Ngoc Ha

ST 557 - HW 5

Problem 1 ¶

In [1]: track <- read.csv('TrackData.csv')
head(track)</pre>

Country	Abbrev	X100m.s	X200m.s	X400m.s	X800m.m	X1500m.m	X5000m.m	X10000m.m	M
Argentina	ARG	10.39	20.81	46.84	1.81	3.70	14.04	29.36	
Australia	AUL	10.31	20.06	44.84	1.74	3.57	13.28	27.66	
Austria	AUS	10.44	20.81	46.82	1.79	3.60	13.26	27.72	
Belgium	BEL	10.34	20.68	45.04	1.73	3.60	13.22	27.45	
Bermuda	BER	10.28	20.58	45.91	1.80	3.75	14.68	30.55	
Brazil	BRA	10.22	20.43	45.21	1.73	3.66	13.62	28.62	

(1a)

```
In [2]: distances <- track[,3:10]
S <- cov(distances)
R <- cor(distances)
S
R</pre>
```

	X100m.s	X200m.s	X400m.s	X800m.m	X1500m.m	X5000m.m	X10000m.
X100m.s	0.12350249	0.20902182	0.43069956	0.016920438	0.03836684	0.17441020	0.40184
X200m.s	0.20902182	0.41557024	0.79905603	0.033115455	0.07788771	0.35913859	0.81171
X400m.s	0.43069956	0.79905603	2.12290020	0.080743131	0.18974209	0.90887976	2.07341
X800m.m	0.01692044	0.03311545	0.08074313	0.004055758	0.00911532	0.04406209	0.10004
X1500m.m	0.03836684	0.07788771	0.18974209	0.009115320	0.02430774	0.11592929	0.26343
X5000m.m	0.17441020	0.35913859	0.90887976	0.044062088	0.11592929	0.64185811	1.41154
X10000m.m	0.40184545	0.81171145	2.07341549	0.100049327	0.26343721	1.41154798	3.26789
Marathon.m	1.68601222	3.54620963	9.47785704	0.473903333	1.24516296	6.89104852	15.73218

	X100m.s	X200m.s	X400m.s	X800m.m	X1500m.m	X5000m.m	X10000m.m	Ma
X100m.s	1.0000000	0.9226384	0.8411468	0.7560278	0.7002382	0.6194618	0.6325389	0
X200m.s	0.9226384	1.0000000	0.8507270	0.8066265	0.7749513	0.6953770	0.6965391	0
X400m.s	0.8411468	0.8507270	1.0000000	0.8701714	0.8352694	0.7786139	0.7872045	0
X800m.m	0.7560278	0.8066265	0.8701714	1.0000000	0.9180442	0.8635939	0.8690489	0
X1500m.m	0.7002382	0.7749513	0.8352694	0.9180442	1.0000000	0.9281140	0.9346970	0
X5000m.m	0.6194618	0.6953770	0.7786139	0.8635939	0.9281140	1.0000000	0.9746354	0
X10000m.m	0.6325389	0.6965391	0.7872045	0.8690489	0.9346970	0.9746354	1.0000000	0
Marathon.m	0.5199490	0.5961837	0.7049905	0.8064764	0.8655492	0.9321884	0.9431763	1

 ${\it R}$ is more appropriate to use for PCA, as all the variables are on the same scale.

(1b) Eigendecomposition of S

```
In [3]: eiDecS <- eigen(S)</pre>
        eiDecS
        eigen() decomposition
        $values
        [1] 8.991362e+01 1.412626e+00 2.598442e-01 1.094203e-01 2.730060e-02
        [6] 1.273280e-02 2.243554e-03 4.455645e-04
        $vectors
                    [,1]
                               [,2]
                                            [,3]
                                                        [,4]
                                                                    [,5]
        [1,] -0.019865407 -0.21068958 -0.029041979 -0.358784470 0.190181784
        [2,] -0.041554499 -0.35892579 -0.018390126 -0.833534544 -0.048582165
        [3,] -0.110631838 -0.82786251 -0.377669011 0.396041212 -0.012020033
        [4,] -0.005487699 -0.02317490 0.005341591 -0.009568087 -0.011107487
        [5,] -0.014386822 -0.04465255 0.050004337 -0.015981502 -0.043222520
        [6,] -0.079308444 -0.12996134 0.336448522 0.018873808 -0.909186992
        [7,] -0.181098994 -0.29885393 0.848722695 0.134662690 0.364239482
        [,6]
                                [,7]
                                              [,8]
        [1,] 0.886865894 -0.052444908 -0.0139585779
        [2,] -0.409969944  0.062270182 -0.0037828046
        [3,] -0.047663812  0.020389912 -0.0094695712
        [4,] -0.007204523 -0.261227847 0.9648302746
        [5,] -0.067333230 -0.959092660 -0.2622644611
        [6,] 0.184076191 0.052548542 -0.0001130819
        [7,] -0.068113893  0.045771467  0.0045055042
        [8,] 0.003532208 -0.001055127 -0.0008700758
```

