

PCA Demos

Test Scores (SAS)

Test Scores (SAS)

	Simple Statistics				
	test1	test2	test3	test4	test5
Mean	96.25	72.68	58.88	65.71	98.84
Std	2.19	18.54	24.68	19.28	0.83

Tests 1 and 5 have very little variability. If we use correlation PCA, we are effectively equating the variance of each test by standardizing them to have variance = 1.

This means our PCA will try to capture the variance in test1 and test5 with the same vigor that it tries to capture the variance in other tests.

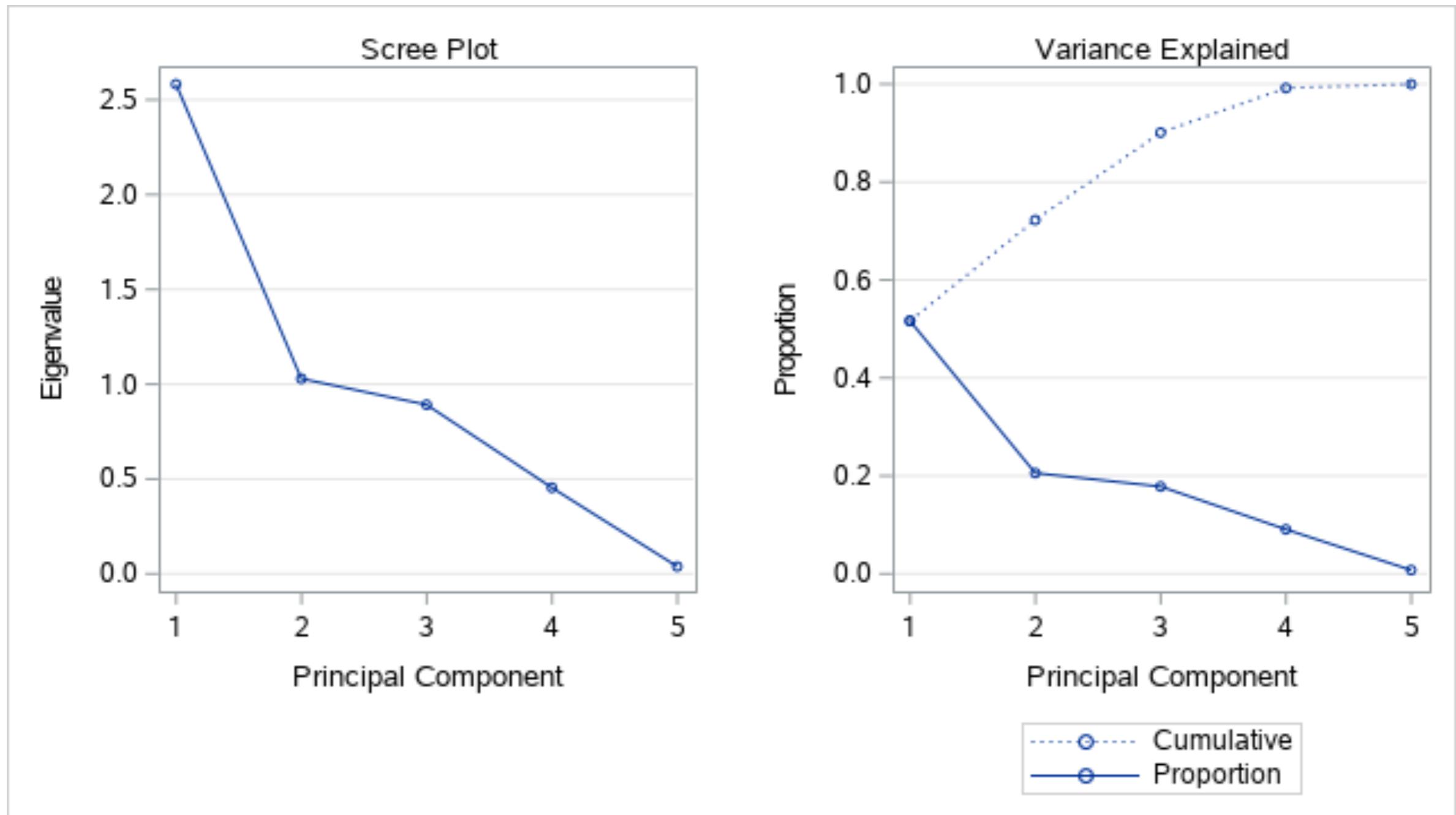
Is this what we want? Do all tests *actually* contribute equally to the total variability in the dataset? Should we want to force them to?

Eigenvalues/Eigenvectors

Eigenvalues of the Correlation Matrix				
	Eigenvalue	Difference	Proportion	Cumulative
1.00	2.58	1.55	0.52	0.52
2.00	1.03	0.14	0.21	0.72
3.00	0.89	0.44	0.18	0.90
4.00	0.45	0.42	0.09	0.99
5.00	0.04		0.01	1.00

Eigenvectors					
	Prin1	Prin2	Prin3	Prin4	Prin5
test1	0.12	-0.84	0.51	0.16	-0.02
test2	0.53	0.15	-0.09	0.73	0.40
test3	0.54	0.07	0.22	-0.65	0.48
test4	0.60	0.15	0.09	-0.03	-0.78
test5	-0.22	0.50	0.82	0.15	0.01

ScreePlots



Scores/Coordinates in Output Dataset

④ test1	④ test2	④ test3	④ test4	④ test5	④ Prin1	④ Prin2	④ Prin3	④ Prin4	④ Prin5
96	99	87	92	98	2.4038309154	0.085085466	-0.654944076	0.0753265065	0.0546923609
96	96	91	100	99	2.6566794704	0.1348273849	-0.568582075	-0.160294559	-0.254039602
100	95	91	86	99	2.1328104259	-0.904282268	1.3008725376	0.3014983566	0.268022596
96	92	93	94	99	2.128961296	0.6674173704	0.4372673519	-0.175696416	-0.044560133
how do you get this number?					1.5300429461	2.3902914062	0.7162378398	-0.229828769	-0.409606229
96	86	95	89	98	2.2428011629	0.8080564864	-0.988020021	-0.70791829	-0.271798135
96	86	95	89	98	1.6876559127	1.2056345731	1.5104424971	-0.443508608	0.1174028267
96	86	95	89	98	2.11339751	-0.02078209	-0.536524828	-0.639914588	0.050142591
97	95	99	100	98	2.8562548475	-0.232386237	-0.260799154	-0.336621647	-0.127521435
95	92	88	90	98	2.1098219889	0.3975601352	-0.854967404	-0.295632444	0.0116293846
100	87	98	88	98	2.3891241998	-1.539627724	0.4127421529	-0.383911192	0.1356199642
95	97	85	99	98	2.4694420353	0.4999114317	-0.863529711	-0.035054058	-0.301019701
96	94	89	96	98	2.4303253864	0.0816396714	-0.594949581	-0.179604094	-0.175714904
95	87	99	100	100	1.9834808735	1.6791531562	1.3052570358	-0.42829456	-0.252556327
98	93	85	89	98	2.2011425493	-0.756464696	-0.191216217	0.0448426502	-0.011862408
99	85	92	91	99	1.9728261331	-0.561288302	1.1476566814	-0.198133564	-0.122059521
98	93	96	92	98	2.5357540027	-0.70164567	-0.081284263	-0.249662522	0.0833615846

Scores/Coordinates in Output Dataset

④ test1	④ test2	④ test3	④ test4	④ test5	④ Prin1	④ Prin2	④ Prin3	④ Prin4	④ Prin5
96	99	87	92	98	2.4038309154	0.085085466	-0.654944076	0.0753265065	0.0546923609
96	96	91	100	98	2.6566794704	0.1348273849	-0.568582075	-0.160294559	-0.254039602
100	95	91	86	99					0.268022596
96	92	93	94	99					-0.044560133
93	87	86	98	100					-0.409606229
94	87	93	97	98					-0.271798135
96	85	100	90	100					0.1174028267
96	86	95	89	98	2.11339751	-0.02078209	-0.536524828	-0.63991458	
97	95	99	100	98	2.8562548475	-0.232386237	-0.260799154	-0.33662164	Eigenvectors
95	92	88	90	98	2.1098219889	0.3975601352	-0.854967404	-0.29563244	
100	87	98	88	98	2.3891241998	-1.539627724	0.4127421529	-0.38391119	Prin1
95	97	85	99	98	2.4694420353	0.4999114317	-0.863529711	-0.03505401	0.12
96	94	89	96	98	2.4303253864	0.0816396714	-0.594949581	-0.17960409	0.53
95	87	90	100	100	1.9834808735	1.6701531562	1.3052570358	0.4282941	0.54
									0.60
									-0.22

0.12 $\left(\frac{96 - 96.25}{2.19} \right) + 0.53 \left(\frac{99 - 72.68}{18.54} \right) + 0.54 \left(\frac{87 - 58.88}{24.68} \right) + 0.60 \left(\frac{92 - 65.71}{19.28} \right) - 0.22 \left(\frac{98 - 98.84}{0.83} \right)$

Scores/Coordinates in Output Dataset

# test1	# test2	# test3	# test4	# test5	# Prin1	# Prin2	# Prin3	# Prin4	# Prin5
96	99	87	92	98	2.4038309154	0.085085466	-0.654944076	0.0753265065	0.0546923609
96	96	91	100	98	2.6566794704	0.1348273849	-0.568582075	-0.160294559	-0.254039602
100	95	91	86	99					0.268022596
96	92	93	94	99					-0.044560133
93	87	86	98	100					-0.409606229
94	87	93	97	98					-0.271798135
96	85	100	90	100					0.1174028267
96	86	95	89	98	2.11339751	-0.02078209	-0.536524828	-0.63991458	
97	95	99	100	98	2.8562548475	-0.232386237	-0.260799154	-0.33662164	Eigenvectors
95	92	88	90	98	2.1098219889	0.3975601352	-0.854967404	-0.2956324	
100	87	98	88	98	2.3891241998	-1.539627724	0.4127421529	-0.38391119	Prin1
95	97	85	99	98	2.4694420353	0.4999114317	-0.863529711	-0.0350540	0.12
96	94	89	96	98	2.4303253864	0.0816396714	-0.594949581	-0.1796040	0.53
95	87	90	100	100	1.9834808735	1.6701531562	1.3052570358	0.428294	0.54
									0.60
									-0.22

0.12 $\left(\frac{96 - 96.25}{2.19} \right) + 0.53 \left(\frac{99 - 72.68}{18.54} \right) + 0.54 \left(\frac{87 - 58.88}{24.68} \right) + 0.60 \left(\frac{92 - 65.71}{19.28} \right) - 0.22 \left(\frac{98 - 98.84}{0.83} \right)$

Scores/Coordinates in Output Dataset

④ test1	④ test2	④ test3	④ test4	④ test5	④ Prin1	④ Prin2	④ Prin3	④ Prin4	④ Prin5
96	99	87	92	98	2.4038309154	0.085085466	-0.654944076	0.0753265065	0.0546923609
96	96	91	100	98	2.6566794704	0.1348273849	-0.568582075	-0.160294559	-0.254039602
100	95	91	86	99					0.268022596
96	92	93	94	99					-0.044560133
93	87	86	98	100					-0.409606229
94	87	93	97	98					-0.271798135
96	85	100	90	100					0.1174028267
96	86	95	89	98	2.11339751	-0.02078209	-0.536524828	-0.63991458	
97	95	99	100	98	2.8562548475	-0.232386237	-0.260799154	-0.33662164	Eigenvectors
95	92	88	90	98	2.1098219889	0.3975601352	-0.854967404	-0.29563244	
100	87	98	88	98	2.3891241998	-1.539627724	0.4127421529	-0.38391119	Prin1
95	97	85	99	98	2.4694420353	0.4999114317	-0.863529711	-0.03505401	0.12
96	94	89	96	98	2.4303253864	0.0816396714	-0.594949581	-0.17960409	0.53
95	87	90	100	100	1.9834808735	1.6701531562	1.3052570358	0.4282941	0.54
									0.60
									-0.22

0.12 $\left(\frac{96 - 96.25}{2.19} \right) + 0.53 \left(\frac{99 - 72.68}{18.54} \right) + 0.54 \left(\frac{87 - 58.88}{24.68} \right) + 0.60 \left(\frac{92 - 65.71}{19.28} \right) - 0.22 \left(\frac{98 - 98.84}{0.83} \right)$

Scores/Coordinates in Output Dataset

④ test1	④ test2	④ test3	④ test4	④ test5	④ Prin1	④ Prin2	④ Prin3	④ Prin4	④ Prin5
96	99	87	92	98	2.4038309154	0.085085466	-0.654944076	0.0753265065	0.0546923609
96	96	91	100	98	2.6566794704	0.1348273849	-0.568582075	-0.160294559	-0.254039602
100	95	91	86	99					0.268022596
96	92	93	94	99					-0.044560133
93	87	86	98	100					-0.409606229
94	87	93	97	98					-0.271798135
96	85	100	90	100					0.1174028267
96	86	95	89	98	2.11339751	-0.02078209	-0.536524828	-0.63991458	
97	95	99	100	98	2.8562548475	-0.232386237	-0.260799154	-0.33662164	Eigenvectors
95	92	88	90	98	2.1098219889	0.3975601352	-0.854967404	-0.29563244	
100	87	98	88	98	2.3891241998	-1.539627724	0.4127421529	-0.38391119	Prin1
95	97	85	99	98	2.4694420353	0.4999114317	-0.863529711	-0.03505401	0.12
96	94	89	96	98	2.4303253864	0.0816396714	-0.594949581	-0.17960409	0.53
95	87	90	100	100	1.9834808735	1.6701531562	1.3052570358	0.4282941	0.54
									0.60
									-0.22

0.12 $\left(\frac{96 - 96.25}{2.19} \right) + 0.53 \left(\frac{99 - 72.68}{18.54} \right) + 0.54 \left(\frac{87 - 58.88}{24.68} \right) + 0.60 \left(\frac{92 - 65.71}{19.28} \right) - 0.22 \left(\frac{98 - 98.84}{0.83} \right)$

Scores/Coordinates in Output Dataset

④ test1	④ test2	④ test3	④ test4	④ test5	④ Prin1	④ Prin2	④ Prin3	④ Prin4	④ Prin5
96	99	87	92	98	2.4038309154	0.085085466	-0.654944076	0.0753265065	0.0546923609
96	96	91	100	98	2.6566794704	0.1348273849	-0.568582075	-0.160294559	-0.254039602
100	95	91	86	99					0.268022596
96	92	93	94	99					-0.044560133
93	87	86	98	100					-0.409606229
94	87	93	97	98					-0.271798135
96	85	100	90	100					0.1174028267
96	86	95	89	98	2.11339751	-0.02078209	-0.536524828	-0.63991458	
97	95	99	100	98	2.8562548475	-0.232386237	-0.260799154	-0.33662164	
95	92	88	90	98	2.1098219889	0.3975601352	-0.854967404	-0.2956324	
100	87	98	88	98	2.3891241998	-1.539627724	0.4127421529	-0.38391119	
95	97	85	99	98	2.4694420353	0.4999114317	-0.863529711	-0.03505401	
96	94	89	96	98	2.4303253864	0.0816396714	-0.594949581	-0.17960409	
95	87	90	100	100	1.9834808735	1.6701531562	1.3052570358	0.4282941	

Simple Statistics

	test1	test2	test3	test4	test5
Mean	96.25	72.68	58.88	65.71	98.84
StD	2.19	18.54	24.68	19.28	0.83

Eigenvectors

	Prin1	Prin2	Prin3	Prin4	Prin5
Prin1	0.12	0.53	0.54	0.60	-0.22
Prin2	0.53	0.54	0.60	-0.22	
Prin3	0.54	0.60	-0.22		
Prin4	0.60	-0.22			
Prin5	-0.22				

$$0.12 \left(\frac{96 - 96.25}{2.19} \right) - 0.53 \left(\frac{99 - 72.68}{18.54} \right) - 0.54 \left(\frac{87 - 58.88}{24.68} \right) - 0.60 \left(\frac{92 - 65.71}{19.28} \right) - 0.22 \left(\frac{98 - 98.84}{0.83} \right)$$

How would this formula be different for covariance PCA?

