

Class 7: Machine Learning 1

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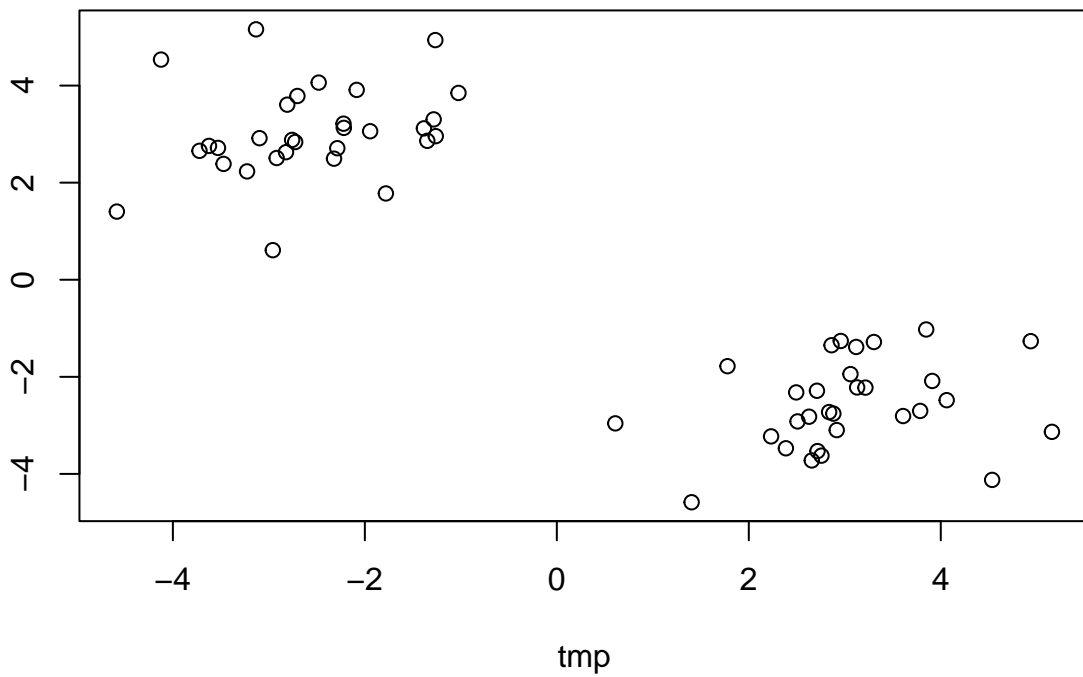
Clustering methods

Find groups (a.k.a) clusters in my data.

K-means clustering

Make up some data to test with.

```
# Make up some data with 2 clear groups  
tmp <- c(rnorm(30, mean = 3), rnorm(30, mean = -3))  
x <- cbind(tmp, rev(tmp))  
plot(x)
```



The `kmeans()` function does k-means clustering.

```
k <- kmeans(x, centers=4, nstart=20)
k

## K-means clustering with 4 clusters of sizes 15, 15, 15, 15
##
## Cluster means:
##      tmp
## 1  3.699284 -2.085837
## 2 -2.085837  3.699284
## 3  2.367528 -3.055250
## 4 -3.055250  2.367528
##
## Clustering vector:
## [1] 1 3 3 1 3 3 1 3 3 3 1 1 1 3 1 3 1 1 3 1 1 3 1 1 3 3 1 3 4 2 4 4 2 2 4 2
## [39] 2 4 2 4 2 2 4 2 4 2 2 2 4 4 4 2 4 4 2 4 4 2
##
## Within cluster sum of squares by cluster:
## [1] 17.81016 17.81016 12.31625 12.31625
## (between_SS / total_SS =  94.2 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

We can use the dollar syntax to get at the results (components of the returned list).

Q2. What 'component' of your result object details -cluster size? -cluster assignment/membership? -cluster center?

