

rnaSeq analysis

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Background

Objective: Analyzing processed microarray data

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This data was provided as counts(?) in Excel spreadsheets.

```
#### Set seed for reproducibility ####
set.seed(200)

#### Set variables ####
# What's the working directory? Preferably in same location as the data and Rproject.
getwd()

[1] "/home/christin/aaa_present_CepkoLab/lab_cepko-code/rnaSeq"
fname <- "dw_microarray_rpe-innateImmunity"

#### Import data ####
d <- read.csv("output/innate immune genes tissue microarraysgrant ed dw copy.csv")
# I ended up manually editing the sample names in this file because it was the easiest way to generate usable
# annotations...thankfully there were only 10 samples. I'm sure there are more elegant ways of doing it,
# though (what if there were 100s of samples?!).

#### * File name * ####
out.name <-
  paste0("output/",
        fname,
        "_",
        "rnaSeq-analysis_",
        Sys.Date())

print(out.name)

[1] "output/dw_microarray_rpe-innateImmunity_rnaSeq-analysis-2018-06-19"
#### START ANALYSIS ####

# look at number/distribution of reads, including only complete cases
sapply(d, class)

      n      Unigene      Name C57B16_na_5w_a C57B16_na_5w_b C57B16_na_8w_a
"integer" "factor"    "factor"    "integer"    "integer"    "integer"
C57B16_na_8w_b C57B16_RPE_6w_a FVB_na_5w_a FVB_na_5w_b FVB_RPE_6w_a gene.name
"integer"    "integer"    "integer"    "integer"    "integer"    "factor"
RNAseq
"factor"

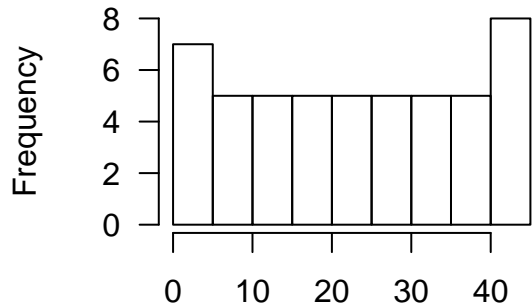
d <- transform(d, RNAseq = as.integer(RNAseq))

par(mfrow=c(1,2), las=1)

hist(d$RNAseq) # This is odd. Are these p-values or read counts?
```

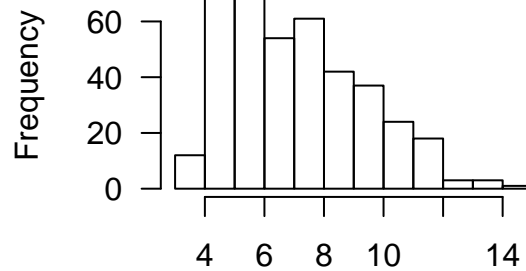
```
# Graph log2(x+1) RNAseq values (log = natural log)
hist(t(log2(d[4:11] + 1)))
```

Histogram of d\$RNAseq



d\$RNAseq

Histogram of t(log2(d[4:11] + 1))



t(log2(d[4:11] + 1))

```
par(mfrow=c(1,1), las=1)
```

```
#### GUESSES #### Are these raw reads...? I hope not. I guess I'll assume that these have at least been
#scaled to library size, since I don't have the full library to scale with anyway. (Not sure if it's
#different for microarray data, but I'm still sure I'm only working with a subset of the data, so assuming
#that it comes scaled is still reasonable.)

# Will also assume data has already been filtered.

# It looks like there are 2 mouse strains, 3 timepoints, and 2 types of tissue (whole retina vs. RPE?). There
# are replicates at the timepoints for the unlabeled tissue type, which I'm going to assume is whole retina.

# which ones are most useful for testing differential expression...?
```

```
#### Editing mislabeled values ####
# duplicate tnfaip8 in gene.name?
dplyr::filter(d, gene.name == "tnfaip8")
```

n	Unigene	Name	C57B16_na_5w_a	C57B16_na_5w_b	C57B16_na_8w_a
1	19 Mm.27740	tumor necrosis factor, alpha-induced protein 8	92	78	78
2	23 Mm.31403	tumor necrosis factor, alpha-induced protein 9	14	14	15

