

Midterm.R

Surya

2019-03-29

```
## Surya Aenuganti Ushasri
```

```
protein <- read.csv("Protein_Consumption.csv",header=TRUE)
head(protein)
```

```
##      i..Country Red.Meat White.Meat Egg Milk Fish Cereals Starchy.Foods
## 1      Albania      10         1    1    9    0      42             1
## 2      Austria       9        14    4   20    2      28             4
## 3      Belgium      14         9    4   18    5      27             6
## 4      Bulgaria       8         6    2    8    1      57             1
## 5 Czechoslovakia     10        11    3   13    2      34             5
## 6      Denmark      11        11    4   25   10      22             5
##      Pulses.Nuts.and.Oilseeds Fruits.and.Vegetables Total
## 1                          6                      2    72
## 2                          1                      4    86
## 3                          2                      4    89
## 4                          4                      4    91
## 5                          1                      4    83
## 6                          1                      2    91
```

```
attach(protein)
#View(protein)
```

```
# 1. Use principal components analysis to investigate the relationships
#between the countries on the basis of these variables
```

```
#The data set does not contain any categorical values and it also does not contain any missing values
```

```
#Removing the last column because it's just sum of all columns across each country
```

```
cor(protein[c(-1,-11)])
```

```
##              Red.Meat White.Meat      Egg      Milk
## Red.Meat      1.0000000  0.18850977  0.57532001  0.5440251
## White.Meat    0.18850977  1.00000000  0.60095535  0.2974816
## Egg           0.57532001  0.60095535  1.00000000  0.6130310
## Milk          0.54402512  0.29748163  0.61303102  1.0000000
## Fish          0.06491072 -0.19719960  0.04780844  0.1624624
## Cereals       -0.50970337 -0.43941908 -0.70131040 -0.5924925
## Starchy.Foods 0.15383673  0.33456770  0.41266333  0.2144917
## Pulses.Nuts.and.Oilseeds -0.40988882 -0.67214885 -0.59519381 -0.6238357
## Fruits.and.Vegetables -0.06393465 -0.07329308 -0.16392249 -0.3997753
##              Fish      Cereals Starchy.Foods
## Red.Meat      0.06491072 -0.50970337    0.1538367
## White.Meat    -0.19719960 -0.43941908    0.3345677
## Egg           0.04780844 -0.70131040    0.4126633
## Milk          0.16246239 -0.59249246    0.2144917
## Fish          1.00000000 -0.51714759    0.4386841
```

```
## Cereals -0.51714759 1.00000000 -0.5781345
## Starchy.Foods 0.43868411 -0.57813449 1.0000000
## Pulses.Nuts.and.Oilseeds -0.12226043 0.63605948 -0.4951880
## Fruits.and.Vegetables 0.22948842 0.04229293 0.0683567
## Pulses.Nuts.and.Oilseeds Fruits.and.Vegetables
## Red.Meat -0.4098888 -0.06393465
## White.Meat -0.6721488 -0.07329308
## Egg -0.5951938 -0.16392249
## Milk -0.6238357 -0.39977527
## Fish -0.1222604 0.22948842
## Cereals 0.6360595 0.04229293
## Starchy.Foods -0.4951880 0.06835670
## Pulses.Nuts.and.Oilseeds 1.0000000 0.35133227
## Fruits.and.Vegetables 0.3513323 1.00000000
```

```
pca <- prcomp(protein[,c(-1,-11)],scale=TRUE)
pca
```

```
## Standard deviations (1, ..., p=9):
## [1] 2.0237432 1.2747169 1.0417887 0.9513238 0.6532516 0.5890163 0.5191570
## [8] 0.3667732 0.3339091
##
## Rotation (n x k) = (9 x 9):
## PC1 PC2 PC3 PC4
## Red.Meat -0.3106693 -0.06957085 -0.35546338 -0.59650142
## White.Meat -0.3159279 -0.21457197 0.62841986 -0.03961214
## Egg -0.4205930 -0.09986721 0.08050675 -0.25525634
## Milk -0.3788776 -0.16867961 -0.40414435 0.03223542
## Fish -0.1341071 0.65161517 -0.29971395 0.23487897
## Cereals 0.4298291 -0.25366332 0.06815673 0.02030764
## Starchy.Foods -0.2959618 0.38888491 0.28085511 0.30524504
## Pulses.Nuts.and.Oilseeds 0.4218085 0.12932932 -0.14030066 -0.25125596
## Fruits.and.Vegetables 0.1223681 0.50377330 0.34041535 -0.60376932
## PC5 PC6 PC7 PC8
## Red.Meat 0.39658595 -0.37671581 0.22797808 -0.049688240
## White.Meat -0.31059983 -0.08129384 0.14601621 -0.028186225
## Egg 0.06707700 0.66453033 0.03595386 -0.467400341
## Milk -0.31800256 0.01779923 -0.71798985 0.102202763
## Fish -0.30432982 -0.04476482 0.23683595 -0.440552318
## Cereals 0.18501820 -0.19398782 -0.34306417 -0.720660760
## Starchy.Foods 0.67317396 0.02444741 -0.32554187 0.082975933
## Pulses.Nuts.and.Oilseeds 0.09378094 0.58676016 -0.03105426 0.217739473
## Fruits.and.Vegetables -0.22763119 -0.15823653 -0.35941199 0.009714519
## PC9
## Red.Meat -0.2506754
## White.Meat -0.5766036
## Egg 0.2750188
## Milk -0.1903416
## Fish -0.2600351
## Cereals -0.1921878
## Starchy.Foods -0.1499922
## Pulses.Nuts.and.Oilseeds -0.5666397
## Fruits.and.Vegetables 0.2114057
```

```
summary(pca)
```

```
## Importance of components:
```

```
##          PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation    2.0237 1.2747 1.0418 0.9513 0.65325 0.58902 0.51916
## Proportion of Variance 0.4551 0.1805 0.1206 0.1006 0.04742 0.03855 0.02995
## Cumulative Proportion 0.4551 0.6356 0.7562 0.8568 0.90417 0.94272 0.97266
##          PC8      PC9
## Standard deviation    0.36677 0.33391
## Proportion of Variance 0.01495 0.01239
## Cumulative Proportion 0.98761 1.00000
```