```
k$size
```

```
## [1] 15 15 15 15
```

```
k$cluster
```

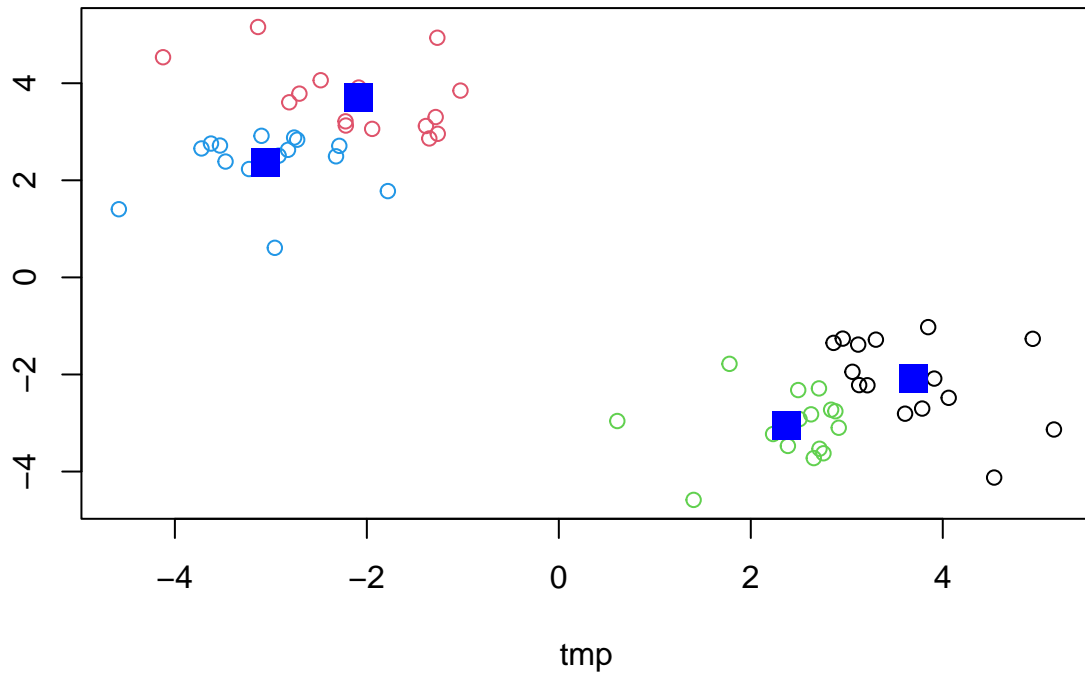
```
## [1] 1 3 3 1 3 3 1 3 3 3 1 1 1 3 1 3 1 1 3 1 1 3 1 1 3 3 1 3 4 2 4 4 2 2 4 2
## [39] 2 4 2 4 2 2 4 2 4 2 2 2 4 4 4 2 4 4 2 4 4 2
```

```
k$centers
```

```
##      tmp
## 1  3.699284 -2.085837
## 2 -2.085837  3.699284
## 3  2.367528 -3.055250
## 4 -3.055250  2.367528
```

Q3. Plot `x` colored by the `kmeans` cluster assignment and add cluster centers as blue points

```
plot(x, col=k$cluster)
points(k$centers, col="blue", pch=15, cex=2)
```



Hierarchical Clustering

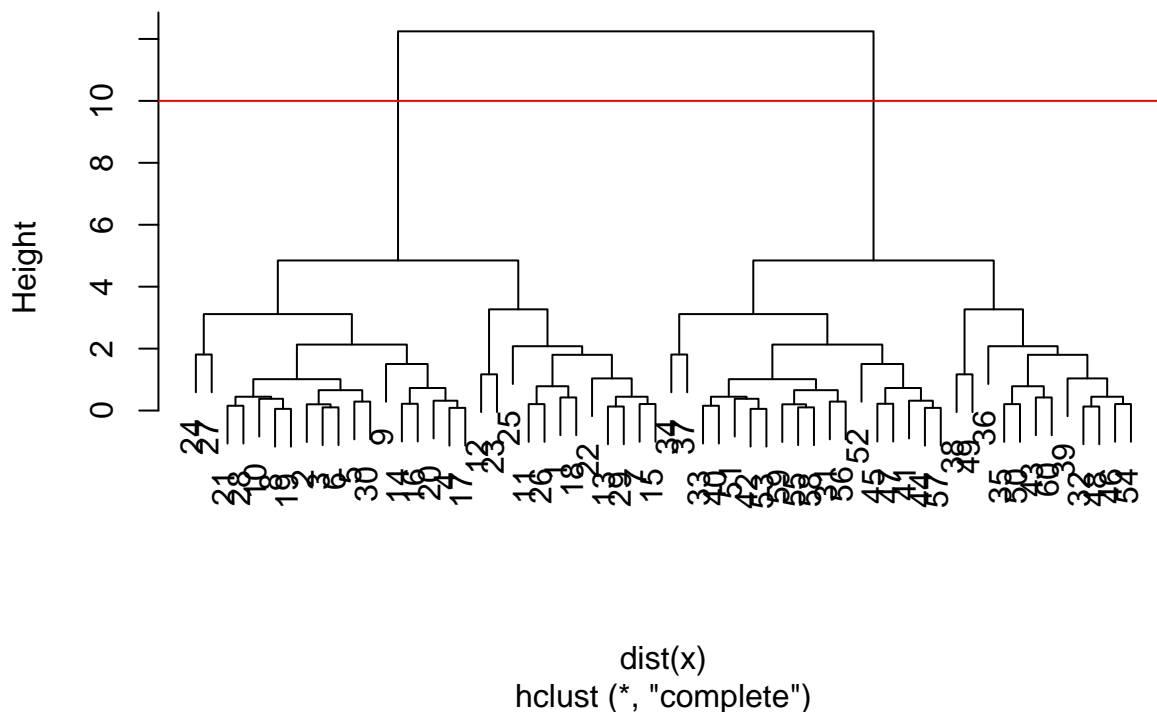
The `hclust()` function needs a distance matrix as input not our original data. For this we use the `dist()` function.

