

Class 17: Analyzing sequencing data in the cloud

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Downstream analysis

```
library(tximport)
library(rhdf5)

# setup the folder and filenames to read
folders <- dir(pattern="SRR21568*")
samples <- sub("_quant", "", folders)
files <- file.path( folders, "abundance.h5" )
names(files) <- samples

txi.kallisto <- tximport(files, type = "kallisto", txOut = TRUE)
```

1 2 3 4

```
head(txi.kallisto$counts)
```

	SRR2156848	SRR2156849	SRR2156850	SRR2156851
ENST00000539570	0	0	0.00000	0
ENST00000576455	0	0	2.62037	0

ENST00000510508	0	0	0.00000	0
ENST00000474471	0	1	1.00000	0
ENST00000381700	0	0	0.00000	0
ENST00000445946	0	0	0.00000	0

The number of transcripts we have for each sample:

```
colSums(txi.kallisto$counts)
```

```
SRR2156848 SRR2156849 SRR2156850 SRR2156851
      2563611      2600800      2372309      2111474
```

How many transcripts are detected in at least one sample:

```
sum(rowSums(txi.kallisto$counts)>0)
```

```
[1] 94561
```

Filtering out annotated transcripts with no reads and those with no change over samples:

```
to.keep <- rowSums(txi.kallisto$counts) > 0
kset.nonzero <- txi.kallisto$counts[to.keep,]
```

```
keep2 <- apply(kset.nonzero,1,sd)>0
x <- kset.nonzero[keep2,]
```

Principal Component Analysis

Computing the principal components, centering and scaling each transcript's measured levels so that each feature contributes equally to the PCA:

```
pca <- prcomp(t(x), scale=TRUE)
```

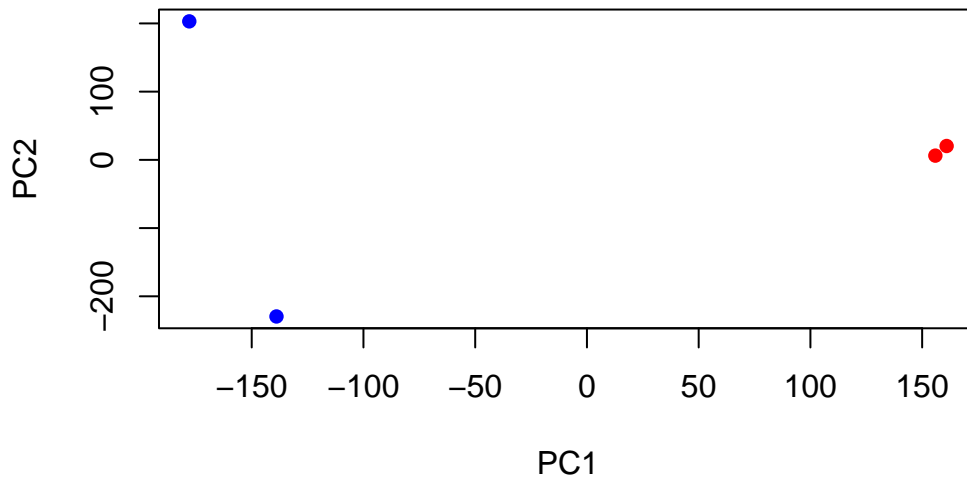
```
summary(pca)
```

Importance of components:

	PC1	PC2	PC3	PC4
Standard deviation	183.6379	177.3605	171.3020	1e+00
Proportion of Variance	0.3568	0.3328	0.3104	1e-05
Cumulative Proportion	0.3568	0.6895	1.0000	1e+00

Visualizing the summarized transcriptomic profiles of each sample using the first two principal components:

```
plot(pca$x[,1], pca$x[,2],  
     col=c("blue", "blue", "red", "red"),  
     xlab="PC1", ylab="PC2", pch=16)
```