UK Food Consumption

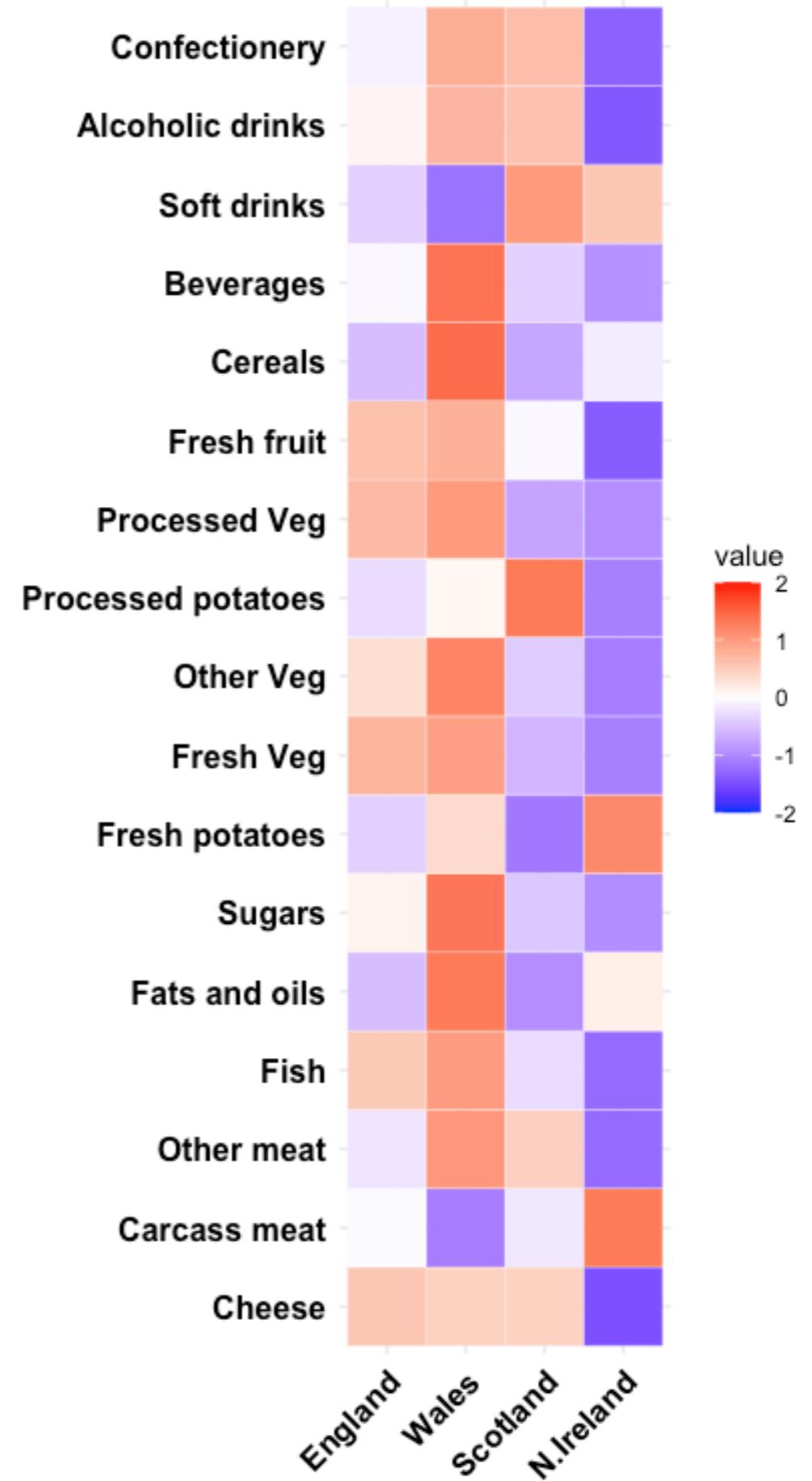
(Learning the BiPlot)

Average Consumption of Certain Food/Drink across the UK (Grams, Per Person, Per Week)

	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

From 'Department for Environment, Food and Rural Affairs' (DEFRA) in 1997.

Standardizing each row and observing a heat map we can clearly see how the countries are different in their consumption. The PCA BiPlot gives us another visual to reveal the same information



We'll opt for the transpose, where the observations are the four countries within the UK.

```
food=read.csv("http://birch.iaa.ncsu.edu/~slrace/LinearAlgebra2021/Code/ukfood.csv",
              header=TRUE, row.names=1)
food=as.data.frame(t(food))
head(food)
```

	Cheese	Carcass meat	Other meat	Fish	Fats and oils	Sugars
England	105	245	685	147	193	156
Wales	103	227	803	160	235	175
Scotland	103	242	750	122	184	147
N.Ireland	66	267	586	93	209	139
	Fresh potatoes	Fresh Veg	Other Veg	Processed Veg	Processed potatoes	Processed Veg
England	720	253	488		198	360
Wales	874	265	570		203	365
Scotland	566	171	418		220	337
N.Ireland	1033	143	355		187	334
	Fresh fruit	Cereals	Beverages	Soft drinks	Alcoholic drinks	
England	1102	1472	57	1374	375	
Wales	1137	1582	73	1256	475	
Scotland	957	1462	53	1572	458	
N.Ireland	674	1494	47	1506	135	
	Confectionery					
England		54				
Wales		64				
Scotland		62				
N.Ireland		41				

We then compute the PCA and observe the output object in our environment:

```
pca=prcomp(food, scale = T)
```

```
▶ pca                                List of 5
  sdev : num [1:4] 3.41 2.06 1.08 6.34e-16
  rotation: num [1:17, 1:4] 0.246 -0.286 0.265 0.286 0.127 ...
  ..- attr(*, "dimnames")=List of 2
  .. .$. : chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  .. .$. : chr [1:4] "PC1" "PC2" "PC3" "PC4"
  center : Named num [1:17] 94.2 245.2 706 130.5 205.2 ...
  ..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  scale : Named num [1:17] 18.9 16.5 93.4 29.6 22.4 ...
  ..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  x : num [1:4, 1:4] 0.827 3.915 -0.423 -4.319 0.284 ...
  ..- attr(*, "dimnames")=List of 2
  .. .$. : chr [1:4] "England" "Wales" "Scotland" "N.Ireland"
  .. .$. : chr [1:4] "PC1" "PC2" "PC3" "PC4"
  - attr(*, "class")= chr "prcomp"
```

We then compute the PCA and observe the output object in our environment:

```
pca=prcomp(food, scale = T)
```

```
▶ pca
```

List of 5

```
sdev : num [1:4] 3.41 2.06 1.08 6.34e-16
```

list of 4 numbers

```
rotation: num [1:17, 1:4] 0.246 -0.286 0.265 0.286 0.127 ...
```

```
..- attr(*, "dimnames")=List of 2
```

```
.. ..$ : chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
```

```
.. ..$ : chr [1:4] "PC1" "PC2" "PC3" "PC4"
```

```
center : Named num [1:17] 94.2 245.2 706 130.5 205.2 ...
```

```
..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
```

```
scale : Named num [1:17] 18.9 16.5 93.4 29.6 22.4 ...
```

```
..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
```

```
x : num [1:4, 1:4] 0.827 3.915 -0.423 -4.319 0.284 ...
```

```
..- attr(*, "dimnames")=List of 2
```

```
.. ..$ : chr [1:4] "England" "Wales" "Scotland" "N.Ireland"
```

```
.. ..$ : chr [1:4] "PC1" "PC2" "PC3" "PC4"
```

```
- attr(*, "class")= chr "prcomp"
```

We then compute the PCA and observe the output object in our environment:

```
pca=prcomp(food, scale = T)
```

```
▶ pca
```

List of 5

```
  sdev : num [1:4] 3.41 2.06 1.08 6.34e-16
  rotation: num [1:17, 1:4] 0.246 -0.286 0.265 0.286 0.127 ...
  ..- attr(*, "dimnames")=List of 2
  ...$ : chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  ...$ : chr [1:4] "PC1" "PC2" "PC3" "PC4"
  center : Named num [1:17] 94.2 245.2 706 130.5 205.2 ...
  ..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  scale : Named num [1:17] 18.9 16.5 93.4 29.6 22.4 ...
  ..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  x : num [1:4, 1:4] 0.827 3.915 -0.423 -4.319 0.284 ...
  ..- attr(*, "dimnames")=List of 2
  ...$ : chr [1:4] "England" "Wales" "Scotland" "N.Ireland"
  ...$ : chr [1:4] "PC1" "PC2" "PC3" "PC4"
  - attr(*, "class")= chr "prcomp"
```

17 x 4 matrix

We then compute the PCA and observe the output object in our environment:

```
pca=prcomp(food, scale = T)
```

```
▶ pca                                         List of 5
  sdev : num [1:4] 3.41 2.06 1.08 6.34e-16
  rotation: num [1:17, 1:4] 0.246 -0.286 0.265 0.286 0.127 ...
  ..- attr(*, "dimnames")=List of 2
  .. .$. : chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  .. .$. : chr [1:4] "PC1" "PC2" "PC3" "PC4"
  center : Named num [1:17] 94.2 245.2 706 130.5 205.2 ...
  ..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  scale : Named num [1:17] 18.9 16.5 93.4 29.6 22.4 ...
  ..- attr(*, "names")= chr [1:17] "Cheese" "Carcass meat" "Other meat" "Fish" ...
  x : num [1:4, 1:4] 0.827 3.915 -0.423 -4.319 0.284 ...
  ..- attr(*, "dimnames")=List of 2
  .. .$. : chr [1:4] "England" "Wales" "Scotland" "N.Ireland"
  .. .$. : chr [1:4] "PC1" "PC2" "PC3" "PC4"
  - attr(*, "class")= chr "prcomp"
```

4 x 4 matrix

If we still need help understanding what these objects are:

?prcomp

1. **sdev**: the standard deviations of the principal components (i.e., the **square roots of the eigenvalues** of the covariance/correlation matrix, though the calculation is actually done with the singular values of the data matrix).
2. **rotation**: the matrix of **variable loadings**(i.e., a matrix whose columns contain the eigenvectors). The function princomp returns this in the element loadings.
3. **x**: the value of the rotated data (**i.e. the scores**)(the centred (and scaled if requested) data multiplied by the rotation matrix) is returned. Hence, cov(x) is the diagonal matrix diag(sdev²)
4. **center, scale**: the centering and scaling used, or FALSE.

The screeplot and % variance explained statistics

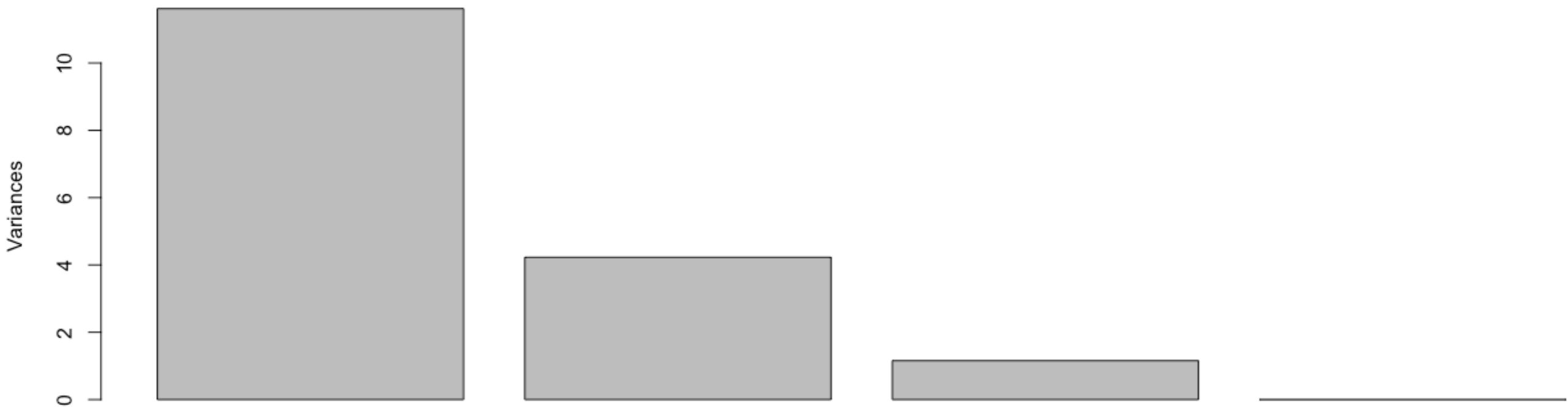
```
summary(pca)
```

```
plot(pca, main = "Bar-style Screeplot")
```

Importance of components:

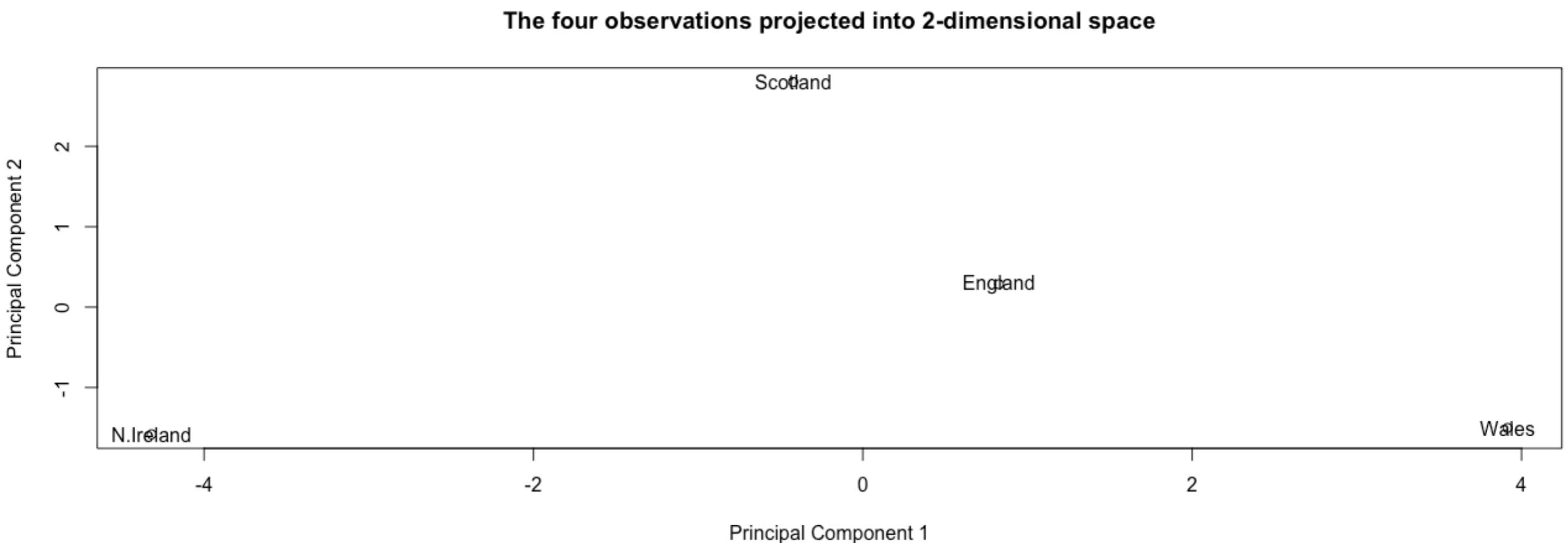
	PC1	PC2	PC3	PC4
Standard deviation	3.4082	2.0562	1.07524	6.344e-16
Proportion of Variance	0.6833	0.2487	0.06801	0.000e+00
Cumulative Proportion	0.6833	0.9320	1.00000	1.000e+00

Bar-style Screeplot



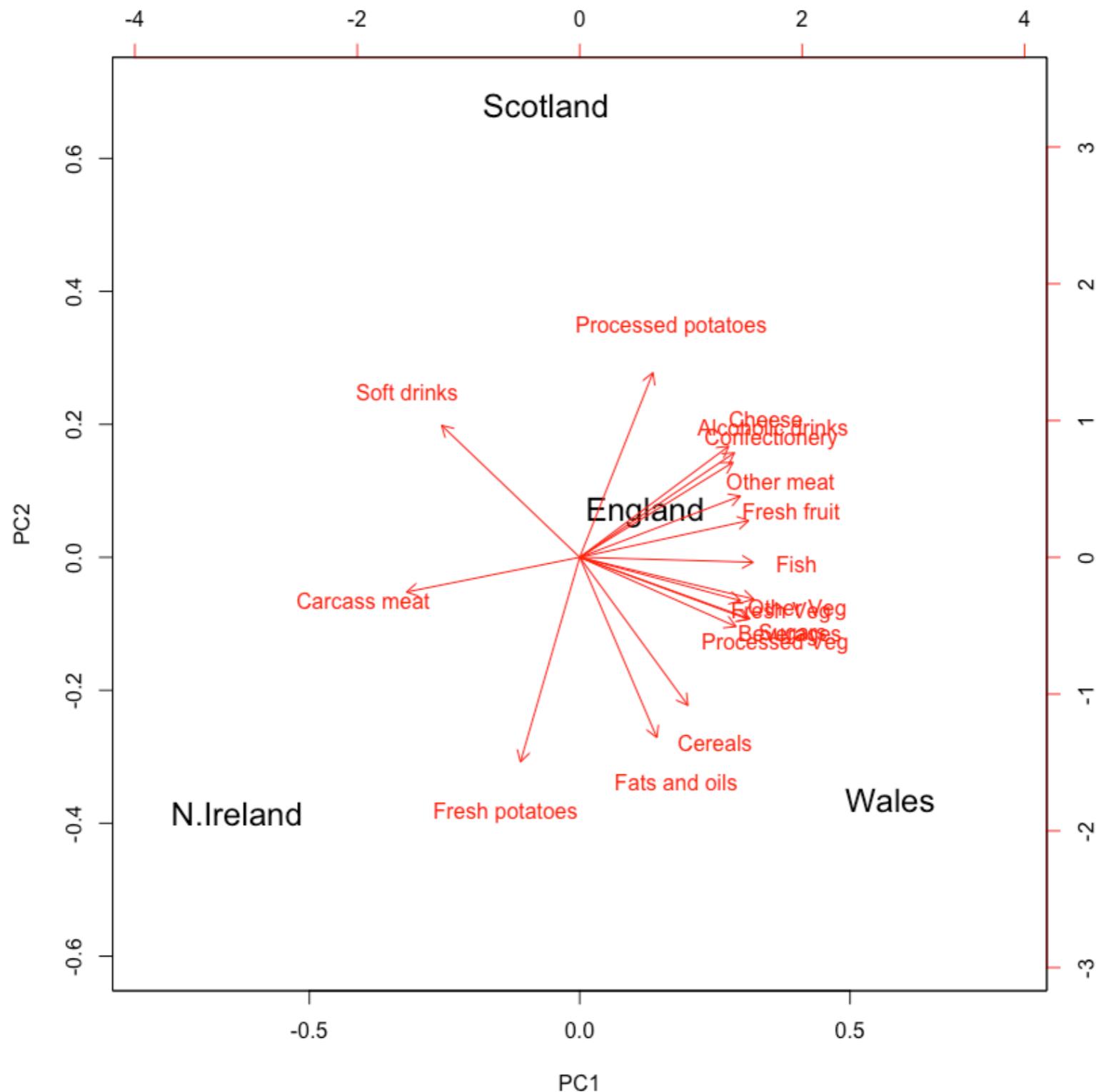
The projection of the data into 2-D (plot of scores)

