

PSC205A Assignment 04: PCA and FA

```
library(factoextra)
library(psych)

data <- read.csv("emotion_short.csv")
```

1. Run a PCA separately to each of the two gender groups and:

```
data_female <- data[data$female==0, -c(1:3)]
data_male <- data[data$female==1, -c(1:3)]

psych::describeBy(data, group = data$female)
```

Descriptive statistics by group
group: 0

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew
id	1	182	91.50	52.68	91.5	91.50	67.46	1	182	181	0.00
female	2	182	0.00	0.00	0.0	0.00	0.00	0	0	0	NaN
day	3	182	91.50	52.68	91.5	91.50	67.46	1	182	181	0.00
interested	4	182	3.80	0.72	4.0	3.82	0.00	1	5	4	-1.01
irritable	5	182	1.34	0.73	1.0	1.15	0.00	1	4	3	2.36
distressed	6	182	1.52	0.88	1.0	1.33	0.00	1	5	4	1.81
alert	7	182	2.21	0.79	2.0	2.19	0.00	1	4	3	0.34
excited	8	182	3.23	0.85	3.0	3.25	1.48	1	5	4	-0.22
ashamed	9	182	1.08	0.29	1.0	1.00	0.00	1	3	2	3.82
upset	10	182	1.36	0.83	1.0	1.13	0.00	1	5	4	2.53
inspired	11	182	2.75	0.82	3.0	2.77	0.00	1	5	4	-0.28
strong	12	182	2.71	0.89	3.0	2.76	1.48	1	4	3	-0.24

nervous	13	182	1.30	0.67	1.0	1.14	0.00	1	5	4	2.67
guilty	14	182	1.10	0.34	1.0	1.00	0.00	1	3	2	3.36
determined	15	182	3.49	0.75	4.0	3.57	0.00	1	5	4	-1.00
scared	16	182	1.31	0.65	1.0	1.16	0.00	1	5	4	2.43
attentive	17	182	3.05	0.86	3.0	3.05	0.00	1	5	4	0.01
hostile	18	182	1.25	0.58	1.0	1.11	0.00	1	4	3	2.54
jittery	19	182	1.71	0.82	1.0	1.63	0.00	1	4	3	0.68
enthusiastic	20	182	3.35	0.81	3.0	3.40	1.48	1	5	4	-0.46
active	21	182	3.05	0.96	3.0	3.03	1.48	1	5	4	0.08
proud	22	182	2.62	0.81	3.0	2.65	0.74	1	4	3	-0.33
afraid	23	182	1.37	0.70	1.0	1.21	0.00	1	5	4	2.17

kurtosis se

id	-1.22	3.91
female	NaN	0.00
day	-1.22	3.91
interested	2.15	0.05
irritable	4.99	0.05
distressed	2.88	0.07
alert	-0.23	0.06
excited	-0.16	0.06
ashamed	15.10	0.02
upset	5.90	0.06
inspired	-0.14	0.06
strong	-0.69	0.07
nervous	7.93	0.05
guilty	11.47	0.03
determined	1.71	0.06
scared	6.85	0.05
attentive	0.31	0.06
hostile	6.51	0.04
jittery	-0.83	0.06
enthusiastic	0.57	0.06
active	-0.65	0.07
proud	-0.37	0.06
afraid	5.21	0.05

group: 1

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew
id	1	182	273.50	52.68	273.5	273.50	67.46	183	364	181	0.00
female	2	182	1.00	0.00	1.0	1.00	0.00	1	1	0	NaN
day	3	182	91.50	52.68	91.5	91.50	67.46	1	182	181	0.00
interested	4	182	3.52	0.65	4.0	3.58	0.00	2	5	3	-0.53
irritable	5	182	1.39	0.57	1.0	1.31	0.00	1	3	2	1.14

distressed	6	182	1.59	0.81	1.0	1.44	0.00	1	4	3	1.31
alert	7	182	3.31	0.63	3.0	3.38	0.00	2	4	2	-0.34
excited	8	182	2.04	1.06	2.0	1.90	1.48	1	5	4	0.76
ashamed	9	182	1.01	0.07	1.0	1.00	0.00	1	2	1	13.27
upset	10	182	1.33	0.70	1.0	1.16	0.00	1	4	3	2.36
inspired	11	182	1.12	0.40	1.0	1.00	0.00	1	3	2	3.45
strong	12	182	2.40	0.68	2.0	2.42	1.48	1	4	3	-0.04
nervous	13	182	1.13	0.43	1.0	1.00	0.00	1	4	3	4.28
guilty	14	182	1.02	0.15	1.0	1.00	0.00	1	2	1	6.47
determined	15	182	2.24	0.90	2.0	2.22	1.48	1	4	3	0.06
scared	16	182	1.01	0.10	1.0	1.00	0.00	1	2	1	9.30
attentive	17	182	3.31	0.72	3.0	3.38	1.48	1	5	4	-0.36
hostile	18	182	1.05	0.25	1.0	1.00	0.00	1	3	2	4.86
jittery	19	182	1.02	0.13	1.0	1.00	0.00	1	2	1	7.53
enthusiastic	20	182	2.37	1.18	2.0	2.32	1.48	1	5	4	0.22
active	21	182	2.48	0.73	2.0	2.45	1.48	1	4	3	0.27
proud	22	182	1.49	0.98	1.0	1.24	0.00	1	5	4	1.93
afraid	23	182	1.00	0.00	1.0	1.00	0.00	1	1	0	NaN
			kurtosis	se							
id			-1.22	3.91							
female			NaN	0.00							
day			-1.22	3.91							
interested			-0.21	0.05							
irritable			0.28	0.04							
distressed			1.06	0.06							
alert			-0.70	0.05							
excited			-0.34	0.08							
ashamed			175.03	0.01							
upset			5.31	0.05							
inspired			11.54	0.03							
strong			-0.29	0.05							
nervous			21.39	0.03							
guilty			40.05	0.01							
determined			-0.95	0.07							
scared			85.04	0.01							
attentive			-0.25	0.05							
hostile			25.41	0.02							
jittery			55.04	0.01							
enthusiastic			-1.25	0.09							
active			-0.28	0.05							
proud			2.51	0.07							
afraid			NaN	0.00							

