Class 07 ML1

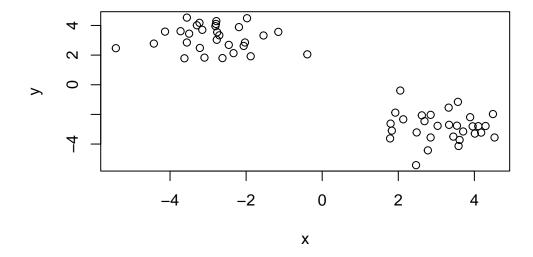
Neva Olliffe (PID A69026930)

#Clustering

We're starting with k-means clustering, one of the most prevalent of clustering methods. It's fast and does a lot for you.

Let's make up some data.

```
tmp <- c(rnorm(30, mean = 3), rnorm(30, mean = -3))
x <- cbind(x = tmp, y = rev(tmp))
plot(x)</pre>
```



The main kmeans function is kmeans.

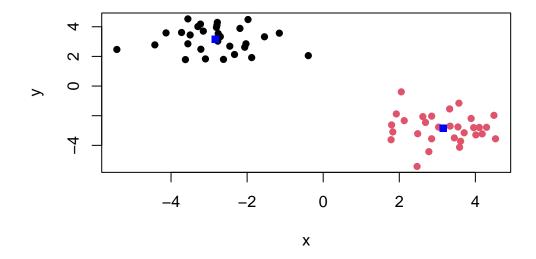
```
k <- kmeans(x, centers = 2, nstart = 20)</pre>
 k
K-means clustering with 2 clusters of sizes 30, 30
Cluster means:
       Х
1 -2.839127 3.161561
2 3.161561 -2.839127
Clustering vector:
Within cluster sum of squares by cluster:
[1] 49.74842 49.74842
(between_SS / total_SS = 91.6 %)
Available components:
[1] "cluster"
             "centers"
                        "totss"
                                   "withinss"
                                              "tot.withinss"
[6] "betweenss"
             "size"
                        "iter"
                                   "ifault"
   Q1: Get info on how many points are in each cluster.
 k$size
[1] 30 30
   Q2. The clustering result or membership vector?
 k$cluster
 Q3. What is the center of each cluster?
 k$centers
```

```
x y
1 -2.839127 3.161561
2 3.161561 -2.839127
```

Q4. Make a plot of our data colored by clustering reuslts with optional cluster centers displayed.

```
library(ggplot2)

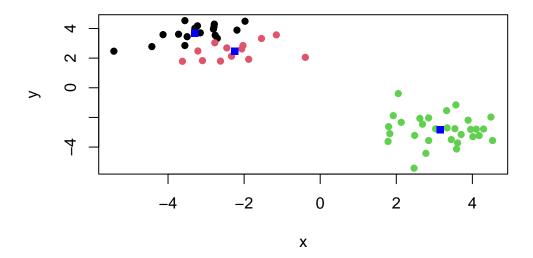
plot(x, col = k$cluster, pch = 16)
points(k$centers, col = "blue", pch = 15)
```



Q5. Run kmeans with cluster = 3 and plot as above.

```
k3 <- kmeans(x, centers = 3, nstart = 20)

plot(x, col = k3$cluster, pch = 16)
points(k3$centers, col = "blue", pch = 15)</pre>
```



K means always returns a result, even if no obvious groupings.

Hierarchical clustering

This clustering method can reveal the structure in data rather than imposing an arbitrary structure (like k-means).

The main function in "base" R is called hclust(). It requires a distance matrix as input, not the raw data itself.

```
hc <- hclust(dist(x))
hc</pre>
```

Call:

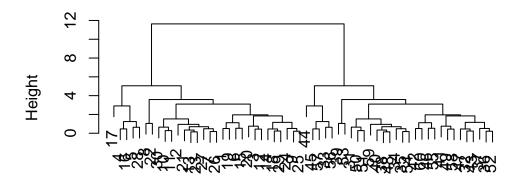
hclust(d = dist(x))

Cluster method : complete
Distance : euclidean

Number of objects: 60

plot(hc)

