12 Introduction to Principal Component Analysis

PCA is a multivariate technique for understanding variation and for summarizing measurement data. It is frequently used for variable reduction.

Given data on p measurement variables X_1, X_2, \dots, X_p , PCA produces a new set of p uncorrelated variables (the principal components) that are unit-length linear combinations of the original variables. That is,

$$PRIN1 = a_{11}X_1 + a_{12}X_2 + \dots + a_{1p}X_p$$

$$PRIN2 = a_{21}X_1 + a_{22}X_2 + \dots + a_{2p}X_p$$

$$\vdots$$

$$PRINp = a_{p1}X_1 + a_{p2}X_2 + \dots + a_{pp}X_p$$

where unit length means $a_{j1}^2 + a_{j2}^2 + \cdots + a_{jp}^2 = 1$ for all $j = 1, \dots, p$.

The first principal component has the largest variability among all such possible linear combinations. The second has the largest variability among all such linear combinations which are uncorrelated with PRIN1. The third principal component has the largest variability among all such linear combinations that are uncorrelated with PRIN1 and PRIN2 and so forth down to PRINp. Thus, the ordered principal components are uncorrelated variables with progressively less variation (from PRIN1 to PRINp).

Example 1

Jolicouer and Moismann provided data on the height, length, and width of the shell for a sample of female painted turtles. Principal component analysis is used to identify the linear combinations of the measurements that account for the most of the variation in the size and shape of the shells.

```
> turtlesF = read.table("turtlesF.txt",header=T)
> turtlesF
   Length Width Height
       98
1
             81
                     38
2
             84
                     38
      103
3
                     42
      103
             86
4
      105
             86
                     40
5
      109
             88
                     44
6
      123
             92
                     50
7
      123
             95
                     46
8
      133
             99
                     51
9
      133
            102
                     51
10
      133
            102
                     51
                     48
11
      134
            100
12
      136
            102
                     49
13
      137
             98
                     51
14
      138
             99
                     51
15
      141
            105
                     53
16
      147
            108
                     57
17
            107
                     55
      149
18
      153
            107
                     56
19
      155
            115
                     63
20
      155
            117
                     60
21
                     62
      158
            115
22
      159
            118
                     63
23
      162
            124
                     61
                     67
24
      177
            132
> ss.pr1 = princomp(as.matrix(turtlesF), cor=T)
> names(ss.pr1)
[1] "sdev"
               "loadings" "center"
                                       "scale"
                                                  "n.obs"
                                                              "scores"
[7] "call"
> ss.pr1$loadings[,1:3]
           Comp.1
                        Comp.2
                                   Comp.3
Length -0.5783865 -0.06171004 0.8134254
Width -0.5769696 -0.67396612 -0.4613846
Height -0.5766932 0.73618037 -0.3542081
> ss.pr1$sdev^2/sum(ss.pr1$sdev^2)
     Comp.1
                 Comp.2
0.980439578 0.011547360 0.008013062
```

> ss.pr1\$scores[,1:3]

```
Comp.1
                      Comp.2
                                   Comp.3
     3.0346502 -0.039113234 -0.091287510
[1,]
[2,]
     2.7606815 -0.211555370 -0.003634567
[3,] 2.3820993 0.051828467 -0.252844118
[4,] 2.4707979 -0.138333171 -0.085985178
[5,]
     1.9809803 0.113182572 -0.178756523
[6,]
     0.9788082 0.414184328 -0.041002066
     1.1325163 -0.111877875 0.028382794
[7,]
     0.3137378 0.108878178 0.054018963
[8,]
[9,]
     0.1788134 -0.048728842 -0.053875852
[10,] 0.1788134 -0.048728842 -0.053875852
[11,] 0.4574286 -0.222965906 0.190123332
[12,] 0.2397031 -0.241857503 0.152092640
[13,] 0.2474771 0.149545757 0.246422107
[14,] 0.1746935 0.094043061 0.249566720
[15,] -0.3228981 -0.045844456 0.062465908
[16,] -0.9133083  0.147201568  0.011948728
[17,] -0.7796349 0.009575602 0.214772607
[18,] -0.9630285  0.089821304  0.326890894
[19,] -1.8835515  0.308398444 -0.192848939
[20,] -1.7570267 -0.073014290 -0.131819059
[21,] -1.8948200 0.207383578 -0.031200366
[22,] -2.1297114  0.138923331  -0.144305547
[23,] -2.3386705 -0.369419370 -0.154126685
[24,] -3.5485506 -0.281527330 -0.121122429
```

