

# Class 7: Clustering and PCA

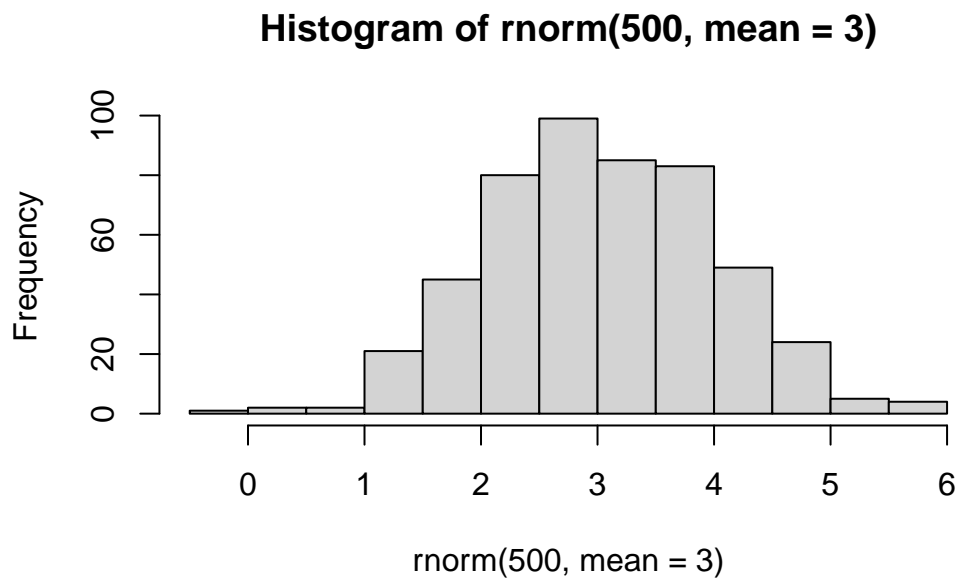
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#CLustering

First let's make up some data to cluster so we can get a feel for these methods and how to work with them.

We can use the `rnorm()` function to get random numbers from a normal distribution around a given `mean`

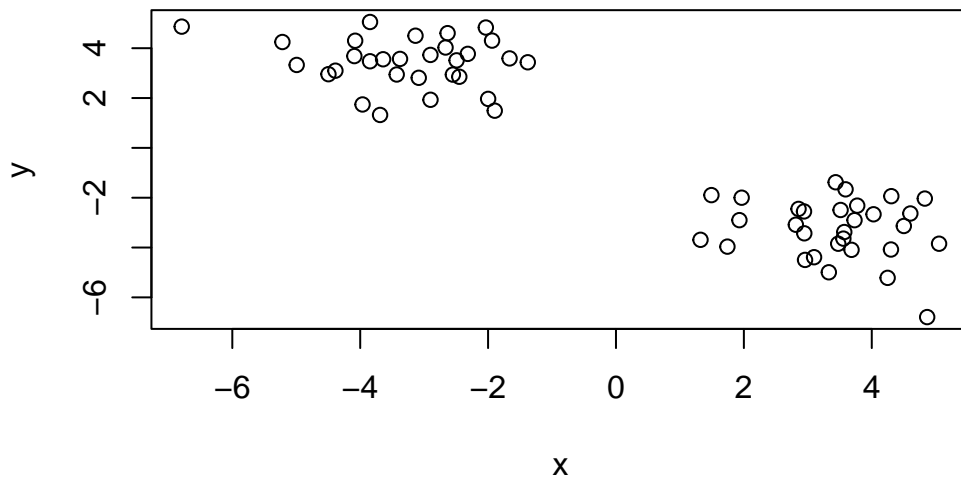
```
hist( rnorm(500, mean= 3))
```



Let's get 30 points for a mean of 3.

```
tmp <- c(rnorm(30, mean= 3), rnorm(30, mean= -3))
```

```
x <- cbind(x= tmp, y= rev(tmp))  
plot(x)
```



## K-means clustering

Very popular clustering method that we can use with the `kmeans()` function in base R.

```
km <- kmeans(x, centers= 2)  
km
```

