# Time Series HW3

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# Problem 1

## a. Correlation matrix

For this problem, I use the following properties:

$$corr(X_i, X_j) = \lambda_{i1} * \lambda_{j1} + \lambda_{i2} * \lambda_{j2} ... + \lambda_{im} * \lambda_{jm}$$
$$corr(X_i, X_i) = 1$$
$$corr(X_j, X_i) = corr(X_i, X_j)$$

Let  $R_{3x3}$  stand for the correlation matrix.

$$\begin{array}{rcl} R_{3x3} & = & \begin{bmatrix} corr(X_1,X_1) & corr(X_1,X_2) & corr(X_1,X_3) \\ corr(X_2,X_1) & corr(X_2,X_2) & corr(X_2,X_3) \\ corr(X_3,X_1) & corr(X_3,X_2) & corr(X_3,X_3) \end{bmatrix} \\ corr(X_1,X_2) & = & \lambda_{X_11} * \lambda_{X_21} + \lambda_{X_12} * \lambda_{X_22} \\ & = & 0.8 * 0.6 + 0.4 * 0.6 \\ & = & 0.72 \\ corr(X_1,X_3) & = & 0.8 * 04 + 0.8 * 0.4 \\ & = & 0.64 \\ corr(X_2,X_3) & = & 0.6 * 0.4 + 0.6 * 0.8 \\ & = & 0.72 \\ R_{3x3} & = & \begin{bmatrix} 1 & 0.72 & 0.64 \\ 0.72 & 1 & 0.72 \\ 0.64 & 0.72 & 1 \end{bmatrix} \\ \end{array}$$

# b. Communalities

Communality is simply the  $\lambda$ s squared. Let  $C_{X_i}$  stand for the communality of  $X_i$ 

$$C_{X_1} = 0.8^2 + 0.4^2$$
  
 $= 0.64 + 0.16$   
 $= 0.80$   
 $C_{X_2} = 0.6^2 + 0.6^2$   
 $= 0.72$   
 $C_{X_3} = 0.4^2 + 0.8^2$   
 $= 0.80$ 

# Problem 2

#### a.

For variance calculations, each factor's variance is simply  $\lambda_{ij}^2$  where i signifies which manifest variable it belongs to and j represents which factor it belongs to. To make things clearer, Let  $F_j$  stand for each factor. The total variance is the sum of the communalities: 2.32.

$$Var(X_i) = \lambda_{i1}^2 + \lambda_{i2}^2 + \dots \lambda_{ip}^2$$

The variance explained by the factors for  $X_1$  taken proportionally are:

$$F_1 = \frac{0.80^2}{2.32}$$
 $\approx 27.59\%$ 
 $F_2 = \frac{0.4^2}{2.32}$ 
 $\approx 6.90\%$ 

For  $X_2$ :

$$F_1 = \frac{0.60^2}{2.32}$$
 $\approx 15.52\%$ 
 $F_2 = \frac{0.6^2}{2.32}$ 
 $\approx 15.52\%$ 

For  $X_3$ :

$$F_1 = \frac{040^2}{2.32}$$
 $\approx 6.90\%$ 
 $F_2 = \frac{0.8^2}{2.32}$ 
 $\approx 27.59\%$ 

I would just like to note that since these are approximations, the proportions do not perfectly add up to 100% but they are still how much each factor explains the total variance.

#### b.

This is not equivalent to PCA. (come back to this later)

# Problem 3

a.

$$\begin{split} \pmb{F*} &= FM \\ &= \begin{bmatrix} 0.8 & 0.4 \\ 0.6 & 0.6 \\ 0.4 & 0.8 \end{bmatrix} \begin{bmatrix} 0.7071 & 0.7071 \\ 0.7071 & -0.7071 \end{bmatrix} \\ &= \begin{bmatrix} 0.8*0.7071 + 0.4*0.7071 & 0.8*0.7071 + 0.4* -0.7071 \\ 0.6*0.7071 + 0.6*0.7071 & 0.6*0.7071 + 0.6* -0.7071 \\ 0.8*0.7071 + 0.4*0.7071 & 0.4*0.7071 + 0.8* -0.7071 \end{bmatrix} \\ &= \begin{bmatrix} 0.84852 & 0.28284 \\ 0.84852 & 0 \\ 0.84852 & -0.28284 \end{bmatrix} \end{aligned}$$

