

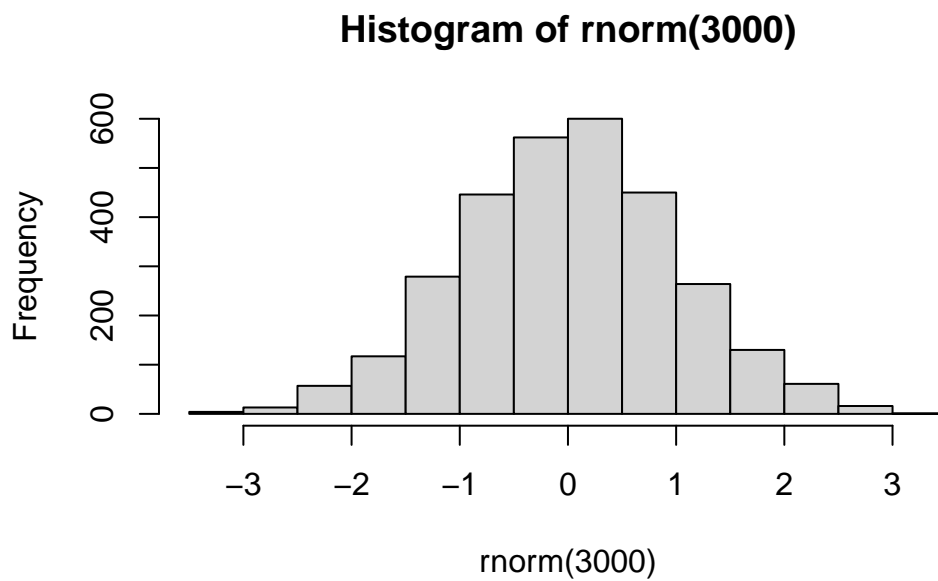
Class07

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Today we will delve into unsupervised machine learning with an initial focus on clustering and dimensionality reduction.

Let's start by making up some data to cluster. The `rnorm()` function can help us here.

```
hist(rnorm(3000))
```



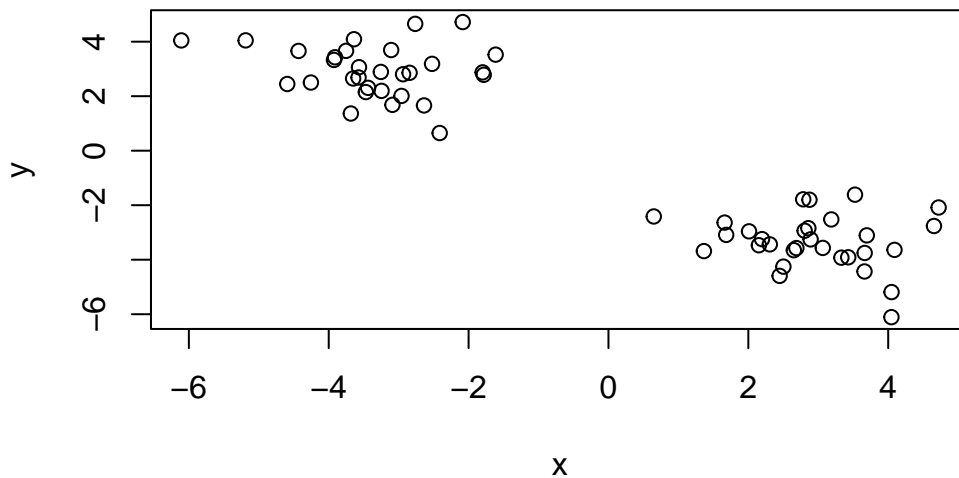
Lets get some data centeres at 3,-3

```
#Combine 30 +3 values with 30 -3 values  
x <- c(rnorm(30, mean = 3), rnorm(30, mean = -3))
```

```
# Bind these values together
z <- cbind(x = x, y = rev(x))
head(z)
```

```
      x      y
[1,] 2.873860 -1.799017
[2,] 2.009860 -2.959311
[3,] 3.693799 -3.107143
[4,] 2.858311 -2.843940
[5,] 1.661003 -2.637604
[6,] 2.447735 -4.592990
```

```
plot(z)
```



K-means

Now we can see how K-means clusters this data. The main function for K-means clustering in “base R” is called `kmeans()`

```
km <- kmeans(z, center = 2)
km
```