Using ggplot to make a better visualization:

```
library(ggplot2)
```

Warning: package 'ggplot2' was built under R version 4.3.3

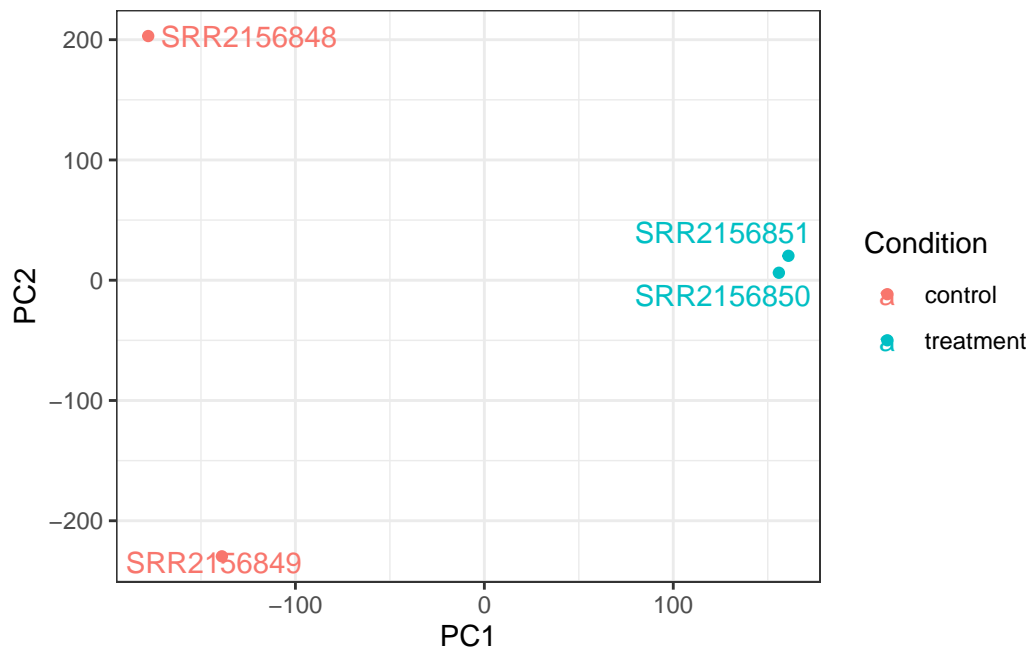
```
library(ggrepel)
```

Warning: package 'ggrepel' was built under R version 4.3.3

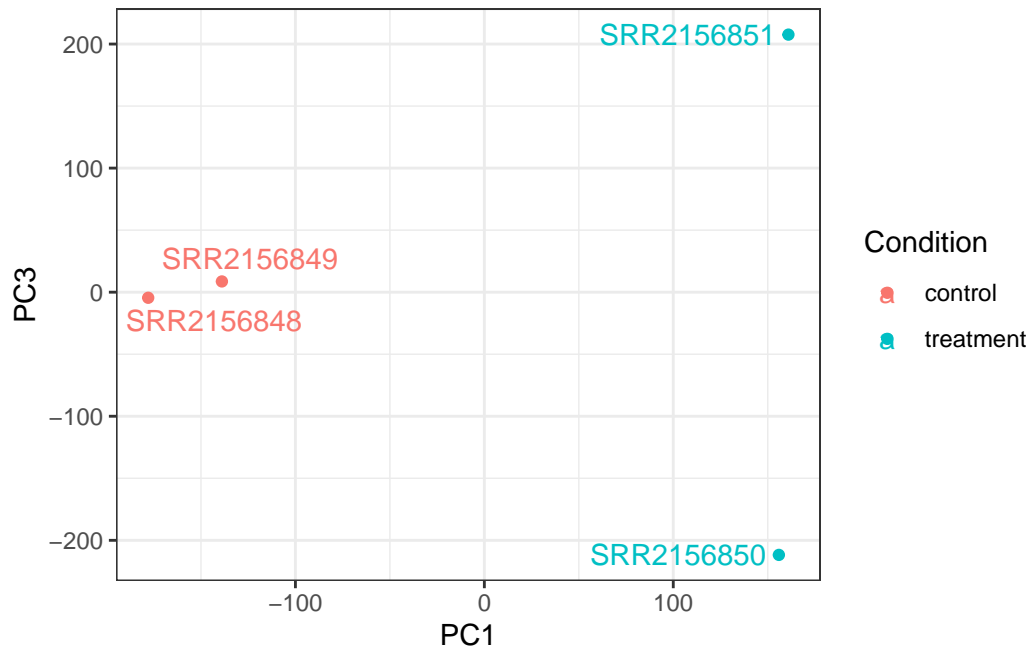
```
colData <- data.frame(condition = factor(rep(c("control", "treatment"), each = 2)))  
rownames(colData) <- colnames(tx1.kallisto$counts)
```

```
y <- as.data.frame(pca$x)
y$Condition <- as.factor(colData$condition)
```