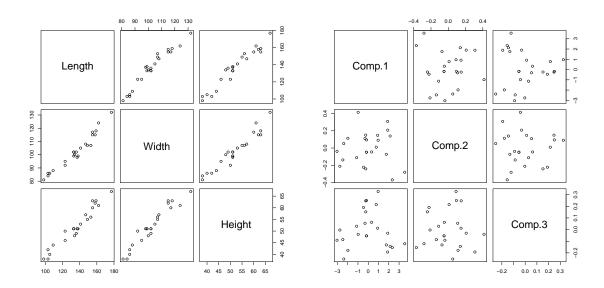


Figure 61: Turtle shell measurements data (left) and Principal Component Scores (right)

Example 2

The data file socsupport in the DAAG package consists of support measures, demographic information, and the Beck depression index (BDI) on a sample of healthy individuals. The variables in the data set are:

- gender: male or female
- age: 18-20, 21-24, 25-30, 31-40, 40+
- country: Australia, other
- marital: married, single, other
- livewith: alone, friends, parents, partner, residences, other
- employment: full-time, part-time, govt assistance, parental support, other
- firstyr: first year, other
- enrolment: full-time, part-time, blank
- emotional: availability of emotional support (5 questions)
- emotionalsat: satisfaction associated with available emotional support (5 questions)
- tangible: availability of tangible support (4 questions)
- tangiblesat associated satisfaction with tangible support (4 questions)
- affect: availability of affectionate support sources (3 questions)
- affectsat: associated satisfaction (3 questions)
- psi: availability of positive social interaction (3 questions)
- psisat: associated satisfaction (3 questions)
- esupport: extent of emotional support sources (4 questions)
- psupport: extent of practical support sources (4 questions)
- supsources extent of social support sources (4 questions)
- BDI: Score on the Beck depression index (total over 21 questions)

One study goal was to examine how the support measures (variables 9 - 19) may impact BDI. Other goals including looking at the impact of the demographic information in variables 1 - 8. We will focus on the support measures for this analysis.

- > library(DAAG)
- > data(socsupport)
- > not.na = complete.cases(socsupport)
- > fullobs = socsupport[not.na,]
- > fullobs[1:10,]

	-	LUTTODD	, ,										
		gender	age	count	ry	marital	li	vewith	•	emp]	Loyment	firsty	<u>-</u>
	1	male 2	21-24	austral	ia	other	р	artner	employed	pai	ct-time	other	:
	2	female 2	21-24	austral	ia	single	р	artner	parenta	al s	support	other	:
	3	male 2	21-24	austral	ia	single	resi	dences	employed	pai	ct-time	other	<u>-</u>
	4	male 1	.8-20	austral	ia	single	p	arents	employed	pai	ct-time	first year	<u>-</u>
	5	female 2	21-24	austral	ia	single	f	riends	employed	pai	ct-time	other	<u>.</u>
	6	female 2	21-24	austral	ia	single	f	riends	govt a	ass	istance	other	<u>-</u>
	7	female 2	25-30	austral	ia	married	р	artner	employed	pai	ct-time	other	<u>-</u>
	8	female 2	25-30	austral	ia 1	married	р	artner	employed	pai	rt-time	other	:
	10	male	40+	austral	ia	other		alone	employed	pai	ct-time	other	<u>-</u>
	11	female 2	21-24	austral	ia	single	p	arents	employed	pai	rt-time	other	-
		enrolmen	it emo	otional	emo	tionals	at ta	ngible	tangibles	sat	${\tt affect}$	${\tt affectsat}$	psi
	1	full-tim	ie	22		2	23	17		18	15	15	12
	2	full-tim	ie	21		2	20	12		10	10	6	9
	3	full-tim	ie	21		-	18	16		16	15	15	13
	4	full-tim	ie	19		-	19	20		17	11	11	13
	5	full-tim	ie	16		-	19	11		15	6	10	11
	6	full-tim	ie	20		-	17	16		15	12	14	12
	7	full-tim	ie	20		2	23	20		20	14	15	15
	8	part-tim	ie	20		2	20	16		16	12	12	12
	10	full-tim	ie	13		-	18	6		14	6	12	6
	11	full-tim	ie	20		-	18	13		13	13	14	11
psisat esupport psupport supsources BDI													
	1	13		13	1	1	13	5					
	2	6		12	•	7	10	8					
	3	12		14	1	3	14	16					
	4	12		15	1	5	15	0					
	5	12		9	•	7	9	9					
	6	11		13	1:	2	13	0					
	7	15		15	1	0	13	1					

