

Lupus Mini Project

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Table of contents

Background	1
Exploratory Analysis	2
Setup for DESeq2	3
Set up DESeq object	5
Running DESeq2	6
Extract Results	6
Vizualizations	8
Extract top genes	10

Background

Lupus arises when the immune system, often responsible for safeguarding the body against infections and diseases, erroneously targets its own tissues. This attack induces inflammation and, in certain instances, irreversible tissue damage, potentially impacting several systems, including the skin, joints, heart, lungs, kidneys, circulating blood cells, and brain.

```
library(GEOquery)
library(dplyr)
library(ggplot2)
library(DESeq2)
```

```
gse <- getGEO("GSE149050")
```

Extract metadata for the 'gse' object

```
#gse list has only one entry
metadata <- pData(phenoData(gse[[1]]))
dim(metadata)
```

[1] 288 64

Exploratory Analysis

```
table(metadata$characteristics_ch1)
```

```
      disease state: healthy control      85
disease state: systemic lupus erythematosus (SLE) 203
```

Q. How many different cell types are there?

```
table(metadata$characteristics_ch1.2)
```

```
cell type: B cells      cell type: cDC      cell type: cMo      cell type: pDC
           32           32           119           33
cell type: PMN cell type: T cells
           36           36
```

Q. How many male and female patients?

```
table(metadata$characteristics_ch1.7)
```

```
gender: Female  gender: Male
          281          7
```

Q. Why are few males affected?

Lupus affects women significantly more than men, with a 9:1 female-to-male ratio, and while the exact reasons are still being researched, hormonal differences, particularly estrogen, and genetics are thought to play a role.

Q. Break down of race by gender?

```
table(metadata$characteristics_ch1.10, metadata$characteristics_ch1.7)
```

	gender: Female	gender: Male
ethnicity: Hispanic	24	0
ethnicity: Hispanic/Latino	53	6
ethnicity: Non Hispanic	37	0
ethnicity: Non-Hispanic/Latino	137	1
ethnicity: Not available	23	0
ethnicity: not listed	1	0
ethnicity: Pacific Islander	6	0

Setup for DESeq2

```
metadata.tc <- filter(metadata, characteristics_ch1.2 == "cell type: T cells" & characteristics_ch1.3 == "disease state: T1")
head(metadata.tc[,1:3])
```

	title	geo_accession	status
GSM4489145	001_L0038_HC_T	GSM4489145	Public on Feb 01 2021
GSM4489147	003_L0140_HC_T	GSM4489147	Public on Feb 01 2021
GSM4489148	004_T4631_HC_T	GSM4489148	Public on Feb 01 2021
GSM4489149	005_T5210_HC_T	GSM4489149	Public on Feb 01 2021
GSM4489150	006_T5466_HC_T	GSM4489150	Public on Feb 01 2021
GSM4489151	007_T5502_HC_T	GSM4489151	Public on Feb 01 2021

Q. How were these samples processed (alignment/mapping software version and genome build used)?

```
metadata.tc$data_processing[1]
```

```
[1] "Bulk RNA-seq data (FASTQ files) were mapped against the hg38 genome (GRCh38.p7) reference"
```

```
metadata.subset <- metadata.tc %>%
  select(title,
         disease_state = characteristics_ch1,
         ifn_status = characteristics_ch1.3,
         patient_id = characteristics_ch1.4) %>%
  mutate(disease_state = gsub("disease state: ", "", disease_state)) %>%
```

```
mutate(ifn_status = gsub("ifn status: ", "", ifn_status)) %>%
mutate(patient_id = gsub("patientuid: ", "", patient_id)) %>%
mutate(state = recode(disease_state,
                      "healthy control" = "control",
                      "systemic lupus erythematosus (SLE)" = "lupus"))
table(metadata.subset$state)
```

```
control  lupus
      10    23
```

```
#Read count data
counts.all <- read.delim("GSE149050_Bulk_Human_RawCounts.txt.gz",
                        check.names=FALSE, row.names = 1)
head(counts.all[,1:3])
```

