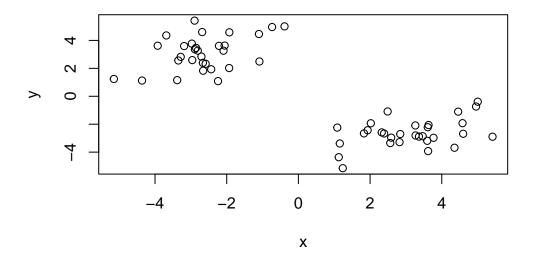
Class 7: Machine Learning I

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K-means

plot(x)

Make up some input data where we know what the answer should be



Use the kmeans() function setting k to 2 and nstart=20

```
km <- kmeans(x, centers = 2, nstart=20)
km</pre>
```

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

Cluster means:

Clustering vector:

Within cluster sum of squares by cluster:

```
[1] 73.28979 73.28979
(between_SS / total_SS = 87.1 %)
```

Available components:

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

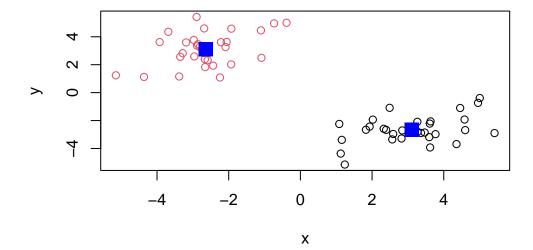
Q. What component if your result object details -cluster assignment / membership? cluster center?

km\$cluster

km\$centers

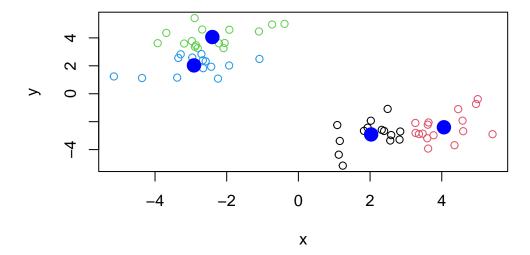
Q. Plot x colored y the kmeans cluster assignment and add cluster centers as blue points.

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



PLay with kmeans and ask for different number of clusters

```
km <- kmeans(x, centers = 4, nstart = 20)
plot(x, col= km$cluster)
points(km$centers, col = "blue", pch = 16, cex =2)</pre>
```



Hierarchical Clustering

This is another very useful and widely employed clustering method which has the advnatage over kmeans in that it can help reveal the somethign of the true grouping in your data.

The hclust() function wants a distance matrix as input. We can get this from the dist() function.

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

```
Call:
hclust(d = d)
```

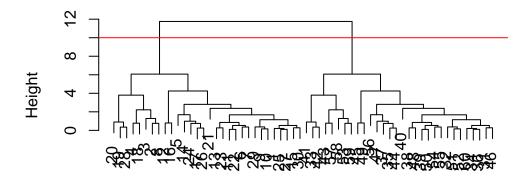
Cluster method : complete
Distance : euclidean

Number of objects: 60

There is a plot method for hclust results:

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

Cluster Dendrogram



d hclust (*, "complete")

To get my cluster membership vector I need to "cut" my tree to yield sub-trees or branches with all the members of a given cluster residing on the same cut branch. The function to do this is called cutree()

It is often helpful to use the k= argument to cutree rather than the h= height of cutting with 'cutree()'. This will cut the tree to yield the number of clusters you want.

```
cutree(hc, k =4)
```

```
[1] 1 2 2 2 1 1 1 2 1 1 1 1 1 1 1 1 1 2 2 2 1 1 1 1 1 1 1 2 1 1 3 3 4 3 3 3 3 3 3 3 3 3 3 4 4 4 4 3 3 3 3 3 3 3 3 3 3 3 4 4 4 3
```

Principal Component Analysis (PCA)

The base R function for PCA is called prcomp() Lets play with some 17D data (very small data set) and see how PCA can help.

PCA of UK food data

Import the data

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

	X	England	Wales	Scotland	N.lreland
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

Q1. How many rows and columns are in your new data frame named x? What R functions could you use to answer this questions?

```
dim(x)
```

[1] 17 5

Preview the first 6 rows

head(x)

	Х	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

Note how the minus indexing works

```
rownames(x) <- x[,1]
x <- x[,-1]
head(x)
```

	England	Wales	${\tt Scotland}$	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

```
dim(x)
```

[1] 17 4

```
x <- read.csv(url, row.names=1)
head(x)</pre>
```

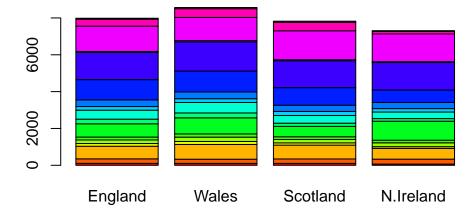
	England	Wales	${\tt Scotland}$	N.Ireland
Cheese	105	103	103	66
Carcass_meat	245	227	242	267
Other_meat	685	803	750	586
Fish	147	160	122	93
Fats_and_oils	193	235	184	209
Sugars	156	175	147	139

Q2. Which approach to solving the 'row-names problem' mentioned above do you prefer and why? Is one approach more robust than another under certain circumstances?