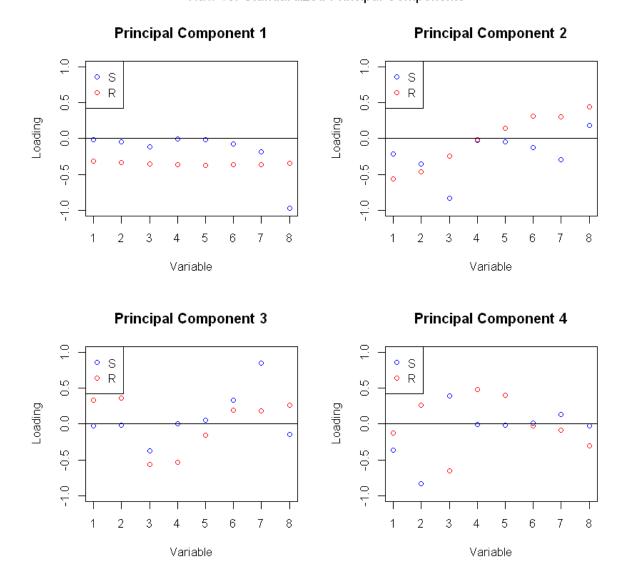
(1c) Eigendecomposition of R

```
In [4]: | eiDecR <- eigen(R)</pre>
       eiDecR
       eigen() decomposition
       $values
       [1] 6.62214613 0.87761829 0.15932114 0.12404939 0.07988027 0.06796515 0.04641
       953
       [8] 0.02260010
       $vectors
                                     [,3]
                                               [,4]
                 [,1]
                           [,2]
                                                         [,5]
       [1,] -0.3175565 -0.56687750 0.3322620 -0.12762827 0.2625555 -0.5937042
       [2,] -0.3369792 -0.46162589  0.3606567  0.25911576 -0.1539571  0.6561367
       [3,] -0.3556454 -0.24827331 -0.5604674 -0.65234077 -0.2183229 0.1566252
       [4,] -0.3686841 -0.01242993 -0.5324823 0.47999895 0.5400528 -0.0146918
       [7,] -0.3667726  0.30685985  0.1817517 -0.08006862 -0.1331764 -0.2190168
       [8,] -0.3419261  0.43896267  0.2632087 -0.29951213  0.4979283  0.3152849
                  [,7]
                              [,8]
       [1,] 0.136241260 -0.1055416752
       [2,] -0.112639528  0.0960543222
       [3,] -0.002853707 0.0001272032
       [4,] -0.238016094 0.0381651151
       [5,] 0.610011482 -0.1392909844
       [6,] -0.591298850 -0.5466969221
       [7,] -0.176871021 0.7967952190
       [8,] 0.398822209 -0.1581638575
```

(1d)

```
In [5]: par(mfrow=c(2,2), oma=c(0,0,2,0))
for(i in 1:4){
    plot(1:8, eiDecS$vec[,i], xlab="Variable", ylab="Loading", main=paste("Pri
    ncipal Component ", i, sep=""), ylim=c(-1, 1), col = 'blue')
    points(1:8, eiDecR$vec[,i], xlab="Variable", ylab="Loading", main=paste("P
    rincipal Component ", i, sep=""), ylim=c(-1, 1), col='red')
    legend("topleft", legend=c("S", "R"), col=c("blue", "red"), pch=21)
        abline(h=0)
}
mtext("Raw vs. Standardized Principal Components", outer=T)
```

Raw vs. Standardized Principal Components



(1e)

For S: marathon times (variable 8) dominate the covariances among running times, which makes sense a marathon is much longer than other formats.

(1f)

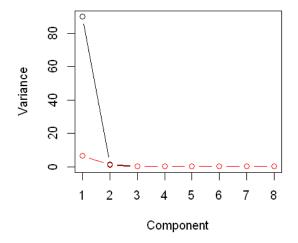
For R: the standardized loadings are roughly equal. This principal component shows how fast or slow a country is in general.

