Class17

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Downstream analysis

Back on our laptop we can now use R and Bioconductor tools to further explore this large scale dataset.

For example there is an R function called tximport() in the tximport package, which enables straightforward import of Kallisto results

With each sample having its own directory containing the Kallisto output, we can import the transcript count estimates into R using:

```
# BiocManager::install("tximport")
```

library(tximport)

```
dir <- "C:/Users/anyol/OneDrive/bimm143/class17/quant_results"
list.files(dir)</pre>
```

[1] "SRR2156848_quant" "SRR2156849_quant" "SRR2156850_quant" "SRR2156851_quant"

```
folders <- list.files(path = dir, pattern = "SRR21568*")
samples <- sub("_quant", "", folders)
files <- file.path(dir, folders, "abundance.h5")
names(files) <- samples

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

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

Q. How many transcripts for each sample?

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

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

Q. How many transcripts are detected in at least one sample?

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

[1] 94561

Might want to filter the ones with no reads:

```
to_keep <- rowSums(txi.kallisto$counts) > 0
kset_nonzero <- txi.kallisto$counts[to_keep,]</pre>
```

```
keep2 <- apply(kset_nonzero,1,sd)>0
kk <- kset_nonzero[keep2,]
head(kk)</pre>
```

```
SRR2156848 SRR2156849 SRR2156850 SRR2156851
ENST00000576455
                  0.00000 0.000000
                                        2.62037
                                                  0.000000
                  0.00000 1.0000000
ENST00000474471
                                        1.00000
                                                  0.000000
ENST00000420022
                  0.00000
                           2.0000000
                                        4.00000
                                                  4.000000
                                                  2.720173
ENST00000553856
                 10.96649
                           5.2579568
                                       13.11994
ENST00000556126
                  0.00000
                           0.0000000
                                        4.00000
                                                  0.000000
ENST00000483851
                  0.00000
                           0.6084246
                                        0.00000
                                                  0.000000
```

PCA (Principal Component Analysis)

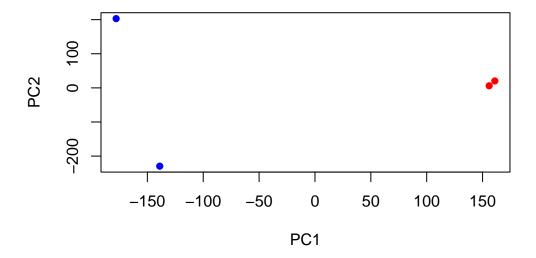
Now we compute the principal components, centering and scaling each transcript's measured levels so that each feature contributes equally to the PCA:

```
pca <- prcomp(t(kk), scale=T)
summary(pca)</pre>
```

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
```

Now can use the first two principal components as a coordinate system for visualizing the summarized transcriptomic profiles of each sample:



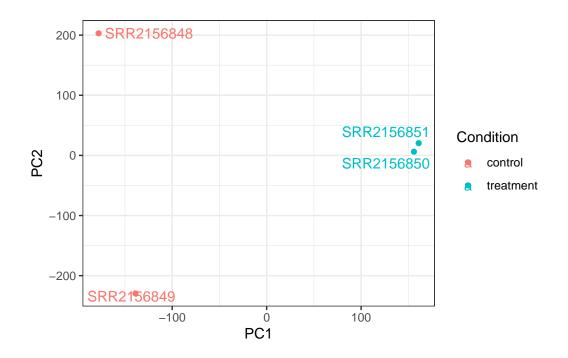
Q. Use ggplot to make a similar figure of PC1 vs PC2 and a separate figure PC1 vs PC3 and PC2 vs PC3.

```
library(ggplot2)
library(ggrepel)
```

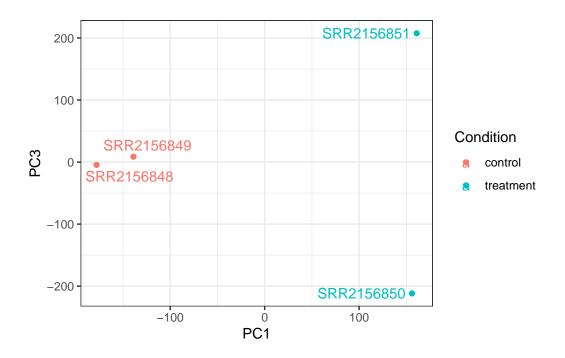
```
colData <- data.frame(condition = factor(rep(c("control", "treatment"), each = 2)))
rownames(colData) <- colnames(txi.kallisto$counts)

# Make the data.frame for ggplot
y <- as.data.frame(pca$x)
y$Condition <- as.factor(colData$condition)

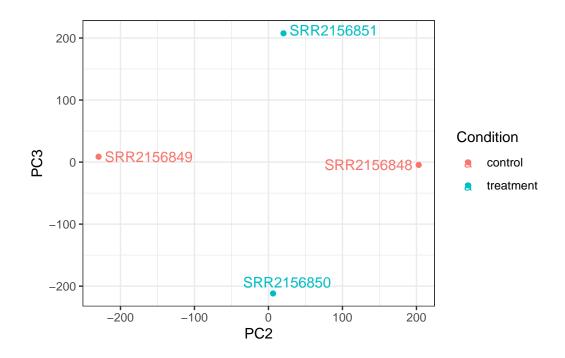
ggplot(y) +
   aes(PC1, PC2, col=Condition) +
   geom_point() +
   geom_text_repel(label=rownames(y)) +
   theme_bw()</pre>
```



```
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()
```



Differiental-expression analysis

We can use DESeq2 to complete the differential-expression analysis that we are already familiar with:

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, aperm, 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, saveRDS, setdiff, table, tapply, union, unique, unsplit, which.max, which.min

Attaching package: 'S4Vectors'

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

findMatches

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

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, rowAvgsPerColSet, 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'

rowMedians

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

The following objects are masked from 'package:matrixStats': anyMissing, rowMedians

```
sampleTable <- data.frame(condition = factor(rep(c("control", "treatment"), each = 2)))</pre>
rownames(sampleTable) <- colnames(txi.kallisto$counts)</pre>
dds <- DESeqDataSetFromTximport(txi.kallisto,</pre>
                                 sampleTable,
                                 ~condition)
using counts and average transcript lengths from tximport
dds is now ready for DESeq().
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)</pre>
head(res)
```

 $\log 2$ fold change (MLE): condition treatment vs control

Wald test p-value: condition treatment vs control

DataFrame with 6 rows and 6 columns

Datarrame with t	TOWS and	O COLUMNIS			
	baseMean	${\tt log2FoldChange}$	lfcSE	stat	pvalue
	<numeric></numeric>	<numeric></numeric>	<numeric></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></numeric>				
ENST00000539570	NA				
ENST00000576455	NA				
ENST00000510508	NA				
ENST00000474471	NA				
ENST00000381700	NA				
ENST00000445946	NA				