_metadata.csv")
```

Check on data structure

```
head(counts)
```

	length	SRR493366	SRR493367	SRR493368	SRR493369	SRR493370
ENSG00000186092	918	0	0	0	0	0
ENSG00000279928	718	0	0	0	0	0
ENSG00000279457	1982	23	28	29	29	28
ENSG00000278566	939	0	0	0	0	0
ENSG00000273547	939	0	0	0	0	0
ENSG00000187634	3214	124	123	205	207	212
		SRR493371				
ENSG00000186092		0				
ENSG00000279928		0				
ENSG00000279457		46				
ENSG00000278566		0				
ENSG00000273547		0				
ENSG00000187634		258				

```
metadata
```

	id	condition
1	SRR493366	control_sirna
2	SRR493367	control_sirna
3	SRR493368	control_sirna
4	SRR493369	hoxa1_kd
5	SRR493370	hoxa1_kd
6	SRR493371	hoxa1_kd

Some book-keeping is required as there looks to be a mismatch between metadata rows and counts columns

```
ncol(counts)
```

```
[1] 7
```

```
nrow(metadata)
```

```
[1] 6
```

Q. Complete the code below to remove the troublesome first column from `counts`

Looks like we need to get rid of the first “length” column of our `counts` object.

```
cleancounts <- counts[, -1]
```

```
colnames(cleancounts)
```

```
[1] "SRR493366" "SRR493367" "SRR493368" "SRR493369" "SRR493370" "SRR493371"
```

```
metadata$id
```

```
[1] "SRR493366" "SRR493367" "SRR493368" "SRR493369" "SRR493370" "SRR493371"
```

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

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

Remove zero count genes

There are lots of genes with zero counts. We can remove these from further analysis.

```
head(cleancounts)
```

	SRR493366	SRR493367	SRR493368	SRR493369	SRR493370	SRR493371
ENSG00000186092	0	0	0	0	0	0
ENSG00000279928	0	0	0	0	0	0
ENSG00000279457	23	28	29	29	28	46
ENSG00000278566	0	0	0	0	0	0
ENSG00000273547	0	0	0	0	0	0
ENSG00000187634	124	123	205	207	212	258

Q. Complete the code below to filter `cleancounts` to exclude genes (i.e. rows) where we have 0 read count across all samples (i.e. columns).

```
to.keep inds <- rowSums(cleancounts) > 0  
nonzero_counts <- cleancounts[to.keep inds, ]
```

DESeq analysis

Load the package

```
library(DESeq2)
```

Warning: package 'matrixStats' was built under R version 4.5.2

Setup DESeq object

```
dds <- DESeqDataSetFromMatrix(countData = nonzero_counts,
                               colData = metadata,
                               design = ~condition)
```

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

Run DESeq

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

estimating size factors

estimating dispersions

gene-wise dispersion estimates

mean-dispersion relationship

final dispersion estimates

fitting model and testing

Get results

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

```

log2 fold change (MLE): condition hoxa1 kd vs control sirna
Wald test p-value: condition hoxa1 kd vs control sirna
DataFrame with 6 rows and 6 columns
      baseMean log2FoldChange      lfcSE      stat     pvalue
      <numeric>      <numeric> <numeric>      <numeric> <numeric>
ENSG00000279457    29.9136     0.1792571  0.3248216   0.551863 5.81042e-01
ENSG00000187634   183.2296     0.4264571  0.1402658   3.040350 2.36304e-03
ENSG00000188976  1651.1881    -0.6927205  0.0548465  -12.630158 1.43990e-36
ENSG00000187961   209.6379     0.7297556  0.1318599   5.534326 3.12428e-08
ENSG00000187583   47.2551     0.0405765  0.2718928   0.149237 8.81366e-01
ENSG00000187642   11.9798     0.5428105  0.5215598   1.040744 2.97994e-01
      padj
      <numeric>
ENSG00000279457 6.86555e-01
ENSG00000187634 5.15718e-03
ENSG00000188976 1.76549e-35
ENSG00000187961 1.13413e-07
ENSG00000187583 9.19031e-01
ENSG00000187642 4.03379e-01

```

Q. Call the summary() function on your results to get a sense of how many genes are up or down-regulated at the default 0.1 p-value cutoff.