When calculating the relevant scores/correlations:

$$corr(X_1, X_2) = 0.84852 * 0.84852 + 0.28284 * 0$$
  
 $\approx 0.72$   
 $corr(X_1, X_3) = 0.84852 * 0.84852 + 0.28284 * -0.28284$   
 $\approx 0.64$   
 $corr(X_2, X_3) = 0.84852 * 0.84852 + 0 * -0.28284$   
 $\approx 0.72$ 

While there are some rounding errors, the correlation matrix for  $F^*$  is equal to the correlation matrix for F.

#### b. Communalities

Again let  $C_{X_i}$  stand for the communality of  $X_i$ 

$$C_{X_1} = 0.84852^2 + 0.28284^2$$
 $\approx 0.80$ 
 $C_{X_2} = 0.85^2 + 0$ 
 $\approx 0.72$ 
 $C_{X_3} = 0.84852^2 + (-0.28284)^2$ 
 $\approx 0.80$ 

Again, there are slight rounding errors that make this an  $\approx$  but they are essentially equivalent. The reason as to why communality is preserved is because the transformation is orthonormal. The information of the factors is preserved in such a transformation. It's essentially a reflection that contains the same information as before the reflection.

# Problem 4

#### а.

For these constants to be equivalent, the main 3 correlations that have to be equivalent are:  $corr(X_1, X_2), corr(X_1, X_3), corr(X_2, X_3)$ . This gives the following system of equations:

$$a*b = 0.72$$
  
 $a*c = 0.64$   
 $b*c = 0.72$ 

Solving this system goes as follows:

$$a*b = b*c$$

$$a = c$$

$$c*c = 0.64$$

$$c = 0.8$$

$$b*0.8 = 0.72$$

$$b = 0.9$$

$$a = 0.8$$

As seen here, it is possible to end up with the same correlation matrix in a one factor model as the two factor model.

#### b.

The main implication here is that the correlation matrix for a factor analysis is not unique so one should not just base their judgement solely off of correlations.

## Problem 5

#### a. SAS code

82 82 39 59 64 78 39 RUN;

## \*Problem 5;

PROC FACTOR DATA = WORK.EvaluateSupervisors METHOD = principal PRIORS = ONE NFACTORS = 6 MIN VAR BEEFS PRIVILEGE NEWLEARN RAISES CRITICAL ADVANCE;

TITLE "PC style Factor Analysis" RUN;

#### b.

# PC style Factor Analysis RUN

The FACTOR Procedure Initial Factor Method: Principal Components

**Prior Communality Estimates: ONE** 

Eigenvalues of the Correlation Matrix: Total = 6 Average = 1						
	Eigenvalue	Difference	Proportion	Cumulative		
1	3.16922321	2.16287646	0.5282	0.5282		
2	1.00634675	0.24343802	0.1677	0.6959		
3	0.76290873	0.21039227	0.1272	0.8231		
4	0.55251646	0.23526997	0.0921	0.9152		
5	0.31724648	0.12548811	0.0529	0.9680		
6	0.19175838		0.0320	1.0000		

# 6 factors will be retained by the NFACTOR criterion.

Factor Pattern						
	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
BEEFS	0.78219	-0.31363	0.38883	-0.23490	-0.10787	0.26797
PRIVILEGE	0.70268	-0.30973	0.18990	0.60569	-0.02123	-0.08333
NEWLEARN	0.82140	-0.21777	-0.23756	-0.16709	0.43688	-0.05153
RAISES	0.87704	0.11590	0.00490	-0.27139	-0.25930	-0.27649
CRITICAL	0.40022	0.80479	0.39938	0.07429	0.16271	0.02533
ADVANCE	0.67791	0.32172	-0.59975	0.15293	-0.14347	0.18237

For retaining factors, I am going with the retention rule of the eigenvalue being greater than 1. As such, I would return factors  ${\bf 1}$  and  ${\bf 2}$ .