	001_L0038_HC_T	002_L0088fresh_HC_T	003_L0140_HC_T
5S_rRNA	2	0	2
5_8S_rRNA	0	0	0
7SK	1	1	2
A1BG	53	56	105
A1BG-AS1	7	24	46
A1CF	0	2	2

```
head(metadata.subset$title)
```

```
[1] "001_L0038_HC_T" "003_L0140_HC_T" "004_T4631_HC_T" "005_T5210_HC_T"
[5] "006_T5466_HC_T" "007_T5502_HC_T"
```

```
counts.subset <- counts.all %>% select(metadata.subset$title)
dim(counts.subset)
```

```
[1] 56269    33
```

```
all(colnames(counts.subset) == metadata.subset$title)
```

```
[1] TRUE
```

```
# Remove title column then use it as row names
colData <- metadata.subset[,-1]
rownames(colData) <- metadata.subset[,1]
head(colData)
```

	disease_state	ifn_status	patient_id	state
001_L0038_HC_T	healthy	control	HC	L0038 control
003_L0140_HC_T	healthy	control	HC	L0140 control
004_T4631_HC_T	healthy	control	HC	T4631 control
005_T5210_HC_T	healthy	control	HC	T5210 control
006_T5466_HC_T	healthy	control	HC	T5466 control
007_T5502_HC_T	healthy	control	HC	T5502 control

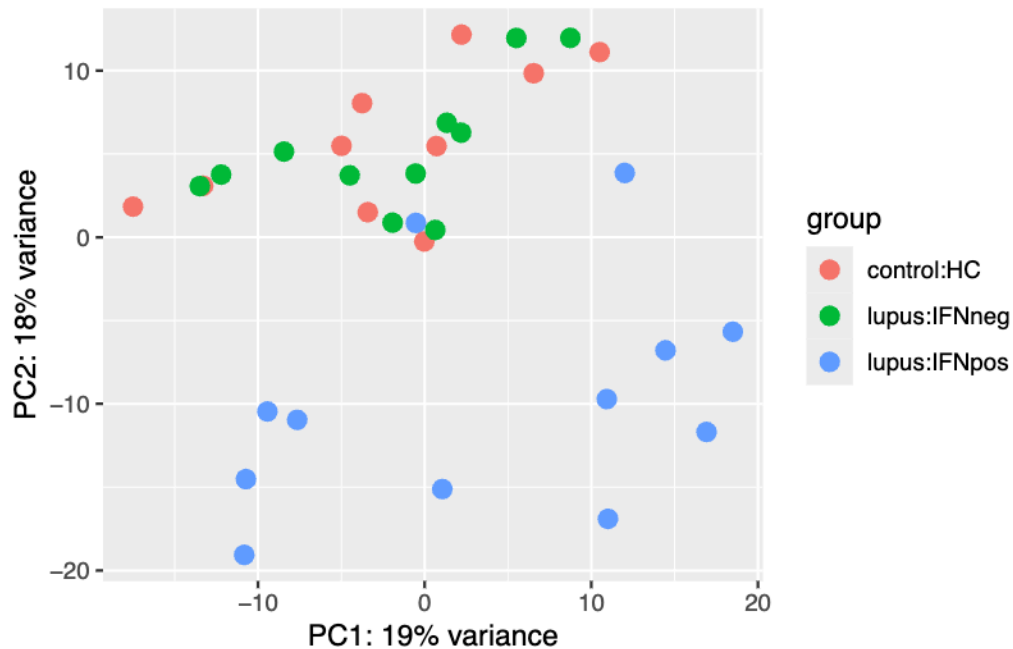
Set up DESeq object

```
dds <- DESeqDataSetFromMatrix(countData = counts.subset, #you already have the matrix
                              colData = colData,
                              design = ~state)
```

```
keep.inds <- rowSums(counts(dds)) >= 10
dds <- dds[keep.inds,]
```

```
#PCA analysis
vsd <- vst(dds, blind = FALSE)
plotPCA(vsd, intgroup = c("state", "ifn_status"))
```

using ntop=500 top features by variance



Running DESeq2

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

Extract Results

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

log2 fold change (MLE): state lupus vs control

Wald test p-value: state lupus vs control

DataFrame with 6 rows and 6 columns

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
5S_rRNA	2.78039	0.4759046	0.457248	1.040802	0.297967	NA
7SK	2.33480	0.3570971	0.489993	0.728781	0.466136	NA
A1BG	81.11733	-0.0226099	0.176306	-0.128243	0.897957	0.974910
A1BG-AS1	21.03977	0.2993010	0.264304	1.132410	0.257462	0.698095
A1CF	3.11018	0.3174058	0.566481	0.560311	0.575267	NA

```
A2M      251.71157      -0.0294669  0.287036 -0.102659  0.918233  0.980429
```

```
summary(res)
```

