# Lab7

### Jae Kim

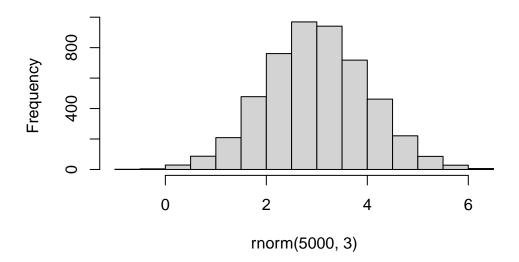
### Clustering

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 rnorm() function to get random numbers from a normal distribution around a given mean.

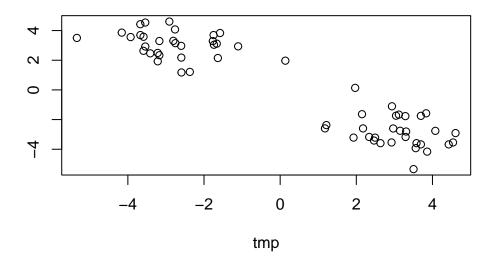
hist(rnorm(5000,3))

## Histogram of rnorm(5000, 3)



Let's get 30 points with a mean of 3 and another 30 with a mean of -3. Then make a matrix whose plot has two clusters at two opposite corners in the Euclidean space.

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



#### K-means clustering

Very popular clustering method, especially for big data set, that we can use with the kmeans() function in base R.

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

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

Cluster means:

```
tmp
1 -2.790689 3.065319
2 3.065319 -2.790689
```

Clustering vector:

#### 

```
Within cluster sum of squares by cluster:
[1] 56.57847 56.57847
(between_SS / total_SS = 90.1 %)
```

Available components:

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

How many points are in each cluster?

km\$size

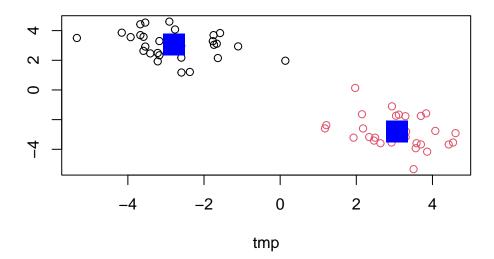
#### [1] 30 30

What component of your result object details

- Cluster size?
  - "size"
- Cluster assignment/membership?
  - "cluster"
- Cluster center?
  - "centers"

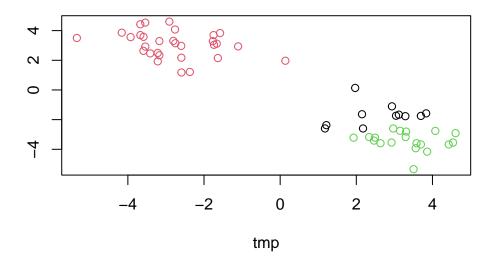
Plot x colored by the kmean cluster assignment and add cluster centers as blue points

```
mycols <- c(1,5)
# col=km$cluster will split them into two colors
plot(x,col=km$cluster)
points(km$centers,col="blue",pch=15,cex=3)</pre>
```



Let's cluster into 3 groups or same  ${\tt x}$  data and make a plot

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



## Hierarchical Clustering

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

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

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

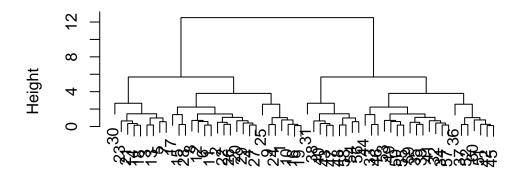
# Call: hclust(d = d)

Cluster method : complete
Distance : euclidean

Number of objects: 60

```
plot(hc)
```

## **Cluster Dendrogram**



d hclust (\*, "complete")

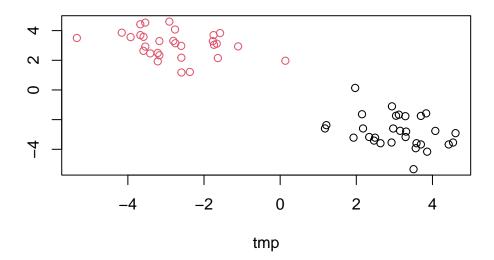
I can now "cut" my tree with the cutree() to yield a cluster membership vector

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

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

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

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



# Principal Component Analysis (PCA)

```
url <- "https://tinyurl.com/UK-foods"
x <- read.csv(url, row.names = 1)
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
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?

```
## Complete the following code to find out how many rows and columns are in x? \dim(x)
```

#### [1] 17 4

## Preview the first 6 rows
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

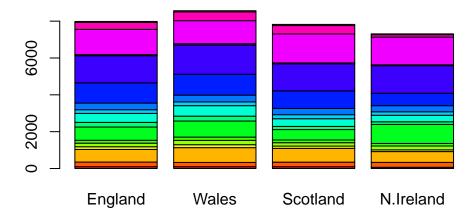
**Q2.** Which approach to solving the 'row-names problem' mentioned above do you prefer and why? Is one approach more robust than another under certain circumstances?

I prefer the row.names=1 approach. When you do x <-x[,-1] multiple times, it removes the columns one by one until you are left with none.

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

Remove beside=T argument.

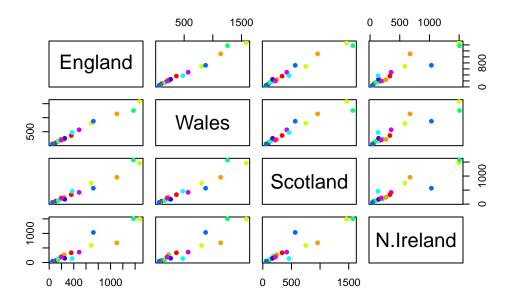
```
barplot(as.matrix(x), col=rainbow(nrow(x)))
```



**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 point lies on the diagonal for a given plot, it means the the values are very similar to one another.

```
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?

There are more wiggles in plots for country vs N. Ireland (less aligned diagonal line). The blue point is of higher value in N. Ireland compared to other countries.

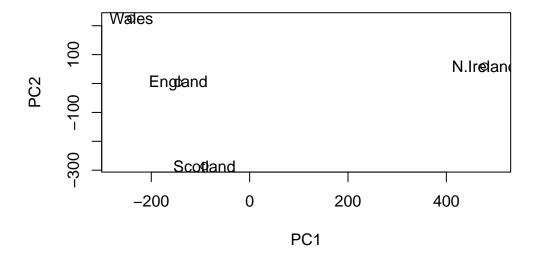
**Q7**. Complete the code below to generate a plot of PC1 vs PC2. The second line adds text labels over the data points.

```
# Use the prcomp() PCA function
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
```

```
# 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.

```
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("orange","red","blue","darkgreen"))
```