```
summary(res)
```

```

out of 15975 with nonzero total read count
adjusted p-value < 0.1
LFC > 0 (up)      : 4349, 27%
LFC < 0 (down)     : 4396, 28%
outliers [1]       : 0, 0%
low counts [2]     : 1237, 7.7%
(mean count < 0)
[1] see 'cooksCutoff' argument of ?results
[2] see 'independentFiltering' argument of ?results

```

Data Visualization

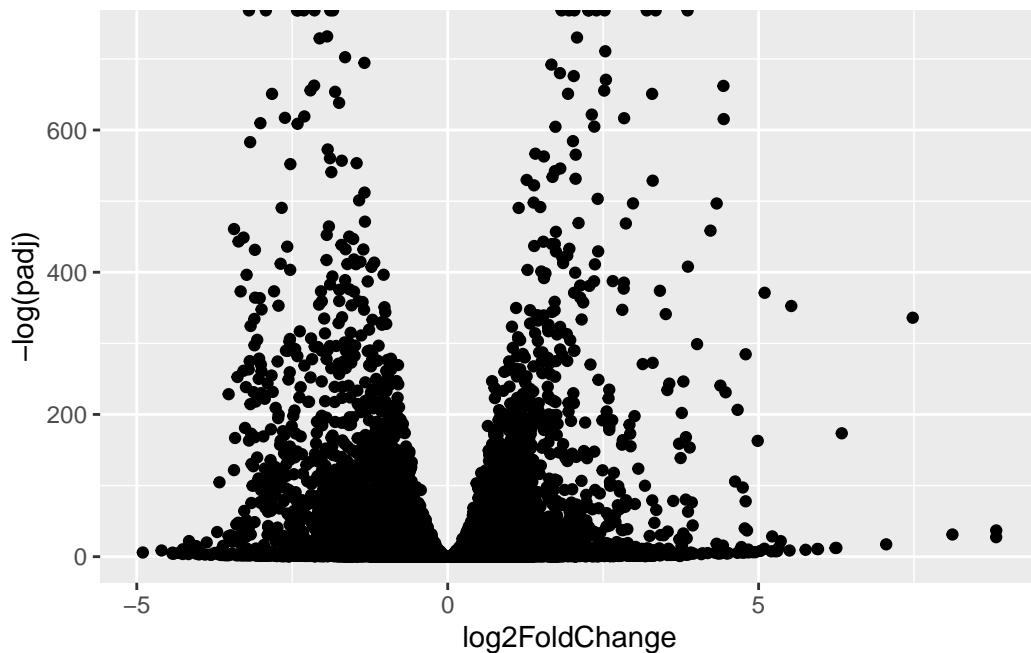
Volcano plot

```
library(ggplot2)
```

Warning: package 'ggplot2' was built under R version 4.5.2

```
ggplot(res) +  
  aes(log2FoldChange, -log(padj)) +  
  geom_point()
```

Warning: Removed 1237 rows containing missing values or values outside the scale range
(`geom_point()`).



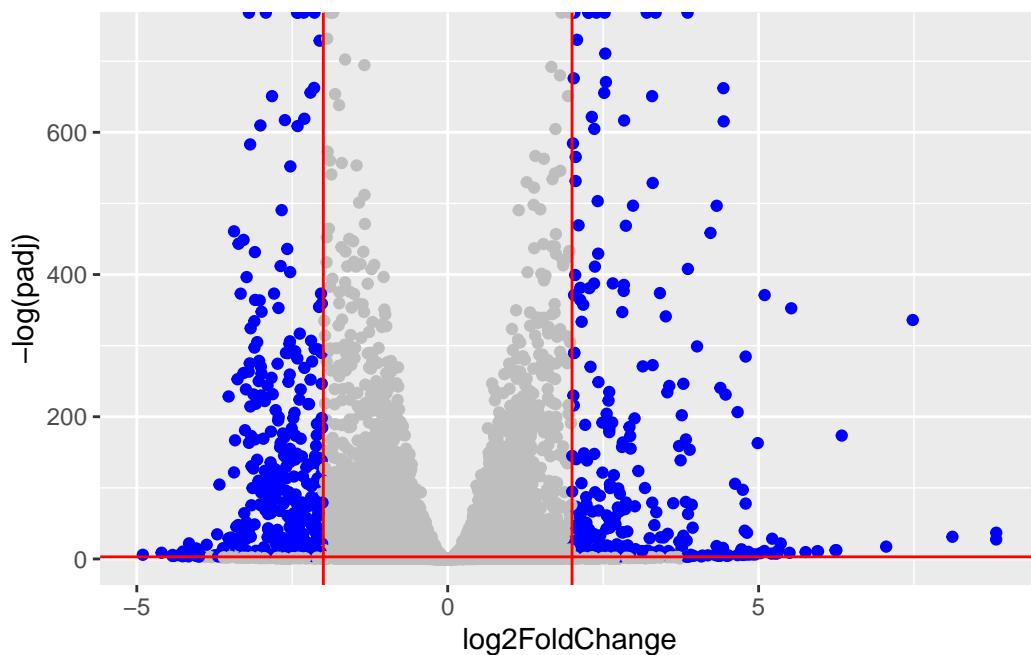
Q. Improve this plot by completing the below code, which adds color and axis labels

Add threshold lines for fold-change and p-value and color our subset of genes that make these threshold cut-offs in the plot

