Machine Learning 1

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Principal Component Analysis (PCA)

PCA of UK food data

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

	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 the new data frame?

```
# Number of rows in the data frame
nrow(x)

[1] 17

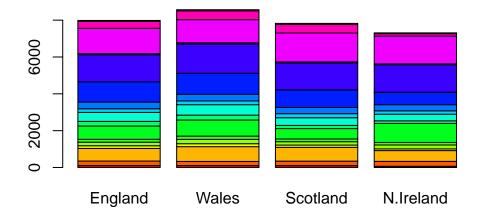
# Number of columns in the data frame
ncol(x)

[1] 4

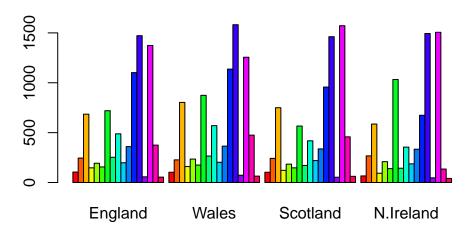
Q2. Which approach do you prefer for the 'row names problem'?
```

I prefer the option to set the row names equal to 1 since that instantly solves the problem of having to write out a code that would normally take you more time to do and edit.

```
>Q3. Changing what optional argument in the 'barplot()' function results in the plot?
##Changing the color argument to a rainbow color and setting the bars to that color
::: {.cell}
```{.r .cell-code}
cols <- rainbow(nrow(x))
barplot(as.matrix(x), col=cols)</pre>
```



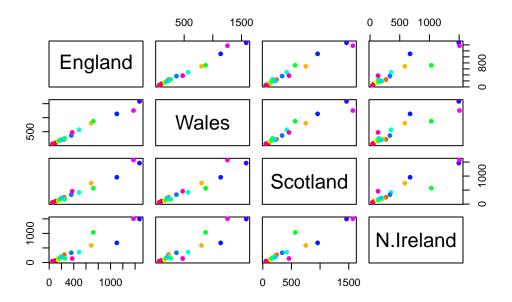
```
barplot(as.matrix(x), col=cols, beside=TRUE)
```



Q5. Can you make sense of the following pairwise plots and what does it mean if a given point lies on the diagonal for a given plot?

##The following plots show the different categories measured compared between two different countries to show how similar or deviant they are from each other. So if a point lies on the diagonal of the plot between the two countries it is most likely very similar in value among the two.

```
pairs(x, col=cols, 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 a couple of data values that are shown to be variant among Ireland compared to the other countries that remains consistent which would need more labeling to discover.

```
::: {.cell}

```{.r .cell-code}
pca <- prcomp(t(x))
summary(pca)</pre>
```

Importance of components:

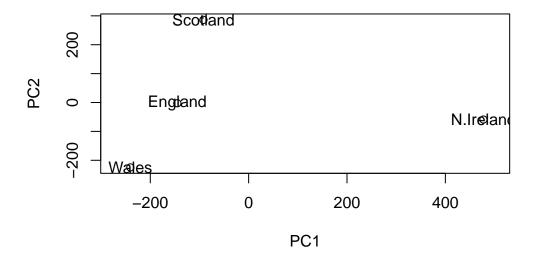
	PC1	PC2	PC3	PC4
Standard deviation	324.1502	212.7478	73.87622	3.176e-14
Proportion of Variance	0.6744	0.2905	0.03503	0.000e+00
Cumulative Proportion	0.6744	0.9650	1.00000	1.000e+00

:::

attributes(pca)

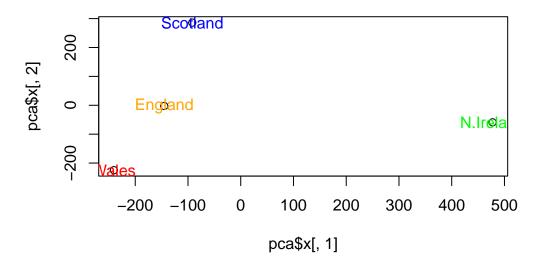
```
$names
[1] "sdev" "rotation" "center" "scale" "x"
$class
[1] "prcomp"
```

Q7. Complete the code to generate a plot of PC1 vs PC2



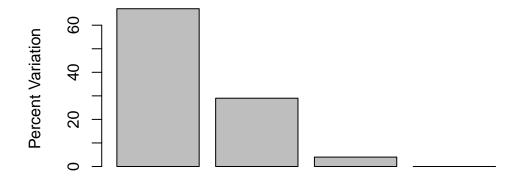
Q8. Customise the plot so color of the country colors in the table match.