#### c.

Looking at the factor pattern, it seems like factor 1 tends to retain high weights on everything except for critical. This implies that this factor is associated with supervisors who handle employee complaints well, play favorites, encourage learning, raise based on merit, and provide a pathway for employees to better jobs. However, the factor is not associated with critical supervisors. With the exception of favoritism, I would say that factor 1 is a good indicator of a good supervisor.

As for factor 2, it seems like the opposite is true. This factor appears to capture critical supervisors and discounts the other variables. As such, I would take factor 2 as an indicator of what makes a bad supervisor.

# Problem 6

Using a linear regression model and the following SAS code:

```
*Problem 6;
PROC REG DATA=prinfactors5;
model OVERALL = Factor1 Factor2 Factor3 Factor4 Factor5 Factor6 /ss1 ss2;
RUN;
```

#### The REG Procedure Model: MODEL1 Dependent Variable: OVERALL

Number of Observations Read	30
Number of Observations Used	30

Analysis of Variance						
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	
Model	6	3147.96634	524.66106	10.50	<.0001	
Error	23	1149.00032	49.95654			
Corrected Total	29	4296.96667				

Root MSE	7.06799	R-Square	0.7326
Dependent Mean	64.63333	Adj R-Sq	0.6628
Coeff Var	10.93552		

Parameter Estimates							
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr >  t	Type I SS	Type II SS
Intercept	1	64.63333	1.29043	50.09	<.0001	125324	125324
Factor1	1	8.22970	1.31249	6.27	<.0001	1964.11131	1964.11131
Factor2	1	-3.41693	1.31249	-2.60	0.0159	338.58649	338.58649
Factor3	1	3.60689	1.31249	2.75	0.0115	377.27898	377.27898
Factor4	1	-3.63138	1.31249	-2.77	0.0110	382.41999	382.41999
Factor5	1	0.94266	1.31249	0.72	0.4799	25.76965	25.76965
Factor6	1	1.43599	1.31249	1.09	0.2852	59.79991	59.79991

From the linear regression model, we can see through the  $\mathbb{R}^2$  score that the factors collectively explain about 73.26% of the variation.

As for the individual factors, that would simply be their squared error over the total sum of square errors. Let  $F_i$  stand for factor i.

$$\begin{array}{lll} F_1 & = & \frac{1964.11131}{4296.96667} \\ & \approx & 45.71\% \\ F_2 & \approx & 7.88\% \\ F_3 & \approx & 8.78\% \\ F_4 & \approx & 8.90\% \\ F_5 & \approx & 0.60\% \\ F_6 & \approx & 1.39\% \end{array}$$

One last thing to note here is that factors 5 and 6 are insignificant due to having rather high P-values.

# Problem 7

#### a.

```
*Problem 7;
PROC FACTOR DATA = WORK.EvaluateSupervisors METHOD = principal PRIORS = SMC
NFACTORS = 6 MINEIGEN = 0 OUT = prinfactors7;
VAR BEEFS PRIVILEGE NEWLEARN RAISES CRITICAL ADVANCE;
TITLE "PC style Factor Analysis SMC"
RUN;
```

## b.

## PC style Factor Analysis SMC RUN

#### The FACTOR Procedure Initial Factor Method: Principal Factors

Prior Communality Estimates: SMC						
BEEFS	PRIVILEGE	NEWLEARN	RAISES	CRITICAL	ADVANCE	
0.62505535	0.37534801	0.55967371	0.67513759	0.18574001	0.48759750	