11 14

9 20

14 13

> # correlations between emotional support measures

> cor(fullobs[,9:19])

```
emotional emotionalsat tangible tangiblesat
                                                            affect affectsat
emotional
             1.0000000
                          0.8404097 0.4184066
                                                0.4466863 0.6327119 0.5598617
emotionalsat 0.8404097
                          1.0000000 0.3005215
                                               0.4700119 0.5551086 0.5916673
tangible
             0.4184066
                          0.3005215 1.0000000
                                               0.8457784 0.5244751 0.3417302
tangiblesat
             0.4466863
                          0.4700119 0.8457784
                                                1.0000000 0.5570396 0.4887023
affect
             0.6327119
                          0.5551086 0.5244751
                                               0.5570396 1.0000000 0.8590008
affectsat
             0.5598617
                         0.5916673 0.3417302
                                               0.4887023 0.8590008 1.0000000
psi
             0.6522592
                         0.6269751 0.4723045
                                               0.5451902 0.6150706 0.5769021
             0.5808499
                         0.6544473 0.2950583
                                               0.4784861 0.4835865 0.6241824
psisat
             0.5648627
                         0.4207017 0.4115311
                                               0.3890842 0.4179985 0.3122408
esupport
psupport
             0.4116978
                         0.3389021 0.5248865
                                               0.5141296 0.3175150 0.2874456
             0.4666297
                         0.3913016 0.3779575
                                               0.3977396 0.3537538 0.3704146
supsources
                  psi
                         psisat esupport psupport supsources
emotional
             0.6522592 0.5808499 0.5648627 0.4116978
                                                      0.4666297
emotionalsat 0.6269751 0.6544473 0.4207017 0.3389021
                                                      0.3913016
tangible
             0.4723045 0.2950583 0.4115311 0.5248865
                                                     0.3779575
tangiblesat
             0.5451902 0.4784861 0.3890842 0.5141296
                                                      0.3977396
affect
             0.6150706 0.4835865 0.4179985 0.3175150
                                                      0.3537538
affectsat
             0.5769021 0.6241824 0.3122408 0.2874456
                                                      0.3704146
             1.0000000 0.8503953 0.6547506 0.5815234
                                                      0.5960882
psi
             0.8503953 1.0000000 0.5669334 0.5115678
psisat
                                                     0.5453711
esupport
             0.6547506 0.5669334 1.0000000 0.5853292
                                                     0.6465774
             0.5815234 0.5115678 0.5853292 1.0000000
psupport
                                                     0.7548660
supsources
             0.5960882 0.5453711 0.6465774 0.7548660
                                                      1.0000000
```

```
> fit = lm(BDI~emotional + emotionalsat + tangible + tangiblesat + affect + affectsat
+ + psi + psisat + esupport + psupport + supsources,data=fullobs)
> summary(fit)
```

Call:

```
lm(formula = BDI ~ emotional + emotionalsat + tangible + tangiblesat +
    affect + affectsat + psi + psisat + esupport + psupport +
    supsources, data = fullobs)
```

Residuals:

```
Min 1Q Median 3Q Max -15.915 -5.678 -1.074 4.446 31.681
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	40.82174	7.22039	5.654	2.47e-07	***
emotional	0.71521	0.58350	1.226	0.2240	
${\tt emotionalsat}$	-0.56894	0.65352	-0.871	0.3867	
tangible	-0.24146	0.55588	-0.434	0.6652	
tangiblesat	0.08959	0.72561	0.123	0.9021	
affect	-1.37376	0.87331	-1.573	0.1198	
affectsat	1.12655	0.88484	1.273	0.2067	
psi	-0.36446	0.96499	-0.378	0.7067	
psisat	-1.82040	1.02679	-1.773	0.0801	
esupport	0.23530	0.57631	0.408	0.6842	
psupport	0.77274	0.48958	1.578	0.1185	
supsources	-1.09534	0.66225	-1.654	0.1022	

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Residual standard error: 8.66 on 78 degrees of freedom Multiple R-squared: 0.3075, Adjusted R-squared: 0.2098 F-statistic: 3.148 on 11 and 78 DF, p-value: 0.001454