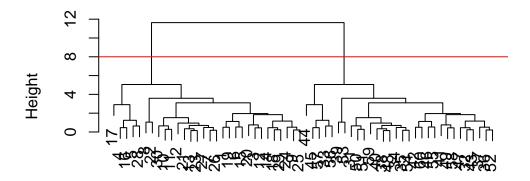
Cluster Dendrogram



dist(x) hclust (*, "complete")

```
plot(hc)
abline(h=8, col = "red")
```

Cluster Dendrogram



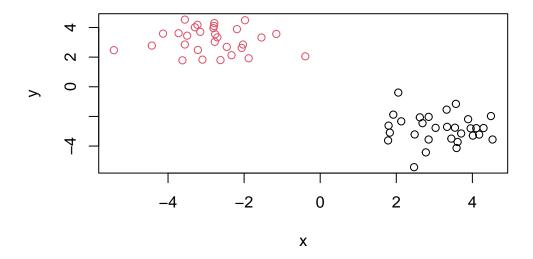
dist(x)
hclust (*, "complete")

The function to get our clusters from hclust is called cutree().

```
cutree(hc, h=8)
```

Q. Plot helust results in terms of our data colored by cluster membership.

```
plot(x, col = cutree(hc, h=8))
```



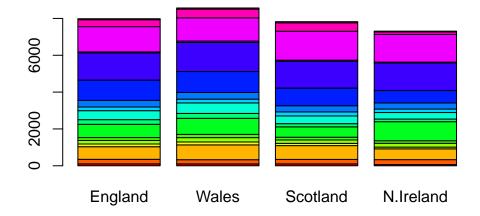
Principal component analysis (PCA)

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

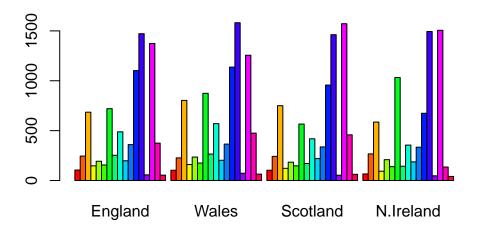
[1] 17 4

head(x)

	England	Wales	${\tt Scotland}$	${\tt N.Ireland}$
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



```
+ barplot(as.matrix(x), beside=T, col=rainbow(nrow(x)))
```

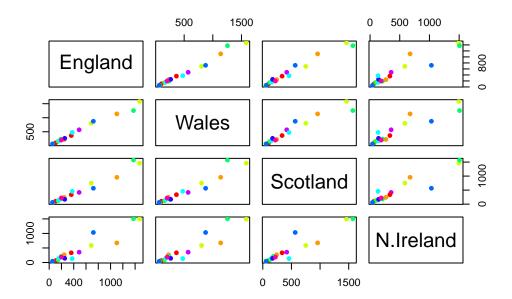


```
[,1] [,2] [,3] [,4]
 [1,]
      1.5 19.5 37.5 55.5
 [2,]
      2.5 20.5 38.5 56.5
 [3,]
      3.5 21.5 39.5 57.5
 [4,]
       4.5 22.5 40.5 58.5
      5.5 23.5 41.5 59.5
 [5,]
 [6,]
       6.5 24.5 42.5 60.5
 [7,]
       7.5 25.5 43.5 61.5
 [8,]
      8.5 26.5 44.5 62.5
      9.5 27.5 45.5 63.5
 [9,]
[10,] 10.5 28.5 46.5 64.5
[11,] 11.5 29.5 47.5 65.5
[12,] 12.5 30.5 48.5 66.5
[13,] 13.5 31.5 49.5 67.5
[14,] 14.5 32.5 50.5 68.5
[15,] 15.5 33.5 51.5 69.5
[16,] 16.5 34.5 52.5 70.5
[17,] 17.5 35.5 53.5 71.5
```

Q3: Changing what optional argument in the above barplot() function results in the following plot?

Changing beside from T to F generates this plot.

Q5: Generating all pairwise plots may help somewhat. Can you make sense of the following code and resulting figure? What does it mean if a given point lies on the diagonal for a given plot?