#Reading from the summary of pca table we can see that upto pc5 about 90% of variance is captured

```
plot(pca)
```

#from the above plot we see that pca1 accounts for maximum variance in the data

```
pca$x
```

```
##          PC1      PC2      PC3      PC4      PC5
## [1,]  3.4062175 -1.43187183 -1.596648133 -0.08434257  0.4124395
## [2,] -1.3961709 -1.07844406  1.234558817 -0.02919248 -0.7564630
## [3,] -1.6271911  0.27394175 -0.009163712 -0.41608341  0.9108462
## [4,]  3.0996115 -1.50333675  0.082356700 -0.30660707 -0.2970873
## [5,] -0.4277883 -0.57418064  1.159335459  0.21991003  0.3701307
## [6,] -2.4422594  0.28305004 -0.676942687  1.02016258 -0.6562849
## [7,] -1.4249913  0.60782538  1.746831101  0.87710306  0.6028516
## [8,] -1.7006498 -0.58298031 -1.972677332  1.58071748 -0.2011453
## [9,] -1.4354297  0.89590251 -0.161539920 -1.95053301  0.3099538
## [10,]  2.3291742  0.86546599 -1.227337046 -1.75741320 -0.6575195
## [11,]  1.4302687 -0.95052166  1.782611863  0.26555332 -0.1057918
## [12,] -2.5809791 -0.82037615 -0.161750192 -0.51252848  0.8610870
## [13,]  1.5501576  0.16192833 -0.053056104 -1.33599650 -0.7676190
## [14,] -1.7115591 -0.78012960  0.766301047 -0.25865817 -0.9164207
## [15,] -0.9571511  1.10929163 -1.319851198  1.21615923 -0.4173226
## [16,] -0.1285106  0.63184836  1.522555810 -0.03104612 -0.1228267
## [17,]  1.8854364  4.23632323  0.235407502  0.64127627 -0.3296311
## [18,]  2.6361730 -1.10164486  0.169166371  0.60431439  0.1965040
## [19,]  1.4042842  2.43957843  0.249276728 -0.24228673  0.6238140
## [20,] -1.9196053 -0.08881654 -1.085799797  0.90373795 -0.7886161
## [21,] -0.8862644 -0.79798276 -0.228906351 -1.06865159 -0.7103254
## [22,] -1.9396765 -0.32877834 -1.274231236 -1.19215725  1.2311866
## [23,]  0.8607657 -0.15774231 -0.215679913  1.04275420  1.2112175
## [24,] -1.8007758 -0.34409820  0.872728311 -0.26262846 -0.1813817
## [25,]  3.7769132 -0.96425165  0.162453908  1.07643653  0.1784042
##          PC6      PC7      PC8      PC9
## [1,] -0.2667144820  0.94892837  0.84693053  0.15478609
## [2,]  0.0237975418  0.05758584 -0.05177819  0.11624278
## [3,] -0.1269263837  0.22683921 -0.22319293 -0.09689498
## [4,] -0.5842119100  0.39976618 -0.90940273  0.25018422
## [5,] -0.7261570266  0.29971869 -0.06798719  0.25074519
## [6,]  0.0627184045  0.48030200 -0.56925372 -0.50886295
## [7,]  0.2138448106  0.53117349 -0.18580431  0.29526903
## [8,] -0.2058406000 -0.97347796  0.28022893  0.12113082
## [9,] -1.4755527601 -0.03008584 -0.06846045 -0.51649154
```

```