```
hc <- hclust(dist(x))
hc
```

```
##
## Call:
## hclust(d = dist(x))
##
## Cluster method   : complete
## Distance        : euclidean
## Number of objects: 60
```

```
plot(hc)
abline(h=10, col="red")
```

Cluster Dendrogram



To get our cluster membership vector we need to cut our tree and for this we use the `cutree()`

```
cutree(hc, h=10)
```

[illegible]

You can cut by a given height $h=$ or into a given number of k groups with $k=$

```
cutree(hc, k=2)
```

[illegible]

Principal Component Analysis

PCA of UK food data

Let's read our data about the weird stuff folks from the UK eat and drink:

```
url <- "https://tinyurl.com/UK-foods"
x <- read.csv(url, row.names=1)
```

Look at the first bit of the file:

```
head(x)
```

```
##           England Wales Scotland N.Ireland
## Cheese           105   103      103        66
## Carcass_meat     245   227      242       267
## Other_meat       685   803      750       586
## Fish            147   160      122        93
## Fats_and_oils    193   235      184       209
## Sugars           156   175      147       139
```

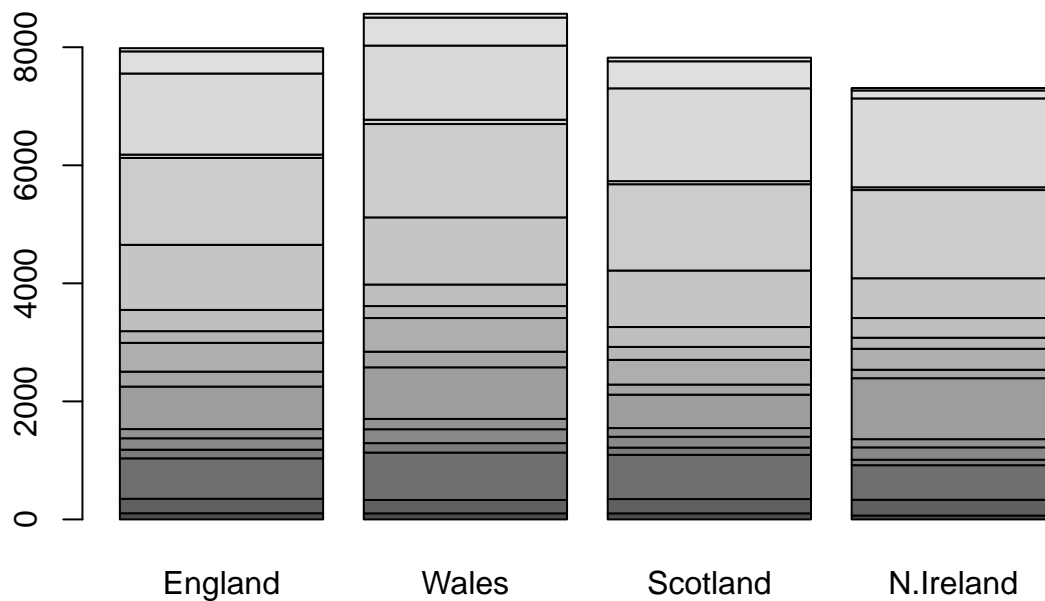
How many columns in this dataset:

```
ncol(x)
```

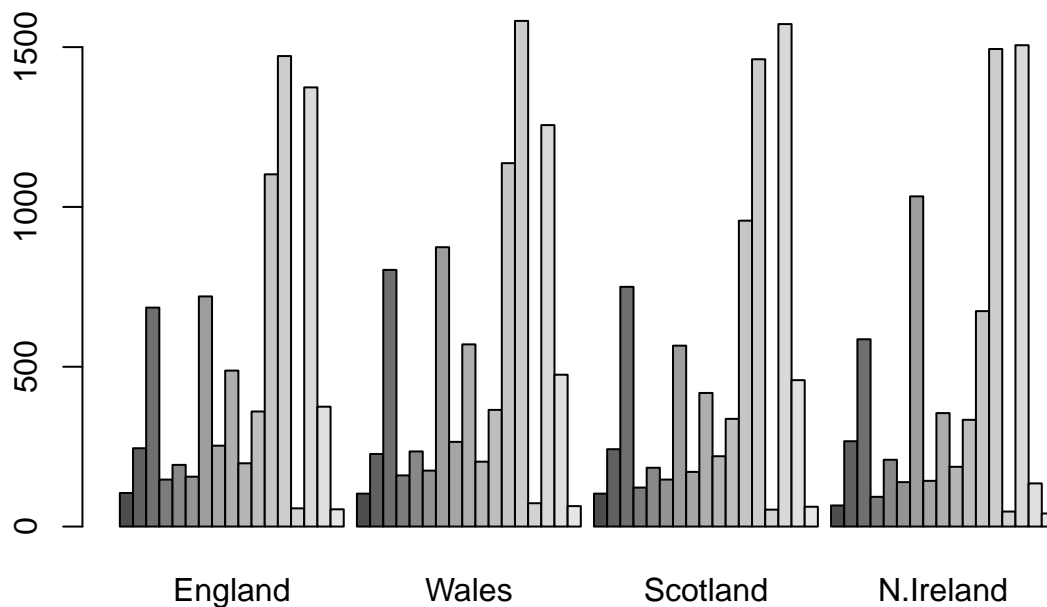
```
## [1] 4
```

We can make some plots to try to understand this data a bit more. For example barplots:

```
barplot(as.matrix(x))
```



```
barplot(as.matrix(x), beside = TRUE)
```



PCA to the rescue

The main base R function for PCA is called `prcomp()`

```
pca <- prcomp(t(x))
summary(pca)
```

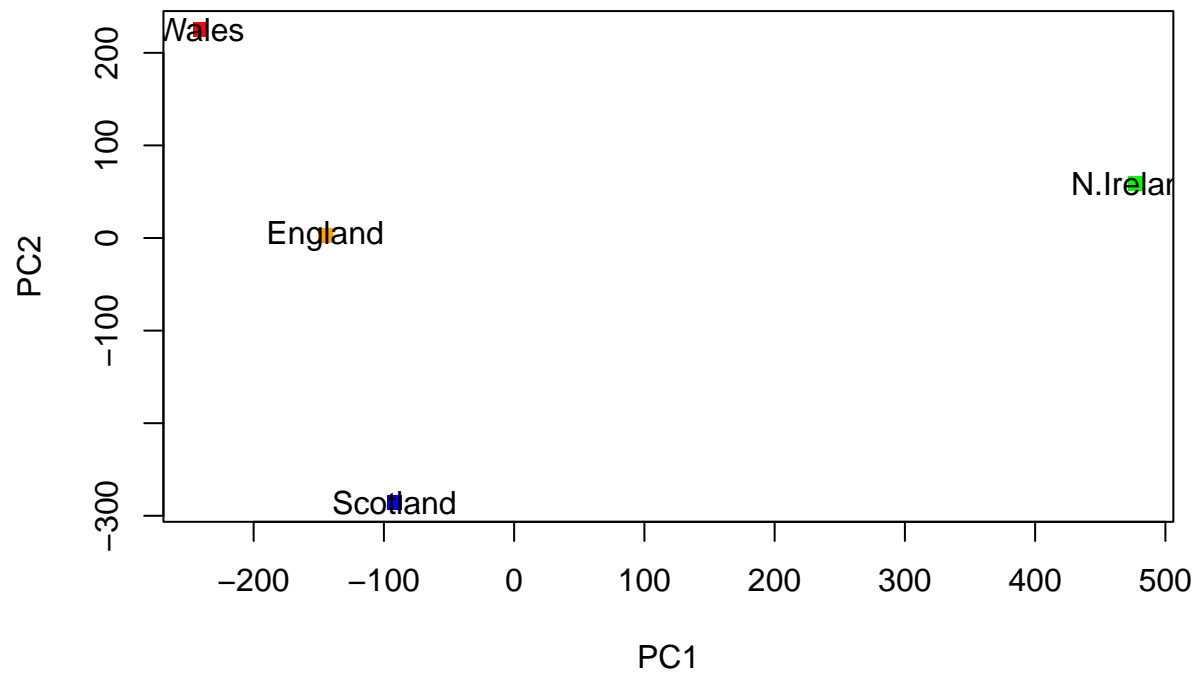
```
## Importance of components:
##              PC1      PC2      PC3      PC4
## Standard deviation  324.1502 212.7478 73.87622 4.189e-14
## Proportion of Variance  0.6744  0.2905  0.03503 0.000e+00
## Cumulative Proportion  0.6744  0.9650  1.00000 1.000e+00
```

What is in this returned `pca` object?

