Class 7: Machine Learning 1

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Invalid Date

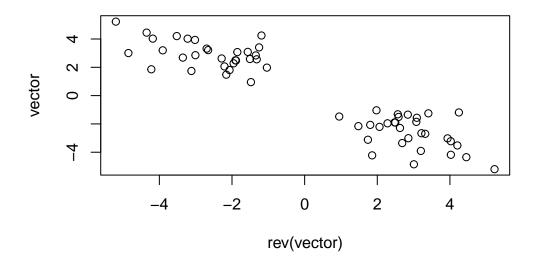
Today we are going to explore some core machine learning methods. Namely clustering and dimensionality reduction approaches.

Kmeans clustering

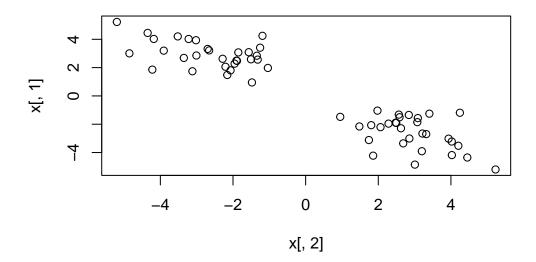
The main function for k-means in "base" R is called 'kmeans()'. Let's first make up some data to see how kmeans works and to get a look at the results.

Make a vector with 60 total points half centered at +3 and half centered at -3.

```
vector <- c(rnorm(30, mean = 3), rnorm(30, mean = -3))
plot(vector ~ rev(vector))</pre>
```



```
x <- cbind(x=vector, y=rev(vector))
plot(x[,1] ~ x[,2])</pre>
```



```
Run 'kmeans()' asking for two clusters:
```

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

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

Cluster means:

```
x y
1 -2.610584 2.923966
2 2.923966 -2.610584
```

Clustering vector:

Within cluster sum of squares by cluster:

```
[1] 67.48677 67.48677
(between_SS / total_SS = 87.2 %)
```

Available components:

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

```
attributes(k)
```

\$names

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

\$class

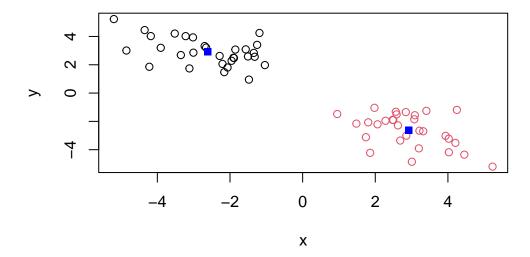
[1] "kmeans"

What is my clustering result? i.e. what cluster does each point reside in?

```
k$cluster
```

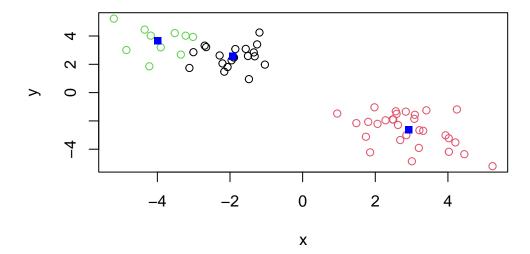
Q. Plot your data 'x' showing your clustering result and the center point for each cluster?

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



Q. Run kmeans, cluster into 3 groups and plot the result

```
k2 <- kmeans(x, centers=3, nstart=20)
plot(x, col=k2$cluster)
points(k2$centers, pch = 15, col = ("blue"))</pre>
```



The big limitation of k-means is that it imposes a structure on your data (i.e. a clustering) that you ask for in the first place. You have to give a number of clusters in order to work.

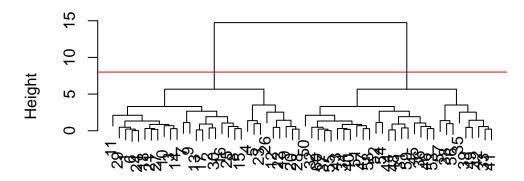
Hierarchical clustering

The main function in "base" R for this is called 'hclust()'. It wants a distance matrix as input not the data itself. We can calculate a distance matrix in lots of different ways but here we will use the 'dist()' function.

Starts by making the same number of clusters as the number of points and then goes down and down in iterations (top-down). It can also be bottom-up.

```
d <- dist(x, diag = T)
hc <- hclust(d)
plot(hc)
abline(h=8, col="red")</pre>
```

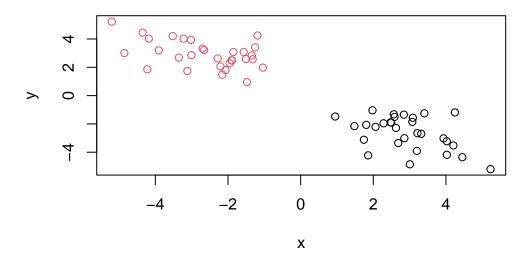
Cluster Dendrogram



d hclust (*, "complete")

To get the cluster membership vector we need to "cut" the tree at a given height that we pick. The function to do this is called 'cutree()'.

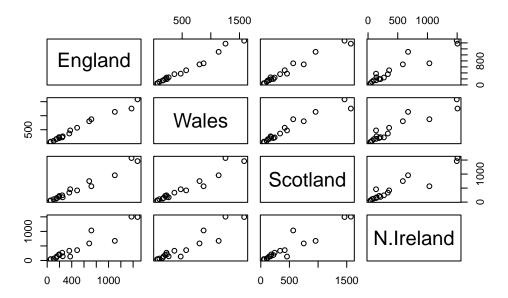
 $grps \leftarrow cutree(hc, h=8)$ # you can also cut the tree in number of clusters (e.g. k=2) plot(x, col=grps)



Principal Component Analysis (PCA)

Eigenvectors: lines of fit to your data. Each one explains a percentage of variance. PC1 is the best one and it goes on. The data is always going to be more spread in 1, then 2, etc., because they capture variance in that order.

```
# Loading data
url <- "https://tinyurl.com/UK-foods"
data <- read.csv(url, row.names = 1)
pairs(data) # scatter plots between the columns</pre>
```



The main function to do PCA in "base" R is called 'prcomp(). It wants the foods as the columns and the countries as the rows, so we have to transpose the data.

```
pca <- prcomp(t(data))
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
```

```
attributes(pca)
```

\$names

[1] "sdev" "rotation" "center" "scale" "x'

\$class

[1] "prcomp"

pca\$x #The values on the new vector for each country

```
      PC1
      PC2
      PC3
      PC4

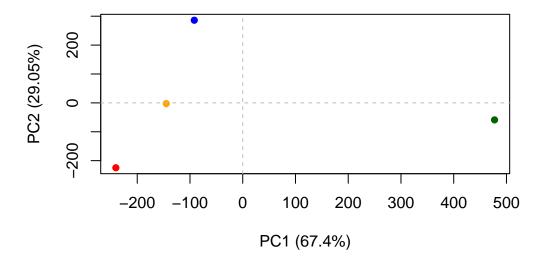
      England
      -144.99315
      -2.532999
      105.768945
      -4.894696e-14

      Wales
      -240.52915
      -224.646925
      -56.475555
      5.700024e-13

      Scotland
      -91.86934
      286.081786
      -44.415495
      -7.460785e-13

      N.Ireland
      477.39164
      -58.901862
      -4.877895
      2.321303e-13
```

```
plot(pca$x[,1], pca$x[,2], xlab="PC1 (67.4%)", ylab = "PC2 (29.05%)", col=c("orange", "red
abline(h=0, col="gray", lty=2)
abline(v=0, col="gray", lty=2)
```



Ireland (green) is the most different country.