If a given point lies on the diagonal, it means that both countries consume the same amount of that particular type of food. So, points above the diagonal are consumed more in the country on the y axis, while those below are consumed more by the country on the x axis.

Q6. What is the main differences between N. Ireland and the other countries of the UK in terms of this data-set?

It is the dark blue point above the diagonal, but it's hard to tell which food type that is.

PCA to the rescue

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

It wants the transpose (using t()) of our data table for analysis.

```
pca <- prcomp(t(x))
summary(pca)</pre>
```

Importance of components:

```
        PC1
        PC2
        PC3
        PC4

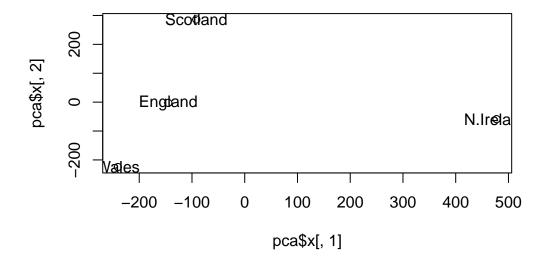
        Standard deviation
        324.1502
        212.7478
        73.87622
        3.176e-14

        Proportion of Variance
        0.6744
        0.2905
        0.03503
        0.000e+00

        Cumulative Proportion
        0.6744
        0.9650
        1.00000
        1.000e+00
```

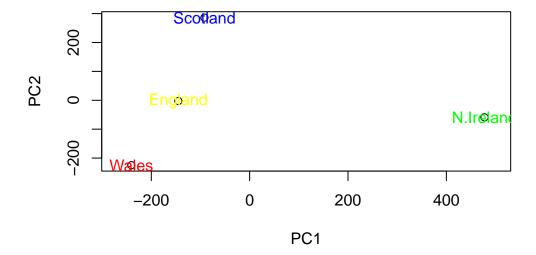
One of the main results is the "score plot", aka PC plot, etc.

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



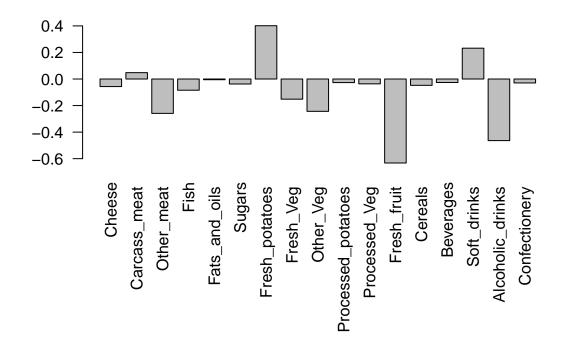
```
Q7 & Q8
```

```
# Plot PC1 vs PC2
plot(pca$x[,1], pca$x[,2], xlab="PC1", ylab="PC2", xlim=c(-270,500))
text(pca$x[,1], pca$x[,2], colnames(x), col=c("yellow", "red", "blue", "green"))
```

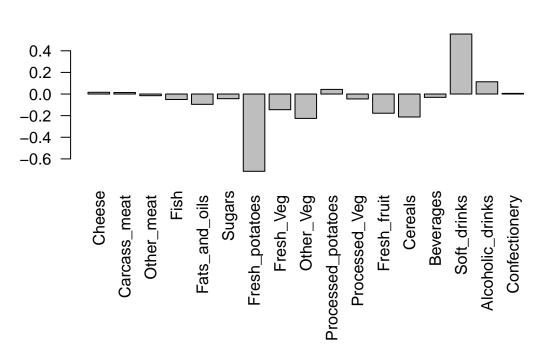


```
Q9

par(mar=c(10, 3, 0.35, 0))
barplot( pca$rotation[,1], las=2 )
```



```
par(mar=c(10, 3, 0.35, 0))
barplot( pca$rotation[,2], las=2 )
```

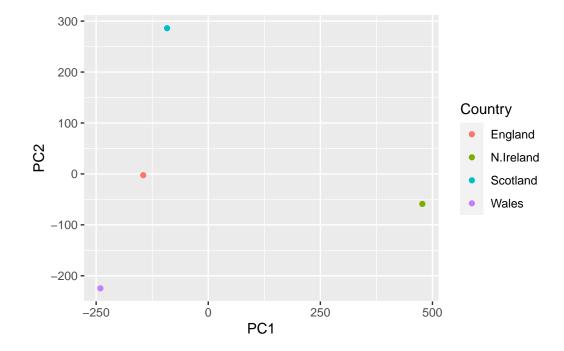


Soft drink consumption is pushing N. Ireland and Wales to the positive side, while differences in fresh potato consumption are pushing Wales, England, and Scotland away from N. Ireland.