```
mycols <- rep("gray", nrow(res))  
mycols[ abs(res$log2FoldChange) > 2 ] <- "blue"  
mycols[ res$padj > 0.05 ] <- "gray"
```

```
ggplot(res) +
  aes(log2FoldChange, -log(padj)) +
  geom_point(col=mycols) +
  geom_vline(xintercept = c(-2,2), col="red") +
  geom_hline(yintercept = -log(0.05), col="red")
```

Warning: Removed 1237 rows containing missing values or values outside the scale range (`geom_point()`).



Add Annotation

Q. Use the mapIDs() function multiple times to add SYMBOL, ENTREZID and GENENAME annotation to our results by completing the code below.

Add gene symbols and entrez ids

```
library(AnnotationDbi)
library(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"
```

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

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

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

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

Pathway Analysis

KEGG pathways

Run gage analysis with KEGG

```
library(gage)
library(gageData)
library(pathview)
```

We need a named vector of fold-change values as input for gage

```
foldchanges = res$log2FoldChange
names(foldchanges) = res$entrez
head(foldchanges)
```

	<NA>	148398	26155	339451	84069	84808
0.17925708	0.42645712	-0.69272046	0.72975561	0.04057653	0.54281049	

```
data(kegg.sets.hs)

keggres = gage(foldchanges, gsets=kegg.sets.hs)

head(keggres$less, 2)
```

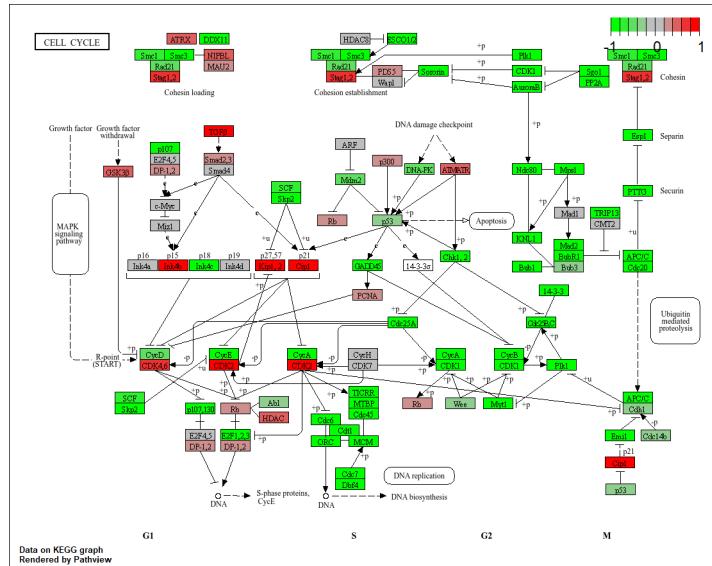
	p.geomean	stat.mean	p.val	q.val
hsa04110 Cell cycle	8.995727e-06	-4.378644	8.995727e-06	0.001889103
hsa03030 DNA replication	9.424076e-05	-3.951803	9.424076e-05	0.009841047
	set.size	exp1		
hsa04110 Cell cycle		121	8.995727e-06	
hsa03030 DNA replication		36	9.424076e-05	