## [10,] 1.0097312103 -0.57538334 -0.34740216 -0.45103458
## [11,] 0.8657732666 0.11900810 0.19668872 -0.44150330
## [12,] 0.6415595029 -0.43471746 0.03742272 -0.05217871
## [13,] 0.0312818001 -0.14708797 -0.12872601 0.85624862
## [14,] 0.3040553671 0.06091030 0.35043459 -0.28870555
## [15,] 0.0038561601 0.04796743 -0.05700862 0.18258443
## [16,] -0.3479854540 -1.31643147 -0.01492251 0.31505313
## [17,] -0.5280805539 0.53140483 0.20289705 -0.20295441
## [18,] 0.1708000230 -0.04058813 -0.17580879 -0.13304725
## [19,] 1.0132276525 -0.14851022 0.27557451 0.36210459
## [20,] 0.2848678709 0.41870881 -0.19737555 0.30259740
## [21,] -0.6895174928 -0.21158255 0.59042991 0.03956071
## [22,] 0.6339274501 0.43367349 -0.24441516 0.13761916
## [23,] -0.5814776989 -0.72141844 -0.05214970 -0.11645720
## [24,] 0.2726945750 0.39030488 0.53225955 -0.13919641
## [25,] 0.0003287263 -0.34700826 -0.01917849 -0.43679928
```

```
pca.cty <- cbind(data.frame(protein[,1]),pca$x)
pca.cty
```

```
##      protein...1.      PC1      PC2      PC3      PC4
## 1      Albania  3.4062175 -1.43187183 -1.596648133 -0.08434257
## 2      Austria -1.3961709 -1.07844406  1.234558817 -0.02919248
## 3      Belgium -1.6271911  0.27394175 -0.009163712 -0.41608341
## 4      Bulgaria 3.0996115 -1.50333675  0.082356700 -0.30660707
## 5 Czechoslovakia -0.4277883 -0.57418064  1.159335459  0.21991003
## 6      Denmark -2.4422594  0.28305004 -0.676942687  1.02016258
## 7    East Germany -1.4249913  0.60782538  1.746831101  0.87710306
## 8      Finland -1.7006498 -0.58298031 -1.972677332  1.58071748
## 9      France -1.4354297  0.89590251 -0.161539920 -1.95053301
## 10     Greece  2.3291742  0.86546599 -1.227337046 -1.75741320
## 11     Hungary  1.4302687 -0.95052166  1.782611863  0.26555332
## 12     Ireland -2.5809791 -0.82037615 -0.161750192 -0.51252848
## 13      Italy  1.5501576  0.16192833 -0.053056104 -1.33599650
## 14 Netherlands -1.7115591 -0.78012960  0.766301047 -0.25865817
## 15     Norway -0.9571511  1.10929163 -1.319851198  1.21615923
## 16     Poland -0.1285106  0.63184836  1.522555810 -0.03104612
## 17     Portugal 1.8854364  4.23632323  0.235407502  0.64127627
## 18     Romania  2.6361730 -1.10164486  0.169166371  0.60431439
## 19      Spain  1.4042842  2.43957843  0.249276728 -0.24228673
## 20     Sweden -1.9196053 -0.08881654 -1.085799797  0.90373795
## 21 Switzerland -0.8862644 -0.79798276 -0.228906351 -1.06865159
## 22 United Kingdom -1.9396765 -0.32877834 -1.274231236 -1.19215725
## 23      USSR  0.8607657 -0.15774231 -0.215679913  1.04275420
## 24 West Germany -1.8007758 -0.34409820  0.872728311 -0.26262846
## 25 Yugoslavia  3.7769132 -0.96425165  0.162453908  1.07643653
##      PC5      PC6      PC7      PC8      PC9
## 1  0.4124395 -0.2667144820  0.94892837  0.84693053  0.15478609
## 2 -0.7564630  0.0237975418  0.05758584 -0.05177819  0.11624278
## 3  0.9108462 -0.1269263837  0.22683921 -0.22319293 -0.09689498
## 4 -0.2970873 -0.5842119100  0.39976618 -0.90940273  0.25018422
## 5  0.3701307 -0.7261570266  0.29971869 -0.06798719  0.25074519
## 6 -0.6562849  0.0627184045  0.48030200 -0.56925372 -0.50886295
## 7  0.6028516  0.2138448106  0.53117349 -0.18580431  0.29526903
## 8 -0.2011453 -0.2058406000 -0.97347796  0.28022893  0.12113082
```

