#### STA 9705: HW6

#### **Tanay Mukherjee**

### # 12.6

The variance of  $y_1$ ,  $y_2$ ,  $x_1$ ,  $x_2$ , and  $x_3$  on diag(**S**)'= (0.016, 70.559, 1106.414, 2381.883, 2136.396).

		Co	ovariance Matri	x	
	Y1	Y2	X1	X2	Х3
Y1	0.016182	0.216029	0.787169	-0.213845	2.189072
Y2	0.216029	70.558937	26.228986	-23.956039	-20.841546
<b>X1</b>	0.787169	26.228986	1106.413527	396.732367	108.383575
X2	-0.213845	-23.956039	396.732367	2381.882609	1142.637681
Х3	2.189072	-20.841546	108.383575	1142.637681	2136.396135

### Eigen Values of S

	Eigenv	alues of the C	ovariance Ma	trix
	Eigenvalue	Cumulative		
1	3466.18182	2201.71128	0.6086	0.6086
2	1264.47054	369.20218	0.2220	0.8306
3	895.26836	825.93313	0.1572	0.9878
4	69.33524	69.32382	0.0122	1.0000
5	0.01142		0.0000	1.0000

Eigen Values of R

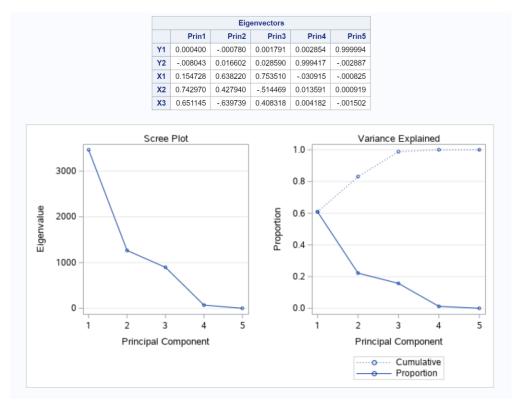
	Eigenvalues of the Correlation Matrix											
	Eigenvalue	Difference	Proportion	Cumulative								
1	1.71724028	0.48339142	0.3434	0.3434								
2	1.23384887	0.27364618	0.2468	0.5902								
3	0.96020268	0.17357027	0.1920	0.7823								
4	0.78663241	0.48455665	0.1573	0.9396								
5	0.30207576		0.0604	1.0000								

From the table above we can look at the proportion column and see for S, 2 principal components account for  $\sim$  83% of the variances whereas for R, 3 principal components account for  $\sim$  78% of the variances. The variances for S is significantly distanced as compared to R.

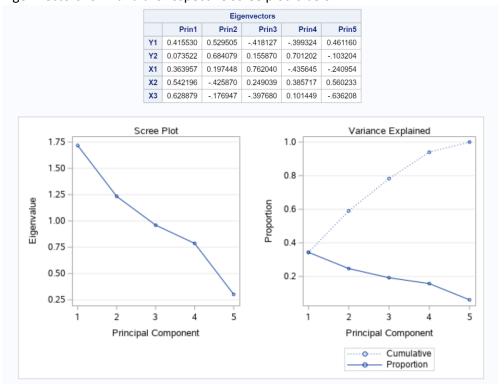
We look at the average eigen values of S and R and also the scree plot. Based on that we can say that based on the  $\lambda_{avg}$  for S and R is 1139.05 and 1 respectively. That makes  $\lambda_1$  and  $\lambda_2$  for S relevant and  $\lambda_1$ ,  $\lambda_2$  and  $\lambda_3$  for R relevant. The values of which are highlighted above. Also, from the scree plot we look for the elbow point and that also gives us the same result, that is, 2 principal components for S and 3 for R. This helps to conclude that we will go with R over S.

The first principal component is largely a weighted average of the last two variables, x2 and x3, which have the largest variances. The second and third components represent contrasts in the last three variables and could be described as "shape" components. The fourth and fifth components are associated uniquely with y2 and y1, respectively. These components are "variable specific". As expected, the principal components of R show an entirely different pattern. All five variables contribute to the first three components of R, whereas in S, y1 and y2 have small variances and contribute almost nothing to the first three components.