I prefer the second approach better because it is more condensed and shorter. Furthermore, the first approach code block starts deleting columns once you run it multiple times. Therefore the second approach code is more robust and sustainable.

Spotting major differences and trends

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



Q3: Changing what optional argument in the above barplot() function results in the following plot? Changing the beside=T to beside =False has made the bar plots wider and combined instead of displayed as a distribution. Leaving this argument out has the same effect as it being false because each bar of the plot will correspond to being stacked.

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?

```
pairs(x, col=rainbow(10), pch=16)
```



I think that it is difficult of make sense of this data. If a given point is on the diagonal for a given plot, I think that it means that it follows the line of best fit and follows the trends of the data. I think that it also shows the density and level of correlation between the variables.

Q6. What is the main differences between N. Ireland and the other countries of the UK in terms of this data-set? The main differences between N. Ireland and the other countries of the UK in terms of this data set would be that N. Ireland eats the most carcass meat and least amount of fish.

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

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
```

a "PCA plot" (a.k.a. "Score Plot", PC1vsPC2 plot, etc.)

```
pca$x
```

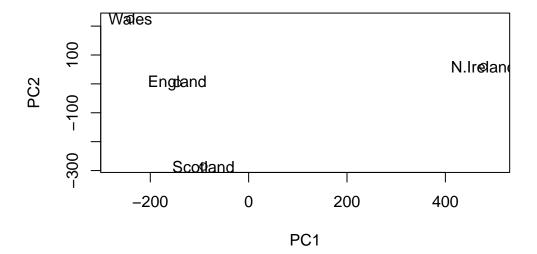
```
PC1
                              PC2
                                           PC3
                                                         PC4
England
          -144.99315
                         2.532999 -105.768945
                                                2.842865e-14
Wales
          -240.52915
                       224.646925
                                    56.475555
                                                7.804382e-13
Scotland
           -91.86934 -286.081786
                                    44.415495 -9.614462e-13
N.Ireland 477.39164
                        58.901862
                                     4.877895
                                                1.448078e-13
  # Use the prcomp() PCA function
  pca <- prcomp( t(x) )</pre>
  summary(pca)
```

Importance of components:

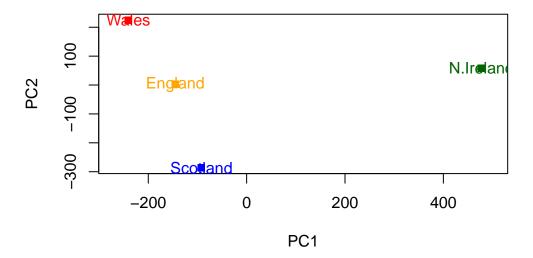
```
PC1 PC2 PC3 PC4
Standard deviation 324.1502 212.7478 73.87622 4.189e-14
Proportion of Variance 0.6744 0.2905 0.03503 0.000e+00
Cumulative Proportion 0.6744 0.9650 1.00000 1.000e+00
```

Q7. Complete the code below to generate a plot of PC1 vs PC2. The second line adds text labels over the data points. # 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))
```



Q8. Customize your plot so that the colors of the country names match the colors in our UK and Ireland map and table at start of this document.



```
v <- round( pca$sdev^2/sum(pca$sdev^2) * 100 )
v

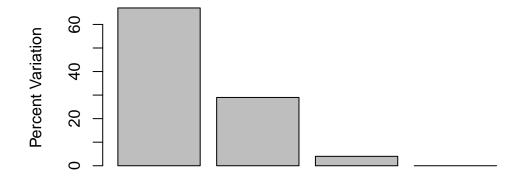
[1] 67 29 4 0

## or the second row here...
z <- summary(pca)
z$importance

PC1 PC2 PC3 PC4

Standard deviation 324.15019 212.74780 73.87622 4.188568e-14</pre>
```

```
barplot(v, xlab="Principal Component", ylab="Percent Variation")
```



Principal Component

```
##Digging deeper (variable loadings)
```

```
## Lets focus on PC1 as it accounts for > 90% of variance
par(mar=c(10, 3, 0.35, 0))
barplot( pca$rotation[,1], las=2 )
```