K-means clustering with 2 clusters of sizes 30, 30

Cluster means:

```
      x      y
1 -3.341254  2.921022
2  2.921022 -3.341254
```

Clustering vector:

```
[1] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1
[39] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

Within cluster sum of squares by cluster:

```
[1] 54.67491 54.67491
(between_SS / total_SS =  91.5 %)
```

Available components:

```
[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
[6] "betweenss"    "size"         "iter"         "ifault"       "
```

```
attributes(km)
```

\$names

```
[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
[6] "betweenss"    "size"         "iter"         "ifault"       "
```

\$class

```
[1] "kmeans"
```

Q. What size is each cluster?

```
km$size
```

```
[1] 30 30
```

Q. The cluster membership vector (i.e. the answer: cluster to which each point is allocated)

```
km$cluster
```

```
[1] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1  
[39] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

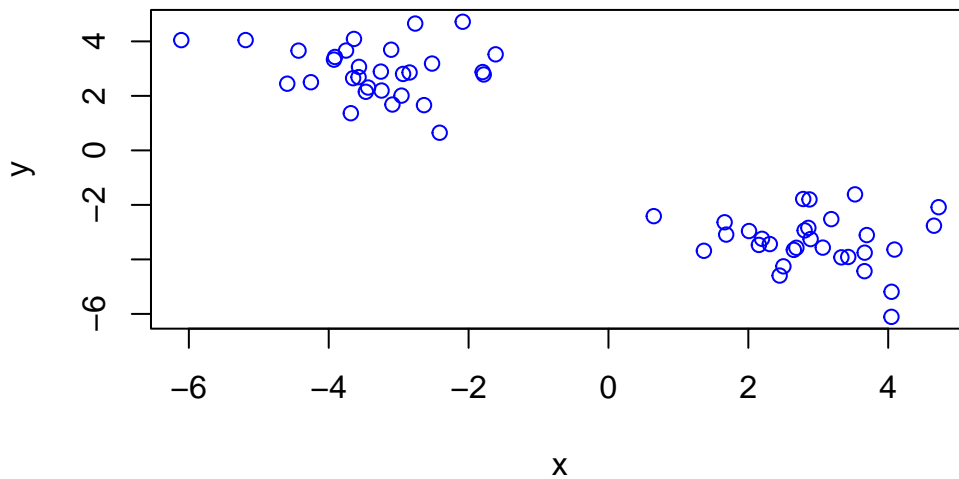
Cluster centers

```
km$centers
```

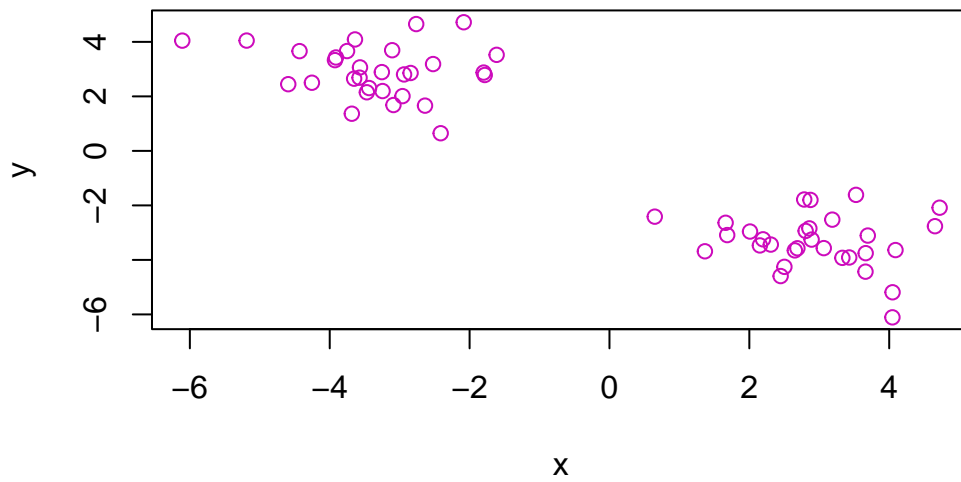
```
      x      y  
1 -3.341254  2.921022  
2  2.921022 -3.341254
```

Q. Make a results figure, i.e. plot the data **z** colored by cluster membership and show the cluster centers.

```
plot(z, col = "blue")
```