# Eigen vectors for S and the respective scree plot is below:



Eigen vectors for R and the respective scree plot is below:



### # 12.9

The variance of  $y_1$ ,  $y_2$ ,  $y_3$ ,  $y_4$ ,  $y_5$ ,  $y_6$  on diag(**S**)'= (0.691, 5.401, 2006682.353, 90.290, 56.374,18.078).

		C	ovariance Ma	ıtrix		
	Y1	Y2	Y3	Y4	Y5	Y6
Y1	5.040	895.000	5.567	1.682	0.270	0.254
Y2	895.000	1930000.000	12679.167	3765.833	-656.667	-71.000
Y3	5.567	12679.167	130.750	-17.100	0.075	1.555
Y4	1.682	3765.833	-17.100	47.823	-5.430	-2.035
Y5	0.270	-656.667	0.075	-5.430	11.927	-0.000
Y6	0.254	-71.000	1.555	-2.035	-0.000	0.655

### **Eigen Values of S**

	Eigenv	alues of the C	ovariance Ma	trix			
	Eigenvalue	Difference	Proportion	Cumulative			
1	1930091.29	1930004.76	0.9999	0.9999			
2	86.53	75.25	0.0000	1.0000			
3	11.27	6.65	0.0000	1.0000			
4	4.62	2.67	0.0000	1.0000			
5	1.95	1.42	0.0000	1.0000			
6	0.53		0.0000	1.0000			

Eigen Values of R

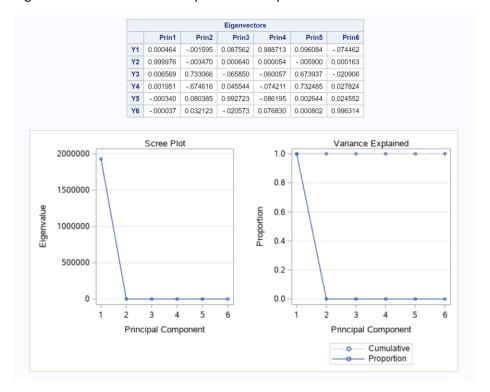
	Eigenv	alues of the C	orrelation Ma	trix
	Eigenvalue	Difference	Proportion	Cumulative
1	1.98091253	0.42126338	0.3302	0.3302
2	1.55964915	0.57499466	0.2599	0.5901
3	0.98465449	0.06242083	0.1641	0.7542
4	0.92223366	0.38232146	0.1537	0.9079
5	0.53991219	0.52727422	0.0900	0.9979
6	0.01263798		0.0021	1.0000

From the table above we can look at the proportion column and see for S, 1 principal components account for  $\sim$  99.99% of the variances whereas for R, 3 principal components account for  $\sim$  85% of the variances. We should definitely go for R in this case.

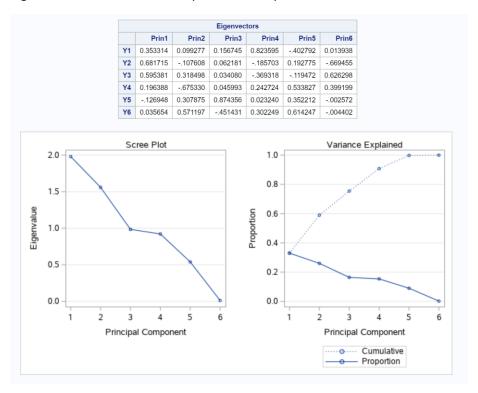
We look at the average eigen values of S and R and also the scree plot. Based on that we can say that based on the  $\lambda_{avg}$  for S and R is 321699.37 and 1 respectively. That makes  $\lambda_1$  only for S relevant and  $\lambda_1$ ,  $\lambda_2$  and  $\lambda_3$  for R relevant. The values of which are highlighted above. Also, from the scree plot we look for the elbow point and that also gives us the same result, that is, 2 principal components for S and 3 for R. This helps to conclude that we will go with R over S.