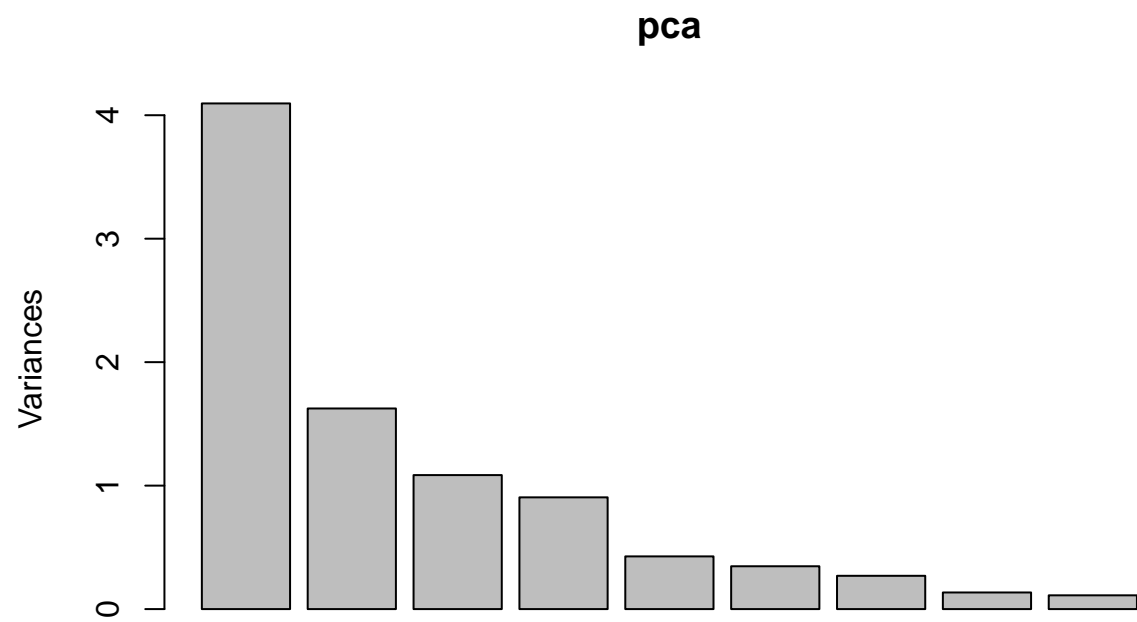
```
## 9 0.3099538 -1.4755527601 -0.03008584 -0.06846045 -0.51649154
## 10 -0.6575195 1.0097312103 -0.57538334 -0.34740216 -0.45103458
## 11 -0.1057918 0.8657732666 0.11900810 0.19668872 -0.44150330
## 12 0.8610870 0.6415595029 -0.43471746 0.03742272 -0.05217871
## 13 -0.7676190 0.0312818001 -0.14708797 -0.12872601 0.85624862
## 14 -0.9164207 0.3040553671 0.06091030 0.35043459 -0.28870555
## 15 -0.4173226 0.0038561601 0.04796743 -0.05700862 0.18258443
## 16 -0.1228267 -0.3479854540 -1.31643147 -0.01492251 0.31505313
## 17 -0.3296311 -0.5280805539 0.53140483 0.20289705 -0.20295441
## 18 0.1965040 0.1708000230 -0.04058813 -0.17580879 -0.13304725
## 19 0.6238140 1.0132276525 -0.14851022 0.27557451 0.36210459
## 20 -0.7886161 0.2848678709 0.41870881 -0.19737555 0.30259740
## 21 -0.7103254 -0.6895174928 -0.21158255 0.59042991 0.03956071
## 22 1.2311866 0.6339274501 0.43367349 -0.24441516 0.13761916
## 23 1.2112175 -0.5814776989 -0.72141844 -0.05214970 -0.11645720
## 24 -0.1813817 0.2726945750 0.39030488 0.53225955 -0.13919641
## 25 0.1784042 0.0003287263 -0.34700826 -0.01917849 -0.43679928
```

```
library(devtools)
install_github("vqv/ggbiplot")
```

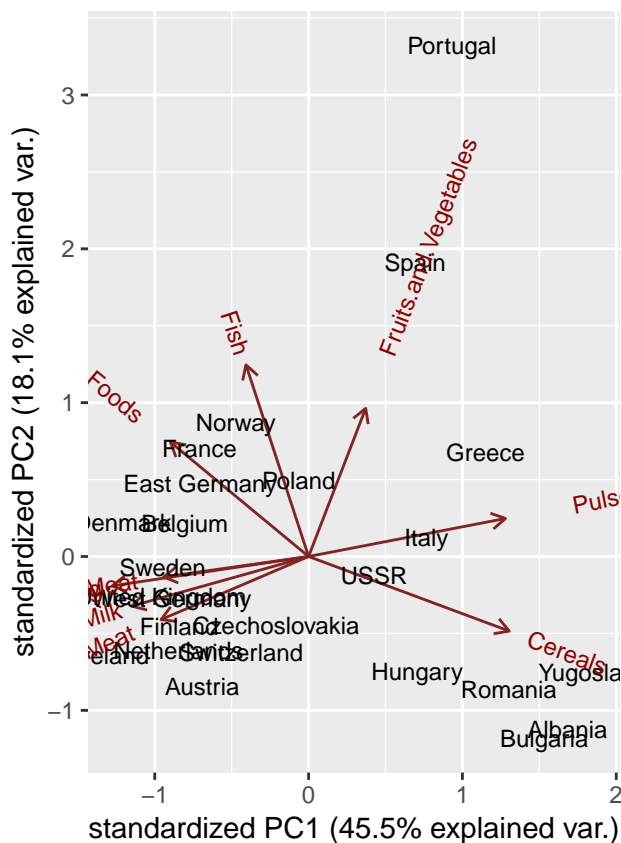
```
## Skipping install of 'ggbiplot' from a github remote, the SHA1 (7325e880) has not changed since last .
## Use `force = TRUE` to force installation
```

```
library(ggbiplot)
```

```
## Loading required package: ggplot2
## Loading required package: plyr
## Loading required package: scales
## Loading required package: grid
```



```
ggbiplot(pca,ellipse=TRUE,labels=protein[,1])
```