Since the variable `afraid` has 0 variance in the `male` subgroup, we might drop it from the analysis

```
data_female <- data[data$female==0, -c(1:3, 23)]  
data_male <- data[data$female==1, -c(1:3, 23)]
```

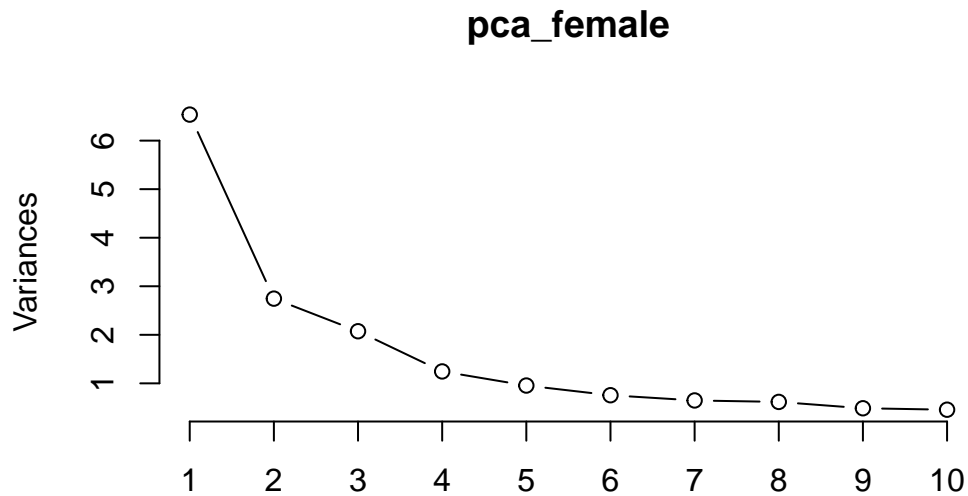
1.1. Attempt to identify an optimal number of components for each group

```
pca_female <- prcomp(data_female, scale = TRUE)  
pca_male <- prcomp(data_male, scale = TRUE)
```

Females

- Screeplot

```
screeplot(pca_female, type = "lines")
```



- Using the Eigenvalue > 1 criteria

```
pca_female$sdev
```

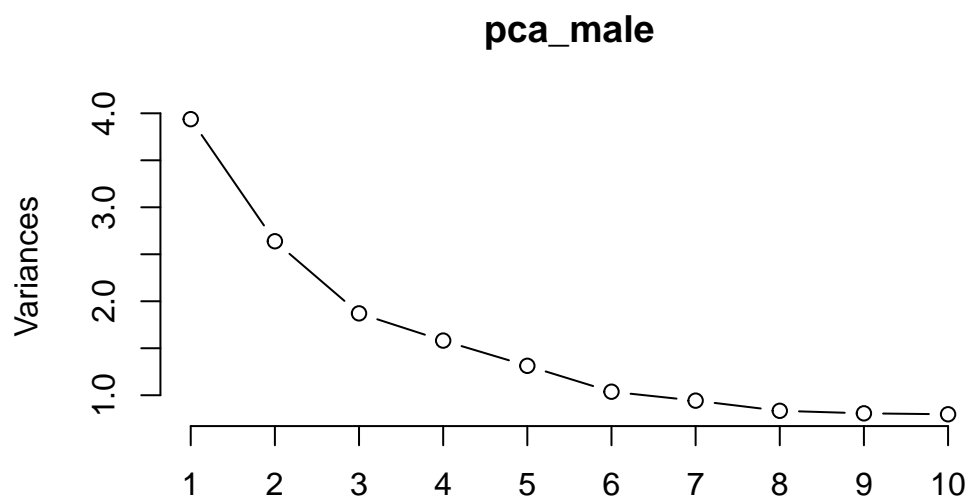
```
[1] 2.5565887 1.6569029 1.4398921 1.1161159 0.9773955 0.8692338 0.8049922  
[8] 0.7859619 0.6979389 0.6761531 0.6248899 0.6220257 0.5940768 0.5531186  
[15] 0.5396619 0.4838238 0.4684340 0.4048798 0.3655874
```

These results suggest that the optimal number of factors for females is 4.