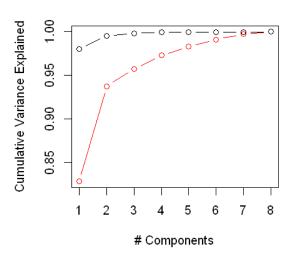
(1g)

The second principal components of R seems to show the contrast between fast marathoners and fast sprinters.

(1h)

```
In [6]: options(repr.plot.width=8, repr.plot.height=4)
    par(mfrow=c(1,2), oma=c(0,0,0,0))
    plot(1:8, eiDecS$val, type="b", xlab="Component", ylab="Variance")
    lines(1:8, eiDecR$val, type="b", col='red')
    plot(1:8, cumsum(eiDecR$val)/sum(eiDecR$val), type="b", col='red', xlab="# Components", ylab="Cumulative Variance Explained")
    lines(1:8, cumsum(eiDecS$val)/sum(eiDecS$val), type="b")
```





(1i)

I'd want to keep the first 3 principal components of R, as they explain 95% of the variance, and the variances seem to taper off starting from the 4th principal component.

Problem 2

JPMorgan	Citibank	WellsFargo	RoyalDutchShell	ExxonMobil
0.0130338	-0.0078431	-0.0031889	-0.0447693	0.0052151
0.0084862	0.0166886	-0.0062100	0.0119560	0.0134890
-0.0179153	-0.0086393	0.0100360	0.0000000	-0.0061428
0.0215589	-0.0034858	0.0174353	-0.0285917	-0.0069534
0.0108225	0.0037167	-0.0101345	0.0291900	0.0409751
0.0101713	-0.0121978	-0.0083768	0.0137083	0.0029895

[4,] 0.6389680 -0.2479475 -0.64249741 -0.3088689

[5,] 0.6509044 -0.3218478 0.64586064 0.2163758 -0.09371777

(2a)

(2b)

```
In [11]: propVar <- sum(eiDecS$values[1:3])/sum(eiDecS$values)
    cat(propVar, "of total variance is explained by the first 3 principal componen
    ts")</pre>
```

0.8988095 of total variance is explained by the first 3 principal components

0.14845546

(2c)

```
In [14]: options(repr.plot.width=9, repr.plot.height=4)
    par(mfrow=c(1,3), oma=c(0,0,2,0))
    for(i in 1:3){
        plot(1:5, eiDecS$vec[,i], xlab="Variable", ylab="Loading", main=paste("Pri ncipal Component ", i, sep=""), ylim=c(-1, 1), col = 'blue')
        abline(h=0)
    }
    mtext("First three Principal Components", outer=T)
```

First three Principal Components Principal Component 1 Principal Component 2 Principal Component 3 9.0 9.0 Loading Loading Loading 0.0 0.0 0:0 -0.5 0.5 Variable Variable Variable

First PC demonstrates the performance of the market in general. Second PC shows the contrast between stock performance of Finance sector and Energy sector. Third PC focuses on stocks with higher market capitalization (JP Morgan, Shell, Exxon).

Problem 4

```
In [1]: corr <- as.matrix(read.csv('PhysioData.csv'))
    head(corr)</pre>
```

	weight	height	physact	ldl	alb	crt	
weight	1.000000000	0.54775881	-0.02803745	0.003570772	0.04673810	0.25399164	-0.149446
height	0.547758814	1.00000000	0.06493509	-0.156549811	0.08819927	0.36485715	-0.294760
physact	-0.028037453	0.06493509	1.00000000	-0.031756690	0.01476370	-0.02632625	-0.009007
ldl	0.003570772	-0.15654981	-0.03175669	1.000000000	0.12453340	-0.13135504	0.196784
alb	0.046738095	0.08819927	0.01476370	0.124533399	1.00000000	0.04428462	-0.06429
crt	0.253991639	0.36485715	-0.02632625	-0.131355039	0.04428462	1.00000000	-0.154817

```
In [2]: eiDecCor <- eigen(corr)</pre>
```

i. m = 2

	Factor 1 Loadings	Factor 2 Loadings	Specific Variances
weight	-1.0452745	-0.1403353	-0.11229274
height	-1.3346010	-0.1595277	-0.80660894
physact	-0.1265833	0.1814451	0.95105432
ldl	0.3651604	0.1599542	0.84107255
alb	-0.2255166	0.0941445	0.94027907
crt	-0.8112691	-0.5135738	0.07808445
plt	0.7143848	0.1338270	0.47174474
sbp	0.2741563	-0.7725324	0.32803205
aai	-0.4325669	0.8560635	0.08004119
fev	-1.1450629	0.2331262	-0.36551677
dsst	-0.1974087	0.7093896	0.45779616
atrophy	-0.2404455	-0.4284885	0.75858351

Factor 1: height, weight and fev contribute the most to factor 1. Interpretation: factor 1 correlates with the size of a person.