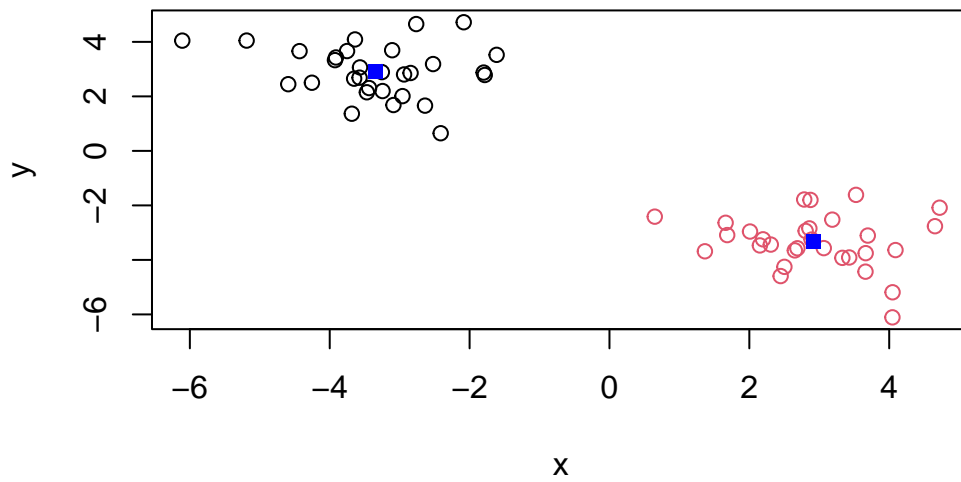


```
plot(z, col = 6)
```



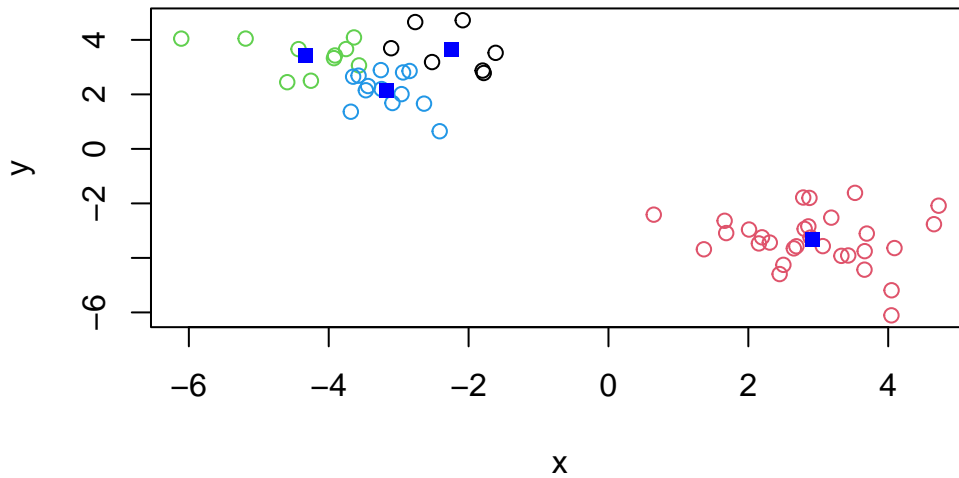
```
# Make each cluster a different color
plot(z, col = km$cluster)

# Add a point that represents the center of each cluster to the plot
points(km$centers, col = "blue", pch = 15)
```



Q. Re-run your k-means clustering and ask for 4 clusters and plot the results as above

```
km4 <- kmeans(z, center = 4)
plot(z, col = km4$cluster)
points(km4$centers, col = "blue", pch = 15)
```



Hierarchical Clustering

The main “base R” function for this is `hclust()`. Unlike `kmeans()` you can’t just give your dataset as input, you need to provide a distance matrix.