The first principal component is largely a weighted average of the y3. The second principal component contrasts with y4 and y5 and third component represent contrasts for y6. Thus, S accounts for most of the variance and y3 would essentially constitute that single principal component. As expected, the principal components of R show an entirely different pattern. The principal components from R, on the other hand, are not dominated by y3.

## Eigen vectors for S and the respective scree plot is below:



## Eigen vectors for R and the respective scree plot is below:



## # 13.8 (a)

The output for each rotation is given below as obtained from SAS:

#### **Principal Component Loadings**

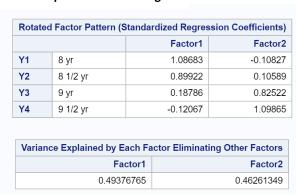
	Factor Pattern								
		Fa	actor1	Factor2					
Y1	8 yr	0.	94913	-0.29528					
Y2	8 1/2 yr	0.	97386	-0.19285					
Y3	9 yr	0.	97822	0.17114					
<b>Y4</b> 9 1/2 yr		0.94292		0.31886					
Varia	ance Expl	aine	ed by Ea	ach Factor					
	Facto		Factor2						
	3 69524	71	1 0.255						

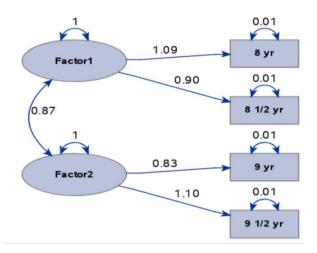
#### **Varimax Rotated Laodings**

	Rotated	Fa	ctor Pat	tern			
		F	actor1	Factor2			
Y1	8 yr	0	.88388	0.45475			
Y2	8 1/2 yr	0.82971		0.54514			
Y3	9 yr	0	.57766	0.80778			
Y4	9 1/2 yr	0	.44893	0.88838			
Varia	ınce Expla	iine	ed by Ea	ach Factor			
	Factor	<b>1</b>	1 Factor2				
	2 004899	1.9456939					

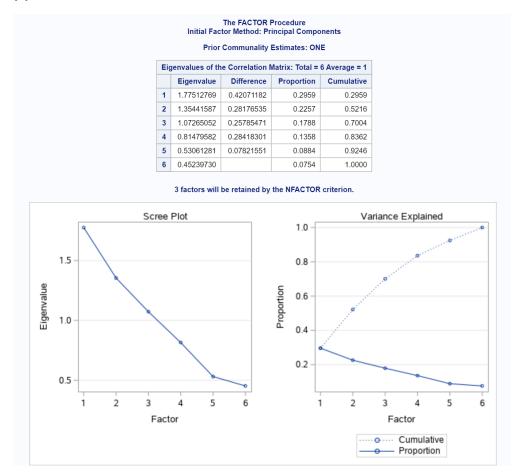
The Harris–Kaiser orthoblique rotation produced loadings for which the variables have a complexity of 1. These oblique loadings provide a much cleaner simple structure than that given by the varimax loadings. For interpretation, we see that one factor represents variables 1 and 2, and the other factor represents variables 3 and 4. This same clustering of variables can be deduced from the varimax loadings if we simply use the larger of the two loadings for each variable.

#### **Orthoblique Pattern Loadings**





(a)



Three of the eigen values are greater than one but it takes 4 eigen values to constitute more than 80% in proportion. Also, from the scree plot we can see the elbow point says the value of 'm' should be 4.