*#When we plot the countries and their 2 principal components leading to 54% of variance
#It Shows the concentraion of countries according to the protein consumption from various sources*

*# 2. Carry out cluster analysis to study relation between countries on their diet
#I will be using agglomerative clustering approach because there are less than 50 points and it's easy
#Creating a distant matrix using euclidean distance*

```
row.names(protein) <- protein[,1]
dist.mat <- dist(protein[,c(-1,-11)], method="euclidean")
dist.mat
```

```
##          Albania  Austria  Belgium  Bulgaria  Czechoslovakia
## Austria      23.194827
## Belgium      21.563859  8.306624
## Bulgaria     16.278821 32.756679 33.075671
## Czechoslovakia 15.264338  9.848858 10.295630 24.698178
## Denmark      30.116441 11.958261 10.862780 40.767634 18.920888
## East Germany  22.737634 10.630146 10.000000 33.674916 10.198039
## Finland      31.288976 17.578396 17.378147 41.255303 23.790755
## France       23.643181 11.180340  5.830952 34.000000 13.266499
## Greece       12.449900 20.024984 18.439089 19.748418 15.362291
## Hungary      13.000000 16.881943 19.026298 18.708287  9.591663
## Ireland      27.784888 10.000000  9.219544 38.794329 17.117243
## Italy         10.488088 14.899664 13.820275 21.283797  8.660254
## Netherlands  28.495614  6.928203  9.949874 39.230090 16.031220
```

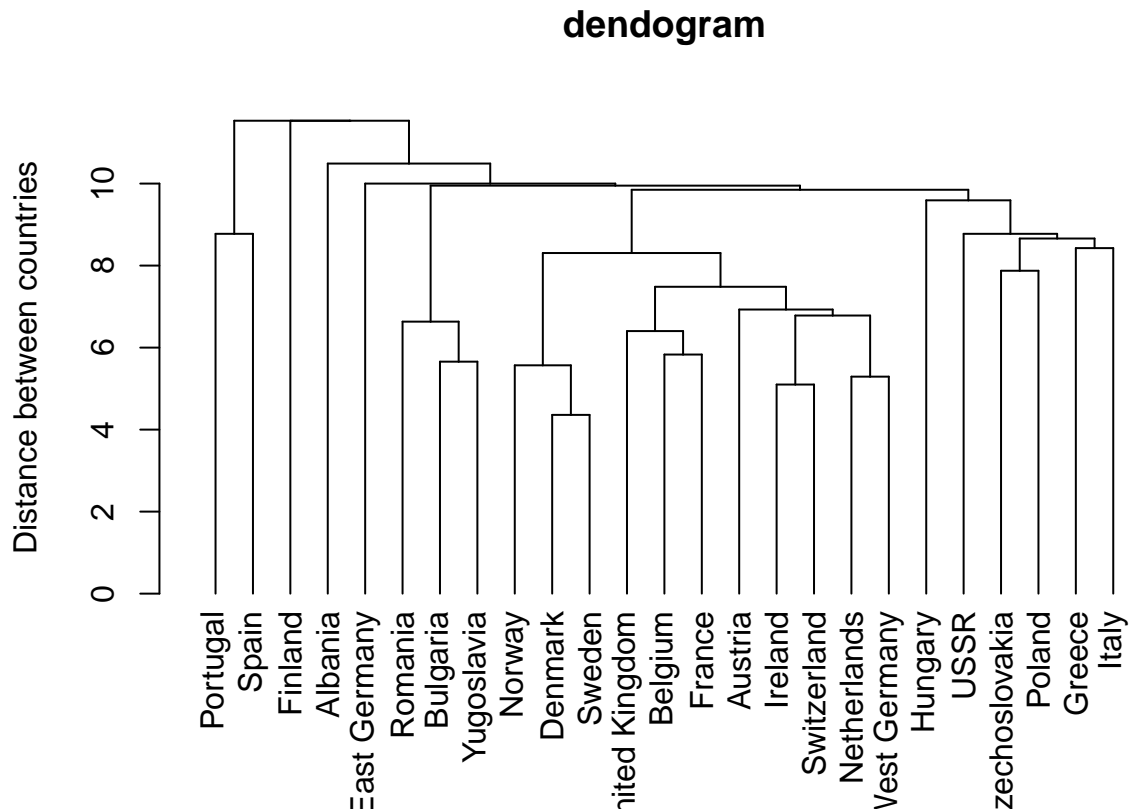
## Norway	26.664583	13.527749	10.488088	38.548671	18.000000
## Poland	17.464249	10.049876	12.083046	24.939928	7.874008
## Portugal	22.891046	22.891046	19.313208	33.600595	18.947295
## Romania	10.816654	25.709920	26.267851	8.246211	18.000000
## Spain	16.881943	17.635192	14.142136	29.495762	13.190906
## Sweden	29.933259	12.884099	11.532563	41.725292	19.773720
## Switzerland	24.657656	7.483315	7.681146	35.623026	14.177447
## United Kingdom	24.494897	12.489996	6.403124	37.080992	15.842980
## USSR	11.401754	18.973666	18.466185	16.822604	12.688578
## West Germany	28.774989	9.486833	9.746794	40.632499	16.401219
## Yugoslavia	15.968719	32.046841	32.741411	5.656854	24.494897
##	Denmark	East Germany	Finland	France	Greece
## Austria					
## Belgium					
## Bulgaria					
## Czechoslovakia					
## Denmark					
## East Germany	15.748016				
## Finland	12.328828	24.454039			
## France	12.409674	14.491377	18.055470		
## Greece	24.779023	22.538855	24.698178	18.920888	
## Hungary	26.608269	16.911535	30.133038	21.725561	15.231546
## Ireland	9.110434	16.703293	11.618950	10.246951	23.259407
## Italy	21.886069	15.842980	24.186773	15.652476	8.426150
## Netherlands	8.306624	13.228757	15.459625	12.041595	24.596748
## Norway	6.928203	15.165751	12.328828	13.114877	21.633308
## Poland	18.055470	14.352700	20.149442	14.000000	12.489996
## Portugal	24.020824	15.198684	31.511903	22.022716	22.472205
## Romania	33.704599	26.795522	34.234486	27.928480	13.784049
## Spain	21.118712	11.916375	26.645825	17.606817	16.733201
## Sweden	4.358899	16.217275	11.532563	13.747727	25.317978
## Switzerland	10.049876	15.066519	13.076697	8.306624	20.174241
## United Kingdom	11.090537	15.132746	15.459625	7.681146	21.189620
## USSR	25.436195	21.470911	25.159491	19.974984	8.774964
## West Germany	10.148892	10.908712	18.947295	12.609520	26.362853
## Yugoslavia	39.824616	33.075671	39.673669	34.205263	18.708287
##	Hungary	Ireland	Italy	Netherlands	Norway
## Austria					
## Belgium					
## Bulgaria					
## Czechoslovakia					
## Denmark					
## East Germany					
## Finland					
## France					
## Greece					
## Hungary					
## Ireland	24.879711				
## Italy	10.630146	20.099751			
## Netherlands	23.259407	7.211103	20.149442		
## Norway	25.179357	11.357817	18.841444	11.618950	
## Poland	11.661904	16.217275	8.660254	15.842980	16.733201
## Portugal	21.886069	27.276363	18.275667	24.979992	20.124612
## Romania	11.916375	31.764760	14.525839	32.046841	31.272992