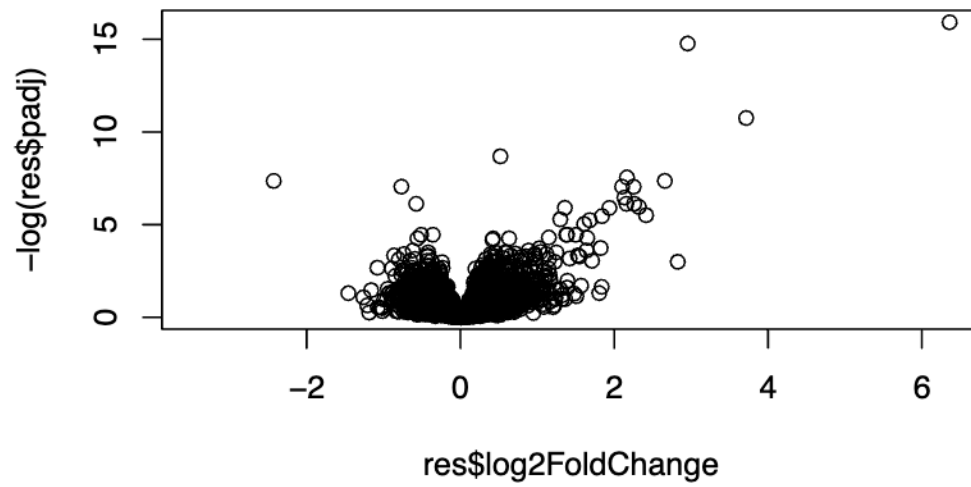
```
out of 31491 with nonzero total read count
adjusted p-value < 0.1
LFC > 0 (up)      : 110, 0.35%
LFC < 0 (down)    : 44, 0.14%
outliers [1]      : 0, 0%
low counts [2]    : 16500, 52%
(mean count < 16)
[1] see 'cooksCutoff' argument of ?results
[2] see 'independentFiltering' argument of ?results
```

After adjusting p-value threshold

```
res_p05 <- results(dds, alpha=0.05)
summary(res_p05)
```

```
out of 31491 with nonzero total read count
adjusted p-value < 0.05
LFC > 0 (up)      : 61, 0.19%
LFC < 0 (down)    : 17, 0.054%
outliers [1]      : 0, 0%
low counts [2]    : 15890, 50%
(mean count < 14)
[1] see 'cooksCutoff' argument of ?results
[2] see 'independentFiltering' argument of ?results
```

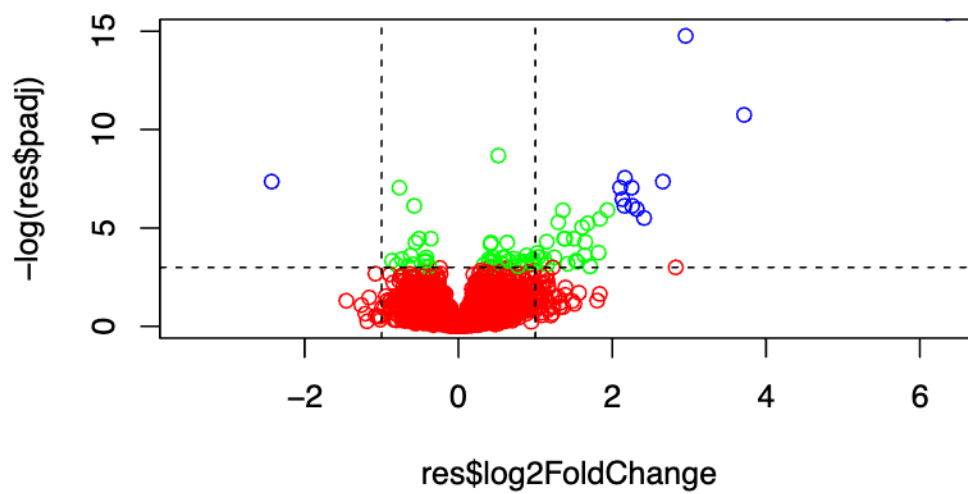
```
write.csv(res_p05, "deseq_results_tc_SLE.csv")
plot(res$log2FoldChange, -log(res$padj))
```