```
attributes(pca)
```

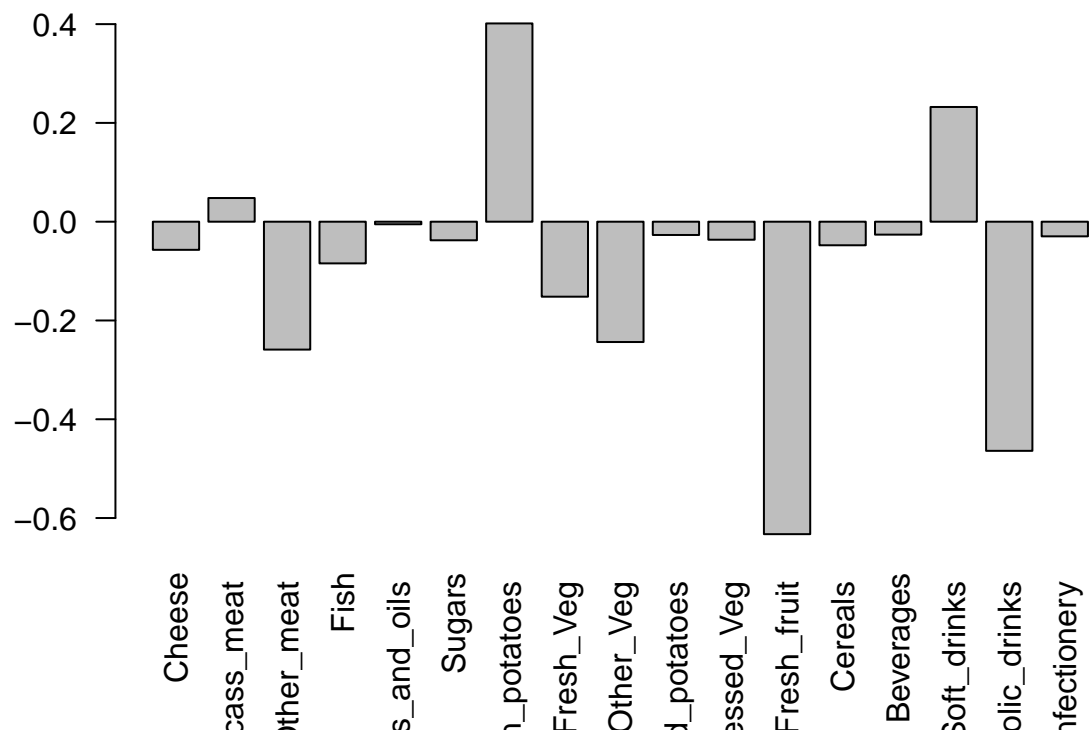
```
## $names
## [1] "sdev"      "rotation" "center"    "scale"     "x"
##
## $class
## [1] "prcomp"
```

```
plot(pca$x[,1:2], col=c("orange", "red", "blue", "green"), pch =15)
text(pca$x[,1], pca$x[,2], labels=colnames(x))
```



We can look at how the variables contribute to our new PCs by examining the `pca$rotation` component of our results.

```
barplot(pca$rotation[,1], las=2)
```



PCA of RNA-seq data

Read the data first.