	Eigenvalue	Difference	Proportion	Cumulative
1	2.71771612	2.31678131	0.9344	0.9344
2	0.40093481	0.22202808	0.1378	1.0722
3	0.17890672	0.18294128	0.0615	1.1337
4	00403456	0.16150739	-0.0014	1.1324
5	16554195	0.05388702	-0.0569	1.0754
6	21942897		-0.0754	1.0000

#### 3 factors will be retained by the MINEIGEN criterion.

Factor Pattern					
	Factor1	Factor2	Factor3		
BEEFS	0.74755	-0.36273	0.12483		
PRIVILEGE	0.61091	-0.17725	-0.06404		
NEWLEARN	0.76629	-0.05146	-0.21483		
RAISES	0.84947	0.11042	0.13720		
CRITICAL	0.32091	0.25308	0.26760		
ADVANCE	0.61147	0.39882	-0.15045		

Looking at the output, factor 1 appears to have almost the same interpretation as the previous factor 1 interpretation in problem 5. However, there exists a higher weighting towards raises and a lower weighting towards critical. This implies that the factor captures what employees consider to be easy to work for supervisors.

Factor 2 appears to retains a similar interpretation as last time as well. However, the critical rating is significantly lower and the advance is higher. It appears that this factor then captures supervisors who may be hard to deal with but are open towards rewarding merit based work and provide company advancement.

#### c.

In question 5, the factors could be interpreted as an indicator of a good or bad supervisor. For question 7, the factors are a bit more nuanced but generally suggest a good or bad supervisor. Additionally, question 7's factors explain a higher proportion of the variation in its correlation matrix.

# Problem 8

#### a.

```
*Problem 8;
PROC FACTOR DATA = WORK.EvaluateSupervisors METHOD = principal PRIORS = SMC
NFACTORS = 2 ROTATE = varimax
OUT = WORK.EvaluateSupervisors_scores;
VAR BEEFS PRIVILEGE NEWLEARN RAISES CRITICAL ADVANCE;
TITLE "PC style Factor Analysis Verimax"
RUN;
```

## b.

# PC style Factor Analysis Verimax RUN

The FACTOR Procedure Initial Factor Method: Principal Factors

Prior Communality Estimates: SMC						
BEEFS	PRIVILEGE	NEWLEARN	RAISES	CRITICAL	ADVANCE	
0.62505535	0.37534801	0.55967371	0.67513759	0.18574001	0.48759750	

	Eigenvalue	Difference	Proportion	Cumulative
1	2.71771612	2.31678131	0.9344	0.9344
2	0.40093481	0.22202808	0.1378	1.0722
3	0.17890672	0.18294128	0.0615	1.1337
4	00403456	0.16150739	-0.0014	1.1324
5	16554195	0.05388702	-0.0569	1.0754
6	21942897		-0.0754	1.0000

#### 2 factors will be retained by the NFACTOR criterion.

Factor Pattern					
	Factor1	Factor2			
BEEFS	0.74755	-0.36273			
PRIVILEGE	0.61091	-0.17725			
NEWLEARN	0.76629	-0.05146			
RAISES	0.84947	0.11042			
CRITICAL	0.32091	0.25308			
ADVANCE	0.61147	0.39882			

Yes, the two factors here are the same as in question 7.

# $\mathbf{c}$

For verifying orthonormality, the magnitude of each vector in a transformation matrix must be 1 which signifies normality and the dot product must be 0 which signifies orthogonality.

# PC style Factor Analysis Verimax RUN

The FACTOR Procedure Rotation Method: Varimax

Ortho	gonal Transform	ation Matrix
	1	2
1	0.79912	0.60117
2	-0.60117	0.79912

Let  $V_1$  be the first vector and  $V_2$  be the second vector. The magnitudes of the vectors are:

$$||V_1|| = (0.79912)^2 + (-0.60117)^2$$
  
= 1  
 $||V_2|| = (0.60117)^2 + (0.79912)^2$   
= 1

While it should be self evident from just glancing at it the dot product is as follows:

$$V_1 \dots V_2 = 0.79912 * 0.60117 - 0.60117 * 0.79912 = 0$$

Thus, both orthogonality and normality are satisfied for the transformation matrix which makes it orthonormal.