We can use the `dist()` function for this

```
d <- dist(z)
```

```
hc <- hclust(d)
hc
```

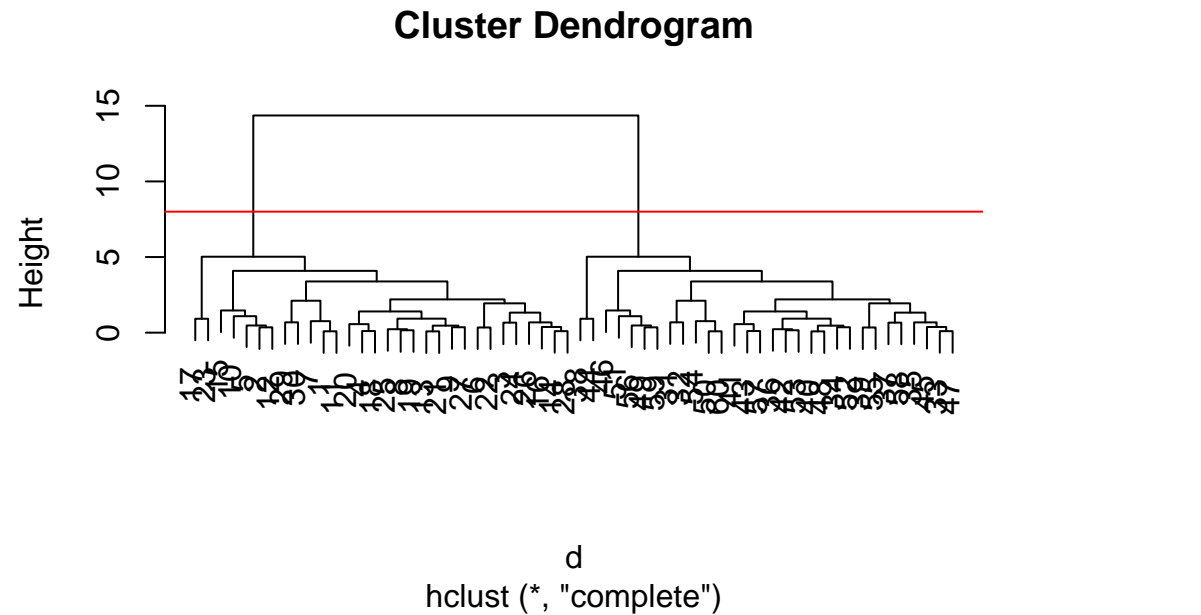
Call:

```
hclust(d = d)
```

```
Cluster method : complete
Distance       : euclidean
Number of objects: 60
```

There is a custom `plot()` for `hclust` objects. Let’s see it.

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



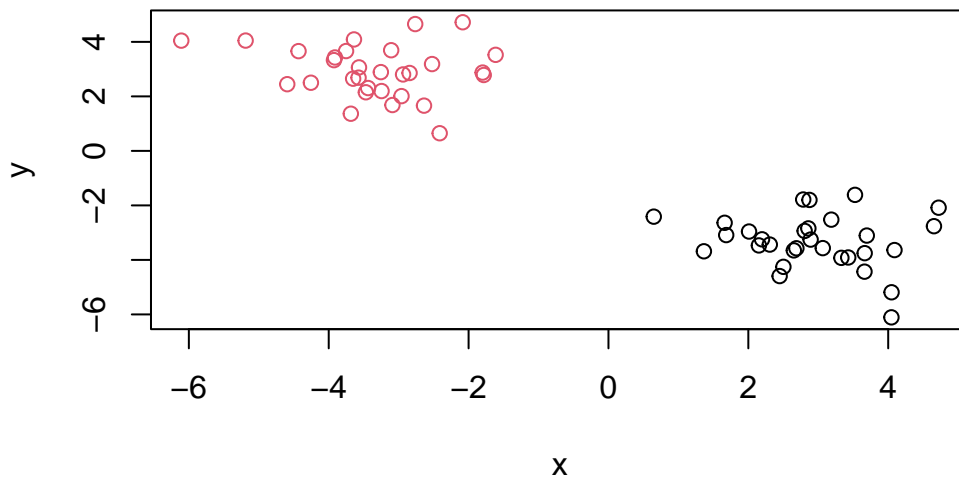
The function to extract clusters/groups from an `hclust` object/tree is called `cutree()`.

```
grps <- cutree(hc, h = 8)
grps
```

[illegible]

Q. Plot data with hlcust clusters

```
plot(z, col = grps)
```

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

[illegible]

Principal Component Analysis (PCA)

the main function for PCA in base R for PCA is called `prcomp()`. There are many, many add on packages with PCA functions tailored to particular data types (RNSASeq, protein, structures, metagenomica, etc...)