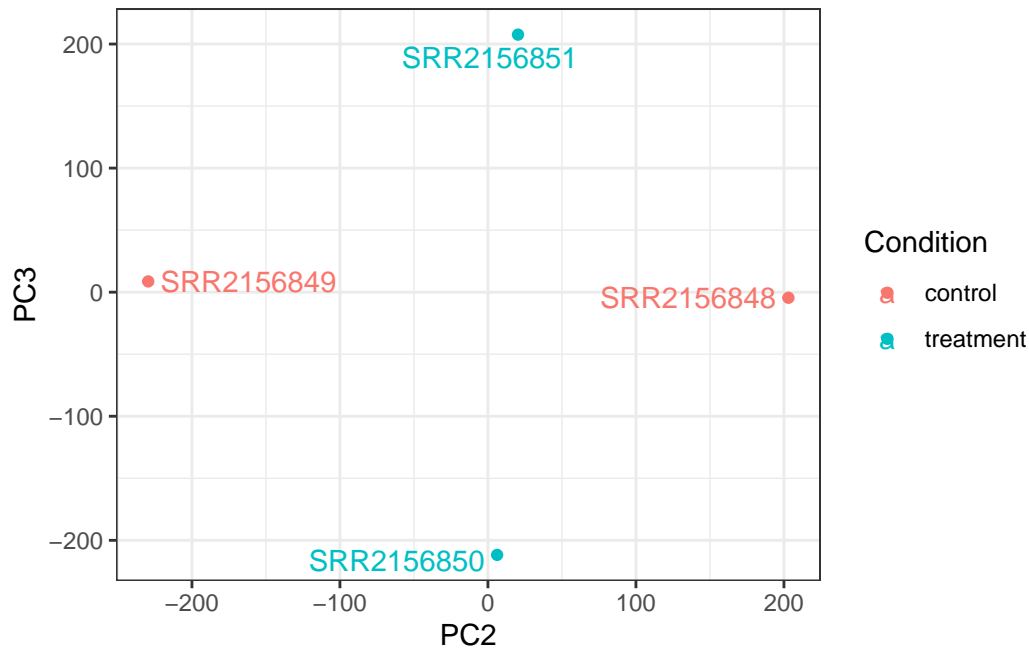
```
ggplot(y) +
  aes(PC1, PC2, col=Condition) +
  geom_point() +
  geom_text_repel(label=rownames(y)) +
  theme_bw()
```



```
ggplot(y) +
  aes(PC1, PC3, col=Condition) +
  geom_point() +
  geom_text_repel(label=rownames(y)) +
  theme_bw()
```



```
ggplot(y) +  
  aes(PC2, PC3, col=Condition) +  
  geom_point() +  
  geom_text_repel(label=rownames(y)) +  
  theme_bw()
```



Differential-expression analysis

Creating a DESeqDataSet for use with DESeq2:

```
library(DESeq2)
```

Warning: package 'DESeq2' was built under R version 4.3.3

Warning: package 'GenomeInfoDb' was built under R version 4.3.3

Warning: package 'matrixStats' was built under R version 4.3.3

```
sampleTable <- data.frame(condition = factor(rep(c("control", "treatment"), each = 2)))
rownames(sampleTable) <- colnames(txi.kallisto$counts)
```

```
dds <- DESeqDataSetFromTximport(txi.kallisto,
                                sampleTable,
                                ~condition)
```

using counts and average transcript lengths from tximport

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

estimating size factors

using 'avgTxLength' from assays(dds), correcting for library size

estimating dispersions

gene-wise dispersion estimates

mean-dispersion relationship

-- note: fitType='parametric', but the dispersion trend was not well captured by the function: $y = a/x + b$, and a local regression fit was automatically substituted. specify fitType='local' or 'mean' to avoid this message next time.

final dispersion estimates

fitting model and testing

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

log2 fold change (MLE): condition treatment vs control

Wald test p-value: condition treatment vs control

DataFrame with 6 rows and 6 columns

	baseMean	log2FoldChange	lfcSE	stat	pvalue
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
ENST00000539570	0.000000	NA	NA	NA	NA
ENST00000576455	0.761453	3.155061	4.86052	0.6491203	0.516261
ENST00000510508	0.000000	NA	NA	NA	NA
ENST00000474471	0.484938	0.181923	4.24871	0.0428185	0.965846
ENST00000381700	0.000000	NA	NA	NA	NA
ENST00000445946	0.000000	NA	NA	NA	NA
	padj				
	<numeric>				
ENST00000539570	NA				
ENST00000576455	NA				
ENST00000510508	NA				
ENST00000474471	NA				
ENST00000381700	NA				
ENST00000445946	NA				