## Spain	16.431677	21.748563	11.532563	20.518285	16.792856
## Sweden	27.404379	8.944272	22.000000	8.602325	5.567764
## Switzerland	21.794495	5.099020	16.492423	6.782330	11.090537
## United Kingdom	24.145393	7.483315	17.720045	11.224972	10.535654
## USSR	12.206556	23.280893	9.591663	24.738634	23.000000
## West Germany	24.062419	9.797959	20.976177	5.291503	12.288206
## Yugoslavia	17.720045	38.039453	20.760539	38.379682	37.255872
##	Poland	Portugal	Romania	Spain	Sweden
## Austria					
## Belgium					
## Bulgaria					
## Czechoslovakia					
## Denmark					
## East Germany					
## Finland					
## France					
## Greece					
## Hungary					
## Ireland					
## Italy					
## Netherlands					
## Norway					
## Poland					
## Portugal	21.189620				
## Romania	17.776389	27.802878			
## Spain	15.165751	8.774964	22.759613		
## Sweden	19.000000	24.124676	34.452866	20.663978	
## Switzerland	13.228757	24.939928	28.722813	19.313208	9.899495
## United Kingdom	16.941074	23.151674	30.380915	17.804494	10.392305
## USSR	10.723805	24.372115	9.949874	18.411953	26.229754
## West Germany	18.027756	22.847319	33.481338	18.947295	9.695360
## Yugoslavia	23.748684	32.787193	6.633250	28.425341	40.632499
##	Switzerland	United Kingdom		USSR	West Germany
## Austria					
## Belgium					
## Bulgaria					
## Czechoslovakia					
## Denmark					
## East Germany					
## Finland					
## France					
## Greece					
## Hungary					
## Ireland					
## Italy					
## Netherlands					
## Norway					
## Poland					
## Portugal					
## Romania					
## Spain					
## Sweden					
## Switzerland					
## United Kingdom	7.874008				

```
## USSR          20.736441      22.181073
## West Germany   9.695360      10.862780 26.532998
## Yugoslavia     35.028560      36.783148 15.524175      39.962482
```

#Invoking hclust using single linkage

```
dist.nn <- hclust(dist.mat, method = "single")
plot(as.dendrogram(dist.nn),ylab="Distance between countries",main="dendrogram")
```



From the plot we can see various clusters

#Note: Portugal and Spain are clustered in 1 and Scandinavian nations are clustered in 1.