PCA of UK food data

Read the data into R, it is a CSV file and we can use `read.csv()` to read it:

```
url <- "https://tinyurl.com/UK-foods"
x <- read.csv(url)
x
```

	X	England	Wales	Scotland	N.Ireland
1	Cheese	105	103	103	66
2	Carcass_meat	245	227	242	267
3	Other_meat	685	803	750	586
4	Fish	147	160	122	93
5	Fats_and_oils	193	235	184	209
6	Sugars	156	175	147	139
7	Fresh_potatoes	720	874	566	1033
8	Fresh_Veg	253	265	171	143
9	Other_Veg	488	570	418	355
10	Processed_potatoes	198	203	220	187
11	Processed_Veg	360	365	337	334
12	Fresh_fruit	1102	1137	957	674
13	Cereals	1472	1582	1462	1494
14	Beverages	57	73	53	47
15	Soft_drinks	1374	1256	1572	1506
16	Alcoholic_drinks	375	475	458	135
17	Confectionery	54	64	62	41

I would like the food names as row names not as their own column of data

```
rownames(x) <- x[,1]
x <- x[,-1]
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
Fresh_potatoes	720	874	566	1033
Fresh_Veg	253	265	171	143
Other_Veg	488	570	418	355
Processed_potatoes	198	203	220	187
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Cereals	1472	1582	1462	1494
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Soft_drinks	1374	1256	1572	1506
Alcoholic_drinks	375	475	458	135
Confectionery	54	64	62	41

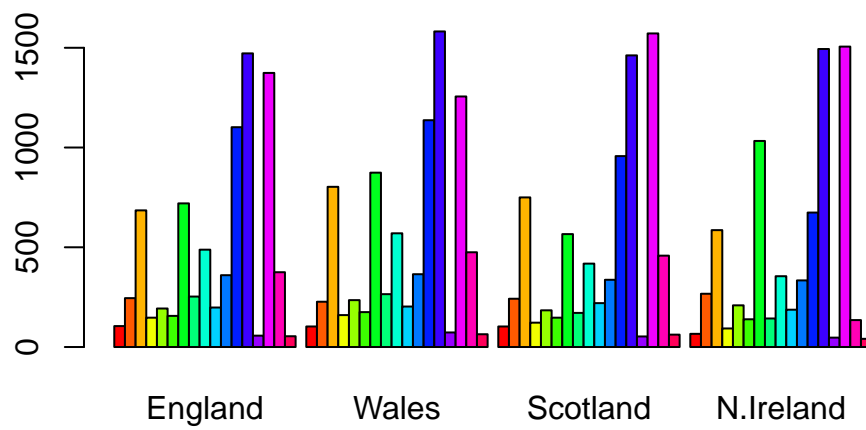
A better way to do this is to do it at the same time of data import with `read.csv()`