Males

- Screeplot

```
screeplot(pca_male, type = "lines")
```



- Using the Eigenvalue > 1 criteria

```
pca_male$sdev
```

```
[1] 1.9843653 1.6243191 1.3679058 1.2575463 1.1459469 1.0186320 0.9708747
[8] 0.9135171 0.8985245 0.8929804 0.7910859 0.7680869 0.6362655 0.6073746
[15] 0.5711229 0.5200113 0.4957251 0.4694256 0.4317487
```

These results suggest that the optimal number of factors for males is 6. However, given that the 6th eigenvalue is very close to one, this dimension might be considered spurious and a solution with 5 components could be more plausible.

1.2. Report a table with eigenvalues (and percent variance explained) for each group

Females

```
knitr::kable(get_eigenvalue(pca_female), caption = "Eigenvalues of PCA for the female group")
```

Table 1: Eigenvalues of PCA for the female group.

	eigenvalue	variance.percent	cumulative.variance.percent
Dim.1	6.5361460	34.4007686	34.40077
Dim.2	2.7453271	14.4490899	48.84986
Dim.3	2.0732893	10.9120491	59.76191
Dim.4	1.2457147	6.5563932	66.31830
Dim.5	0.9553019	5.0279046	71.34621
Dim.6	0.7555674	3.9766705	75.32288
Dim.7	0.6480124	3.4105918	78.73347
Dim.8	0.6177360	3.2512423	81.98471
Dim.9	0.4871187	2.5637827	84.54849
Dim.10	0.4571830	2.4062265	86.95472
Dim.11	0.3904874	2.0551966	89.00992
Dim.12	0.3869160	2.0363999	91.04632
Dim.13	0.3529273	1.8575119	92.90383
Dim.14	0.3059402	1.6102115	94.51404
Dim.15	0.2912350	1.5328156	96.04685
Dim.16	0.2340854	1.2320286	97.27888
Dim.17	0.2194304	1.1548971	98.43378
Dim.18	0.1639276	0.8627771	99.29656
Dim.19	0.1336541	0.7034427	100.00000

Males

```
knitr::kable(get_eigenvalue(pca_male), caption = "Eigenvalues of PCA for the male group.")
```

Table 2: Eigenvalues of PCA for the male group.

	eigenvalue	variance.percent	cumulative.variance.percent
Dim.1	3.9377056	20.7247666	20.72477
Dim.2	2.6384124	13.8863810	34.61115
Dim.3	1.8711662	9.8482434	44.45939
Dim.4	1.5814228	8.3232778	52.78267
Dim.5	1.3131943	6.9115490	59.69422
Dim.6	1.0376112	5.4611116	65.15533
Dim.7	0.9425977	4.9610406	70.11637
Dim.8	0.8345135	4.3921764	74.50855
Dim.9	0.8073462	4.2491908	78.75774
Dim.10	0.7974141	4.1969161	82.95465
Dim.11	0.6258169	3.2937733	86.24843
Dim.12	0.5899574	3.1050391	89.35347
Dim.13	0.4048338	2.1307045	91.48417
Dim.14	0.3689038	1.9415992	93.42577
Dim.15	0.3261813	1.7167439	95.14251
Dim.16	0.2704118	1.4232199	96.56573
Dim.17	0.2457433	1.2933860	97.85912
Dim.18	0.2203604	1.1597917	99.01891
Dim.19	0.1864070	0.9810892	100.00000

1.3. Rotate the solution using the VARIMAX procedure and report differences between this solution and the unrotated one (include the loading matrix in your report).

After Varimax rotation, we see that variables cluster clearly onto separate components more often, compared to raw loadings.

Females

```
rawLoadings_female    <- principal(data_female, nfactors = 4,
                                   rotate = 'none')$loadings[,1:4]
rotatedLoadings_female <- principal(data_female, nfactors = 4,
                                   rotate = 'varimax')$loadings[,1:4]

knitr::kable(as.data.frame(rawLoadings_female), caption = "Standardized unrotated loadings")
```

Table 3: Standardized unrotated loadings for the female group.

	PC1	PC2	PC3	PC4
interested	0.7687471	0.2412117	0.0588106	0.0682854
irritable	-0.6311260	0.4717450	-0.3891541	-0.0199612
distressed	-0.5602572	0.4575516	0.3539441	0.1833807
alert	0.2341650	0.4908503	0.1999490	-0.6009711
excited	0.6856646	0.2610759	0.0753683	0.2775845
ashamed	-0.2041123	0.5171441	-0.5013316	-0.0766111
upset	-0.6525146	0.5290099	0.0795141	0.1214069
inspired	0.6874195	0.1943067	-0.0279863	-0.0290933
strong	0.7047671	0.0917970	-0.2323330	0.1144944
nervous	-0.2231304	0.5353189	0.6413314	0.0936218
guilty	-0.3526252	0.5016574	-0.5596924	-0.0564985
determined	0.7297744	0.3936168	-0.1249042	0.1238487
scared	-0.4113232	0.3374829	0.7002517	0.1513261
attentive	0.6982973	0.1083375	0.0694033	-0.3321064
hostile	-0.5481011	0.4912758	-0.3415161	-0.0228635
jittery	0.5033275	0.2465930	0.1622448	-0.5851675
enthusiastic	0.7899253	0.2825817	-0.0411068	0.2180851
active	0.6061801	0.1948778	-0.1799464	0.4195939
proud	0.6021786	0.3374894	0.1505876	0.0847787

```
knitr::kable(as.data.frame(rotatedLoadings_female[,1:4]), caption = "Standardized rotated loadings")
```

Table 4: Standardized rotated loadings for the female group.