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

Cluster means:

	x	y
1	-3.26312	3.41505
2	3.41505	-3.26312

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 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 1 1 1 1
```

Within cluster sum of squares by cluster:

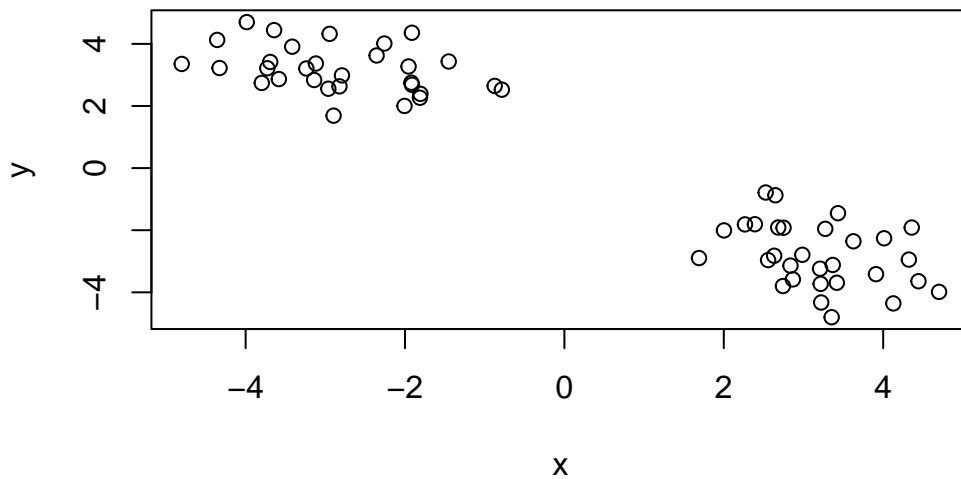
```
[1] 70.52749 70.52749
(between_SS / total_SS = 90.5 %)
```

Available components:

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

```
# Generate some example data for clustering
tmp1 <- c(rnorm(30,-3), rnorm(30,3))
x <- data.frame(x=tmp1, y=rev(tmp1))

plot(x)
```



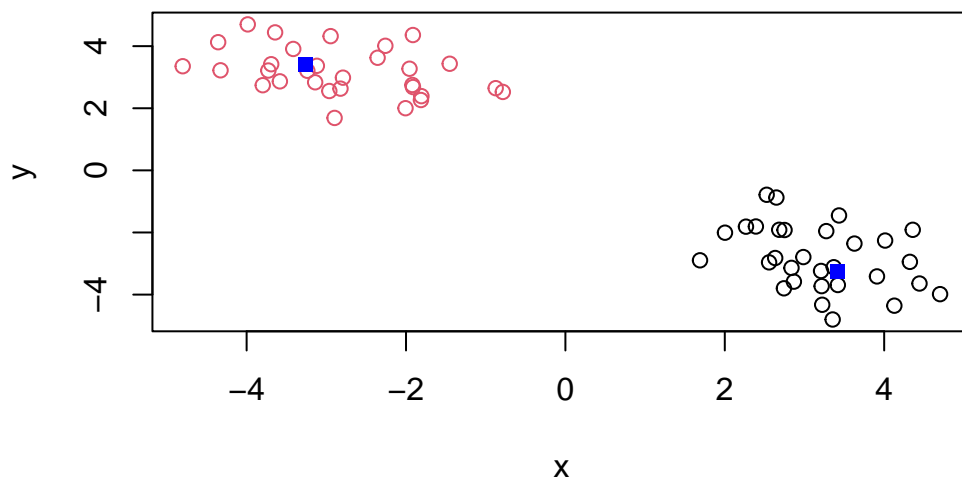
## Generate some example data for clustering