Factor 2 shows the contrast between systolic blood pressure vs. ankle-to-arm sbp ratio and coginite performance.

ii. m = 3

```
In [4]: L3 <- cbind(eiDecCor$val[1]*eiDecCor$vec[,1], eiDecCor$val[2]*eiDecCor$vec[,2]
    , eiDecCor$val[3]*eiDecCor$vec[,3])
    errorCov3 <- corr - L3%*%t(L3)
    specVars3 <- diag(errorCov3)
    L3_table <- data.frame(L3,specVars3)
    colnames(L3_table) <- c("Factor 1 Loadings","Factor 2 Loadings","Factor 3 Loadings","Specific Variances")
    L3_table</pre>
```

	Factor 1 Loadings	Factor 2 Loadings	Factor 3 Loadings	Specific Variances
weight	-1.0452745	-0.1403353	0.254226398	-0.17692380
height	-1.3346010	-0.1595277	0.041405944	-0.80832339
physact	-0.1265833	0.1814451	-0.351258636	0.82767169
ldl	0.3651604	0.1599542	0.756781166	0.26835482
alb	-0.2255166	0.0941445	0.606733197	0.57215390
crt	-0.8112691	-0.5135738	-0.007366511	0.07803019
plt	0.7143848	0.1338270	0.299009230	0.38233822
sbp	0.2741563	-0.7725324	0.023902569	0.32746072
aai	-0.4325669	0.8560635	-0.156188604	0.05564631
fev	-1.1450629	0.2331262	0.027012246	-0.36624644
dsst	-0.1974087	0.7093896	0.239375966	0.40049530
atrophy	-0.2404455	-0.4284885	0.326469376	0.65200126

Factor 3 correlates with the cholesterol level in the subject's blood.

(4b)

i. m = 2

In [5]: res2 <- corr - (L2%*%t(L2)+errorCov2)
 res2</pre>

	weight	height	physact	ldl	alb	crt
weight	0.000000e+00	0.000000e+00	1.040834e-17	-3.903128e- 18	1.387779e-17	0.000000e+00
height	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	-5.551115e-17
physact	1.040834e-17	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
ldl	-3.903128e- 18	0.000000e+00	0.000000e+00	0.000000e+00	1.387779e-17	0.000000e+00
alb	1.387779e-17	0.000000e+00	0.000000e+00	1.387779e-17	0.000000e+00	0.000000e+00
crt	0.000000e+00	-5.551115e-17	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
plt	2.775558e-17	0.000000e+00	3.469447e-18	0.000000e+00	0.000000e+00	0.000000e+00
sbp	5.204170e-18	0.000000e+00	-1.040834e- 17	0.000000e+00	3.469447e-18	-7.806256e- 18
aai	0.000000e+00	-1.387779e- 17	0.000000e+00	0.000000e+00	1.040834e-17	0.000000e+00
fev	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	5.551115e-17
dsst	0.000000e+00	6.938894e-18	6.938894e-18	3.361027e-18	0.000000e+00	0.000000e+00
atrophy	0.000000e+00	-2.775558e- 17	0.000000e+00	1.387779e-17	0.000000e+00	0.000000e+00

In [6]: res3 <- corr - (L3%*%t(L3)+errorCov3)
 res3</pre>

	weight	height	physact	ldl	alb	crt
weight	0.000000e+00	0.000000e+00	-3.469447e- 18	-3.903128e- 18	1.387779e-17	0.000000e+00
height	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	-5.551115e-17
physact	-3.469447e- 18	0.000000e+00	0.000000e+00	-6.938894e- 18	1.040834e-17	0.000000e+00
ldl	-3.903128e- 18	0.000000e+00	-6.938894e- 18	0.000000e+00	0.000000e+00	-2.775558e- 17
alb	1.387779e-17	0.000000e+00	1.040834e-17	0.000000e+00	0.000000e+00	0.000000e+00
crt	0.000000e+00	-5.551115e-17	0.000000e+00	-2.775558e- 17	0.000000e+00	0.000000e+00
plt	2.775558e-17	0.000000e+00	-1.040834e- 17	0.000000e+00	0.000000e+00	0.000000e+00
sbp	5.204170e-18	0.000000e+00	-1.040834e- 17	0.000000e+00	3.469447e-18	-7.806256e- 18
aai	0.000000e+00	-1.387779e- 17	0.000000e+00	0.000000e+00	-3.469447e- 18	0.000000e+00
fev	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	-5.551115e-17
dsst	-6.938894e- 18	6.938894e-18	6.938894e-18	-3.577867e- 18	1.387779e-17	0.000000e+00
atrophy	2.775558e-17	-2.775558e- 17	0.000000e+00	0.000000e+00	6.938894e-18	0.000000e+00

