class07 (Machine Learning 1)

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PCA of UK food data

Read data from website, and try some visualizations

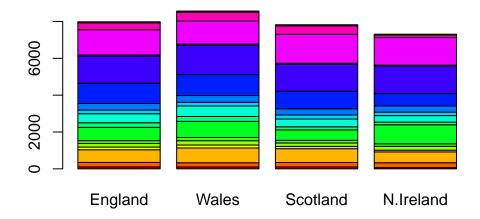
```
url <- "https://tinyurl.com/UK-foods"
x <- read.csv(url, row.names=1)
x</pre>
```

	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

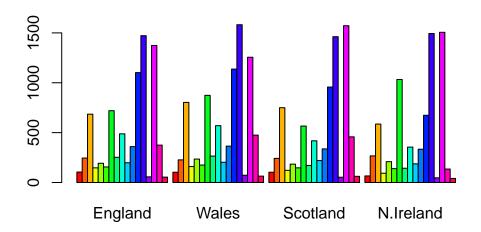
```
dim(x)
```

[1] 17 4

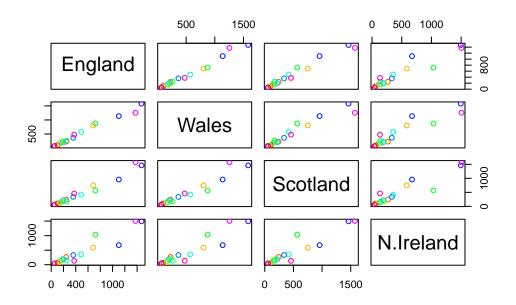
```
cols <- rainbow(nrow(x))
barplot( as.matrix(x), col=cols )</pre>
```



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



pairs(x, col=cols)



The main base R PCA function is called <code>prcomp()</code>, we will need to give it the transpose of our input data.

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

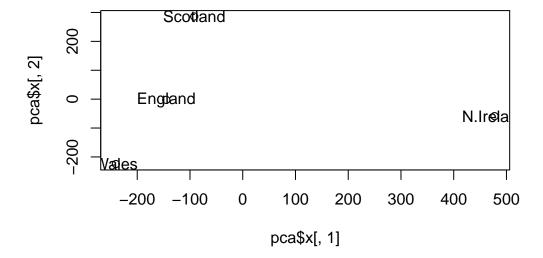
attributes(pca)

$names
[1] "sdev" "rotation" "center" "scale" "x"

$class
[1] "prcomp"</pre>
```

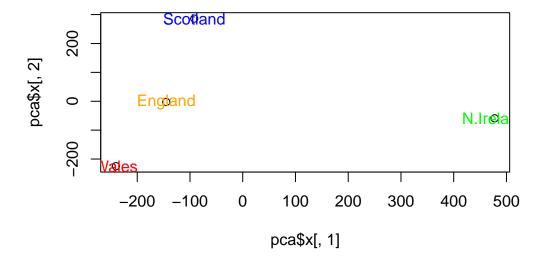
To make our new PCA plot (a.k.a PCA score plot) we access pca\$x

```
plot(pca$x[,1], pca$x[,2])
text(pca$x[,1], pca$x[,2], colnames(x))
```



Now to add some colors

```
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>
```



We can use the square of pca\$sdev (standard deviation), to calculate the amount of variation in the original data each PC accounts for

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

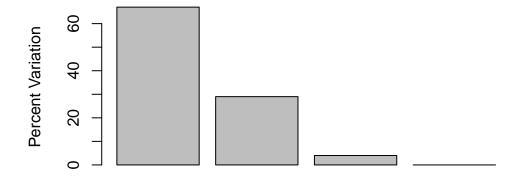
[1] 67 29 4 0

z <- summary(pca)
z$importance</pre>
```

```
PC1 PC2 PC3 PC4
Standard deviation 324.15019 212.74780 73.87622 2.921348e-14
Proportion of Variance 0.67444 0.29052 0.03503 0.000000e+00
Cumulative Proportion 0.67444 0.96497 1.00000 1.000000e+00
```

Let's turn this into a bar plot

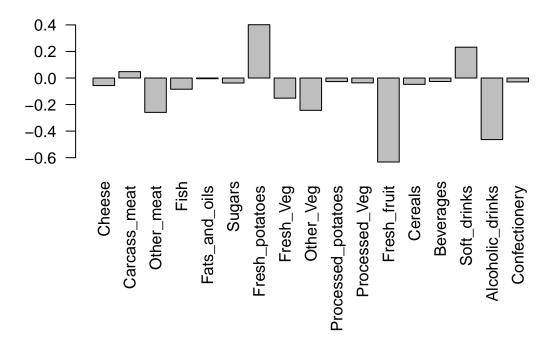
```
barplot(v, xlab="Principal Component", ylab="Percent Variation")
```



Principal Component

We can also consider the influence of each orignal variable

```
par(mar=c(10, 3, 0.35, 0))
barplot( pca$rotation[,1], las=2 )
```