3. Identify the important factors underlying the observed variables and examine the relationships between them

```
library(psych)
```

```
##
```

```
## Attaching package: 'psych'
```

```
## The following objects are masked from 'package:scales':
```

```
##
```

```
## alpha, rescale
```

```
## The following objects are masked from 'package:ggplot2':
```

```
##
```

```
## %>%, alpha
```

#Do an eigen value decomposition removing the last column

```
pc <- principal(protein[c(-1,-11)], nfactors=4, rotate="varimax")
pc
```

```
## Principal Components Analysis
## Call: principal(r = protein[c(-1, -11)], nfactors = 4, rotate = "varimax")
## Standardized loadings (pattern matrix) based upon correlation matrix
##          RC3   RC1   RC2   RC4   h2   u2 com
## Red.Meat      0.08  0.92  0.01  0.02  0.86  0.138 1.0
## White.Meat     0.94  0.14 -0.08 -0.01  0.91  0.086 1.1
## Egg            0.59  0.66  0.13 -0.09  0.81  0.193 2.1
## Milk           0.20  0.68  0.21 -0.51  0.81  0.188 2.3
## Fish          -0.21  0.10  0.92  0.09  0.91  0.089 1.2
## Cereals       -0.42 -0.56 -0.61  0.07  0.87  0.133 2.8
## Starchy.Foods  0.52  0.01  0.71  0.03  0.77  0.226 1.8
## Pulses.Nuts.and.Oilseeds -0.69 -0.34 -0.28  0.41  0.83  0.166 2.6
## Fruits.and.Vegetables -0.05 -0.04  0.14  0.95  0.93  0.071 1.1
##
##          RC3   RC1   RC2   RC4
## SS loadings      2.25  2.21  1.89  1.36
## Proportion Var    0.25  0.25  0.21  0.15
## Cumulative Var    0.25  0.50  0.71  0.86
## Proportion Explained 0.29  0.29  0.25  0.18
## Cumulative Proportion 0.29  0.58  0.82  1.00
##
## Mean item complexity = 1.8
## Test of the hypothesis that 4 components are sufficient.
##
## The root mean square of the residuals (RMSR) is 0.05
## with the empirical chi square 4.94 with prob < 0.55
##
## Fit based upon off diagonal values = 0.98

#From the summary we can see that upto 4 factors the variables explain about 86% of the variance
round(pc$values, 3)

## [1] 4.096 1.625 1.085 0.905 0.427 0.347 0.270 0.135 0.111

pc$loadings

##
## Loadings:
##          RC3   RC1   RC2   RC4
## Red.Meat      0.925
## White.Meat     0.941  0.142
## Egg            0.594  0.655  0.128
## Milk           0.197  0.684  0.208 -0.513
## Fish          -0.214      0.921
## Cereals       -0.418 -0.557 -0.614
## Starchy.Foods  0.518      0.711
## Pulses.Nuts.and.Oilseeds -0.688 -0.337 -0.277  0.413
## Fruits.and.Vegetables      0.144  0.951
##
##          RC3   RC1   RC2   RC4
## SS loadings  2.249  2.207  1.895  1.361
## Proportion Var 0.250  0.245  0.211  0.151
## Cumulative Var 0.250  0.495  0.706  0.857

# Communalities
pc$communality
```

##	Red.Meat	White.Meat	Egg
##	0.8623000	0.9136165	0.8067014
##	Milk	Fish	Cereals
##	0.8123492	0.9110157	0.8666324
##	Starchy.Foods	Pulses.Nuts.and.Oilseeds	Fruits.and.Vegetables
##	0.7744128	0.8343631	0.9293892

#We can see that fish,white meat and fruits&vegetables account for most common variance among the count

```
fa.parallel(protein[-1]) # See factor recommendation
```

```
## Warning in cor.smooth(R): Matrix was not positive definite, smoothing was
## done
```

```
## Warning in cor.smooth(R): Matrix was not positive definite, smoothing was
## done
```

```
## Warning in cor.smooth(R): Matrix was not positive definite, smoothing was
## done
```

```
## Warning in cor.smooth(r): Matrix was not positive definite, smoothing was
## done
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.
```

```
## In factor.scores, the correlation matrix is singular, an approximation is used
```

```
## Warning in cor.smooth(r): Matrix was not positive definite, smoothing was
## done
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully
```

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## incorrect. Try a different factor extraction method.

## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : A loading greater than abs(1) was detected. Examine the loadings
## carefully.