```
url2 <- "https://tinyurl.com/expression-CSV"
rna.data <- read.csv(url2, row.names=1)
head(rna.data)
```

```
##          wt1 wt2  wt3  wt4 wt5 ko1 ko2 ko3 ko4 ko5
## gene1    439 458  408  429 420  90  88  86  90  93
## gene2    219 200  204  210 187 427 423 434 433 426
## gene3   1006 989 1030 1017 973 252 237 238 226 210
## gene4    783 792  829  856 760 849 856 835 885 894
## gene5    181 249  204  244 225 277 305 272 270 279
## gene6    460 502  491  491 493 612 594 577 618 638
```

How many genes (how many rows)?

```
nrow(rna.data)
```

```
## [1] 100
```

How many experiments (how many columns)?


```
ncol(rna.data)
```

```
## [1] 10
```

Let's do PCA of this dataset. First take the transpose as that is what the `prcomp()` function wants.

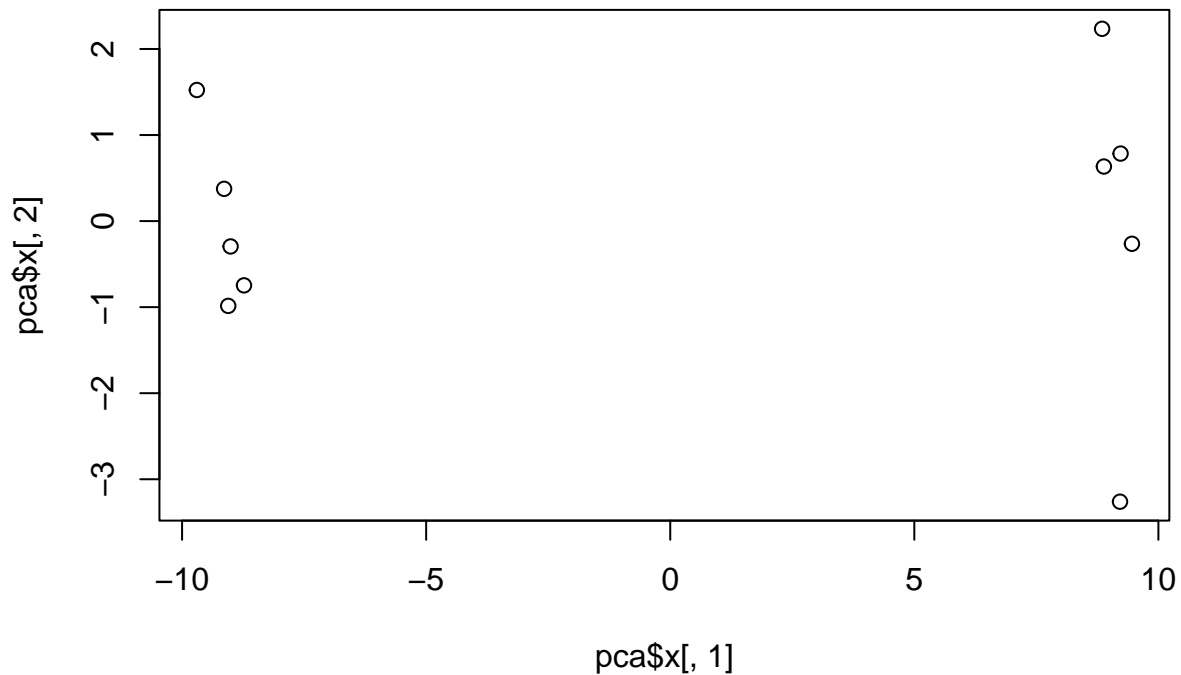
```
pca <- prcomp(t(rna.data), scale=TRUE)
summary(pca)
```

```
## Importance of components:
```

```
##              PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation    9.6237  1.5198  1.05787  1.05203  0.88062  0.82545  0.80111
## Proportion of Variance 0.9262  0.0231  0.01119  0.01107  0.00775  0.00681  0.00642
## Cumulative Proportion 0.9262  0.9493  0.96045  0.97152  0.97928  0.98609  0.99251
##              PC8      PC9      PC10
## Standard deviation    0.62065  0.60342  3.348e-15
## Proportion of Variance 0.00385  0.00364  0.000e+00
## Cumulative Proportion 0.99636  1.00000  1.000e+00
```

We can make our score plot (a.k.a. PCA plot) from the `pca$x`.

```
plot(pca$x[,1], pca$x[,2])
```



Make a little color vector to color up our plot by WT and KO

```
colvec <- c(rep("red", 5), rep("blue", 5))
plot(pca$x[,1], pca$x[,2], col=colvec, pch=15)
text(pca$x[,1], pca$x[,2], labels=colnames(rna.data))
```