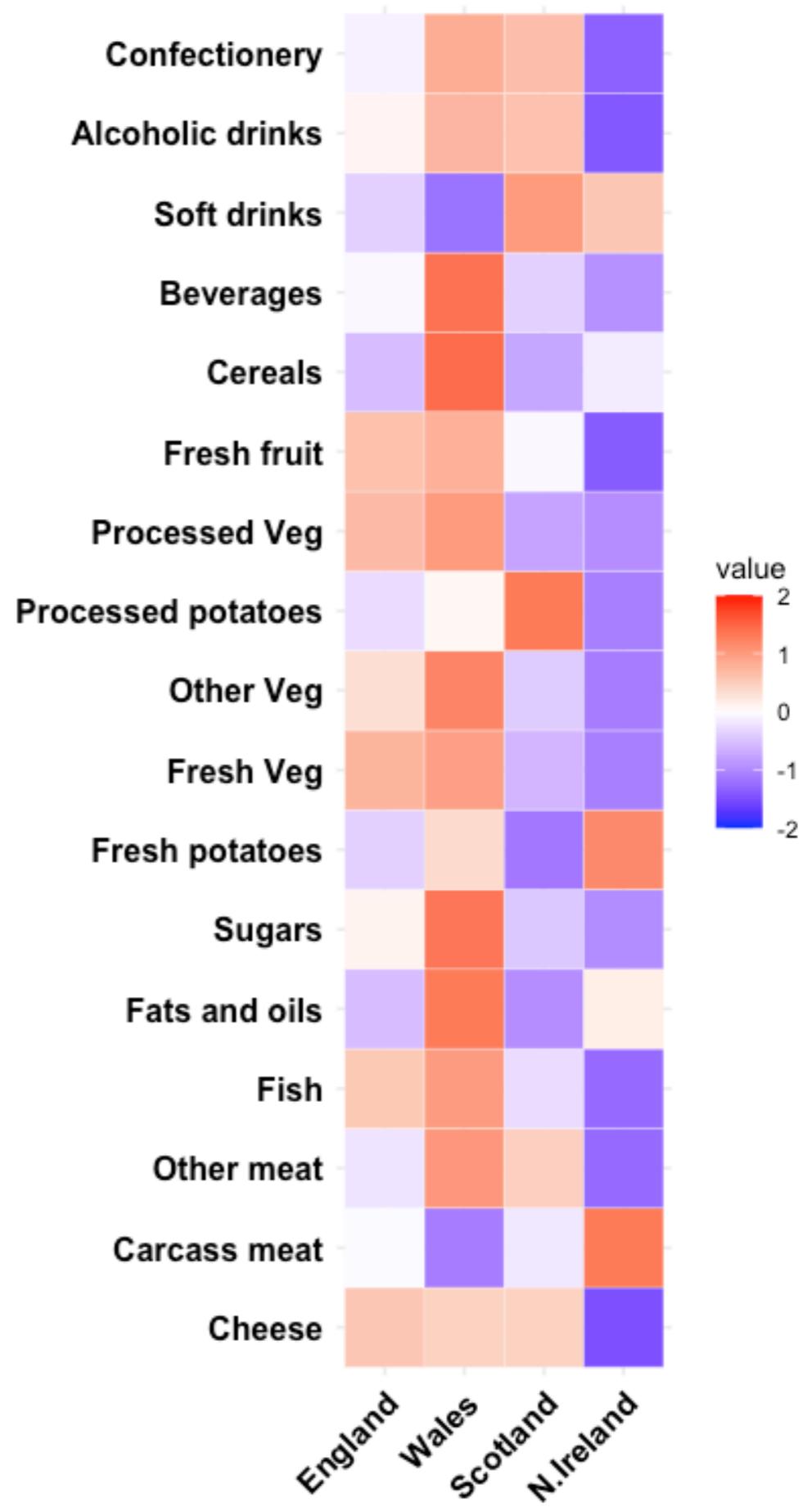
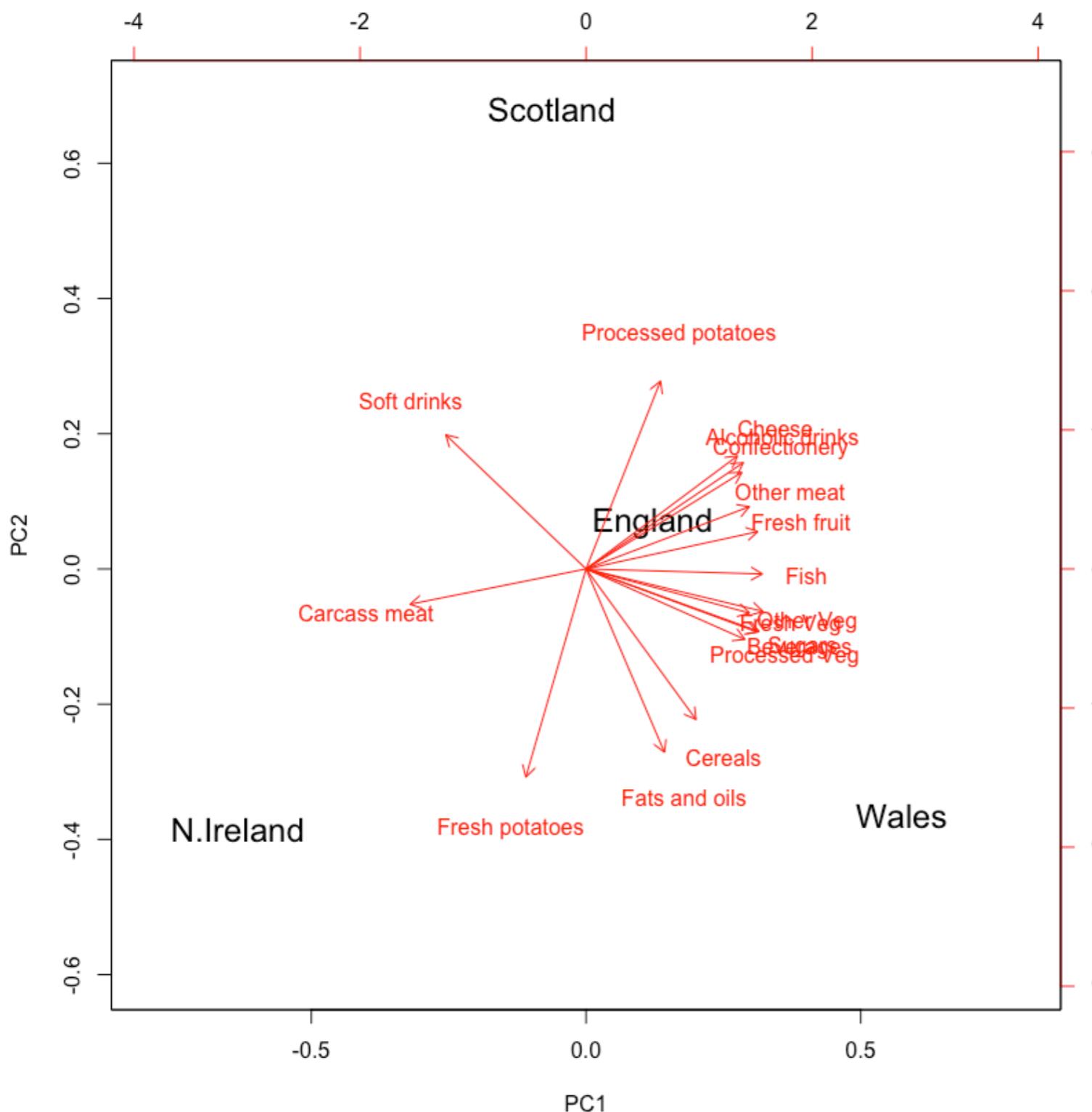
```
plot(pca$x,
  xlab= "Principal Component 1",
  ylab= "Principal Component 2",
  main= 'The four observations projected into 2-dimensional space')
text(pca$x[,1], pca$x[,2], row.names(food))
```

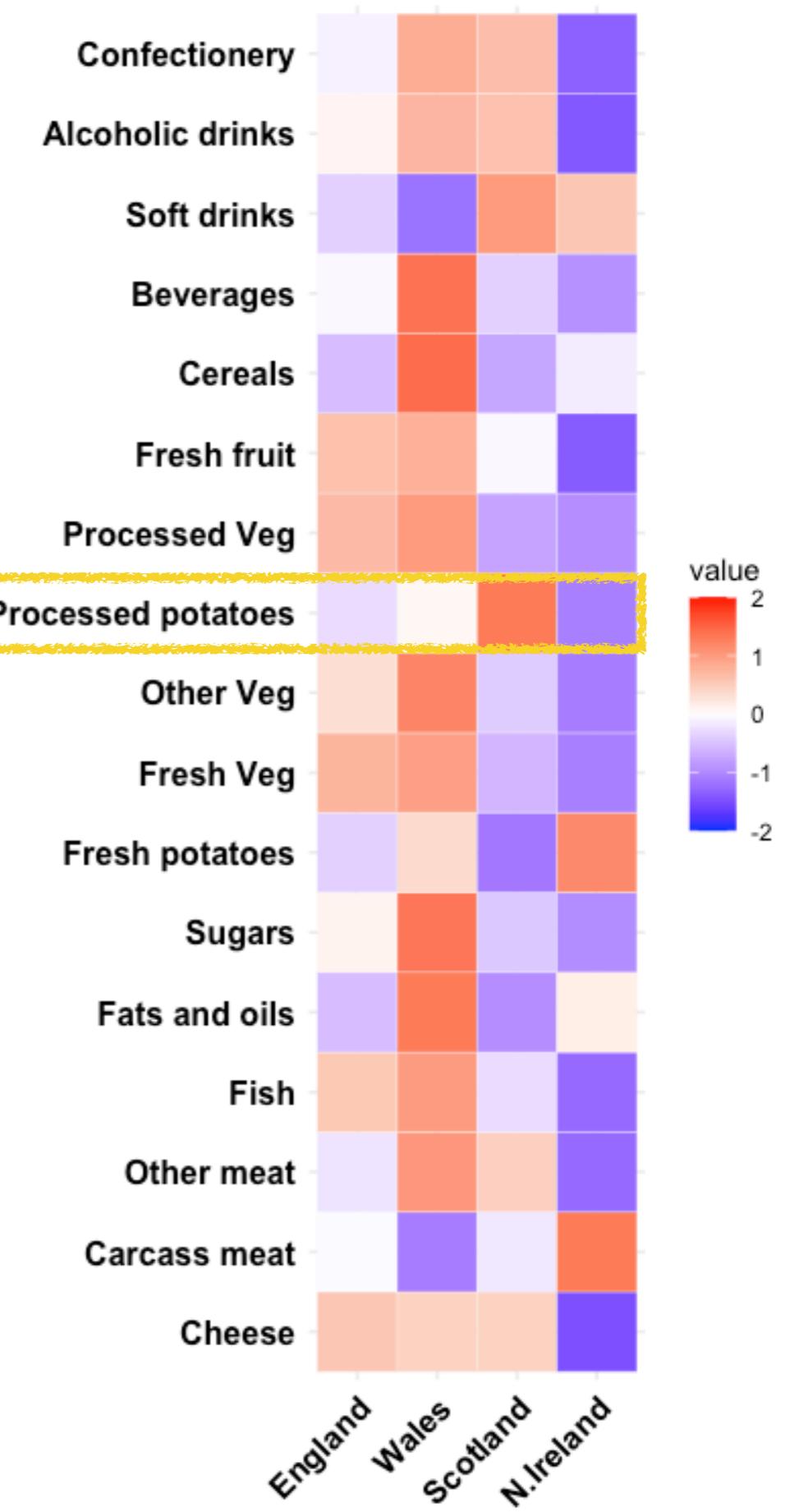
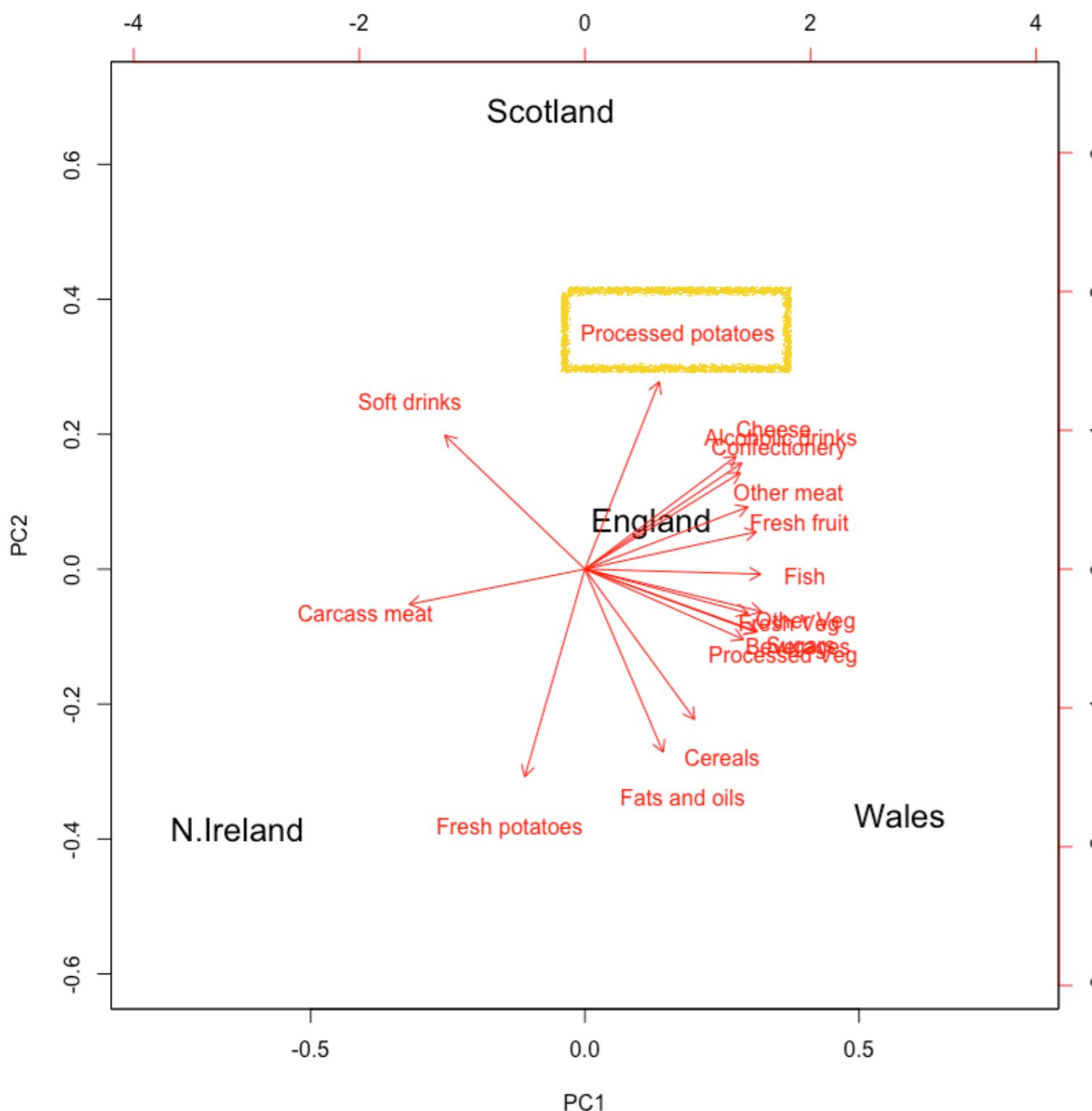