```
km$size
```

```
[1] 30 30
```

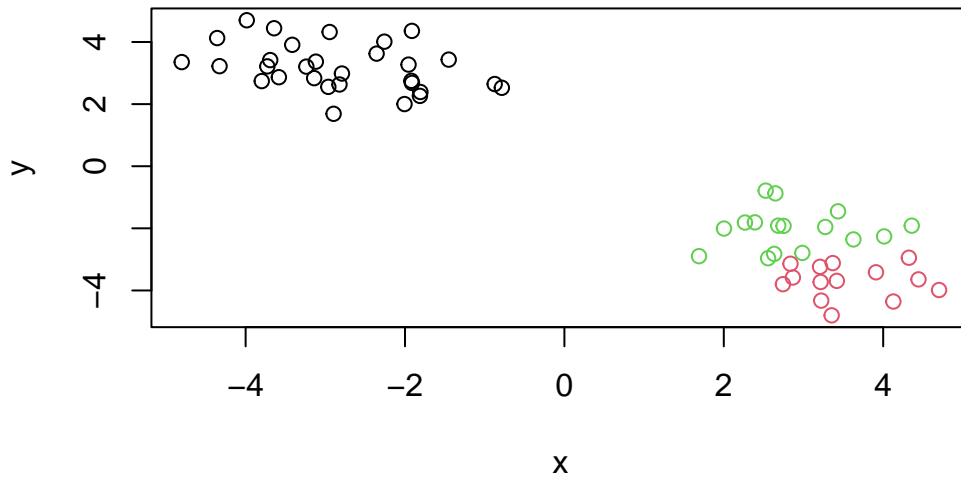
Q. Plot x colored by the means

```
mycols <- c(1, 2)
plot(x, col= km$cluster)
points(km$centers, col= "blue", pch =15, )
```



Q. Let's cluster into 3 groups or some xdata and make a plot.

```
km <- kmeans(x, centers= 3)
plot(x, col= km$cluster)
```



## Hierarchical cluster

We can use the `hclust()` function for Hierarchical Clustering. Unlike `kmeans()`, where we could just pass in our data as input, we need to give `hclust()` a “distance mark”.

We will use the `dist()` function to start with.

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

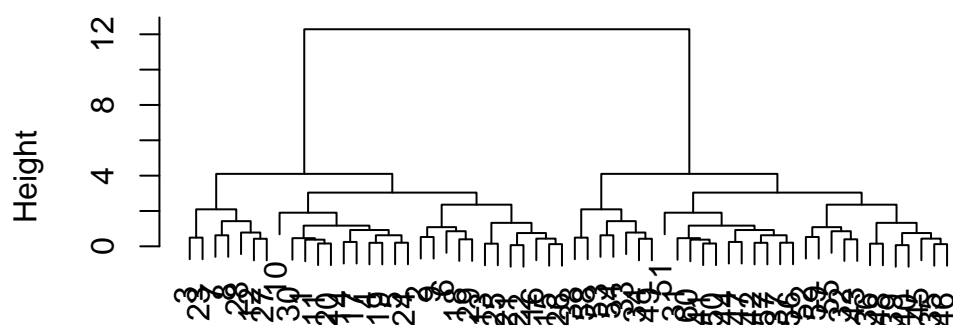
Call:

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

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

```
plot(hc)
```

## Cluster Dendrogram



d  
hclust (\*, "complete")

I can now cut my tree to yield a cluster membership function with `cutree()`.

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

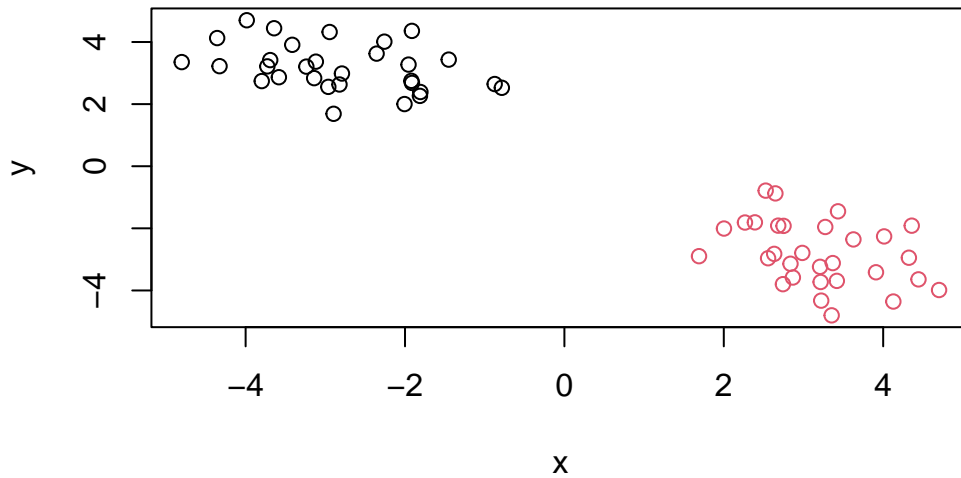
```
[1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2
[39] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
```

You can also tell 'cutree()' to cut where it yields "k" groups.