```
food <- read.csv(url, row.names =1)
food
```

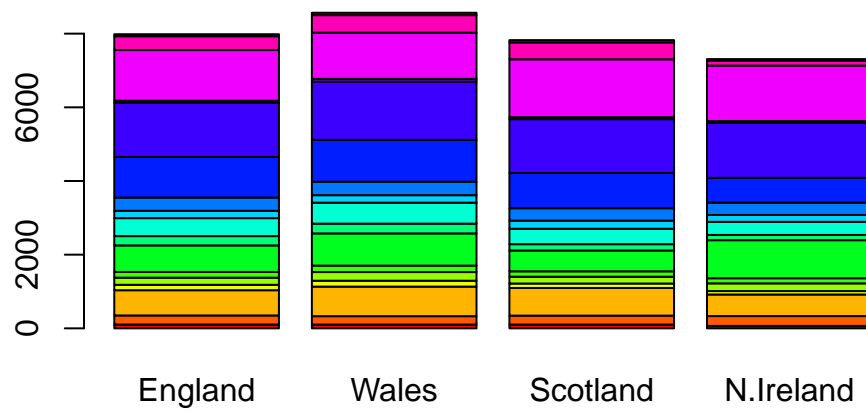
	England	Wales	Scotland	N.Ireland
Cheese	105	103	103	66
Carcass_meat	245	227	242	267
Other_meat	685	803	750	586
Fish	147	160	122	93
Fats_and_oils	193	235	184	209
Sugars	156	175	147	139
Fresh_potatoes	720	874	566	1033
Fresh_Veg	253	265	171	143
Other_Veg	488	570	418	355
Processed_potatoes	198	203	220	187
Processed_Veg	360	365	337	334
Fresh_fruit	1102	1137	957	674
Cereals	1472	1582	1462	1494
Beverages	57	73	53	47
Soft_drinks	1374	1256	1572	1506
Alcoholic_drinks	375	475	458	135
Confectionery	54	64	62	41

Let's make some plots and dig into the data a little.

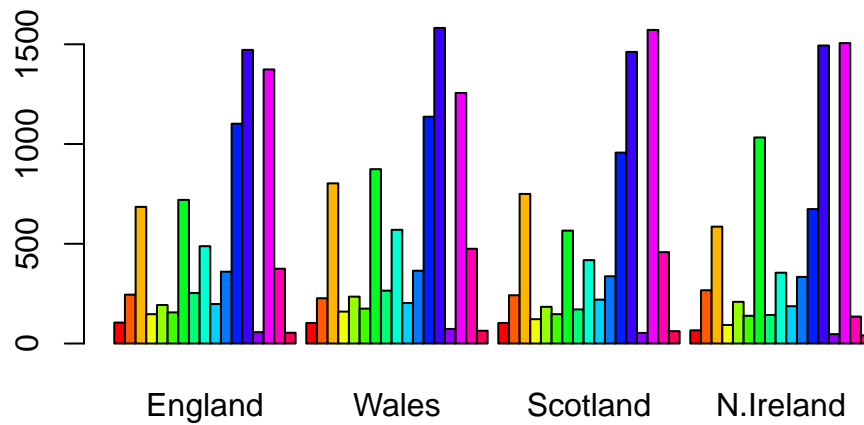
```
barplot(as.matrix(x), beside=T, col=rainbow(nrow(food)))
```



```
barplot(as.matrix(x), beside=F, col=rainbow(nrow(food)))
```

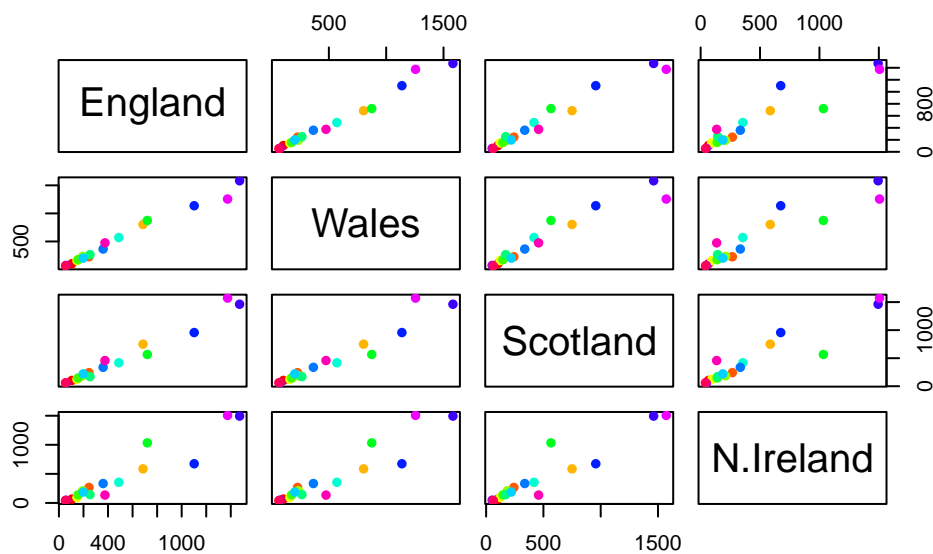


```
barplot(as.matrix(x), beside=T, col=rainbow(nrow(food)))
```



How about a “pairs” plot where we plot each country against all other countries.

```
pairs(food, col=rainbow(nrow(food)), pch=16)
```



Really there has to be a better way.....

PCA to the rescue!

We can run a Principal Component Analysis (PCA). We need to take the transpose to get the foods in the columns and the countries in the rows

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

Importance of components:

	PC1	PC2	PC3	PC4
Standard deviation	324.1502	212.7478	73.87622	2.921e-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 my pca results object?