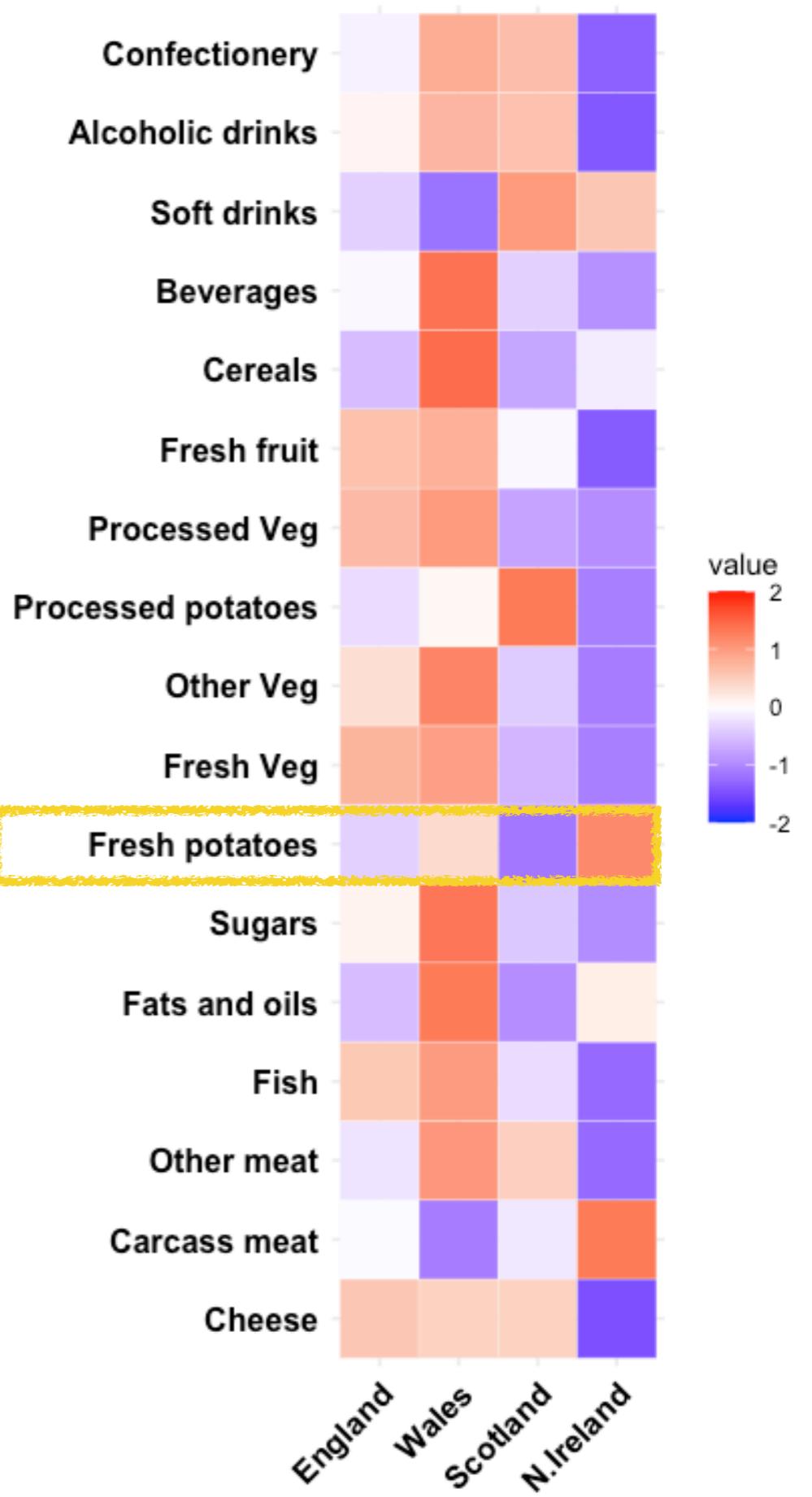
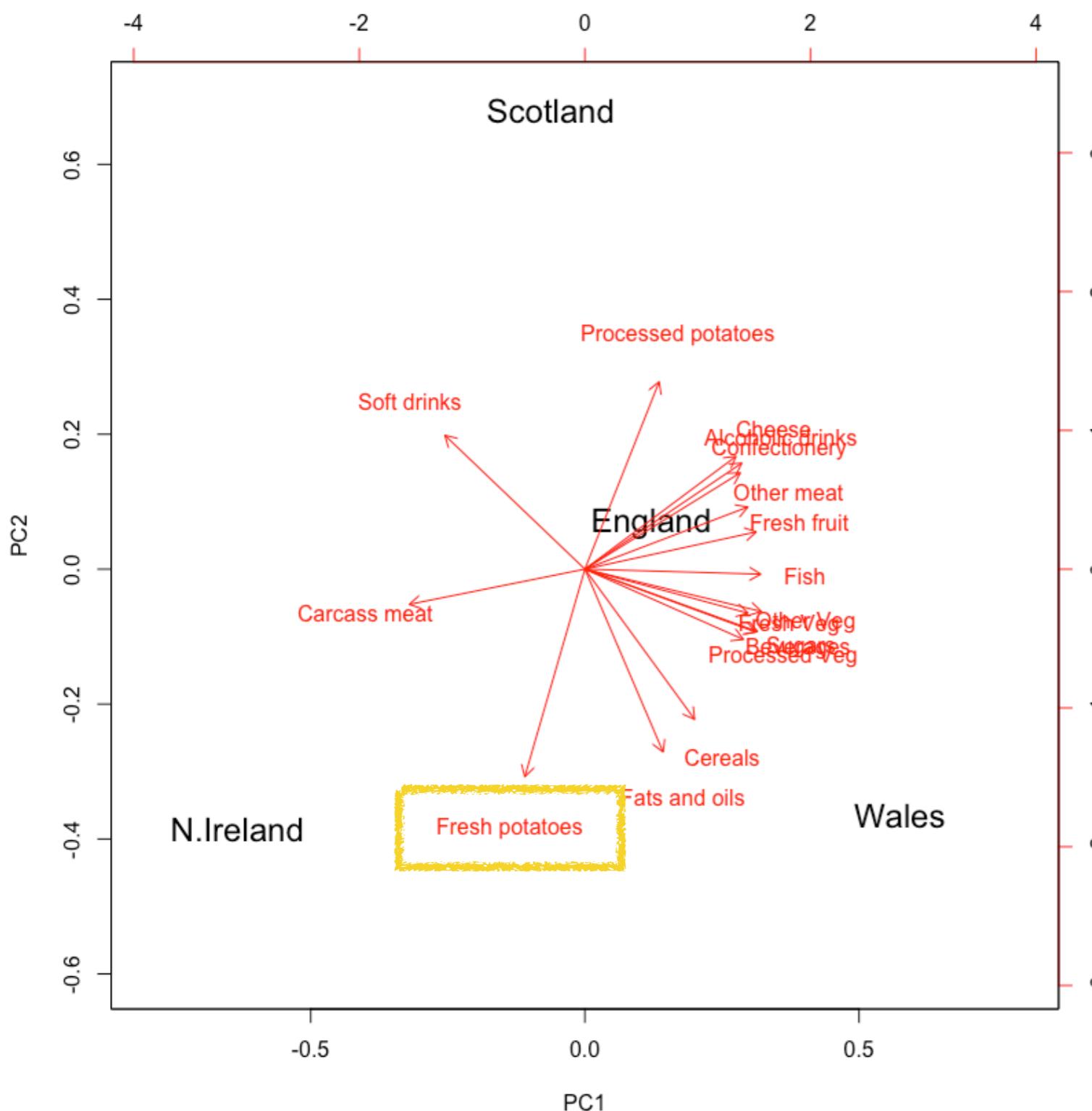
The Biplot

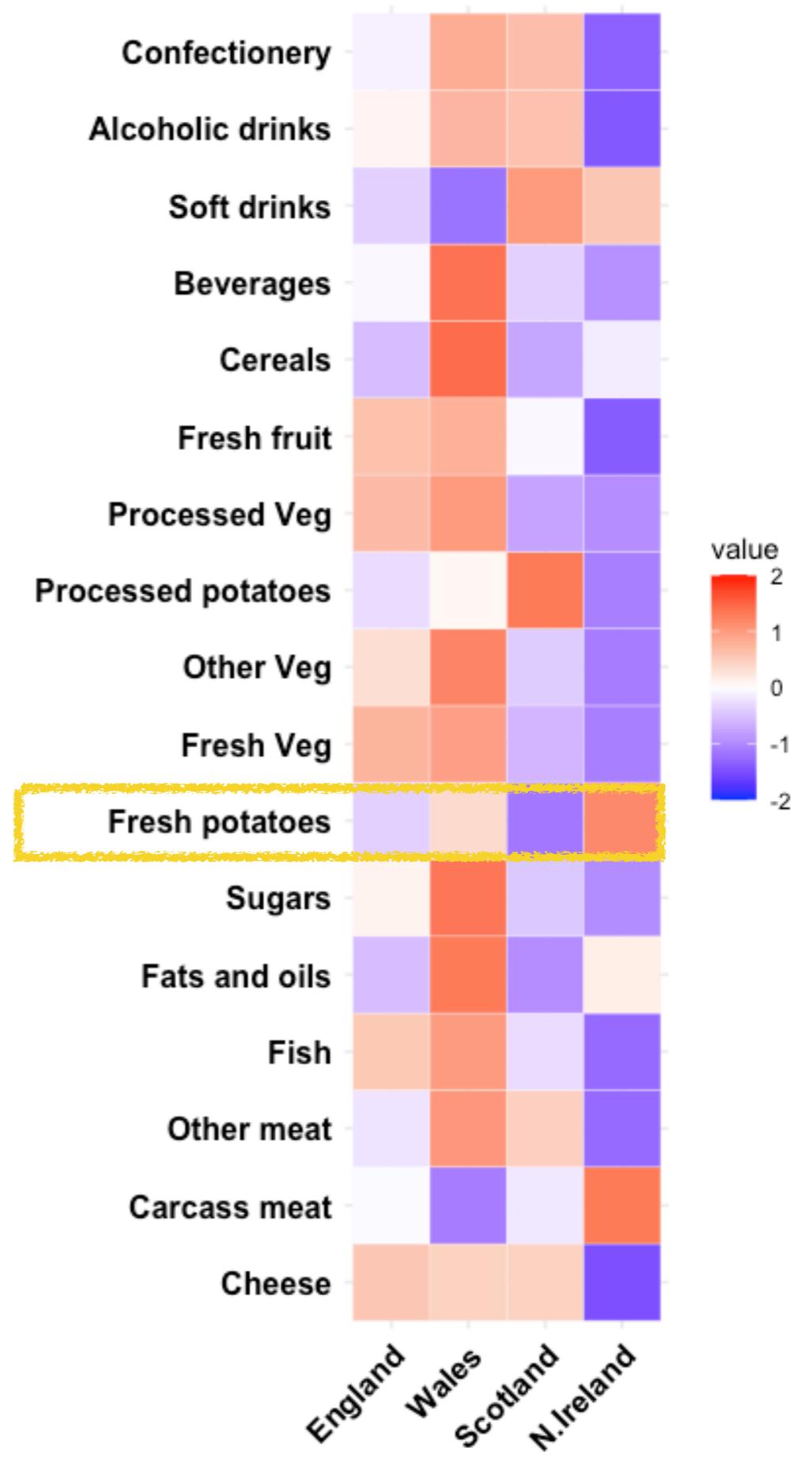
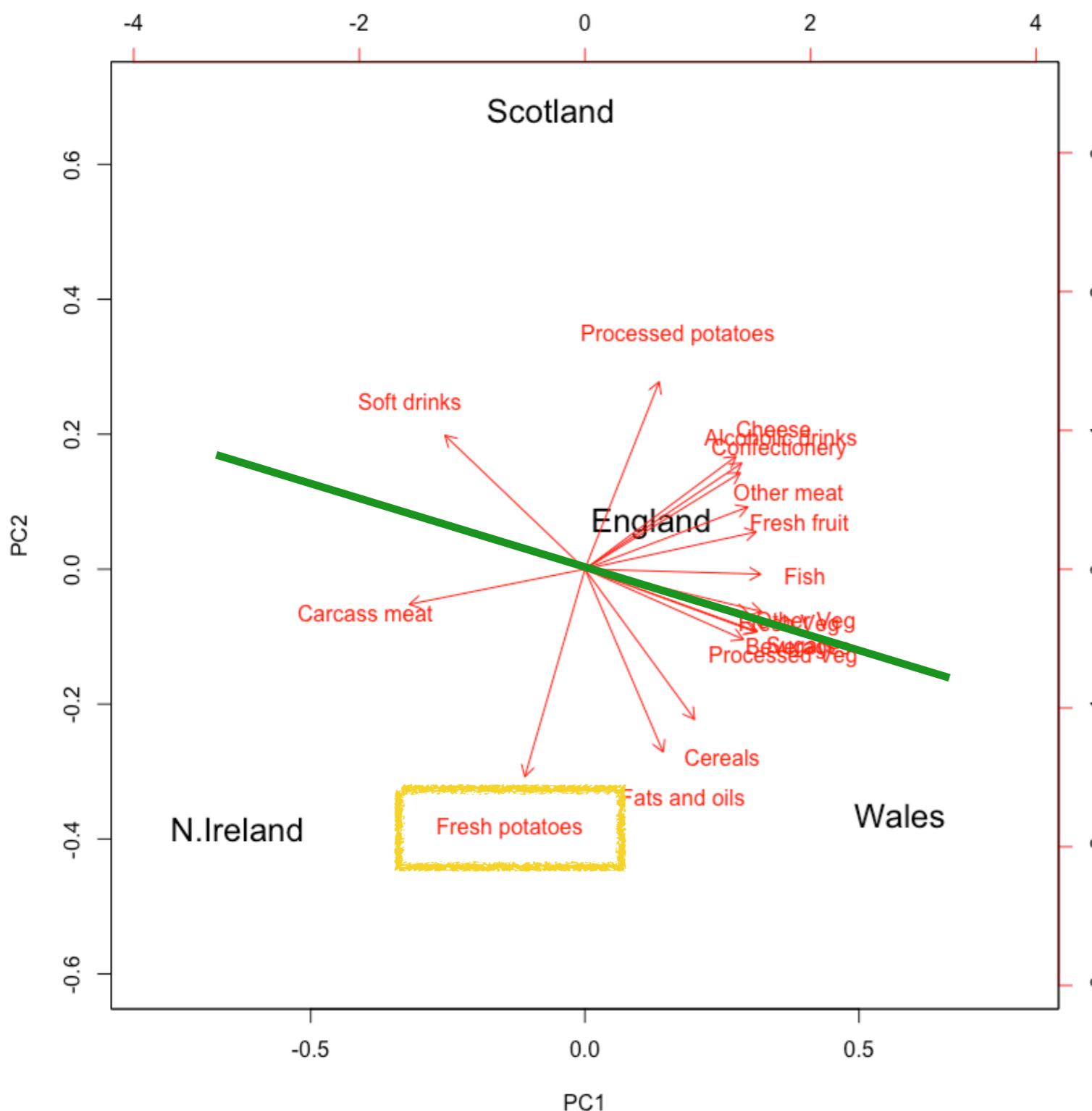
```
biplot(pca, cex = c(1.5, 1), col = c('black','red'),  
       xlim = c(-0.8,0.8), ylim = c(-0.6,0.7))
```