```
country_cols <- c("orange", "red", "blue", "green")
plot(pca$x[,1], pca$x[,2])
text(pca$x[,1], pca$x[,2], colnames(x), col=country_cols)</pre>
```

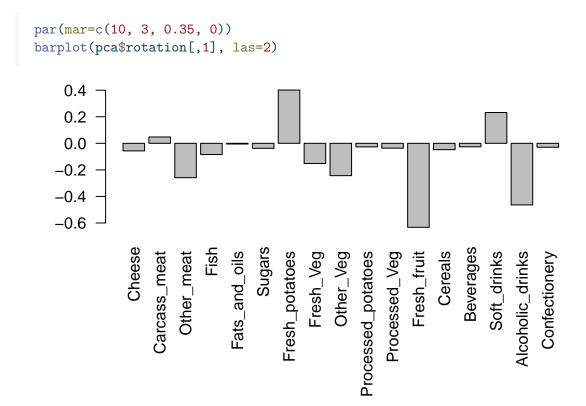


Defining Variables below

```
v <- round( pca$sdev^2/sum(pca$sdev^2) * 100)</pre>
[1] 67 29 4 0
  z <- summary(pca)</pre>
  z$importance
                              PC1
                                        PC2
                                                  PC3
                                                                PC4
Standard deviation
                        324.15019 212.74780 73.87622 3.175833e-14
Proportion of Variance
                          0.67444
                                    0.29052
                                              0.03503 0.000000e+00
Cumulative Proportion
                          0.67444
                                    0.96497
                                              1.00000 1.000000e+00
  barplot(v, xlab="Principal Component", ylab="Percent Variation")
```

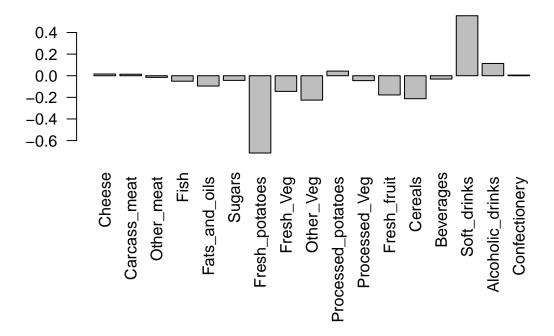


Principal Component



Q9. Generate a similar 'loadings plot' for PC2. What two food groups feature prominantly and what does PC2 mainly tell us?

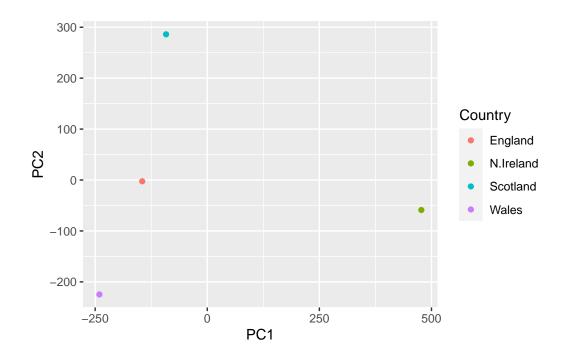
```
par(mar=c(10, 3, 0.35, 0))
barplot(pca$rotation[,2], las=2)
```



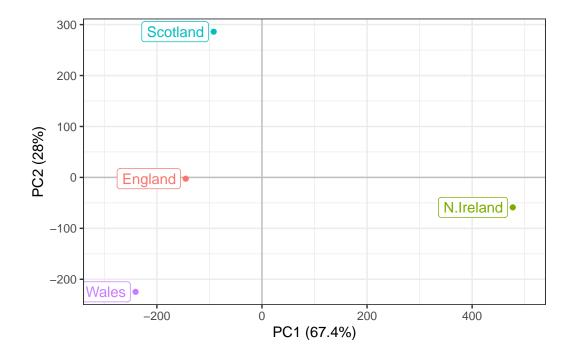
The two food groups that feature prominantely are fresh potatoes and soft drinks. This mainly tells us about the trends in quantities among the PC2 variable which accounts for 29% of the sample variance that can help us study the data set.

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

# First basic Plot
library(ggplot2)
ggplot(df_lab) + aes(PC1, PC2, col=Country) +geom_point()</pre>
```