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## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

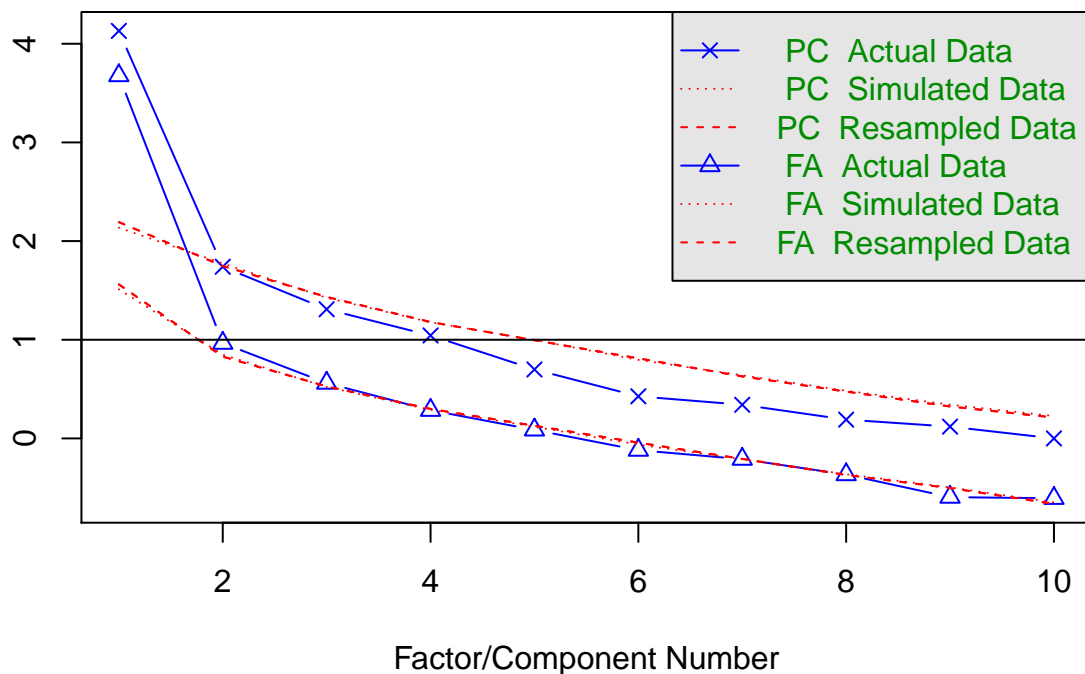
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate =
## rotate, : An ultra-Heywood case was detected. Examine the results carefully

## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs
## = np.obs, : The estimated weights for the factor scores are probably
## incorrect. Try a different factor extraction method.

```

eigenvalues of principal components and factor analysis

Parallel Analysis Scree Plots



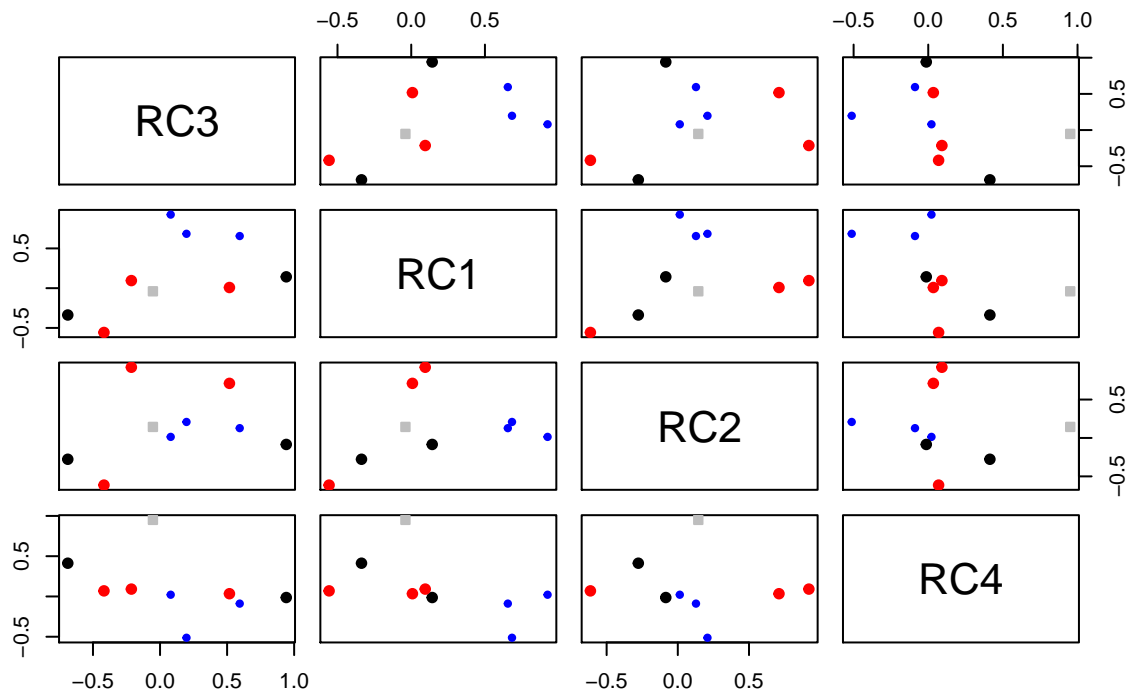
```

## Parallel analysis suggests that the number of factors = 1 and the number of components = 1
##From the above plot of "PC Actual Data" we can see that after 4 factors the eigen value crosses at 1 a

```

```
fa.plot(pc) # See Correlations within Factors
```

Principal Component Analysis



```
fa.diagram(pc) # Visualizing the relationship
```

Components Analysis