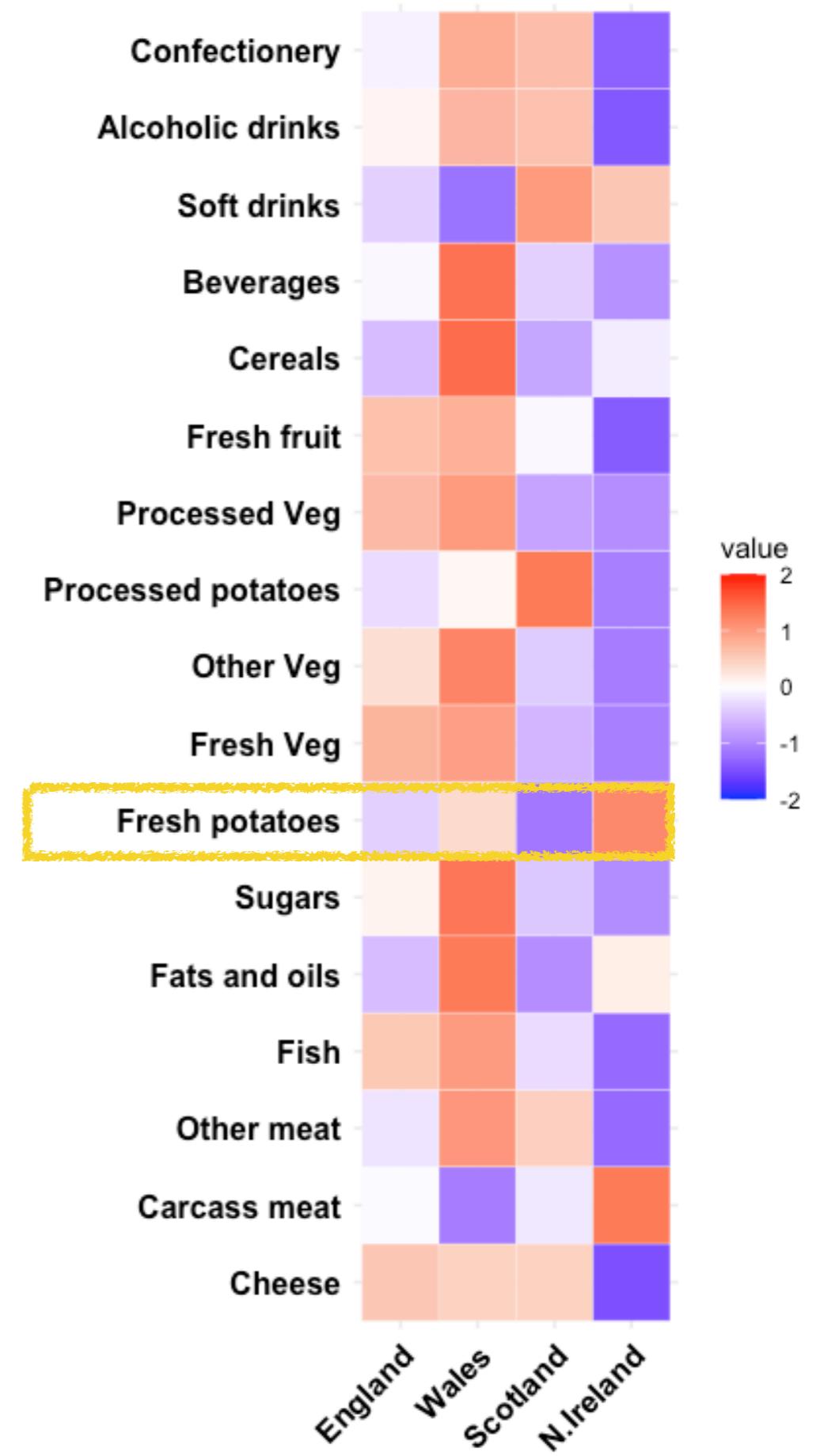
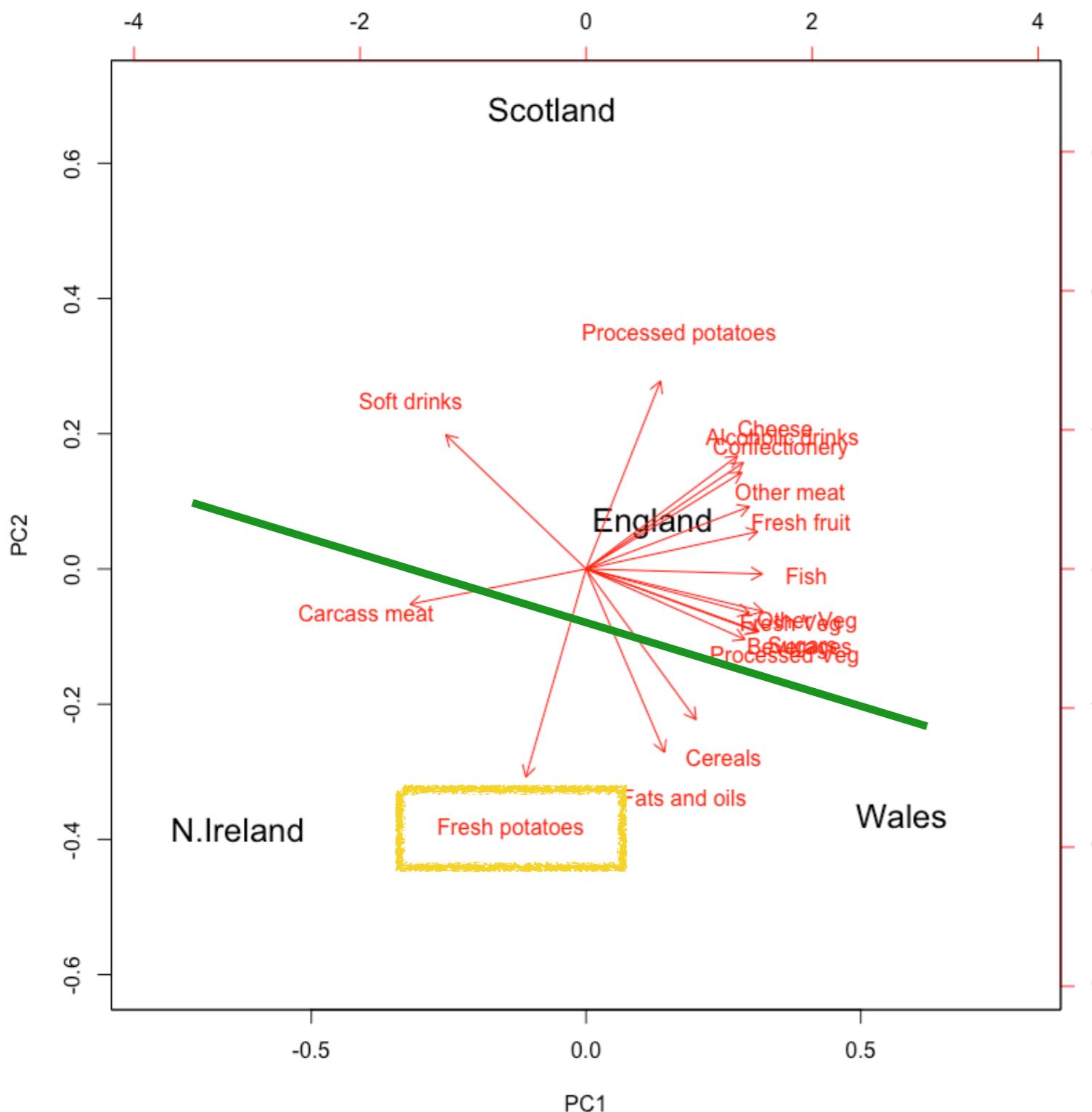


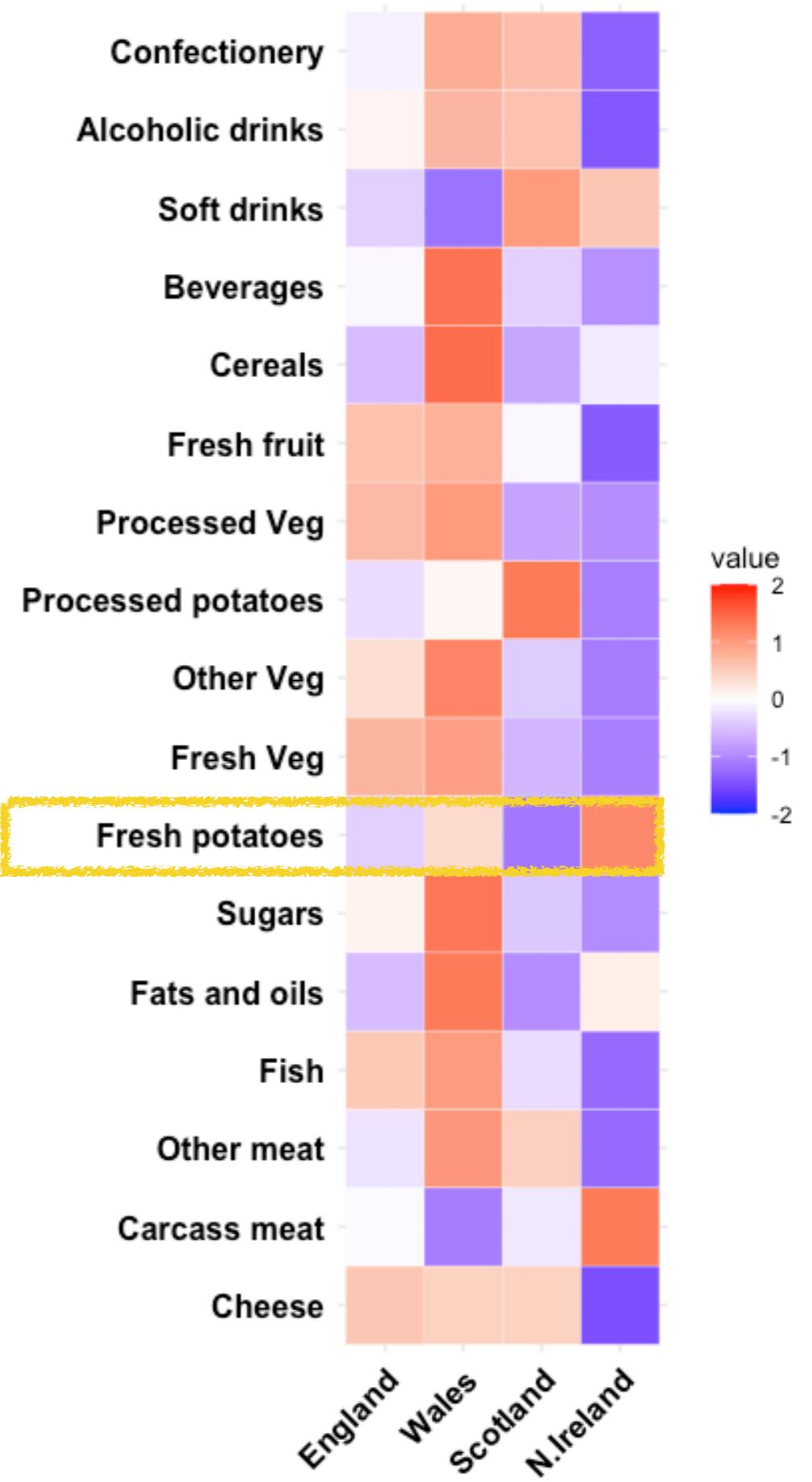
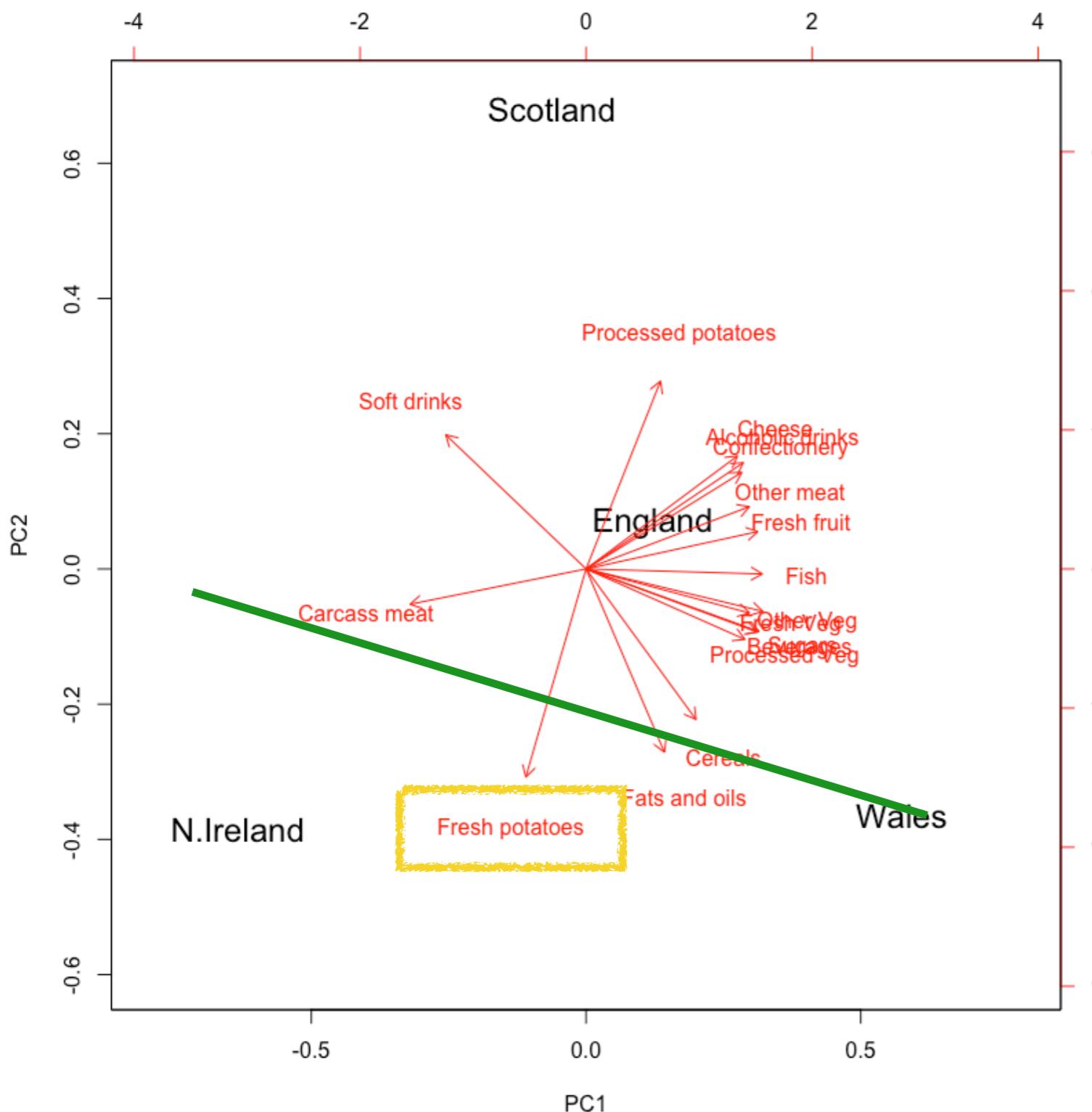