Vizualizations

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

plot(res$log2FoldChange, -log(res$padj), ylim=c(0,15), col=mycols)
abline(v=c(-1,1), lty=2)
abline(h=-log(0.05), lty=2)
```

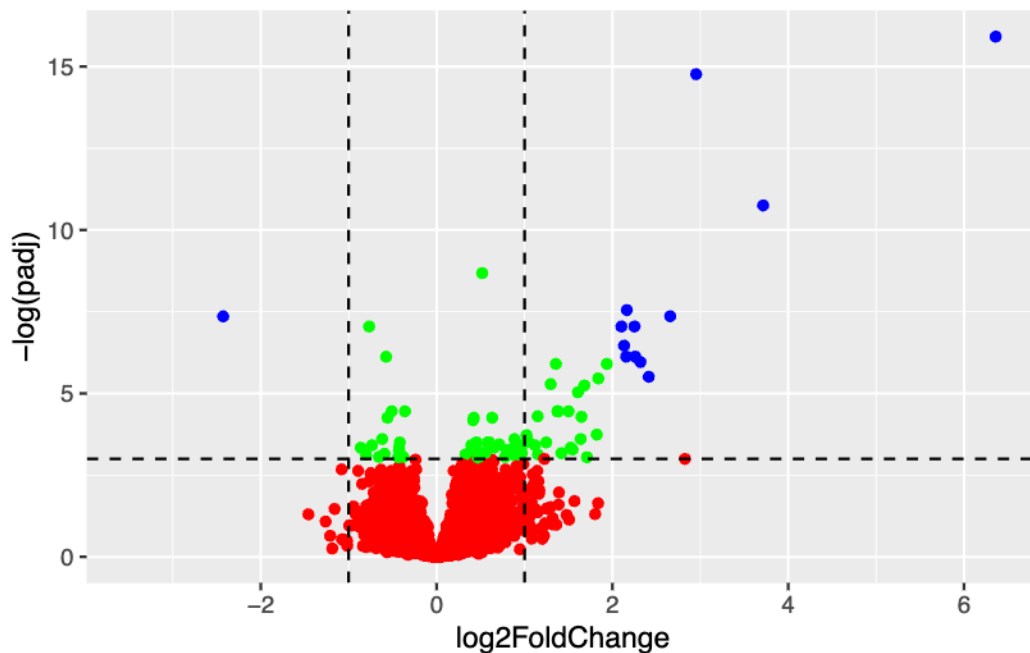



```
results <- as.data.frame(res)

library(ggplot2)

ggplot(results) +
  aes(log2FoldChange, -log(padj)) +
  geom_point(col=mycols) +
  geom_vline(xintercept = c(-1,+1), linetype=2) +
  geom_hline(yintercept = -log(0.05), linetype=2)
```

Warning: Removed 16500 rows containing missing values or values outside the scale range (`geom_point()`).



Extract top genes

```
top.genes <- results %>% filter(padj <= 0.05 & abs(log2FoldChange) >= 2)
head(top.genes)
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
CMPK2	218.7990	2.251249	0.4504244	4.998062	5.790927e-07	8.690444e-04
GSTM1	124.9589	2.953416	0.4497644	6.566585	5.148243e-11	3.862984e-07
IFI27	885.4340	6.360160	0.9304322	6.835705	8.160257e-12	1.224610e-07
IFI44	1207.3932	2.102190	0.4196298	5.009631	5.453450e-07	8.690444e-04
IFI44L	2167.9605	3.714660	0.6325324	5.872679	4.288088e-09	2.145045e-05
IFIT1	285.4165	2.132057	0.4382361	4.865088	1.144060e-06	1.560810e-03

#Save Results

```
save(top.genes, file = "top_genes.RData")
write.csv(res, file="results.csv")
```