# **(b)** The value of loadings is below:

# 1. Principal Component Loadings

			F	actor	Patteri	1			
			Facto	r1	Factor2	Fac	tor3		
		X1	0.536	12	0.46140	0.47	7826		
		X2	-0.129	45	0.86962	-0.18	3155		
		Х3	0.513	50 -	0.25389	-0.44	1841		
		<b>X</b> 4	0.723	91 -	0.36597	-0.1	1031		
		<b>X</b> 5	-0.415	54 -	0.41424	0.64	1920		
		<b>X</b> 6	0.714	52	0.12367	0.4	1982		
		Var	iance E	xplain	ed by E	ach Fa	ctor		
		F	actor1	Fa	actor2	Fac	tor3		
		1.77	51277	1.35	44159	1.0726	3505		
	Fina	I Con	nmunali	ty Est	imates	Total =	4.202	2194	
X1		X2		<b>X</b> 3		X4		<b>X</b> 5	Х
0.72905685	0.80595	5890	0.5292	21335	0.670	14233	0.76	573408	0.7020885

# 2. Varimax Rotated Loadings

		Orthogonal Transformation Matrix           1         2         3           1         0.72707         0.68234         0.07603           2         -0.41710         0.35103         0.83833           3         -0.54534         0.64124         -0.53983           Rotated Factor Pattern           Factor1         Factor2         Factor3           X1         -0.06347         0.83447         0.16939           X2         -0.35783         0.10052         0.81720           X3         0.72378         -0.02628         0.06826           X4         0.73913         0.29475         -0.19222           X5         -0.48338         -0.01266         -0.72932           X6         0.23898         0.80017         -0.06863							
				1	2		3		
		1	0.7270	7 (	0.68234	0.07	603		
		2	-0.4171	0 0	0.35103	0.83	833		
		3	-0.5453	34 (	).64124	-0.53	983		
			Rotat	ed Fa	actor Pa	ttern			
			Facto	r1	Factor2	Fac	tor3		
	<b>X1</b> -0.06347 0.83447 0.16939								
		<b>X2</b> -0.35783 0.10052 0.81720							
		Х3	0.723	78 -	-0.02628	0.0	826		
		<b>X</b> 4	0.739 <sup>-</sup>	13	0.29475	-0.19	9222	1	
		<b>X5</b>	-0.483	38 -	-0.01266	-0.72	2932	]	
		<b>X</b> 6	0.2389	98	0.80017	-0.0	863		
								_	
		Var	iance Ex	cplair	ned by E	ach Fa	ctor		
		F	actor1	F	actor2	Fac	tor3		
		1.49	30209	1.43	344375	1.2747	357		
	L								
	Final	Con	nmunali	ty Es	timates:	Total =	4.20	2194	
X1		X2		Х3		X4		X5	X6
0.72905685	0.80595	890	0.5292	1335	0.670	14233	0.76	6573408	0.70208857

# (c) The value of loadings is below:

# 1. Principal Component Loadings

				Facto	r Pattern				
			Facto	or1	Factor2	Fac	tor3		
		X1	0.402	292	0.31201	0.22	2658		
		X2	-0.106	324	0.56866	-0.10	0018		
		Х3	0.342	267	-0.13858	-0.19	9721		
		X4	0.558	361	-0.24673	-0.08	3970		
		<b>X</b> 5	-0.286	641	-0.24640	0.32	2767		
		<b>X</b> 6	0.555	571	0.08897	0.19	9721		
		Var	iance E	xplai	ned by Ea	ach Fa	ctor		
		Fa	ctor1		Factor2	Fa	ctor3		
		0.993	95196	0.56	942354	0.254	56943		
	Fit	nal Con	nmunal	ity Es	stimates:	Total =	1.817	945	
X1		X2	X2		3	X4		X5	X6
0.31103433	0.344	69386	0.175	51746	0.3809	96675	0.250	10590	0.35562663