Now to use ggplot for these figures

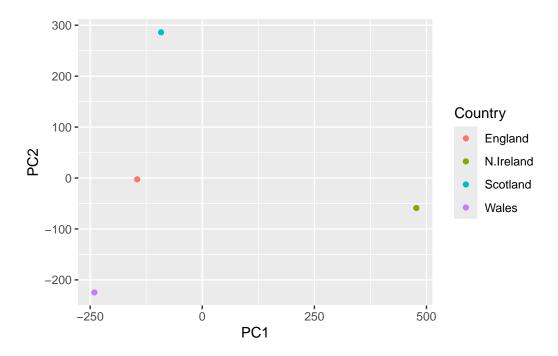
```
library(ggplot2)

df <- as.data.frame(pca$x)

df_lab <- tibble::rownames_to_column(df, "Country")

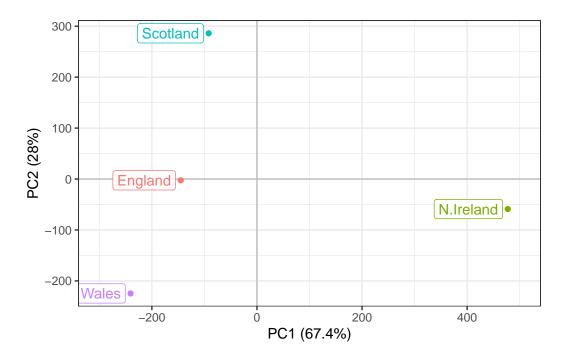
# Our first basic plot

ggplot(df_lab) +
   aes(PC1, PC2, col=Country) +
   geom_point()</pre>
```



We can also make the plot look much nicer by adding aesthetics and organization

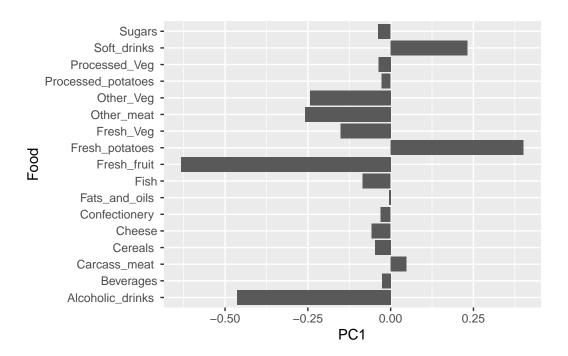
```
ggplot(df_lab) +
  aes(PC1, PC2, col=Country, label=Country) +
  geom_hline(yintercept = 0, col="gray") +
  geom_vline(xintercept = 0, col="gray") +
  geom_point(show.legend = FALSE) +
  geom_label(hjust=1, nudge_x = -10, show.legend = FALSE) +
  expand_limits(x = c(-300,500)) +
  xlab("PC1 (67.4%)") +
  ylab("PC2 (28%)") +
  theme_bw()
```



Now customise the plot with layers

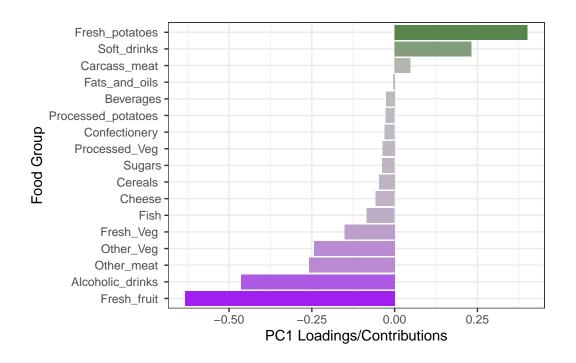
```
ld <- as.data.frame(pca$rotation)
ld_lab <- tibble::rownames_to_column(ld, "Food")

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



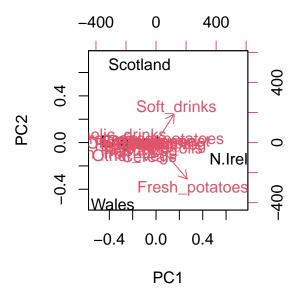
Now let's reorder the y-axis by PC1 loadings and add a color scale

```
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()
```



We can also utilize a biplot to view the data

biplot(pca)



PCA of RNA-Seq data

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

```
wt1 wt2
                     wt4 wt5 ko1 ko2 ko3 ko4 ko5
                wt3
      439 458
                408
                     429 420
                                              93
gene1
                              90
                                 88
                                      86
                                         90
gene2 219 200
                204
                     210 187 427 423 434 433 426
gene3 1006 989 1030 1017 973 252 237 238 226 210
gene4
      783 792
                829
                     856 760 849 856 835 885 894
gene5
       181 249
                204
                     244 225 277 305 272 270 279
gene6
      460 502
                491
                     491 493 612 594 577 618 638
```

There is a nice summary of how well PCA is doing

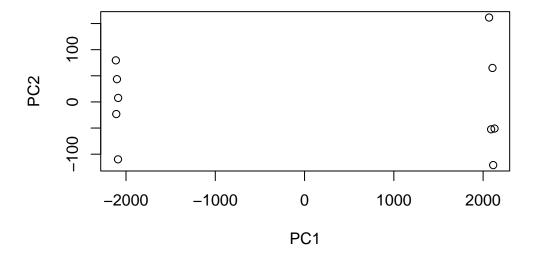
```
pca <- prcomp( t(rna.data) )
summary(pca)</pre>
```

Importance of components:

```
PC1
                                     PC2
                                              PC3
                                                       PC4
                                                                PC5
                                                                         PC6
Standard deviation
                       2214.2633 88.9209 84.33908 77.74094 69.66341 67.78516
Proportion of Variance
                          0.9917
                                 0.0016 0.00144
                                                  0.00122
                                                            0.00098
                                                                     0.00093
Cumulative Proportion
                          0.9917
                                  0.9933
                                          0.99471
                                                   0.99593
                                                            0.99691
                                                                     0.99784
                            PC7
                                              PC9
                                                       PC10
                                     PC8
Standard deviation
                       65.29428 59.90981 53.20803 2.662e-13
                                 0.00073
Proportion of Variance 0.00086
                                          0.00057 0.000e+00
Cumulative Proportion
                        0.99870
                                 0.99943
                                         1.00000 1.000e+00
```

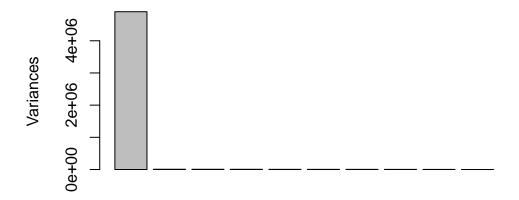
Now to add our PCA plot

```
plot(pca$x[,1], pca$x[,2], xlab="PC1", ylab="PC2")
```



plot(pca, main="Quick scree plot")

Quick scree plot



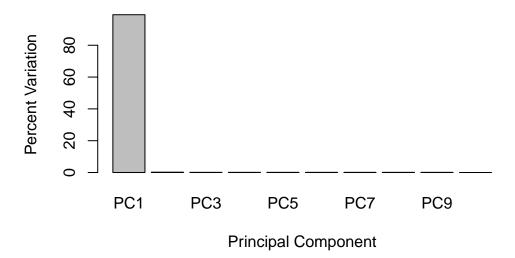
Now to calculate the variation in the original data

```
## Variance captured per PC
pca.var <- pca$sdev^2

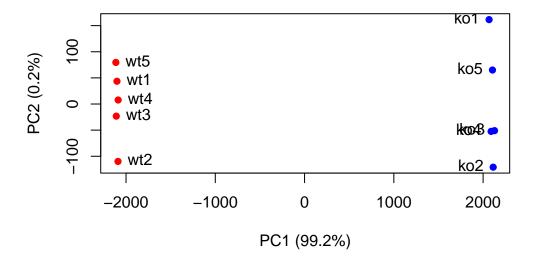
## Percent variance is often more informative to look at
pca.var.per <- round(pca.var/sum(pca.var)*100, 1)
pca.var.per</pre>
[1] 99.2 0.2 0.1 0.1 0.1 0.1 0.1 0.1 0.0
```

Let's use this to make a bar plot

Scree Plot



Let us add a vector of colors for our samples

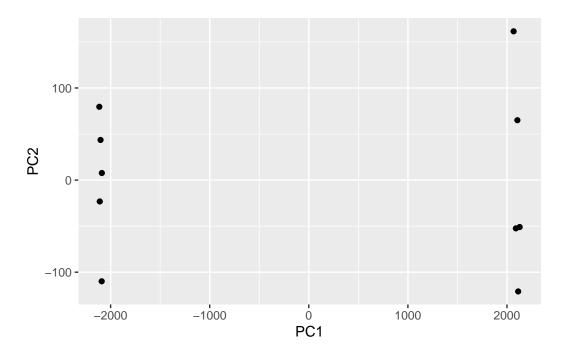


Now to use ggplot

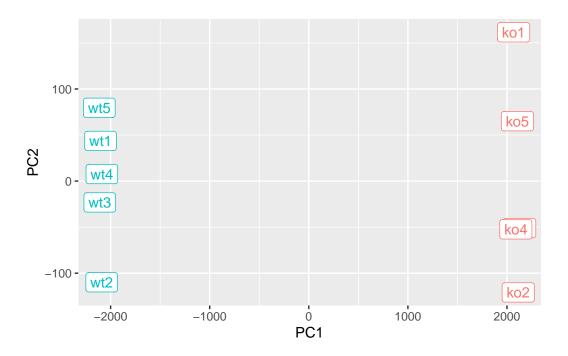
```
library(ggplot2)

df <- as.data.frame(pca$x)

# Our first basic plot
ggplot(df) +
   aes(PC1, PC2) +
   geom_point()</pre>
```



Now to add some condition specific colors and aesthetics



Now let's polish up the plot

PCA of RNASeq Data

PC1 clealy seperates wild-type from knock-out samples