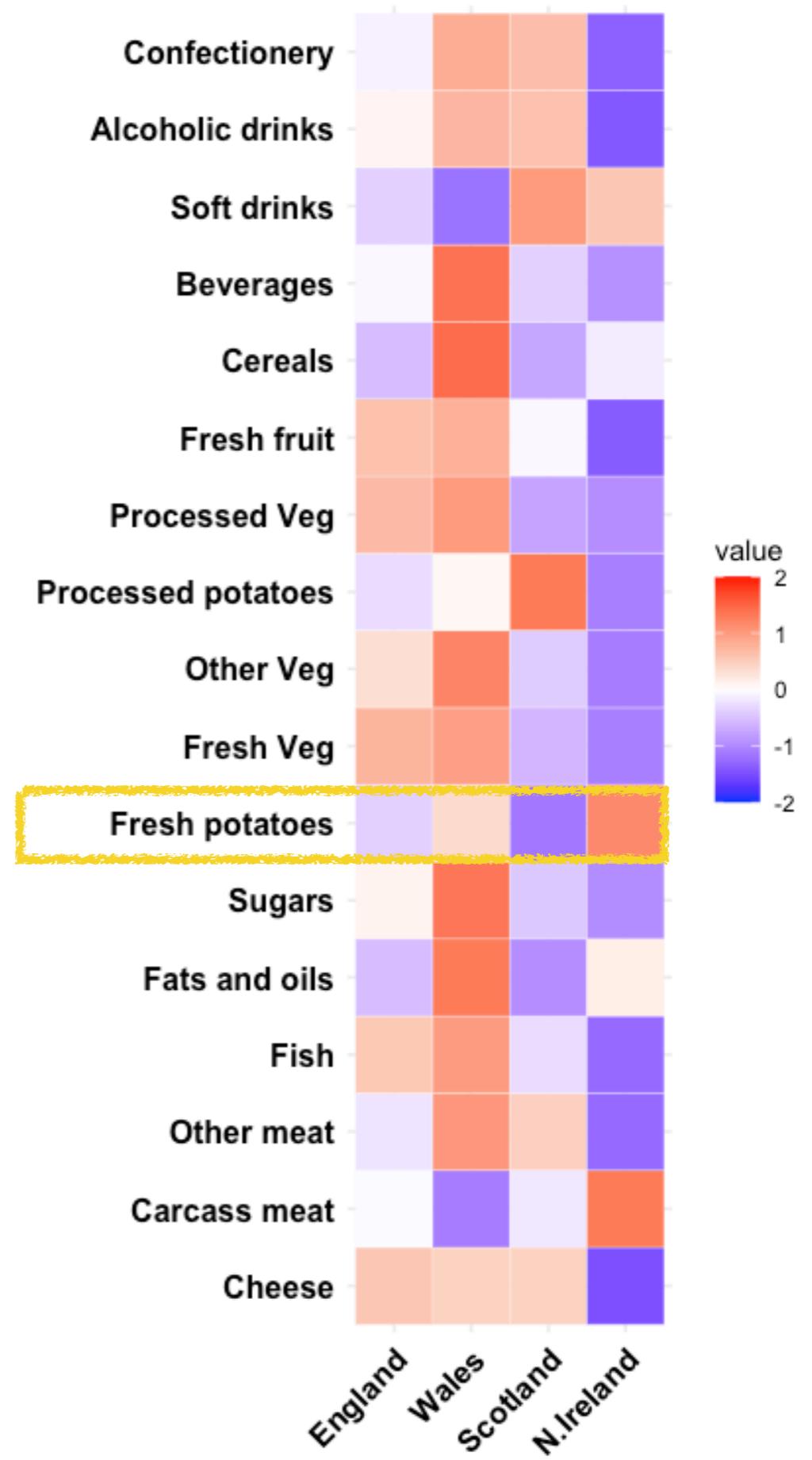
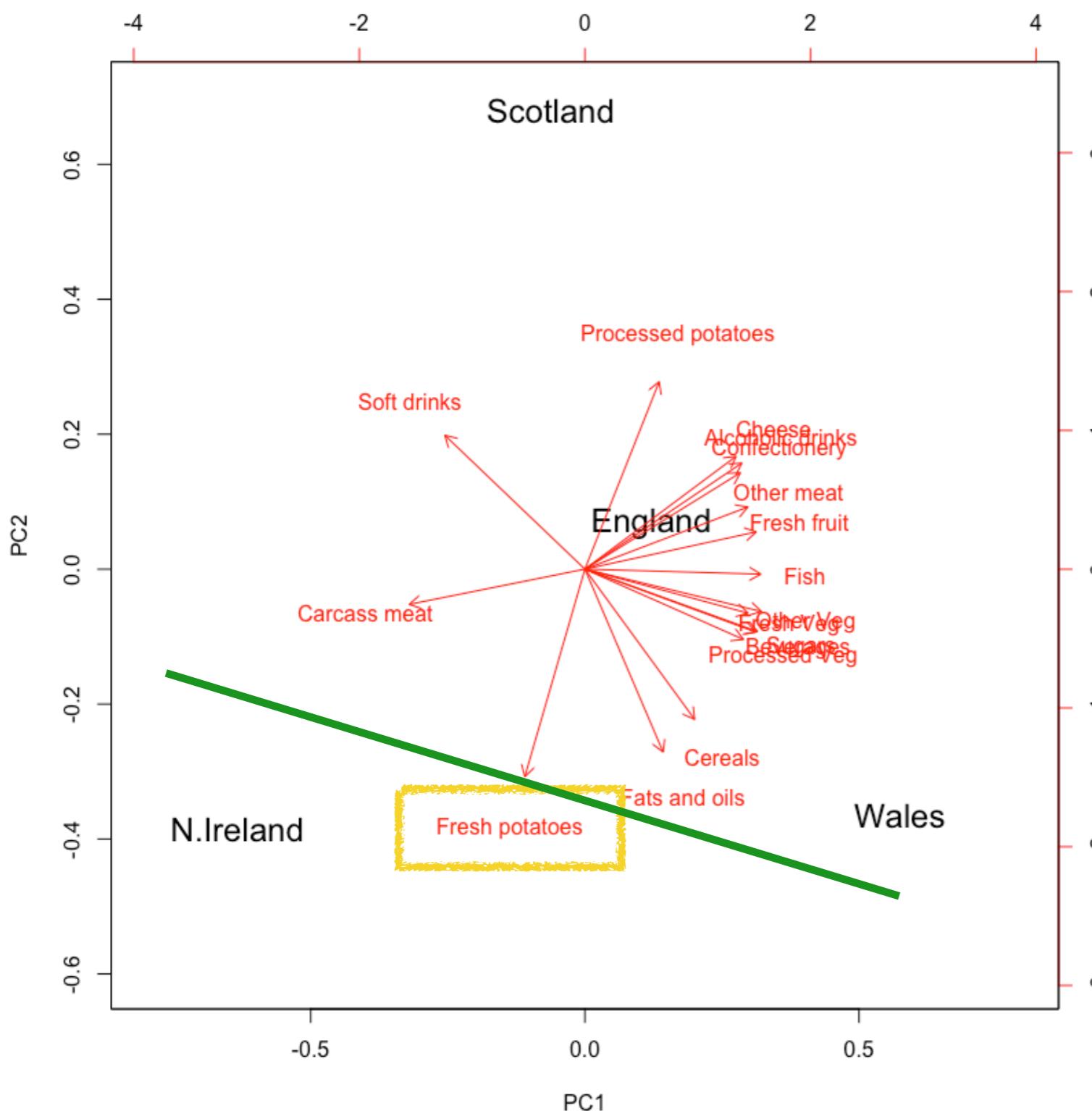


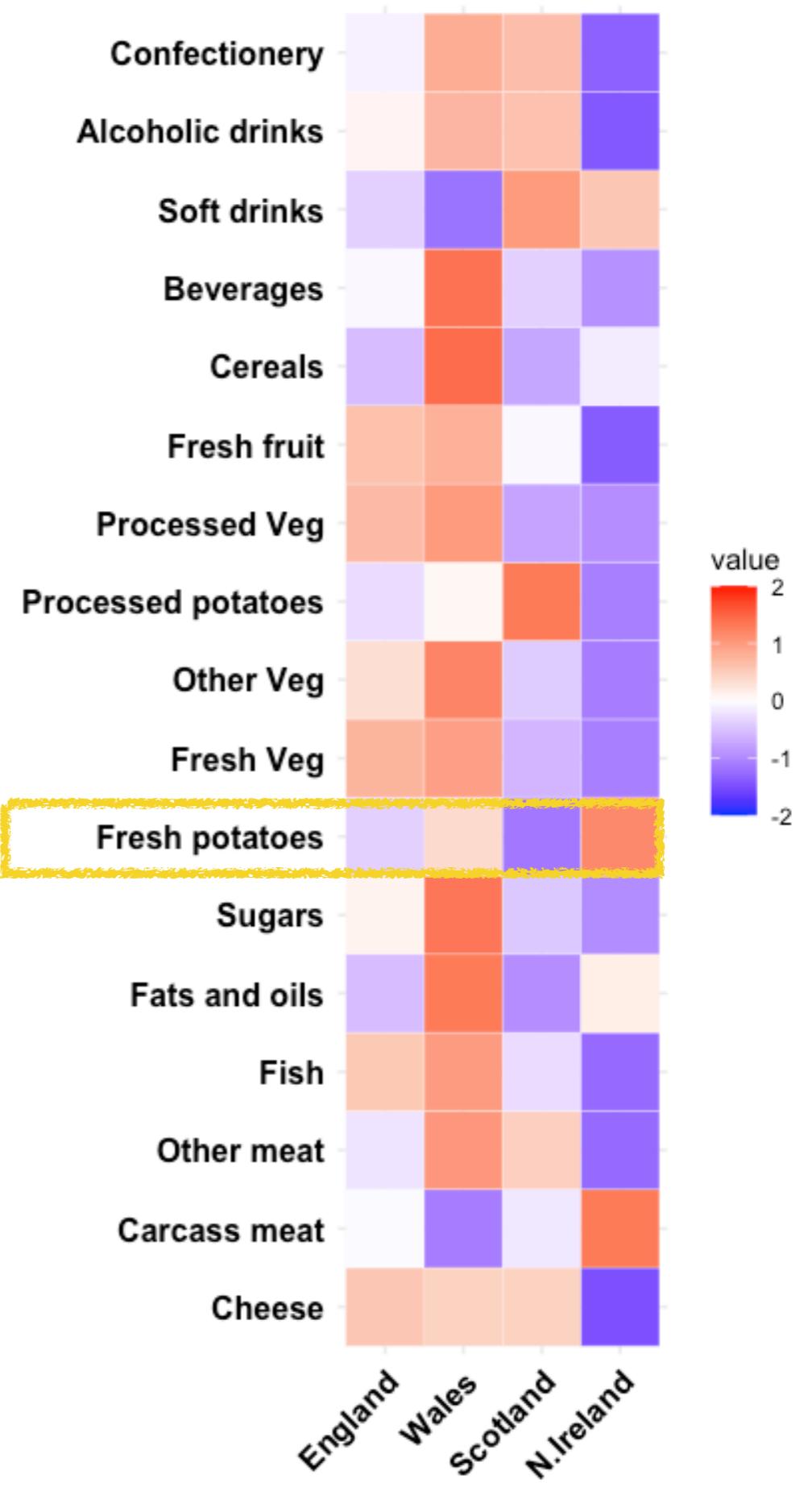
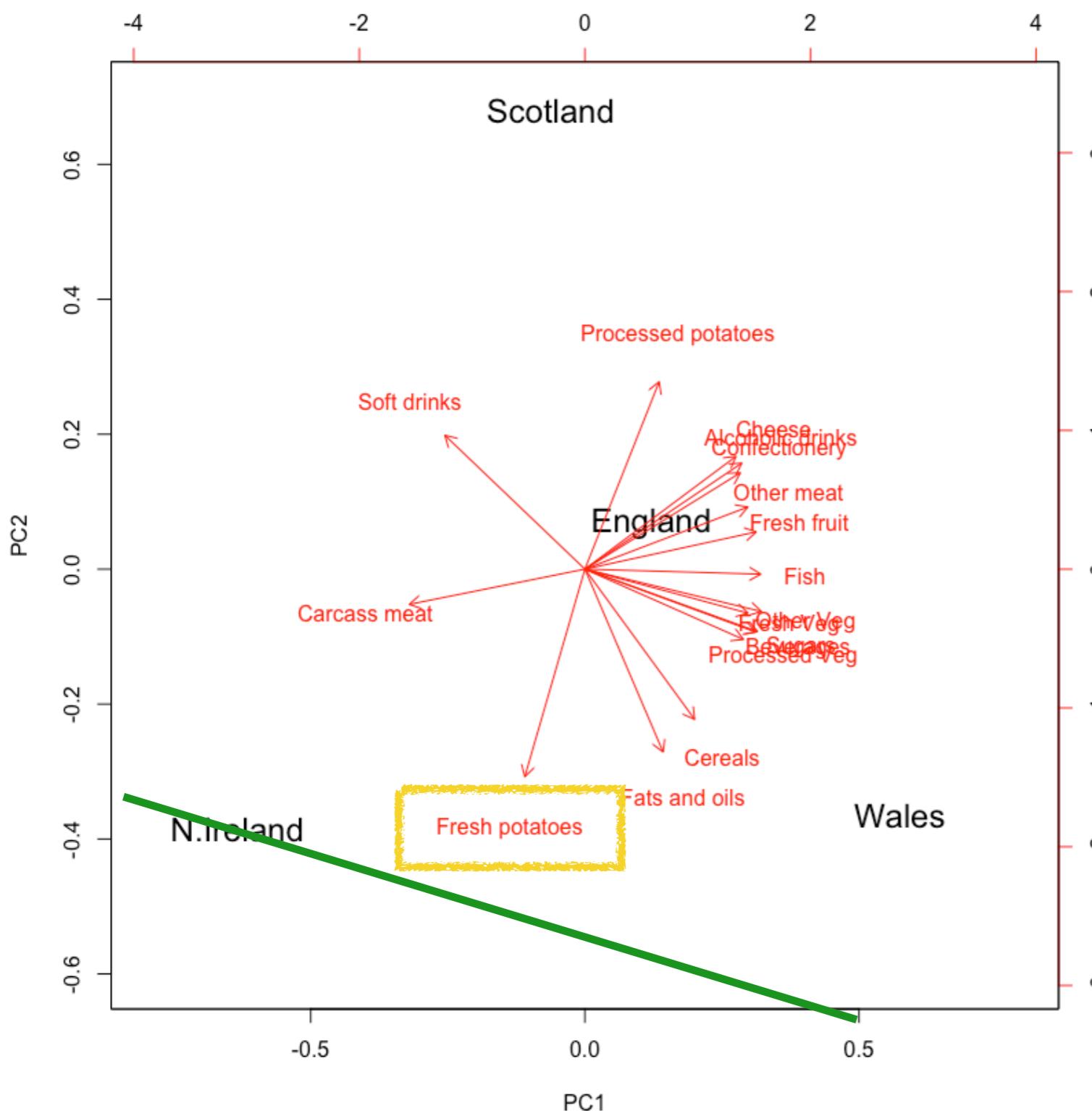












FIFA Soccer Players

The Data

```
load('fifa.RData')  
colnames(fifa)
```

[1] "Name"	"Age"	"Photo"	"Nationality"
[5] "Flag"	"Overall"	"Potential"	"Club"
[9] "Club.Logo"	"Value"	"Wage"	"Special"
[13] "Acceleration"	"Aggression"	"Agility"	"Balance"
[17] "Ball.control"	"Composure"	"Crossing"	"Curve"
[21] "Dribbling"	"Finishing"	"Free.kick.accuracy"	"GK.diving"
[25] "GK.handling"	"GK.kicking"	"GK.positioning"	"GK.reflexes"
[29] "Heading.accuracy"	"Interceptions"	"Jumping"	"Long.passing"
[33] "Long.shots"	"Marking"	"Penalties"	"Positioning"
[37] "Reactions"	"Short.passing"	"Shot.power"	"Sliding.tackle"
[41] "Sprint.speed"	"Stamina"	"Standing.tackle"	"Strength"
[45] "Vision"	"Volleys"	"position"	

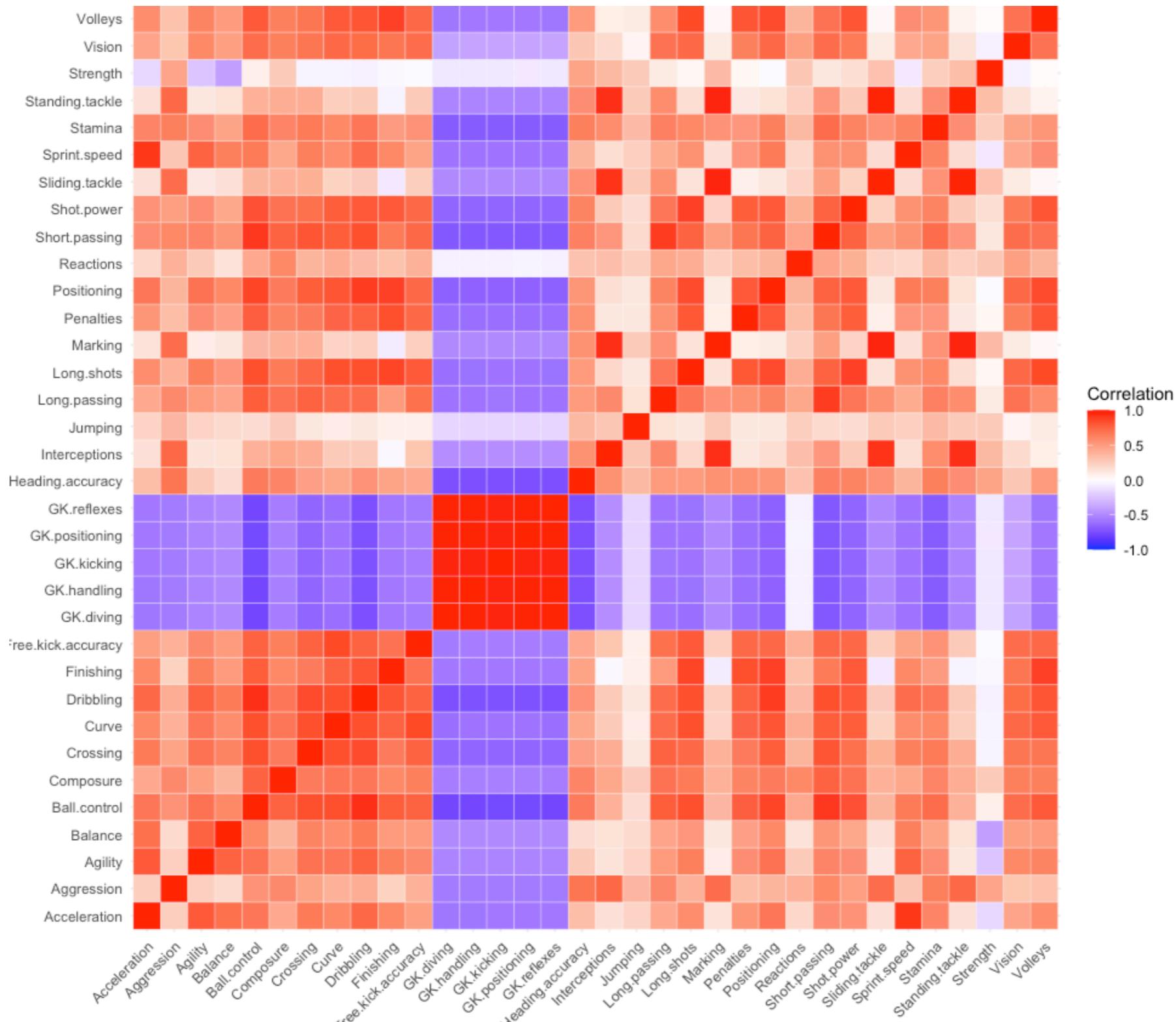
Exploring the Data

```
summary(fifa[,13:46])
```