```
> ## Principal components regression
> ss.pr1 = princomp(fullobs[,9:19], cor=TRUE)
> ss.pr1$loadings
Loadings:
             Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8 Comp.9
             -0.321 -0.217 -0.153 0.508 0.299
emotional
                                                       0.208 0.147 -0.460
emotionalsat -0.304 -0.319 -0.192 0.487
                                                 0.318 -0.164 -0.152 0.414
            -0.262 0.209 0.615 0.184
                                                               0.222 - 0.334
tangible
                                                -0.121
tangiblesat -0.294
                            0.530 0.122 -0.306
                                                      -0.385 -0.147
                                                                     0.229
affect
            -0.307 -0.354 0.222 -0.312 0.393 -0.126 0.224
                                                                      0.299
affectsat
            -0.294 -0.427
                                  -0.500 0.106 0.148 -0.165 -0.233 -0.252
            -0.351
                           -0.168
                                         -0.333 -0.299
                                                       0.388 0.455 0.348
psi
                           -0.297 -0.168 -0.592 -0.114
             -0.324
psisat
                                                                     -0.416
             -0.289
                    0.294 - 0.237
                                          0.336 -0.655 -0.263 -0.372
esupport
                                                 0.408 0.524 -0.472
             -0.279 0.492
                                  -0.114
psupport
             -0.284 0.401 -0.230 -0.221 0.259 0.373 -0.440 0.501
supsources
             Comp.10 Comp.11
              0.437
emotional
emotionalsat -0.448
tangible
             -0.540
tangiblesat
            0.540
affect
                     -0.564
affectsat
            -0.106
                     0.536
                      0.396
psi
                     -0.469
psisat
esupport
psupport
supsources
> vars = (ss.pr1$sd^2)
> por.vars = vars/(sum(ss.pr1$sd^2))
> data.frame(variance = vars, portion = por.vars, cum.var = cumsum(por.vars))
         variance
                      portion
                                 cum.var
Comp.1
        6.23353658 0.566685144 0.5666851
Comp.2 1.35041288 0.122764808 0.6894500
Comp.3 1.16131376 0.105573978 0.7950239
```

Comp.4 0.62929371 0.057208519 0.8522324 Comp.5 0.51807128 0.047097389 0.8993298 Comp.6 0.44343136 0.040311942 0.9396418

Comp.8 0.19190191 0.017445628 0.9779395

0.22937251 0.020852046 0.9604938

Comp.7

Comp.9 0.11405360 0.010368509 0.9883080 Comp.10 0.07926632 0.007206030 0.9955140 Comp.11 0.04934609 0.004486008 1.0000000

> ss.pr1\$loadings[,1] # all of the loadings of the first principal component emotional emotionalsat tangible tangiblesat affect affectsat -0.3213099 -0.3037267 -0.2615739 -0.2936168 -0.3070059 -0.2935072 supsources psisat esupport psupport psi -0.3510474 -0.3237180 -0.2887159 -0.2786228 -0.2836617

> ss.pr1\$loadings[,2] # all of the loadings of the second principal component emotional emotionalsat tangible tangiblesat affect affectsat 0.20861591 -0.21706010 -0.31946007 0.08448239 -0.35380957 -0.42660133 supsources esupport psi psisat psupport 0.01462971 -0.06040658 0.29403945 0.49214145 0.40059581

- > plot(ss.pr1,main="PCA variances from socsupport study full data")
- > pairs(ss.pr1\$scores[, 1:3],main="full data")

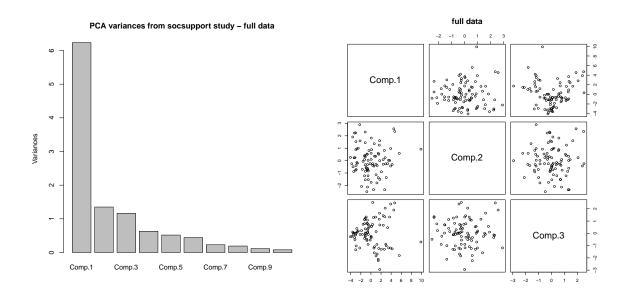


Figure 62: Scree plot for PCA of support measures (left); Plots of first three principal components (right) for support data.

```
> ss.lm = lm(BDI ~ ss.pr1$scores[, 1:6], data=fullobs)
> summary(ss.lm)
```

Call:

lm(formula = BDI ~ ss.pr1\$scores[, 1:6], data = fullobs)

Residuals:

Min 1Q Median 3Q Max -14.559 -5.287 -0.200 3.689 34.900

Coefficients:

		${\tt Estimate}$	Std. Error	t value	Pr(> t)	
(Intercept)		10.8556	0.9205	11.793	< 2e-16	***
ss.pr1\$scores[,	1:6]Comp.1	1.7585	0.3687	4.770	7.8e-06	***
ss.pr1\$scores[,	1:6]Comp.2	0.5262	0.7921	0.664	0.508	
ss.pr1\$scores[,	1:6]Comp.3	0.6218	0.8542	0.728	0.469	
ss.pr1\$scores[,	1:6]Comp.4	1.1348	1.1604	0.978	0.331	
ss.pr1\$scores[,	1:6]Comp.5	1.9708	1.2789	1.541	0.127	
ss.pr1\$scores[,	1:6]Comp.6	1.1676	1.3824	0.845	0.401	

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Residual standard error: 8.733 on 83 degrees of freedom Multiple R-squared: 0.2507, Adjusted R-squared: 0.1965 F-statistic: 4.627 on 6 and 83 DF, p-value: 0.0004208

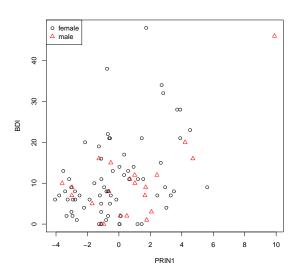


Figure 63: Plot of BDI vs. PRIN1 (bottom) for suppport data.