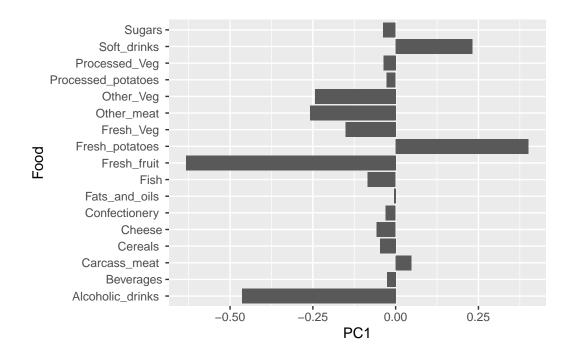


A nicer plot
ggplot(df_lab) + aes(PC1, PC2, col=Country, label=Country) + geom_hline(yintercept=0, col=

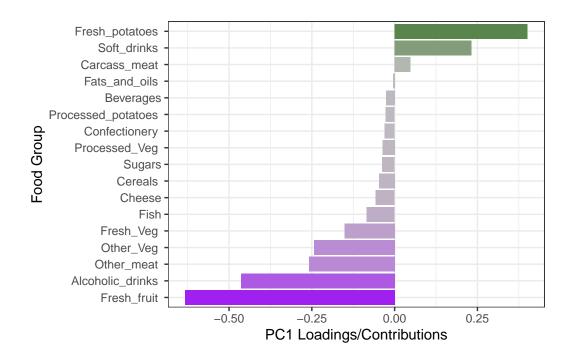


```
ld <- as.data.frame(pca$rotation)
ld_lab <- tibble::rownames_to_column(ld, "Food")

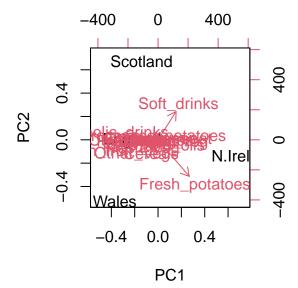
ggplot(ld_lab) + aes(PC1, Food) + geom_col()</pre>
```



```
ggplot(ld_lab) +
  aes(PC1, reorder(Food, PC1), bg=PC1) +
  geom_col() +
  xlab("PC1 Loadings/Contributions") +
  ylab("Food Group") +
  scale_fill_gradient2(low="purple", mid="gray", high="darkgreen", guide=NULL) +
  theme_bw()
```



biplot(pca)



PCA of RNA-Seq data

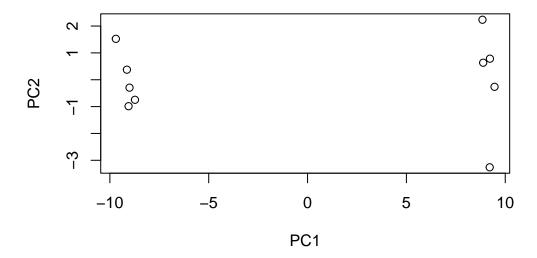
Data from the website

```
url2 <- "https://tinyurl.com/expression-CSV"
rna.data <- read.csv(url2, row.names=1)
head(rna.data)</pre>
```

```
wt1 wt2
               wt3
                    wt4 wt5 ko1 ko2 ko3 ko4 ko5
      439 458
                408
                    429 420
                              90
                                 88
                                      86
                                          90
gene1
      219 200
                204
                    210 187 427 423 434 433 426
gene2
gene3 1006 989 1030 1017 973 252 237 238 226 210
gene4
                829
                    856 760 849 856 835 885 894
      783 792
gene5
      181 249
                204
                    244 225 277 305 272 270 279
gene6
      460 502
               491
                    491 493 612 594 577 618 638
```

Q10. How many genes and samples are in this data set?

```
pca2 <-prcomp(t(rna.data), scale=TRUE)
plot(pca2$x[,1], pca2$x[,2], xlab="PC1", ylab="PC2")</pre>
```



```
summary(pca2)
```

Importance of components:

```
PC5
                          PC1
                                 PC2
                                         PC3
                                                 PC4
                                                                 PC6
                                                                          PC7
Standard deviation
                       9.6237 1.5198 1.05787 1.05203 0.88062 0.82545 0.80111
Proportion of Variance 0.9262 0.0231 0.01119 0.01107 0.00775 0.00681 0.00642
Cumulative Proportion 0.9262 0.9493 0.96045 0.97152 0.97928 0.98609 0.99251
                           PC8
                                   PC9
                                            PC10
Standard deviation
                       0.62065 0.60342 3.457e-15
Proportion of Variance 0.00385 0.00364 0.000e+00
Cumulative Proportion 0.99636 1.00000 1.000e+00
```