Acceleration	Aggression	Agility	Balance	Ball.control	Composure	Crossing	Curve
Min. :11.00	Min. :11.00	Min. :14.00	Min. :11.00	Min. : 8	Min. : 5.00	Min. : 5.0	Min. : 6.0
1st Qu.:56.00	1st Qu.:43.00	1st Qu.:55.00	1st Qu.:56.00	1st Qu.:53	1st Qu.:51.00	1st Qu.:37.0	1st Qu.:34.0
Median :67.00	Median :58.00	Median :65.00	Median :66.00	Median :62	Median :60.00	Median :54.0	Median :48.0
Mean :64.48	Mean :55.74	Mean :63.25	Mean :63.76	Mean :58	Mean :57.82	Mean :49.7	Mean :47.2
3rd Qu.:75.00	3rd Qu.:69.00	3rd Qu.:74.00	3rd Qu.:74.00	3rd Qu.:69	3rd Qu.:67.00	3rd Qu.:64.0	3rd Qu.:62.0
Max. :96.00	Max. :96.00	Max. :96.00	Max. :96.00	Max. :95	Max. :96.00	Max. :91.0	Max. :92.0
Dribbling	Finishing	Free.kick.accuracy	GK.diving	GK.handling	GK.kicking	GK.positioning	GK.reflexes
Min. : 2.00	Min. : 2.00	Min. : 4.00	Min. : 1.00	Min. : 1.00	Min. : 1.00	Min. : 1.00	Min. : 1.00
1st Qu.:48.00	1st Qu.:29.00	1st Qu.:31.00	1st Qu.: 8.00	1st Qu.: 8.00	1st Qu.: 8.00	1st Qu.: 8.00	1st Qu.: 8.00
Median :60.00	Median :48.00	Median :42.00	Median :11.00	Median :11.00	Median :11.00	Median :11.00	Median :11.00
Mean :54.94	Mean :45.18	Mean :43.08	Mean :16.78	Mean :16.55	Mean :16.42	Mean :16.54	Mean :16.91
3rd Qu.:68.00	3rd Qu.:61.00	3rd Qu.:57.00	3rd Qu.:14.00	3rd Qu.:14.00	3rd Qu.:14.00	3rd Qu.:14.00	3rd Qu.:14.00
Max. :97.00	Max. :95.00	Max. :93.00	Max. :91.00	Max. :91.00	Max. :95.00	Max. :91.00	Max. :90.00
Heading.accuracy	Interceptions	Jumping	Long.passing	Long.shots	Marking	Penalties	Positioning
Min. : 4.00	Min. : 4.00	Min. :15.00	Min. : 7.00	Min. : 3.00	Min. : 4.00	Min. : 5.00	Min. : 2.00
1st Qu.:44.00	1st Qu.:26.00	1st Qu.:58.00	1st Qu.:42.00	1st Qu.:32.00	1st Qu.:22.00	1st Qu.:39.00	1st Qu.:38.00
Median :55.00	Median :52.00	Median :66.00	Median :56.00	Median :51.00	Median :48.00	Median :50.00	Median :54.00
Mean :52.26	Mean :46.53	Mean :64.84	Mean :52.37	Mean :47.11	Mean :44.09	Mean :48.92	Mean :49.53
3rd Qu.:64.00	3rd Qu.:64.00	3rd Qu.:73.00	3rd Qu.:64.00	3rd Qu.:62.00	3rd Qu.:63.00	3rd Qu.:61.00	3rd Qu.:64.00
Max. :94.00	Max. :92.00	Max. :95.00	Max. :93.00	Max. :92.00	Max. :92.00	Max. :92.00	Max. :95.00

Exploring the Data

```
cor.matrix = cor(fifa[,13:46])
```



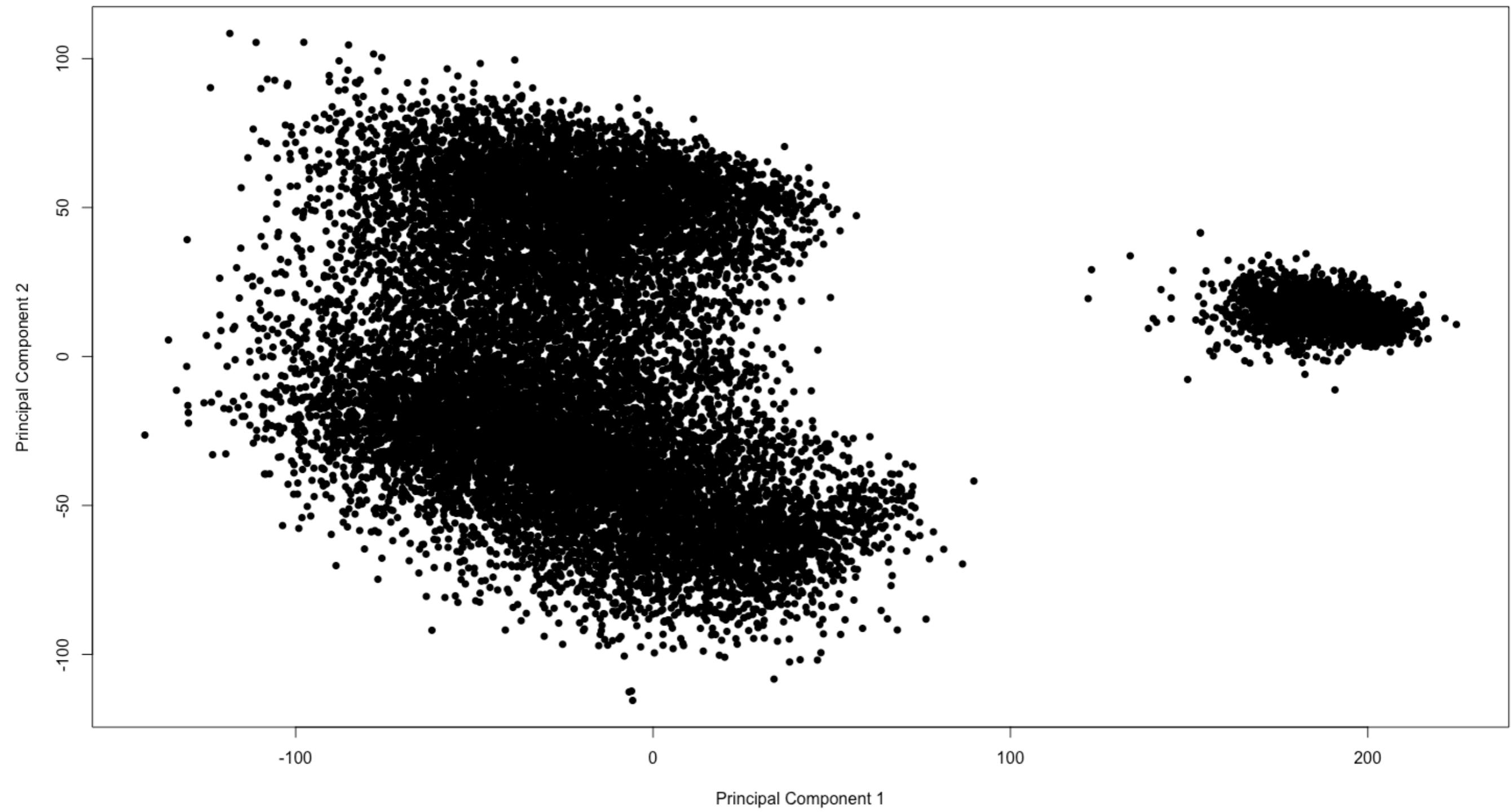
Compute the PCA

```
fifa.pca = prcomp(fifa[,13:46])  
summary(fifa.pca)
```

Importance of components:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Standard deviation	74.8371	43.5787	23.28767	20.58146	16.12477	10.71539	10.17785
Proportion of Variance	0.5647	0.1915	0.05468	0.04271	0.02621	0.01158	0.01044
Cumulative Proportion	0.5647	0.7561	0.81081	0.85352	0.87973	0.89131	0.90175
	PC8	PC9	PC10	PC11	PC12	PC13	PC14
Standard deviation	9.11852	8.98065	8.5082	8.41550	7.93741	7.15935	7.06502
Proportion of Variance	0.00838	0.00813	0.0073	0.00714	0.00635	0.00517	0.00503
Cumulative Proportion	0.91013	0.91827	0.9256	0.93270	0.93906	0.94422	0.94926
	PC15	PC16	PC17	PC18	PC19	PC20	PC21
Standard deviation	6.68497	6.56406	6.50459	6.22369	6.08812	6.00578	5.91320
Proportion of Variance	0.00451	0.00434	0.00427	0.00391	0.00374	0.00364	0.00353
Cumulative Proportion	0.95376	0.95811	0.96237	0.96628	0.97001	0.97365	0.97718
	PC22	PC23	PC24	PC25	PC26	PC27	PC28
Standard deviation	5.66946	5.45018	5.15051	4.86761	4.34786	4.1098	4.05716
Proportion of Variance	0.00324	0.00299	0.00267	0.00239	0.00191	0.0017	0.00166
Cumulative Proportion	0.98042	0.98341	0.98609	0.98848	0.99038	0.9921	0.99374

Plot the Projection



Examine Loadings

```
fifa.pca$rotation[,1:3]
```

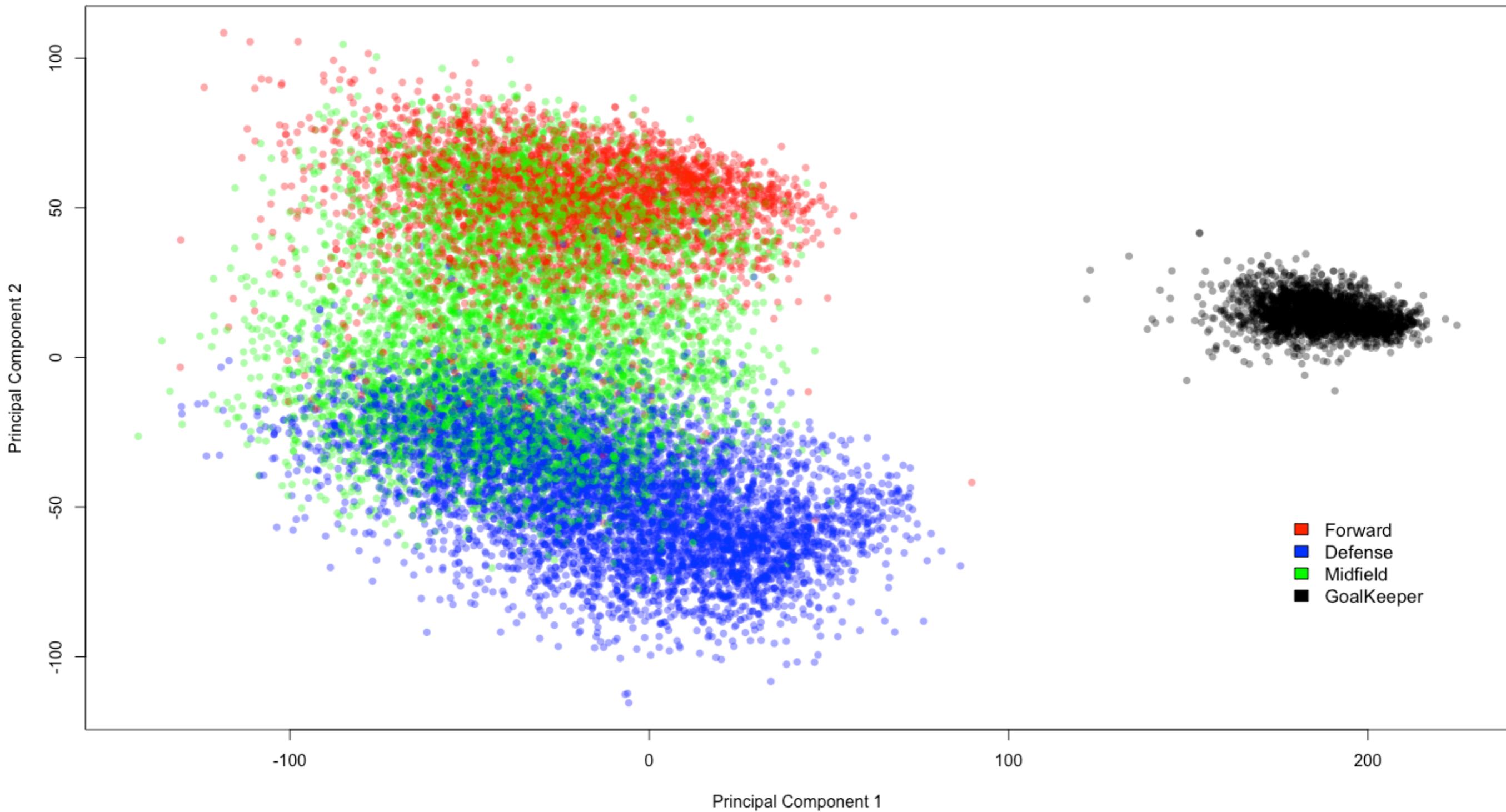
	PC1	PC2	PC3
Acceleration	-0.13674335	0.0944478107	-0.141193842
Aggression	-0.15322857	-0.2030537953	0.105372978
Agility	-0.13598896	0.1196301737	-0.017763073
Balance	-0.11474980	0.0865672989	-0.072629834
Ball.control	-0.21256812	0.0585990154	0.038243802
Composure	-0.13288575	-0.0005635262	0.163887637
Crossing	-0.21347202	0.0458210228	0.124741235
Curve	-0.20656129	0.1254947094	0.180634730
Dribbling	-0.23090613	0.1259819707	-0.002905379
Finishing	-0.19431248	0.2534086437	0.006524693
Free.kick.accuracy	-0.18528508	0.0960404650	0.219976709
GK.diving	0.20757999	0.0480952942	0.326161934
GK.handling	0.19811125	0.0464542553	0.314165622
GK.kicking	0.19261876	0.0456942190	0.304722126
GK.positioning	0.19889113	0.0456384196	0.317850121
GK.reflexes	0.21081755	0.0489895700	0.332751195
Heading.accuracy	-0.17218607	-0.1115416097	-0.125135161
Interceptions	-0.15038835	-0.3669025376	0.162064432
Jumping	-0.03805419	-0.0579221746	0.012263523
Long.passing	-0.16849827	-0.0435009943	0.224584171
Long.shots	-0.21415526	0.1677851237	0.157466462
Marking	-0.14863254	-0.4076616902	0.078298039
Penalties	-0.16328049	0.1407803994	0.024403976
Positioning	-0.22053959	0.1797895382	0.020734699
Reactions	-0.04780774	0.0001844959	0.250247098
Short.passing	-0.18176636	-0.0033124240	0.118611543
Shot.power	-0.19592137	0.0989340925	0.101707386
Sliding.tackle	-0.14977558	-0.4024030355	0.069945935
Sprint.speed	-0.13387287	0.0804847541	-0.146049405
Stamina	-0.17231648	-0.0634639786	-0.016509650
Standing.tackle	-0.15992073	-0.4039763876	0.086418583
Strength	-0.02186264	-0.1151018222	0.096053864
Vision	-0.13027169	0.1152237536	0.260985686
Volleys	-0.18465028	0.1888480712	0.076974579