```
grps <- cutree(hc, k= 2)
grps
```

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

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



## Principal Component Analysis (PCA)

### Start of Lab Part 1

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

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  4
```

```
head(x)
```

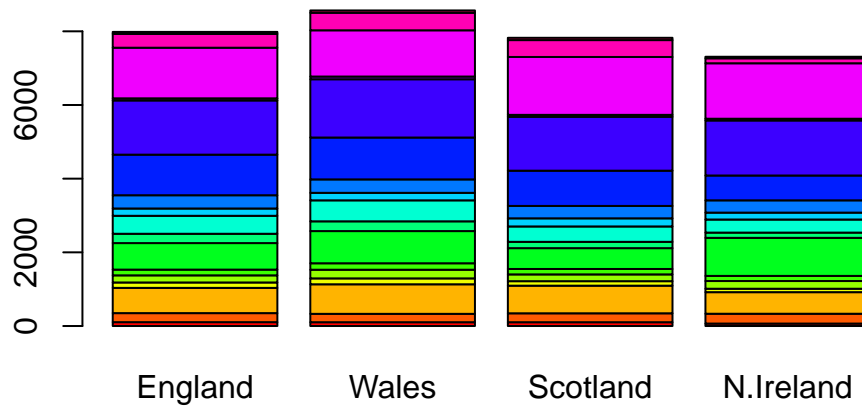
	England	Wales	Scotland	N.Ireland
Cheese	105	103	103	66
Carcass_meat	245	227	242	267
Other_meat	685	803	750	586
Fish	147	160	122	93
Fats_and_oils	193	235	184	209
Sugars	156	175	147	139

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 method. Much faster and easier.

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



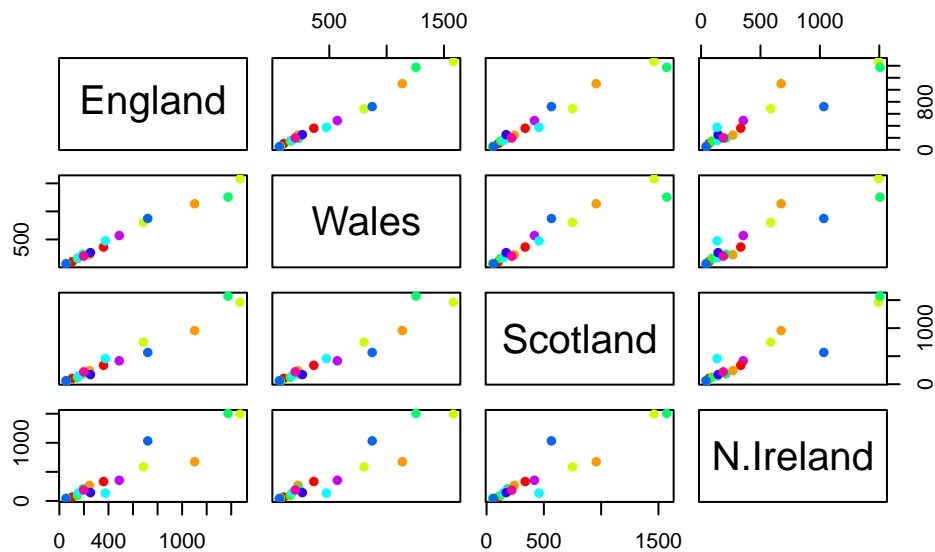


Q3: Changing what optional argument in the above `barplot()` function results in the following plot?

Changing the `beside` argument will give the second plot result.

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)
```



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

The main PCA function in base R is called `prcomp()` it expects the transpose of our data.

```
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

```
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

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

```
plot(pca$x[, 1], pca$x[, 2], col= c("orange", "red", "blue", "darkgreen"), pch= 16)
```