	RC1	RC2	RC3	RC4
interested	0.7378941	-0.1823528	-0.0814070	0.2700174
irritable	-0.2767868	0.8069309	0.1818253	-0.1090597

	RC1	RC2	RC3	RC4
distressed	-0.1957429	0.2804058	0.7430203	-0.1145629
alert	0.1264466	0.1328403	0.1783273	0.7946554
excited	0.7683173	-0.1584550	0.0214441	0.0717687
ashamed	0.0655747	0.7458107	-0.0395436	0.0648470
upset	-0.2439926	0.5433206	0.5972785	-0.1233599
inspired	0.6183160	-0.1204875	-0.1651355	0.2963590
strong	0.6642573	-0.0700976	-0.3401744	0.1016905
nervous	0.0453784	0.0195454	0.8547030	0.1531864
guilty	-0.0459220	0.8300355	-0.0335668	-0.0160565
determined	0.8099163	0.0483698	-0.1077334	0.2203041
scared	-0.1688185	-0.0779485	0.8727596	-0.0069560
attentive	0.4538558	-0.2282956	-0.2172749	0.5560172
hostile	-0.2073513	0.7568672	0.1972824	-0.0644973
jittery	0.2442634	-0.1085896	-0.0693877	0.7788582
enthusiastic	0.8436299	-0.1067467	-0.1034256	0.1388599
active	0.7562503	-0.0136263	-0.1380924	-0.1506709
proud	0.6474290	-0.1144268	0.0992569	0.2535203

Males

```

rawLoadings_male    <- principal(data_female, nfactors = 5,
                                rotate = 'none')$loadings[,1:5]
rotatedLoadings_male <- principal(data_female, nfactors = 5,
                                rotate = 'varimax')$loadings[,1:5]

knitr::kable(as.data.frame(rawLoadings_male), caption = "Standardized unrotated loadings f

```

Table 5: Standardized unrotated loadings for the male group.

	PC1	PC2	PC3	PC4	PC5
interested	0.7687471	0.2412117	0.0588106	0.0682854	-0.2305985
irritable	-0.6311260	0.4717450	-0.3891541	-0.0199612	-0.0303620
distressed	-0.5602572	0.4575516	0.3539441	0.1833807	-0.0240938
alert	0.2341650	0.4908503	0.1999490	-0.6009711	0.1897554
excited	0.6856646	0.2610759	0.0753683	0.2775845	-0.1013123
ashamed	-0.2041123	0.5171441	-0.5013316	-0.0766111	0.0021832
upset	-0.6525146	0.5290099	0.0795141	0.1214069	-0.0126022
inspired	0.6874195	0.1943067	-0.0279863	-0.0290933	0.2268792
strong	0.7047671	0.0917970	-0.2323330	0.1144944	0.4639583

	PC1	PC2	PC3	PC4	PC5
nervous	-0.2231304	0.5353189	0.6413314	0.0936218	0.1035530
guilty	-0.3526252	0.5016574	-0.5596924	-0.0564985	-0.1099571
determined	0.7297744	0.3936168	-0.1249042	0.1238487	0.1015267
scared	-0.4113232	0.3374829	0.7002517	0.1513261	0.1365907
attentive	0.6982973	0.1083375	0.0694033	-0.3321064	-0.3001719
hostile	-0.5481011	0.4912758	-0.3415161	-0.0228635	-0.0211223
jittery	0.5033275	0.2465930	0.1622448	-0.5851675	0.1686073
enthusiastic	0.7899253	0.2825817	-0.0411068	0.2180851	-0.2364275
active	0.6061801	0.1948778	-0.1799464	0.4195939	0.3754749
proud	0.6021786	0.3374894	0.1505876	0.0847787	-0.4688517

```
knitr::kable(as.data.frame(rotatedLoadings_male[,1:5]), caption = "Standardized rotated loadings for the male group")
```

Table 6: Standardized rotated loadings for the male group.

	RC1	RC2	RC3	RC5	RC4
interested	0.7383840	-0.1584635	-0.1088631	0.3045822	0.1884391
irritable	-0.2350614	0.8066823	0.1778470	-0.1661101	-0.0917194
distressed	-0.0999538	0.2865940	0.7331998	-0.2006711	-0.1129127
alert	0.1171175	0.1174614	0.1844978	0.0784881	0.8156021
excited	0.6467030	-0.1454511	0.0168273	0.4369484	0.0265786
ashamed	0.0071061	0.7425151	-0.0360974	0.0863084	0.0785868
upset	-0.1731646	0.5460251	0.5912146	-0.1920576	-0.1108945
inspired	0.3443083	-0.1392157	-0.1302665	0.5479603	0.3290067
strong	0.1678565	-0.1117113	-0.2643018	0.7983064	0.1991594
nervous	0.0647493	0.0172619	0.8571176	-0.0174175	0.1664431
guilty	-0.0190386	0.8360763	-0.0450839	-0.0509116	-0.0230723
determined	0.5458182	0.0414282	-0.0850643	0.6095315	0.2243962
scared	-0.1330222	-0.0835725	0.8799584	-0.1246672	0.0210362
attentive	0.6219170	-0.2000375	-0.2654147	0.0266160	0.4545565
hostile	-0.1784185	0.7564078	0.1941394	-0.1237321	-0.0488183
jittery	0.2072216	-0.1226099	-0.0624085	0.1611747	0.7896033
enthusiastic	0.7882124	-0.0824600	-0.1259389	0.4018627	0.0595868
active	0.2607987	-0.0456143	-0.0681966	0.8217810	-0.0691484
proud	0.8382414	-0.0682510	0.0360071	0.0633051	0.1165903