(4c)

i. m = 2

```
mlfa2 <- factanal(covmat=corr, factors=2, rotation="none")</pre>
In [9]:
        mlfa2
        Call:
        factanal(factors = 2, covmat = corr, rotation = "none")
        Uniquenesses:
         weight height physact
                                     ldl
                                             alb
                                                     crt
                                                              plt
                                                                      sbp
                                                                              aai
                                                                                      f
        ev
          0.675
                           0.988
                                   0.974
                                           0.990
                                                   0.828
                                                           0.903
                                                                    0.801
                                                                            0.526
                                                                                    0.5
                  0.084
        69
           dsst atrophy
          0.883
                  0.960
        Loadings:
                Factor1 Factor2
        weight
                 0.570
        height
                 0.956
        physact
        ldl
                 -0.160
        alb
        crt
                 0.385 -0.154
        plt
                -0.310
                         -0.438
        sbp
                 0.105
                         0.681
        aai
        fev
                 0.610
                         0.241
        dsst
                          0.340
        atrophy 0.121 -0.160
                        Factor1 Factor2
        SS loadings
                          1.930
                                  0.889
        Proportion Var
                          0.161
                                  0.074
        Cumulative Var
                          0.161
                                  0.235
```

The degrees of freedom for the model is 43 and the fit was 0.1927

Factor 1 correlates with the **size** of the subject. Factor 2 shows a contrast between **systolic blood pressure** and **arm-to-length blood pressure ratio**.

ii. m = 3

```
mlfa3 <- factanal(covmat=corr, factors=3, rotation="none")</pre>
In [10]:
          mlfa3
         Call:
         factanal(factors = 3, covmat = corr, rotation = "none")
         Uniquenesses:
          weight height physact
                                      ldl
                                               alb
                                                       crt
                                                                plt
                                                                        sbp
                                                                                        f
                                                                                aai
         ev
                                             0.969
                            0.988
                                    0.005
                                                     0.821
           0.659
                    0.097
                                                             0.881
                                                                      0.800
                                                                              0.517
                                                                                      0.5
         64
            dsst atrophy
           0.884
                    0.960
         Loadings:
                  Factor1 Factor2 Factor3
         weight
                   0.584
         height
                   0.935 -0.165
         physact
         ldl
                           0.997
         alb
                   0.119
                           0.124
                   0.369 -0.135
         crt
                                  -0.158
         plt
                  -0.281
                           0.200
         sbp
                                  -0.437
         aai
                   0.102
                                   0.685
         fev
                   0.613
                                   0.235
         dsst
                                   0.337
         atrophy 0.119
                                  -0.160
                         Factor1 Factor2 Factor3
         SS loadings
                           1.858
                                   1.106
                                            0.891
         Proportion Var
                           0.155
                                   0.092
                                            0.074
         Cumulative Var
                           0.155
                                   0.247
                                            0.321
```

Factor 1 correlates with the **size** of the subject. Factor 2 correlates with **cholesterol level** in the subject's blood. Factor 3 shows a contrast between **systolic blood pressure** and **arm-to-length blood pressure ratio**.

The degrees of freedom for the model is 33 and the fit was 0.1187

(4d)

i. m = 2

In [11]: mle2Fit <- mlfa2\$load %*% t(mlfa2\$load) + diag(mlfa2\$uni)
 mle2Res <- corr - mle2Fit
 mle2Res</pre>