	C57B16_na_8w_b	C57B16_RPE_6w_a	FVB_na_5w_a	FVB_na_5w_b	FVB_RPE_6w_a	gene.name	RNAseq
1	62	1325	58	65	910	tnfaip8	42
2	13	667	14	29	1015	tnfaip8	42

```
# Oh, I see, it's mislabeled in one row---should be tnfaip9 in row with Unigene Mm.31403.
```

```
dplyr::filter(d, grepl("26103", gene.name)) # filtering for partial match with grep
```

n	Unigene	Name	C57B16_na_5w_a	C57B16_na_5w_b	C57B16_na_8w_a	C57B16_na_8w_b
1	7 Mm.45995	RIKEN cDNA 2610307008 gene sting	76	62	62	77

	C57B16_RPE_6w_a	FVB_na_5w_a	FVB_na_5w_b	FVB_RPE_6w_a	gene.name	RNAseq
1	247	86	77	234	2610307008Rik	43

```
# correcting
```

```
d$gene.name <- as.character(d$gene.name)
```

```
# subset for correct values (AND to keep values that are correct for all counts)
d.ok <- dplyr::filter(d, Unigene != "Mm.31403" & Unigene != "Mm.45995")
```

```
# subset for incorrect (OR to get all errors)
```

```
d.error <- dplyr::filter(d, Unigene == "Mm.31403" | Unigene == "Mm.45995")
```

```
d.error$gene.name[1] <- "sting"
d.error$gene.name[2] <- "tnfaip9"
d.error
```

```
      n Unigene                                     Name C57Bl6_na_5w_a C57Bl6_na_5w_b C57Bl6_na_8w_a
1  7 Mm.45995          RIKEN cDNA 2610307008 gene sting              76          62          62
2 23 Mm.31403 tumor necrosis factor, alpha-induced protein 9              14          14          15
      C57Bl6_na_8w_b C57Bl6_RPE_6w_a FVB_na_5w_a FVB_na_5w_b FVB_RPE_6w_a gene.name RNAseq
1              77          247          86          77          234      sting      43
2              13          667          14          29          1015    tnfaip9      42
```

```
# merge
```

```
d.corrected <- rbind(d.ok, d.error)
```

```
# check
```

```
dplyr::filter(d.corrected, gene.name == "tnfaip8")
```

```
      n Unigene                                     Name C57Bl6_na_5w_a C57Bl6_na_5w_b C57Bl6_na_8w_a
1 19 Mm.27740 tumor necrosis factor, alpha-induced protein 8              92          78          78
      C57Bl6_na_8w_b C57Bl6_RPE_6w_a FVB_na_5w_a FVB_na_5w_b FVB_RPE_6w_a gene.name RNAseq
1              62          1325          58          65          910    tnfaip8      42
```

```
tail(d.corrected, 2)
```

```
      n Unigene                                     Name C57Bl6_na_5w_a C57Bl6_na_5w_b C57Bl6_na_8w_a
49  7 Mm.45995          RIKEN cDNA 2610307008 gene sting              76          62          62
50 23 Mm.31403 tumor necrosis factor, alpha-induced protein 9              14          14          15
      C57Bl6_na_8w_b C57Bl6_RPE_6w_a FVB_na_5w_a FVB_na_5w_b FVB_RPE_6w_a gene.name RNAseq
49              77          247          86          77          234      sting      43
50              13          667          14          29          1015    tnfaip9      42
```

```
#### tidying ####
```

```
# Renaming rows by gene name
```

```
d2 <- d.corrected
```

```
rownames(d2) <- d.corrected[, 12]
```

```
# log2(x+1) scaling
```

```
d.val <- log2(d2[4:11] + 1)
```

```
#### PCA and k means ####
```

```
autoplot(
```

```
  kmeans(
```

```
    d.val,
```

```
    centers = 5,
```

```
    iter.max = 100,
```

```
    nstart = 20,
```

```
    algorithm = "Lloyd"
```