Using ggplot

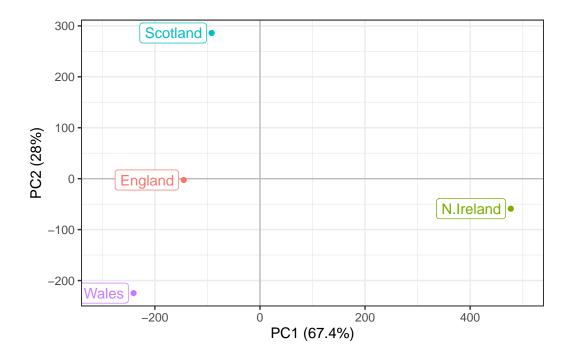
```
library(ggplot2)
df <- as.data.frame(pca$x)
df_lab <- tibble::rownames_to_column(df, "Country")

# Our first basic plot
ggplot(df_lab) +
   aes(PC1, PC2, col=Country) +
   geom_point()</pre>
```



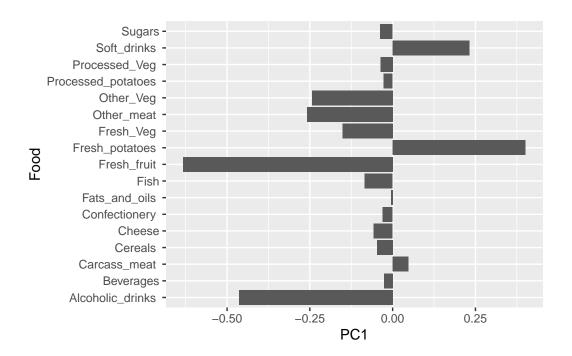
```
ggplot(df_lab) +
  aes(PC1, PC2, col=Country, label=Country) +
  geom_hline(yintercept = 0, col="gray") +
  geom_vline(xintercept = 0, col="gray") +
  geom_point(show.legend = FALSE) +
  geom_label(hjust=1, nudge_x = -10, show.legend = FALSE) +
```

```
expand_limits(x = c(-300,500)) +
xlab("PC1 (67.4%)") +
ylab("PC2 (28%)") +
theme_bw()
```

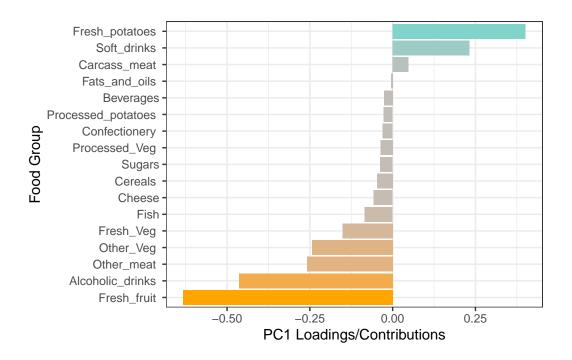


```
ld <- as.data.frame(pca$rotation)
ld_lab <- tibble::rownames_to_column(ld, "Food")

ggplot(ld_lab) +
  aes(PC1, Food) +
  geom_col()</pre>
```



```
ggplot(ld_lab) +
  aes(PC1, reorder(Food, PC1), bg=PC1) +
  geom_col() +
  xlab("PC1 Loadings/Contributions") +
  ylab("Food Group") +
  scale_fill_gradient2(low="orange", mid="grey", high="turquoise", guide=NULL) +
  theme_bw()
```



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

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

Q10

dim(rna.data)

[1] 100 10

There are 100 genes and 10 samples.