# 2. Varimax Rotated Loadings

	Or	thogona	l Trar	nsformat	ion Ma	trix			
			1	2		3			
	1	0.7218	34 (	0.68616	0.09	013			
	2	-0.4639	99 (	0.38321	0.79	367			
	3	-0.5134	48 (	0.61833	-0.59	199			
		Rota	ted Fa	actor Pat	tern				
		Facto	r1	Factor2	Fac	tor3			
	X1	0.029	73	0.53614	0.15	069			
	X2	-0.289	10	0.08307	0.50	)419			
	Х3	0.412	91	0.06009	0.03	3754			
	X4	0.563	77	0.23329	-0.09	9333			
	X5	-0.260	67 ·	-0.08834	<b>-</b> 0.4′	756			
	X6	0.258	59	0.53735	0.00	381			
	Var	iance E	xplair	ned by E	ach Fa	ctor			
	F	actor1	F	actor2	Fa	ctor3			
	0.707	61307	0.64	892094	0.461	41092			
F	inal Cor	nmunali	ty Es	timates:	Total =	1.8179	945		
X1	X2		Х3		X4		<b>X</b> 5		
0.31103433 0.34	469386	0.1755	51746	0.3809	96675	0.250	10590	0.	0.35

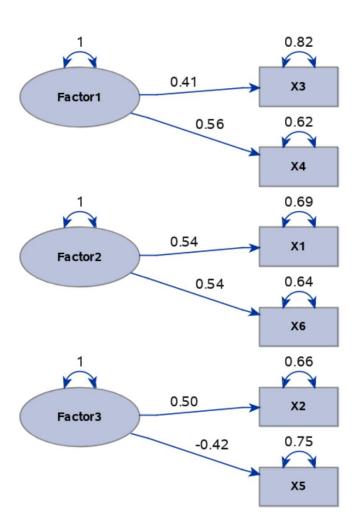
(d) The pattern of loadings is similar in parts (b) and (c), and the interpretation of the three factors would be the same. This means, the interpretation of the three factors in terms of variables are like:

factor 1 represents x3 and x4,

factor 2 represents x1 and x6, and

factor 3 represents x2 and x5.

## Path Diagram



# APPENDIX:

This section will have the entire SAS code.

# 12.6

```
DATA work.DIABETES;

INFILE "/folders/myfolders/data/T3_4_DIABETES.dat";
INPUT OBS Y1 Y2 X1 X2 X3;

TITLE "HW6 Q-12.6";

PROC PRINCOMP COV;

VAR Y1 Y2 X1 X2 X3;

RUN;

PROC PRINCOMP;

VAR Y1 Y2 X1 X2 X3;

RUN;
```

```
DATA work.HEMATOL;

INFILE "/folders/myfolders/data/T4_3_HEMATOL.dat";
INPUT OBS Y1 Y2 Y3 Y4 Y5 Y6;

TITLE "HW6 Q-12.9";

PROC PRINCOMP COV;

VAR Y1 Y2 Y3 Y4 Y5 Y6;

RUN;

PROC PRINCOMP;

VAR Y1 Y2 Y3 Y4 Y5 Y6;

RUN;
```

## # 13.8 (a)

```
DATA work.BONE;

INFILE "/folders/myfolders/data/T3_6_BONE.dat";
INPUT OBS Y1 Y2 Y3 Y4;

TITLE "HW6 Q-13.8 (a)";

LABEL Y1='8 yr' Y2='8 1/2 yr' Y3='9 yr' Y4='9 1/2 yr';

PROC FACTOR METHOD=PRIN NFACT=2 ROTATE=VARIMAX PLOT = ALL;
VAR Y1-Y4;
RUN;

PROC FACTOR METHOD=PRIN NFACT=2 ROTATE=HK PLOT = ALL;
VAR Y1-Y4;
RUN;
```

### # 13.12

```
DATA work.PILOT;

INFILE "/folders/myfolders/data/T5_6_PILOT.dat";
INPUT OBS X1 X2 X3 X4 X5 X6;

TITLE "HW6 Q-13.12";

PROC FACTOR METHOD=PRIN NFACT=3 ROTATE=VARIMAX PLOT = ALL;
VAR X1-X6;

RUN;

PROC FACTOR METHOD=PRIN PRIORS=SMC NFACT=3 ROTATE=VARIMAX PLOT = ALL;
VAR X1-X6;
RUN;
```