2. Run a FA (using Principal Axis Factoring) separately to each of the two groups and:

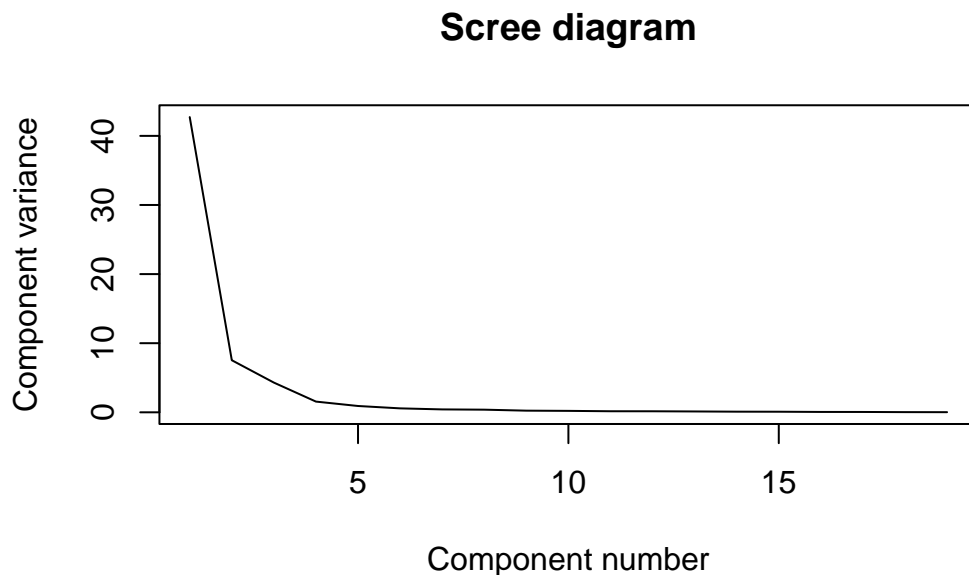
2.1. Attempt to identify an optimal number of factors for each group

Females

```
fa_female <- fa(data_female, nfactors = 4, rotate = "none", fm = "pa")
```

- Screeplot

```
plot(fa_female$e.values^2, xlab = "Component number", ylab = "Component variance",  
     type = "l", main = "Scree diagram")
```



- Eigenvalues

```
fa_female$e.values
```

```
[1] 6.5361460 2.7453271 2.0732893 1.2457147 0.9553019 0.7555674 0.6480124  
[8] 0.6177360 0.4871187 0.4571830 0.3904874 0.3869160 0.3529273 0.3059402  
[15] 0.2912350 0.2340854 0.2194304 0.1639276 0.1336541
```

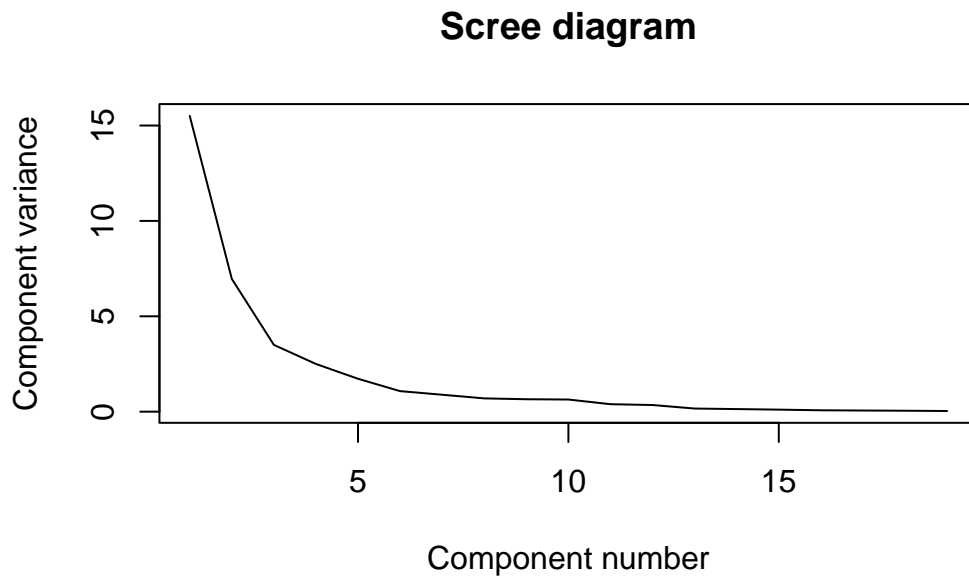
These results suggest that the optimal number of factors for females is 4.

Males

```
fa_male <- fa(data_male, nfactors = 5, rotate = "none", fm = "pa")
```

- Screeplot

```
plot(fa_male$e.values^2, xlab = "Component number", ylab = "Component variance",  
     type = "l", main = "Scree diagram")
```



- Eigenvalues

```
fa_male$e.values
```

```
[1] 3.9377056 2.6384124 1.8711662 1.5814228 1.3131943 1.0376112 0.9425977  
[8] 0.8345135 0.8073462 0.7974141 0.6258169 0.5899574 0.4048338 0.3689038  
[15] 0.3261813 0.2704118 0.2457433 0.2203604 0.1864070
```

These results suggest that the optimal number of factors for males is 6. However, given that the 6th eigenvalue is very close to one, this dimension might be considered spurious and a solution with 5 factors could be more plausible.