```
attributes(pca)
```

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

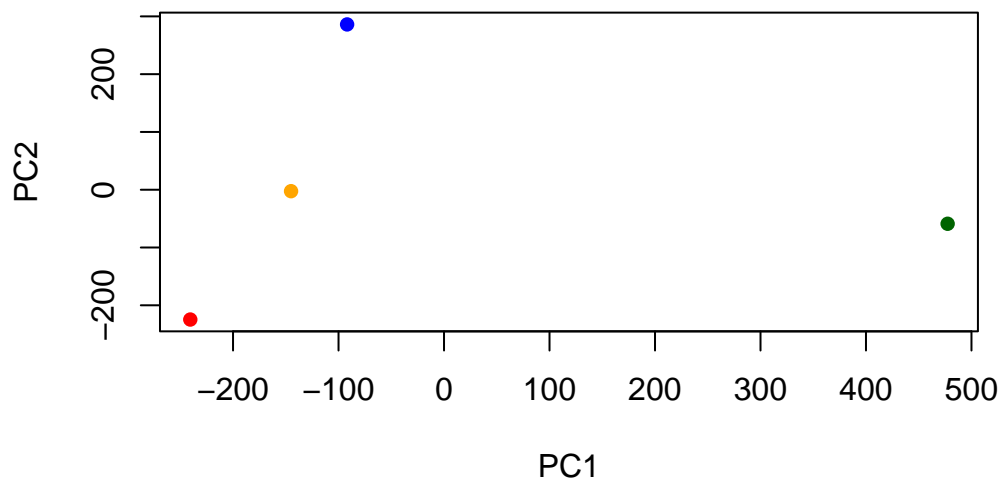
```
$class
[1] "prcomp"
```

```
pca$x
```

	PC1	PC2	PC3	PC4
England	-144.99315	-2.532999	105.768945	-9.152022e-15
Wales	-240.52915	-224.646925	-56.475555	5.560040e-13
Scotland	-91.86934	286.081786	-44.415495	-6.638419e-13
N.Ireland	477.39164	-58.901862	-4.877895	1.329771e-13

To make my main result figure, often called a PC plot (or score plot, ordination plot, or PC1 vs PC2 plot)

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



To see the contributions of the original variables (foods) to these new PCs we can look at the `pca$rotation` component of our results

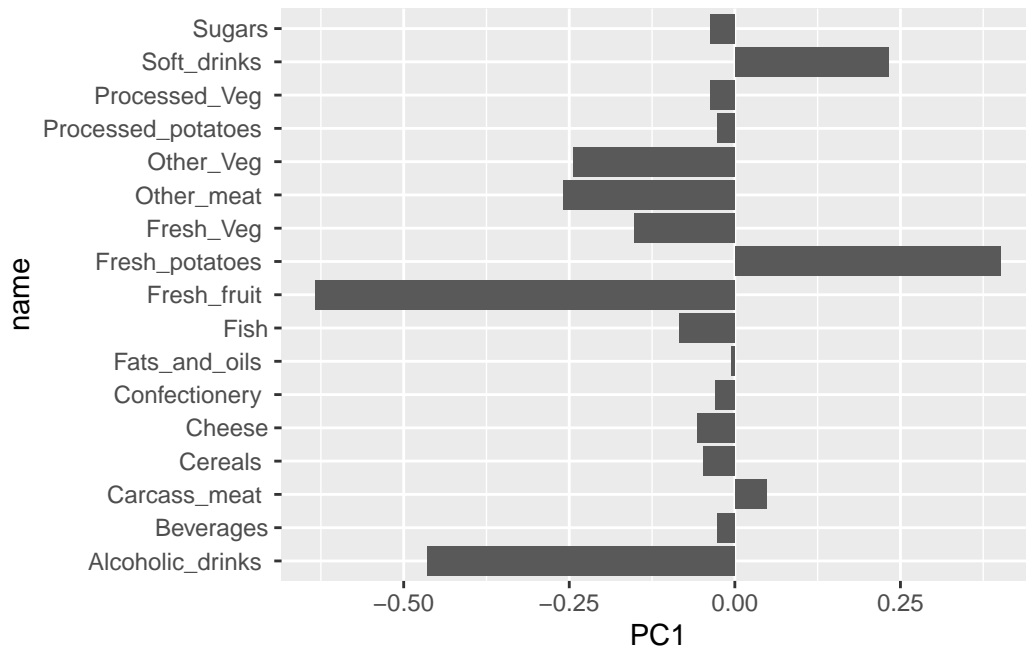
```
pca$rotation
```

	PC1	PC2	PC3	PC4
Cheese	-0.056955380	0.016012850	0.02394295	-0.409382587
Carcass_meat	0.047927628	0.013915823	0.06367111	0.729481922
Other_meat	-0.258916658	-0.015331138	-0.55384854	0.331001134
Fish	-0.084414983	-0.050754947	0.03906481	0.022375878
Fats_and_oils	-0.005193623	-0.095388656	-0.12522257	0.034512161
Sugars	-0.037620983	-0.043021699	-0.03605745	0.024943337
Fresh_potatoes	0.401402060	-0.715017078	-0.20668248	0.021396007
Fresh_Veg	-0.151849942	-0.144900268	0.21382237	0.001606882
Other_Veg	-0.243593729	-0.225450923	-0.05332841	0.031153231
Processed_potatoes	-0.026886233	0.042850761	-0.07364902	-0.017379680
Processed_Veg	-0.036488269	-0.045451802	0.05289191	0.021250980
Fresh_fruit	-0.632640898	-0.177740743	0.40012865	0.227657348
Cereals	-0.047702858	-0.212599678	-0.35884921	0.100043319
Beverages	-0.026187756	-0.030560542	-0.04135860	-0.018382072
Soft_drinks	0.232244140	0.555124311	-0.16942648	0.222319484
Alcoholic_drinks	-0.463968168	0.113536523	-0.49858320	-0.273126013
Confectionery	-0.029650201	0.005949921	-0.05232164	0.001890737