	weight	height	physact	ldl	alb	crt	plt	
weight	-2.295501e- 06	2.316174e- 03	-6.600738e- 02	9.474229e- 02	-6.364201e- 03	3.444910e- 02	2.744664e- 02	•
height	2.316174e- 03	5.795176e- 08	4.071739e- 03	-3.665135e- 03	4.081529e- 04	-8.229091e- 03	1.002223e- 03	•
physact	-6.600738e- 02	4.071739e- 03	-4.414328e- 07	-2.110953e- 02	5.157061e- 03	-3.857461e- 02	1.400327e- 02	
ldl	9.474229e- 02	-3.665135e- 03	-2.110953e- 02	1.515341e- 07	1.394198e- 01	-6.982532e- 02	1.472004e- 01	
alb	-6.364201e- 03	4.081529e- 04	5.157061e- 03	1.394198e- 01	-3.679141e- 07	1.442844e- 02	-3.435965e- 02	
crt	3.444910e- 02	-8.229091e- 03	-3.857461e- 02	-6.982532e- 02	1.442844e- 02	2.907133e- 06	-3.956903e- 02	•
plt	2.744664e- 02	1.002223e- 03	1.400327e- 02	1.472004e- 01	-3.435965e- 02	-3.956903e- 02	2.774056e- 06	
sbp	5.876081e- 02	-8.040394e- 03	4.604408e- 02	-4.377930e- 02	8.276838e- 03	-3.556760e- 02	-7.107719e- 03	
aai	2.805056e- 02	-4.595808e- 03	1.118192e- 02	-4.186461e- 02	-5.241403e- 03	1.837698e- 02	-2.818814e- 02	
fev	-1.168937e- 02	1.341863e- 03	4.041874e- 02	3.369120e- 02	-7.839537e- 04	2.507144e- 02	1.605121e- 02	
dsst	3.688456e- 02	-2.267373e- 03	-6.381315e- 02	6.538309e- 03	5.216409e- 02	-1.080193e- 01	3.696668e- 02	
atrophy	-4.485594e- 03	7.105641e- 05	-7.647922e- 02	7.147184e- 04		8.309776e- 02	-2.852986e- 02	

```
In [12]: mle3Fit <- mlfa3$load %*% t(mlfa3$load) + diag(mlfa3$uni)
    mle3Res <- corr - mle3Fit
    mle3Res</pre>
```

	weight	height	physact	ldl	alb	crt	plt	
weight	1.769072e- 06	1.715552e- 03		4.930838e- 05	-2.203323e- 02	3.741820e- 02	1.466025e- 02	_
height	1.715552e- 03	-1.434591e- 07		-8.841224e- 06	-7.031566e- 04	-8.562872e- 03	-1.919501e- 04	
physact	-6.367751e- 02	5.151534e- 03	-9.850525e- 07	1.740750e- 05	8.126802e- 03	-3.980536e- 02	1.700254e- 02	
ldl	4.930838e- 05	-8.841224e- 06	1.740750e- 05	-1.488487e- 07	7.889531e- 05	-3.531039e- 05	5.173403e- 06	
alb	-2.203323e- 02	-7.031566e- 04	8.126802e- 03	7.889531e- 05	2.104358e- 07	2.320952e- 02	-5.476550e- 02	
crt	3.741820e- 02	-8.562872e- 03	-3.980536e- 02	-3.531039e- 05	2.320952e- 02	2.870971e- 08	-2.811321e- 02	•
plt	1.466025e- 02	-1.919501e- 04	1.700254e- 02	5.173403e- 06	-5.476550e- 02	-2.811321e- 02	2.484733e- 07	
sbp	6.251392e- 02	-9.205252e- 03	4.505925e- 02	-9.551266e- 05	1.464274e- 02	-3.922948e- 02	-2.902823e- 04	
aai	3.219461e- 02	-4.912088e- 03	9.644994e- 03	-4.221580e- 06	3.195008e- 04	1.661071e- 02	-2.148498e- 02	
fev	-2.015677e- 02	1.870694e- 03	4.145989e- 02	3.735397e- 05	-7.565595e- 03	2.440522e- 02	1.214759e- 02	
dsst	3.581256e- 02	-3.353576e- 03	-6.361512e- 02	-1.814167e- 04	5.108954e- 02	-1.079476e- 01	3.622663e- 02	
atrophy	-5.758711e- 03	4.482889e- 04	-7.637260e- 02	4.381138e- 05	4.217393e- 02	8.238260e- 02	-2.842938e- 02	

(4e)

```
In [17]: cat("Determinant of PCA residual matrix:", det(res3))
    cat("\nDeterminant of MLE residual matrix:", det(mle3Res))
```

Determinant of PCA residual matrix: 3.02803e-200 Determinant of MLE residual matrix: 3.220028e-56

PCA Factor Analysis has smaller residuals => better for this problem.

Τn []:			

The factors are similar in both methods (PCA and MLE) for both m = 2 and m = 3.