2.2. Report a table with eigenvalues (and percent variance explained) for each group

Females

```
knitr::kable(fa_female$Vaccounted, caption = "Variance explained by the four factors of the female group")
```

Table 7: Variance explained by the four factors of the female group.

	PA1	PA2	PA3	PA4
SS loadings	6.1283619	2.3399273	1.6968085	0.7705281
Proportion Var	0.3225454	0.1231541	0.0893057	0.0405541
Cumulative Var	0.3225454	0.4456994	0.5350051	0.5755593
Proportion Explained	0.5604034	0.2139729	0.1551634	0.0704604
Cumulative Proportion	0.5604034	0.7743763	0.9295396	1.0000000

Males

```
knitr::kable(fa_male$Vaccounted, caption = "Variance explained by the five factors of the male group")
```

Table 8: Variance explained by the five factors of the male group.

	PA1	PA2	PA3	PA4	PA5
SS loadings	3.5424263	2.2545951	1.4671739	1.1106875	0.8487203
Proportion Var	0.1864435	0.1186629	0.0772197	0.0584572	0.0446695
Cumulative Var	0.1864435	0.3051064	0.3823261	0.4407833	0.4854528
Proportion Explained	0.3840610	0.2444376	0.1590673	0.1204180	0.0920161
Cumulative Proportion	0.3840610	0.6284986	0.7875659	0.9079839	1.0000000

2.3. Rotate the solution using the PROMAX procedure and report differences between this solution and the unrotated one (include the loading matrix in your report and the factor intercorrelation matrix)

Promax yielded clearer clusters of variables with high loadings on specific factors for both groups.

Females

```
fa_female_pmx <- fa(data_female, nfactors = 4, rotate = "promax", fm = "pa")
```

Loading required namespace: GPArotation

Loading matrix

```
fa_female_pmx$loadings[,1:4] |> knitr::kable(caption = "Rotated loadings matrix for females")
```

Table 9: Rotated loadings matrix for females.

	PA1	PA2	PA3	PA4
interested	0.6965343	-0.0703328	0.0387261	0.1184242
irritable	-0.1299749	0.8107552	0.0184816	-0.0038452
distressed	-0.0150788	0.1512083	0.6652368	-0.0651415
alert	-0.0618907	0.1645205	0.1552956	0.7317729
excited	0.8020090	-0.0737417	0.1403155	-0.0831573
ashamed	0.1234024	0.6839322	-0.0984977	0.0802264
upset	-0.0392560	0.4373241	0.5068499	-0.0597719
inspired	0.5234451	-0.0209031	-0.0648176	0.1700524
strong	0.6116220	0.0376876	-0.2236127	-0.0145020
nervous	0.1478354	-0.0881718	0.8643402	0.1555720
guilty	0.0533617	0.8202824	-0.1446506	0.0373307
determined	0.8373697	0.1778749	-0.0014262	0.0633518
scared	-0.0235132	-0.2508882	0.9261353	0.0101905
attentive	0.2471004	-0.1147250	-0.1301048	0.4534179
hostile	-0.0802002	0.7148551	0.0593427	0.0222331
jittery	-0.0252629	-0.0213286	-0.0384811	0.7295041
enthusiastic	0.9181572	0.0145075	0.0392727	-0.0678958
active	0.8207373	0.0673654	-0.0314055	-0.2628243
proud	0.6079370	-0.0361507	0.1711827	0.1212037

Factor intercorrelation matrix

```
fa_female_prmx$Phi |> knitr::kable(caption = "Factor correlations for females.")
```

Table 10: Factor correlations for females.

	PA1	PA2	PA3	PA4
PA1	1.0000000	-0.3615331	-0.3960397	0.5916515
PA2	-0.3615331	1.0000000	0.3791157	-0.2668833
PA3	-0.3960397	0.3791157	1.0000000	-0.1635304
PA4	0.5916515	-0.2668833	-0.1635304	1.0000000

Males

```
fa_male_prmx <- fa(data_male, nfactors = 5, rotate = "promax", fm = "pa")
```

Loading matrix

```
fa_male_prmx$loadings[,1:5] |> knitr::kable(caption = "Rotated loadings matrix for males.")
```

Table 11: Rotated loadings matrix for males.

	PA1	PA2	PA4	PA3	PA5
interested	0.8143266	-0.0100438	0.1249537	-0.0670092	-0.0847398
irritable	-0.0419301	0.3209045	0.0865906	-0.0604536	-0.2058776
distressed	0.0329152	0.7187559	-0.1655876	0.2503234	-0.0700756
alert	0.7947068	-0.0204536	0.0155375	-0.0514692	0.0650564
excited	0.2195154	-0.0688981	0.7132367	0.0127402	0.0549012
ashamed	-0.0662521	0.3392139	-0.0261270	-0.0416998	0.1646068
upset	0.0513639	0.9251282	0.0173585	-0.0191966	-0.0193698
inspired	-0.0540435	-0.0992053	0.3766823	-0.0366656	0.1610784
strong	-0.0350204	0.0652512	0.1818008	0.0689509	0.6994785
nervous	-0.0171792	0.0014510	0.0722155	0.9020405	-0.0407504
guilty	-0.0332507	0.1949563	0.2271714	0.0196508	-0.1121335
determined	0.2087329	0.2427162	-0.1079403	0.0577270	0.3914769
scared	-0.0787300	-0.0347098	-0.0120828	0.7968449	0.0686176
attentive	0.8763290	0.0073292	0.0732081	0.0070080	-0.0851527
hostile	0.0804227	0.6683769	-0.0848383	-0.0642623	0.1613558