Plot of Variance

```
plot(pca2, main="Quick screen plot")
```

Quick screen plot



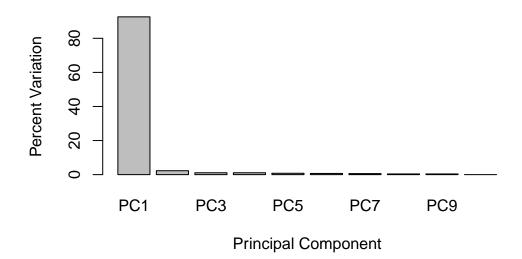
```
pca.var <- pca2$sdev^2
pca2.var.per <- round(pca.var/sum(pca.var)*100, 1)</pre>
```

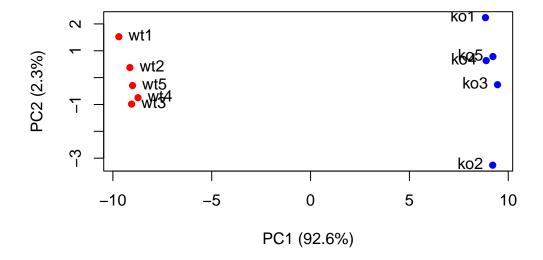
```
pca2.var.per

[1] 92.6 2.3 1.1 1.1 0.8 0.7 0.6 0.4 0.4 0.0

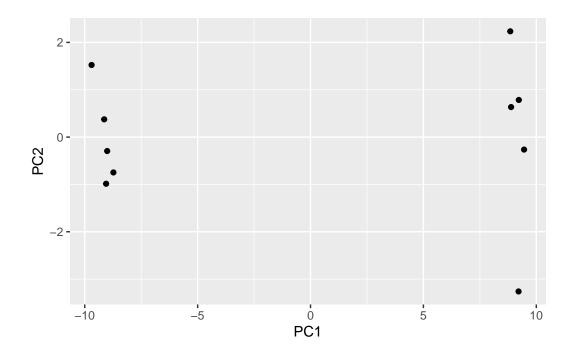
barplot(pca2.var.per, main="Screen Plot", names.arg=paste0("PC", 1:10), xlab= "Principal Content of the content
```

Screen Plot



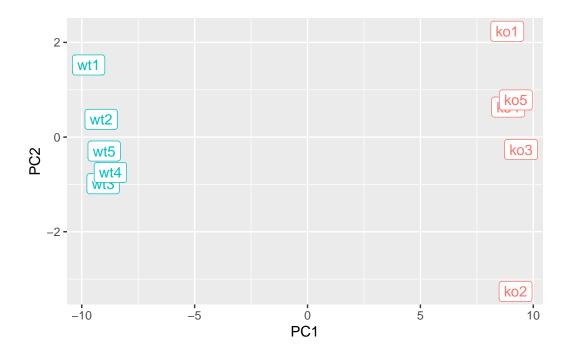


```
library(ggplot2)
df <- as.data.frame(pca2$x)
# Basic plot
ggplot(df) + aes(PC1, PC2) + geom_point()</pre>
```



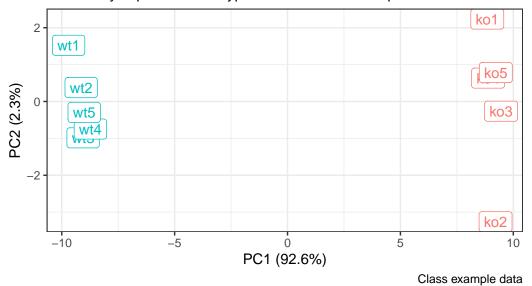
```
df$samples <- colnames(rna.data)
df$condition <- substr(colnames(rna.data),1,2)

p <- ggplot(df) +
        aes(PC1, PC2, label=samples, col=condition) +
        geom_label(show.legend = FALSE)
p</pre>
```



PCA of RNASeq Data

PC1 clealy seperates wild-type from knock-out samples



```
plot(pca2$x[,1], pca2$x[,2], xlab="PC1", ylab="PC2")
text(pca2$x[,1], pca2$x[,2], colnames(rna.data))
```