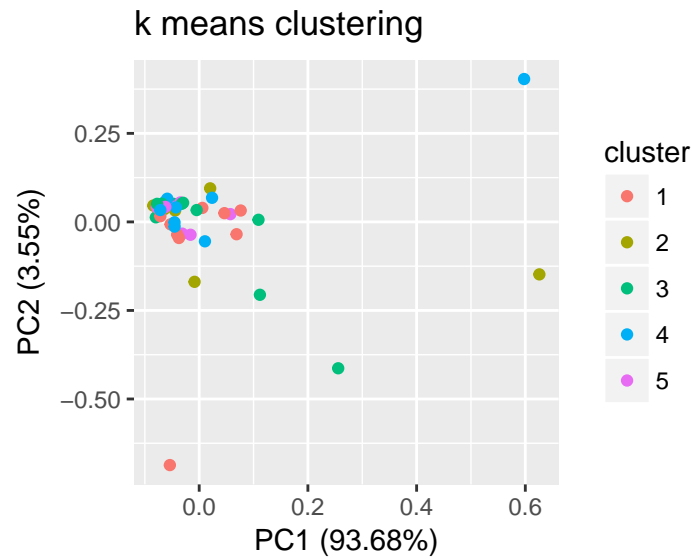
```
  ),
```

```
  main = paste0("k means clustering"),
```

```
  data = d,
```

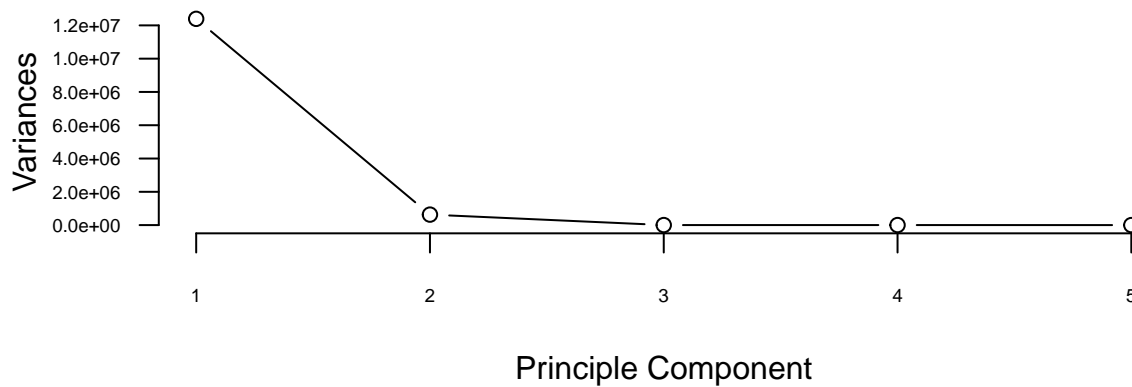
```
  asp = 1
```

```
)
```



```
flow_pcaPr <- prcomp(d[, c(4:8)], center = F, scale. = F)
par(cex.axis = 0.6)
plot(flow_pcaPr, type = "lines", main = "PCA by prcomp")
title(xlab = "Principle Component")
```

PCA by prcomp



```
par(cex.axis = 1)

#### Heatmap ####
# From Kam's tutorial: http://slowkow.com/notes/heatmap-tutorial/

# Setting coloring scheme based on quantile breaks so coloring will represent equal proportion of data
quantile_breaks <- function(xs, n = 10) {
  breaks <- quantile(xs, probs = seq(0, 1, length.out = n))
  breaks[!duplicated(breaks)]
}

# Quantile function dislikes data.frames -> coerce into matrix
flowHM_breaks <- quantile_breaks(as.matrix(d.val), n = 11))

## Sorting the dendrograms for easier interpretation
# Cluster by column
flowHM_cluster_cols <- hclust(dist(t(d.val)))
```