	PA1	PA2	PA4	PA3	PA5
jittery	0.0343887	-0.0390355	0.2628672	0.0848325	0.0501314
enthusiastic	0.1404843	-0.0242005	0.7668681	-0.0526634	0.1008676
active	-0.1277701	0.0196949	0.2363479	-0.0825660	0.7205546
proud	-0.0495883	0.0695427	0.6083073	-0.0201766	0.0093394

Factor intercorrelation matrix

```
fa_male_prmx$Phi |> knitr::kable(caption = "Factor correlations for males.")
```

Table 12: Factor correlations for males.

	PA1	PA2	PA4	PA3	PA5
PA1	1.0000000	-0.1044495	0.2367600	0.2525255	0.4739554
PA2	-0.1044495	1.0000000	-0.0330360	0.0846099	-0.1431625
PA4	0.2367600	-0.0330360	1.0000000	0.0052147	0.1182753
PA3	0.2525255	0.0846099	0.0052147	1.0000000	0.0661271
PA5	0.4739554	-0.1431625	0.1182753	0.0661271	1.0000000

2.4. Report differences between the factor matrix and structure matrix for each group (include matrices in your report)

The factor matrix emphasizes the relationships between observed variables and the common factors. Common factors represent the shared variance among a set of variables that explains their intercorrelations. The structure matrix shows the relationship between observed variables and both common and unique factors. Unique factors account for the item-specific variance not shared with other variables in the analysis.

Females Factor Matrix (Loadings)

```
fa_female_prmx$loadings
```

Loadings:

	PA1	PA2	PA3	PA4
interested	0.697			0.118
irritable	-0.130	0.811		

distressed		0.151	0.665	
alert		0.165	0.155	0.732
excited	0.802		0.140	
ashamed	0.123	0.684		
upset		0.437	0.507	
inspired	0.523			0.170
strong	0.612		-0.224	
nervous	0.148		0.864	0.156
guilty		0.820	-0.145	
determined	0.837	0.178		
scared		-0.251	0.926	
attentive	0.247	-0.115	-0.130	0.453
hostile		0.715		
jittery				0.730
enthusiastic	0.918			
active	0.821			-0.263
proud	0.608		0.171	0.121

	PA1	PA2	PA3	PA4
SS loadings	4.495	2.684	2.488	1.456
Proportion Var	0.237	0.141	0.131	0.077
Cumulative Var	0.237	0.378	0.509	0.585

Females Structure Matrix

```
fa_female_prmx$loadings %*% fa_female_prmx$Phi
```

	PA1	PA2	PA3	PA4
interested	0.77669068	-0.33907682	-0.28315939	0.54296747
irritable	-0.43268422	0.86577832	0.37795562	-0.30014432
distressed	-0.37174685	0.42624662	0.73918662	-0.22320428
alert	0.25008096	0.05047307	0.12251195	0.62585184
excited	0.72389848	-0.28830548	-0.19166987	0.38808712
ashamed	-0.03738666	0.58056506	0.09880004	-0.01318504
upset	-0.43345994	0.65962330	0.69796775	-0.28259758
inspired	0.65728446	-0.28010341	-0.30785616	0.49592789
strong	0.67797610	-0.26433878	-0.44917985	0.37387439
nervous	-0.07055628	0.14454624	0.74692347	0.12522464
guilty	-0.16382336	0.73618812	0.13909323	-0.12636260
determined	0.81110906	-0.14231025	-0.27598269	0.51154422
scared	-0.29356599	0.10600538	0.83866541	-0.08821456

attentive	0.60836932	-0.37439437	-0.34560801	0.65150949
hostile	-0.34899184	0.76041427	0.35848221	-0.22570466
jittery	0.42930037	-0.22147648	-0.15585811	0.72654237
enthusiastic	0.85718807	-0.28442757	-0.30775101	0.46503920
active	0.65331995	-0.17112126	-0.28793105	0.20992320
proud	0.62492186	-0.22338924	-0.10311028	0.46254495

Males Factor Matrix (Loadings)

```
fa_male_prmx$loadings
```

Loadings:

	PA1	PA2	PA4	PA3	PA5
interested	0.814		0.125		
irritable		0.321			-0.206
distressed		0.719	-0.166	0.250	
alert	0.795				
excited	0.220		0.713		
ashamed		0.339			0.165
upset		0.925			
inspired			0.377		0.161
strong			0.182		0.699
nervous				0.902	
guilty		0.195	0.227		-0.112
determined	0.209	0.243	-0.108		0.391
scared				0.797	
attentive	0.876				
hostile		0.668			0.161
jittery			0.263		
enthusiastic	0.140		0.767		0.101
active	-0.128		0.236		0.721
proud			0.608		