```
pathview(pathway.id = "hsa04110", gene.data = foldchanges)
```

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

Info: Working in directory C:/BIMM143/class14

Info: Writing image file hsa04110.pathview.png

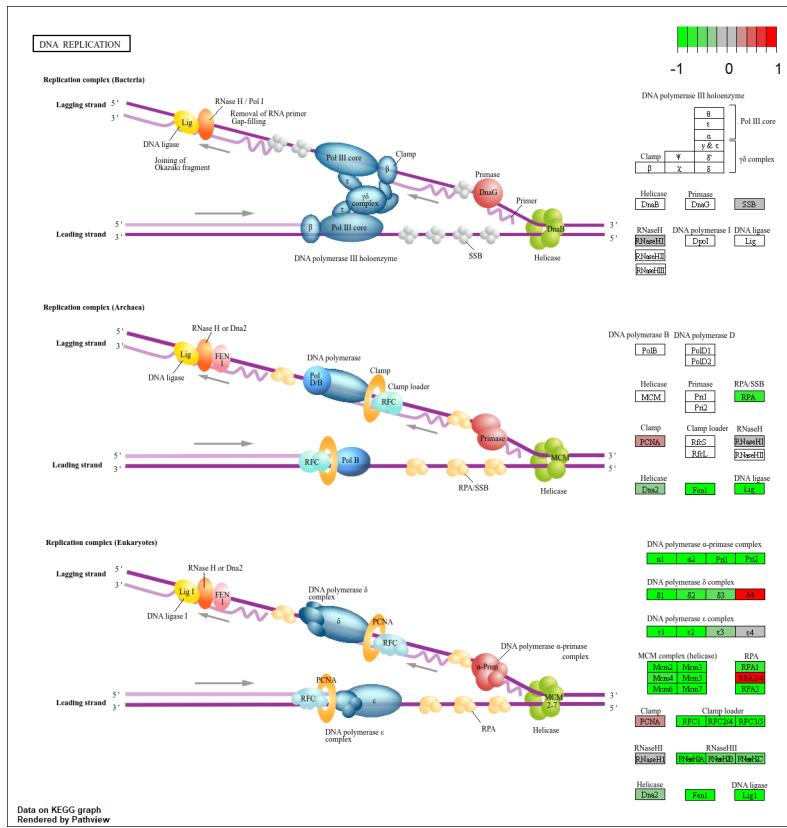


```
pathview(pathway.id = "hsa03030", gene.data = foldchanges)
```

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

Info: Working in directory C:/BIMM143/class14

Info: Writing image file hsa03030.pathview.png



GO terms

Same analysis but using GO genesets rather than KEGG

```
data(go.sets.hs)
data(go.subs.hs)

# Focus on Biological Process subset of GO
```

```

gobpsets = go.sets.hs[go.subs.hs$BP]

gobpres = gage(foldchanges, gsets=gobpsets)

```

```

head(gobpres$less, 4)

```

	p.geomean	stat.mean	p.val
GO:0048285 organelle fission	1.536227e-15	-8.063910	1.536227e-15
GO:0000280 nuclear division	4.286961e-15	-7.939217	4.286961e-15
GO:0007067 mitosis	4.286961e-15	-7.939217	4.286961e-15
GO:0000087 M phase of mitotic cell cycle	1.169934e-14	-7.797496	1.169934e-14
	q.val	set.size	exp1
GO:0048285 organelle fission	5.841698e-12	376	1.536227e-15
GO:0000280 nuclear division	5.841698e-12	352	4.286961e-15
GO:0007067 mitosis	5.841698e-12	352	4.286961e-15
GO:0000087 M phase of mitotic cell cycle	1.195672e-11	362	1.169934e-14

Reactome

Lots of folks like the reactome web interface. You can also run this as an R function but lets look at the website first < <https://reactome.org/> >

The website wants a text file with one gene symbol per line of the genes you want to map to pathways.

```

sig_genes <- res[res$padj <= 0.05 & !is.na(res$padj), ]$symbol
head(sig_genes) #res$symbol

```

```

ENSG00000187634 ENSG00000188976 ENSG00000187961 ENSG00000188290 ENSG00000187608
      "SAMD11"          "NOC2L"          "KLHL17"          "HES4"          "ISG15"
ENSG00000188157
      "AGRN"

```

and write out to a file:

```

write.table(sig_genes, file="significant_genes.txt",
            row.names=FALSE, col.names=FALSE, quote=FALSE)

```

Save Our Results

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