```
library(ggplot2)
loadings <- as.data.frame(pca$rotation)

loadings$name <- rownames(loadings)

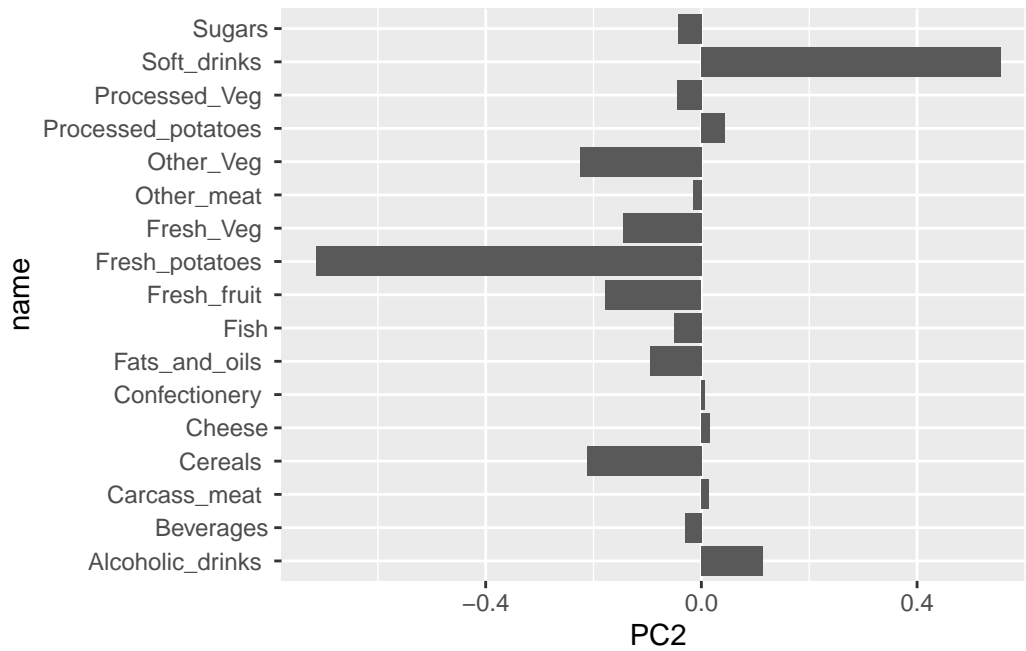
ggplot(loadings) + aes(PC1, name) + geom_col()
```

```
loadings <- as.data.frame(pca$rotation)

loadings$name <- rownames(loadings)

ggplot(loadings) + aes(PC2, name) + geom_col()
```



```
loadings <- as.data.frame(pca$x)
loadings_lab <- tibble::rownames_to_column(loadings, "Country")

ggplot(loadings_lab) +
  aes(PC1, PC2, col=Country) +
  geom_point()
```