	PA1	PA2	PA4	PA3	PA5
SS loadings	2.222	2.162	1.900	1.556	1.342
Proportion Var	0.117	0.114	0.100	0.082	0.071
Cumulative Var	0.117	0.231	0.331	0.413	0.483

Males Structure Matrix

```
fa_male_prmx$loadings %*% fa_male_prmx$Phi
```

	PA1	PA2	PA4	PA3	PA5
interested	0.78787531	-0.09276591	0.307713427	0.132827233	0.31300038
irritable	-0.16779010	0.34678242	0.041396384	-0.057052905	-0.26544820
distressed	-0.05136276	0.75200033	-0.188522314	0.313951754	-0.16040598
alert	0.81835841	-0.11764207	0.211794174	0.151867034	0.44307435
excited	0.42481571	-0.12217074	0.774045213	0.069693801	0.25400610
ashamed	-0.04038261	0.31990334	-0.033767697	-0.018980588	0.07879592
upset	-0.05518358	0.92033865	-0.003434183	0.070858743	-0.12668563
inspired	0.11258673	-0.13216724	0.386024741	-0.046090799	0.19179432
strong	0.35014084	-0.03140208	0.254444367	0.112830814	0.69960098
nervous	0.20824142	0.08301517	0.067984336	0.895507020	0.01909034
guilty	-0.04801262	0.20864046	0.199698265	0.021518979	-0.12763506
determined	0.35794552	0.17331950	-0.019935984	0.156297952	0.44670977
scared	0.15578010	0.03151021	-0.017305120	0.778501277	0.08753618
attentive	0.85430728	-0.07383783	0.270410701	0.223674370	0.33826096
hostile	0.05077235	0.63424219	-0.069128631	0.022825356	0.08950233
jittery	0.14588476	-0.05131070	0.278670278	0.094899599	0.10871890
enthusiastic	0.35908362	-0.08310464	0.812584149	-0.008566058	0.25813457
active	0.24679125	-0.08490987	0.290239660	-0.064284119	0.67967196
proud	0.08650218	0.05158196	0.595268753	-0.023025151	0.04649437

2.5. Report differences between the results from PCA and FA

PCA and FA yielded similar results in terms of number of components/factors extracted considering the analysis of the screeplot and examining the eigenvalues. However, using a criteria of factor loading greater than 0.4, it was not the case that the items grouped identically across both methods.

In general, PCA loadings tended to be higher than FA loadings in both groups. This might be explained by the fact that PCA accounts for all variance, while FA partitions out the unique variance.

3. Based on these analyses, interpret the structure of affect for these two groups of individuals

Female group

For females, both PCA and FA suggested the variables can be grouped in four components or factors:

Principal components for females

- PC1: interested, excited, inspired, strong, determined, attentive, enthusiastic, active, proud
- PC2: irritable, ashamed, upset, guilty, hostile
- PC3: distressed, upset, nervous, scared
- PC4: alert, attentive, jittery

Factors for females

- PA1: interested, excited, inspired, strong, determined, enthusiastic, active, proud
- PA2: irritable, ashamed, upset, guilty, hostile
- PA3: distressed, upset, nervous, scared
- PA4: alert, attentive, jittery

The correlations between rotated factors are generally moderate to strong. The factors comprised of emotionally positive items are positively correlated with each other (PA1 and PA4), and negatively correlated with those that are formed by items measuring negative emotions (PA2 and PA3).

Male group

Similarly, for males both techniques indicated the data can be summarized in five factors:

Principal components for males

- PC1: interested, excited, determined, attentive, enthusiastic, proud
- PC2: irritable, ashamed, upset, guilty, hostile
- PC3: distressed, upset, nervous, scared
- PC4: excited, inspired, strong, determined, enthusiastic, active
- PC5: alert, attentive, jittery

Factors for males

- PA1: interested, alert, attentive
- PA2: distressed, upset, hostile
- PA3: nervous, scared
- PA4: excited, enthusiastic, proud
- PA5: strong, active

The correlations between rotated factors were generally weaker than those found for the female group, with most of them having a small value. It was also found a similar pattern to the female results, of positive correlation between factors comprised of emotionally positive items (PA1, PA4 and PA5), and negative correlation between these factors and those formed by items measuring negative emotions (PA2 and PA3).

PCA focuses on maximizing variance explained and finding linear combinations of variables to create components. It does not distinguish between common and unique variance. In this data we are exploring variables measuring affect, therefore FA appears to be more suitable. Each emotion measure also contains uniqueness (e.g., the specific situational triggers for sadness vs. fear) and possibly measurement error. FA partitions this out, isolating the shared core.

4. Discuss whether or not PCA and FA are relevant to the notion of multivariate static and dynamic concepts.

Both methods are suitable for static and dynamic concepts, given some differences between them.

For static concepts, where relationships among variables are expected to remain stable, PCA captures the dominant structure at that moment. Static latent factors in FA presume an underlying construct that remains relatively stable over time, even if its manifestations on observed variables might fluctuate.

When applied to datasets collected over time components might represent different trajectories and patterns of development. PCA could identify components representing typical trajectories of mood variation. Dynamic FA allows the latent factors themselves to have time-dependent properties and capture complex dynamic relationships among variables.

5. Discuss whether or not PCA and FA are relevant to the study of the individual and individual processes

Classical PCA/FA primarily reveal structure at the group level. They are concerned with dimensions shared by most individuals but might not directly uncover a single individual's unique configuration.