Examine Loadings

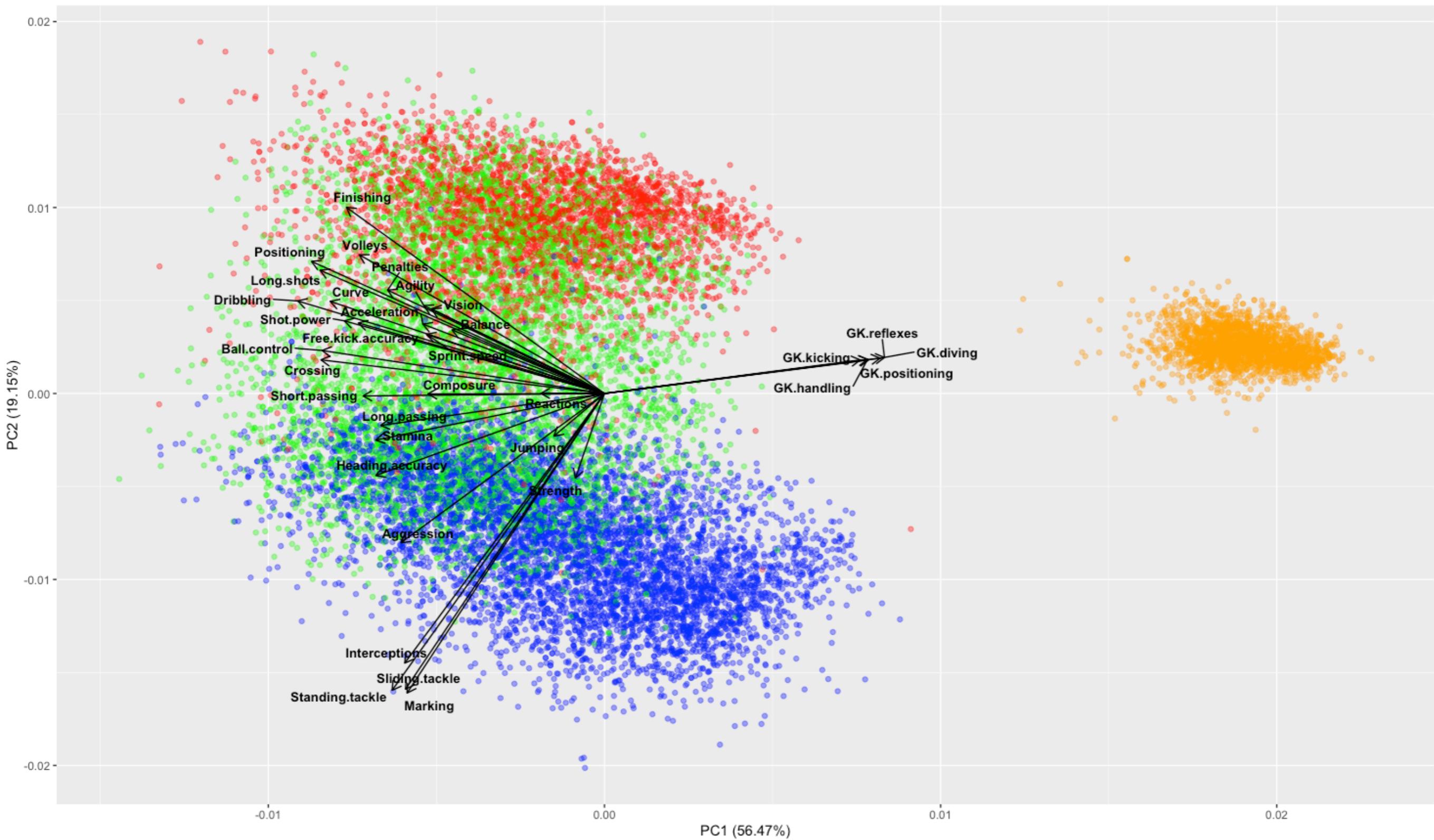
```
fifa.pca$rotation[,1:3]
```

	PC1	PC2	PC3
Acceleration	-0.13674335	0.0944478107	-0.141193842
Aggression	-0.15322857	-0.2030537953	0.105372978
Agility	-0.13598896	0.1196301737	-0.017763073
Balance	-0.11474980	0.0865672989	-0.072629834
Ball.control	-0.21256812	0.0585990154	0.038243802
Composure	-0.13288575	-0.0005635262	0.163887637
Crossing	-0.21347202	0.0458210228	0.124741235
Curve	-0.20656129	0.1254947094	0.180634730
Dribbling	-0.23090613	0.1259819707	-0.002905379
Finishing	-0.19431248	0.2534086437	0.006524693
Free.kick.accuracy	-0.18528508	0.0960404650	0.219976709
GK.diving	0.20757999	0.0480952942	0.326161934
GK.handling	0.19811125	0.0464542553	0.314165622
GK.kicking	0.19261876	0.0456942190	0.304722126
GK.positioning	0.19889113	0.0456384196	0.317850121
GK.reflexes	0.21081755	0.0489895700	0.332751195
Heading.accuracy	-0.17218607	-0.1115416097	-0.125135161
Interceptions	-0.15038835	-0.3669025376	0.162064432
Jumping	-0.03805419	-0.0579221746	0.012263523
Long.passing	-0.16849827	-0.0435009943	0.224584171
Long.shots	-0.21415526	0.1677851237	0.157466462
Marking	-0.14863254	-0.4076616902	0.078298039
Penalties	-0.16328049	0.1407803994	0.024403976
Positioning	-0.22053959	0.1797895382	0.020734699
Reactions	-0.04780774	0.0001844959	0.250247098
Short.passing	-0.18176636	-0.0033124240	0.118611543
Shot.power	-0.19592137	0.0989340925	0.101707386
Sliding.tackle	-0.14977558	-0.4024030355	0.069945935
Sprint.speed	-0.13387287	0.0804847541	-0.146049405
Stamina	-0.17231648	-0.0634639786	-0.016509650
Standing.tackle	-0.15992073	-0.4039763876	0.086418583
Strength	-0.02186264	-0.1151018222	0.096053864
Vision	-0.13027169	0.1152237536	0.260985686
Volleys	-0.18465028	0.1888480712	0.076974579

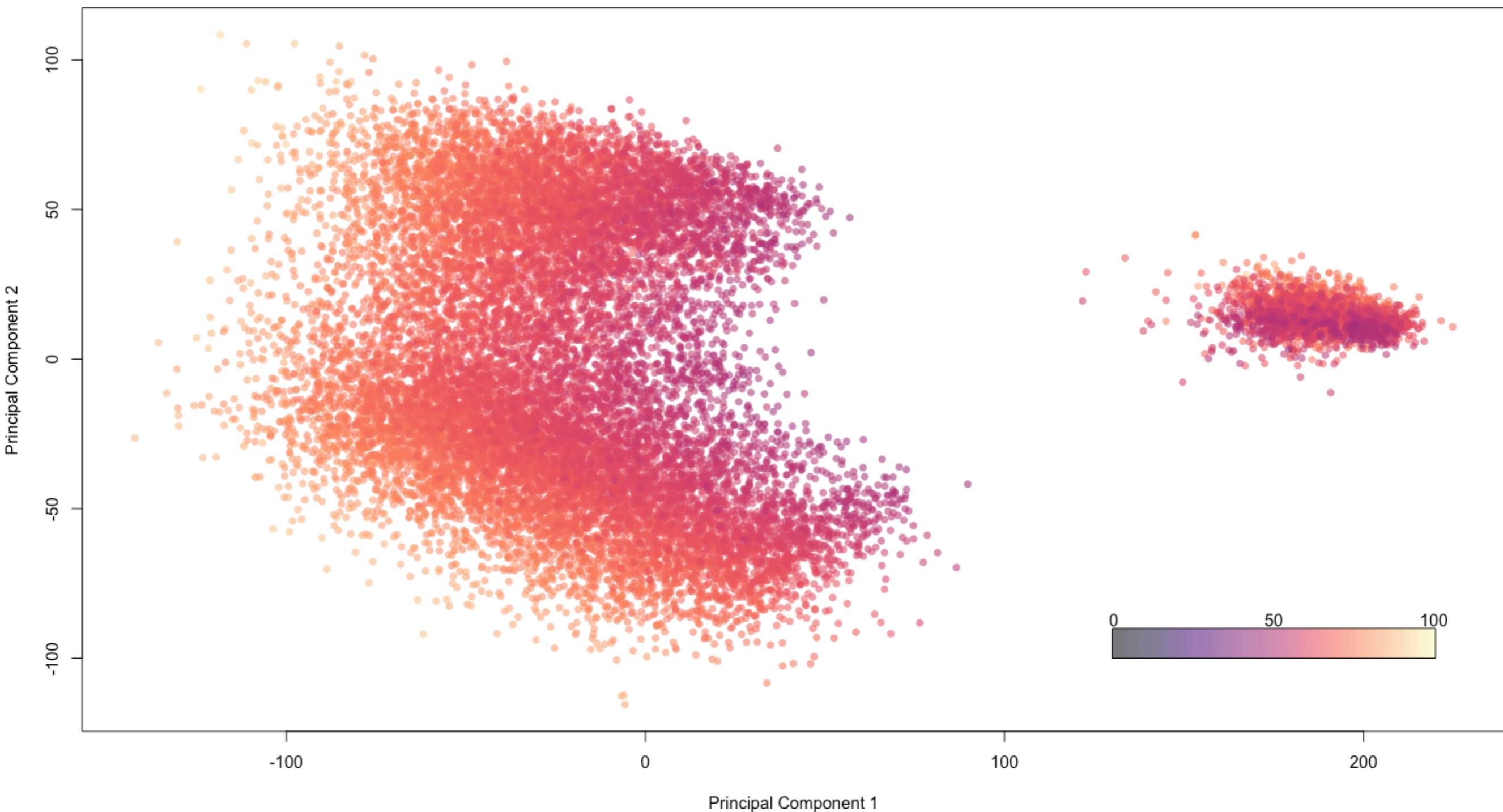
Color Projection by Position



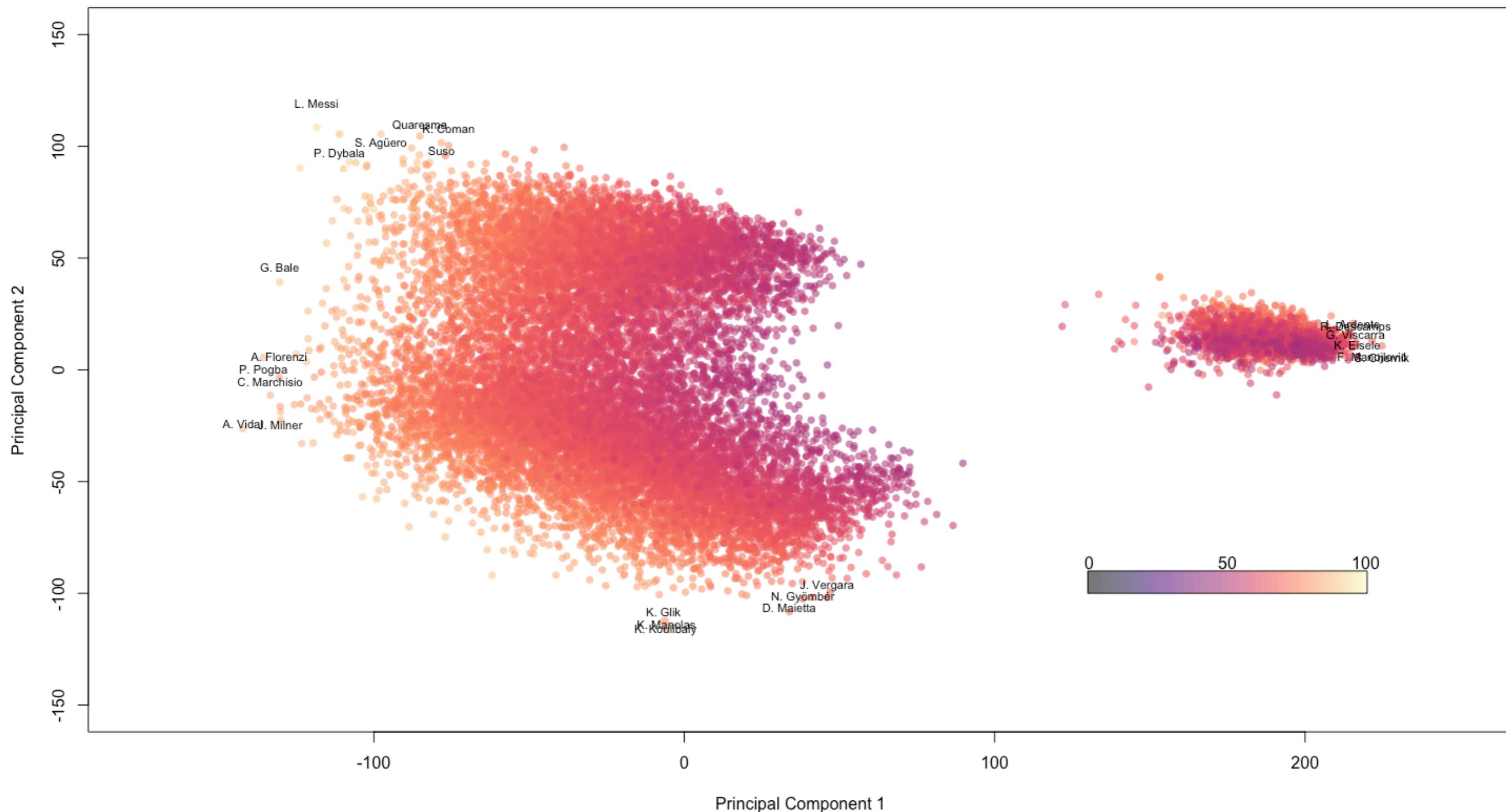
Make it a Biplot



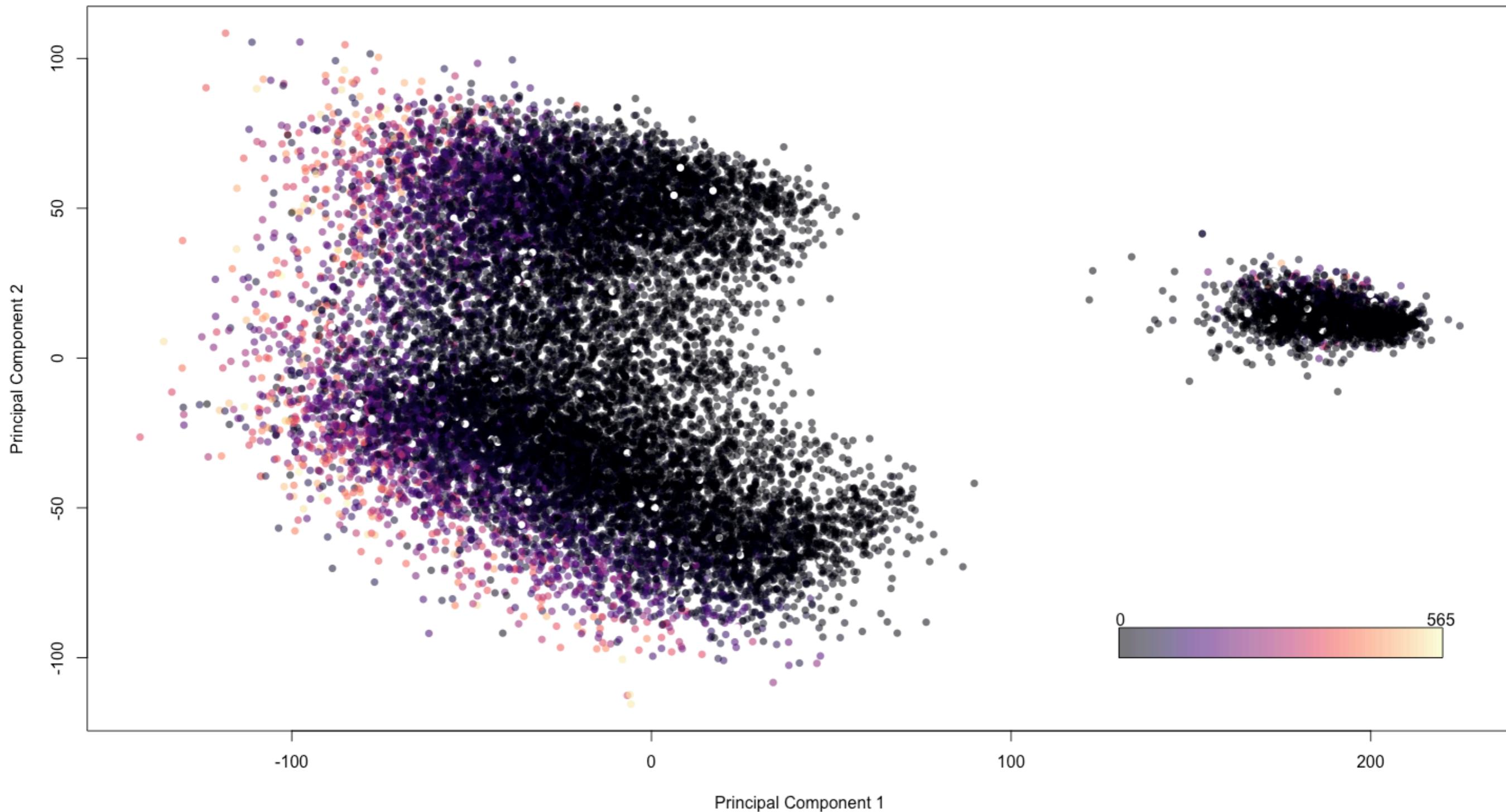
Color by “Overall” ability



Label some Outliers



Color by Wage



Lab Exercise 1

1. Use a logistic regression to try to differentiate midfielders from forwards, with 2 principal components as input.
2. Create one model using correlation PCA and one model using covariance PCA.
3. Which model can more accurately differentiate between midfielders and forwards?

Lab Exercise 2

1. Use a linear regression model to predict the variable *overall* using just 2 principal components. You may use functions of these components (polynomial terms etc.) if you'd like.
2. Compare the resulting model using correlation and covariance PCA. Which was more successful?