 $\mathbf{d}$ 

-		TOR Proce Method: Va	
Orthog	gonal Tr	ansforma	tion Matrix
		1	2
1	0.7	9912	0.60117
2	-0.6	0117	0.79912
F	Rotated	Factor Pa	Factor2
- 1	Rotated		
DEEE			
BEEF	S	0.81544	0.15954
PRIVI	LEGE	0.59475	0.22561
NEWL	EARN	0.64329	0.41955
RAISE	S	0.61245	0.59891
CRITIC	CAL	0.10431	0.39516
ADVA	NCE	0.24889	0.68630
Variano	ce Expla	ained by E	ach Factor
	Facto		Factor2
	1 880419		1.2382317

Looking at the rotated factor pattern, it seems like factor yet again has high weights on everything except for being critical. However, this time handling employee complaints plays a bigger role in the meaning of the factor. Thus, I see factor 1 as a measurement of good supervisors who can handle complaints well and are not too critical on their employees.

For factor 2, it seems like it puts more emphasis on supervisors who provide new opportunities and raise based on merit. I would consider this factor to indicate supervisors that you can go to if you are looking to advance your career.

# Problem 9

The SAS code and output are as follows:

```
*Problem 9;
PROC CORR DATA = Work.evaluatesupervisors_scores;
RUN;
```

	9 Variables:	OVERALL B	EEFS	PRIVILE	BE NEWLEAR	N RAISES	CRITICALA	DVANCE Facto	r1 Factor2	
					Simple Statis	stics				
		Variable	N	Mea	an Std Dev	Sum	Minimum	Maximum		
		OVERALL	30	64.6333	33 12.17256	1939	40.00000	85.00000		
		BEEFS	30	66.6000	00 13.31476	1998	37.00000	90.00000		
		PRIVILEGE	30	53.1333	33 12.23543	1594	30.00000	83.00000		
		NEWLEARN	30	56.3666	11.73701	1691	34.00000	75.00000		
		RAISES	30	64.6333	33 10.39723	1939	43.00000	88.00000		
		CRITICAL	30	74.7686	9.89491	2243	49.00000	92.00000		
		ADVANCE	30	42.933			25.00000	72.00000		
		Factor1	30		0 0.85285		-1.86118	1.36525		
		Factor2	30		0 0.77645	0	-1.31002	2.01667		
	OVERAL	L BEEFS			orrelation Coe >  r  under H NEWLEARN	0: Rho=0		L ADVANCE	Factor1	Factor
OVERALL	1.0000	00 0.82542		.42612 0.0189	0.62368 0.0002	0.59014			0.82349	0.1909-
BEEFS	0.8254			.55829 0.0013	0.59874 0.0005	0.66920			0.95614 <.0001	0.2054
	0.426		1	.00000	0.49333 0.0056	0.44548			0.69736 <.0001	0.2905
PRIVILEGE									0.75429	0.5403
	0.6236 0.000			.49333 0.0056	1.00000	0.64031			<.0001	
NEWLEAR		0.0005 0.0005 0.0005	0		1.00000 0.64031 0.0001		0.541	7 0.0025 8 0.57419	<.0001 0.71812	0.002
PRIVILEGE NEWLEARI RAISES CRITICAL	0.000	02 0.0005 14 0.66920 06 <.0001 44 0.18771	0	0.0056	0.64031	0.0001	0.541 0.3768 0.040 1.0000	7 0.0025 8 0.57419 1 0.0009	<.0001 0.71812 <.0001	0.0021 0.77138 <.0001 0.50894
NEWLEAR!	0.000 0.590 0.000 0.158	02 0.0005 14 0.66920 06 <.0001 44 0.18771 91 0.3205 09 0.22458	0	0.0056 .44548 0.0136 .14723	0.64031 0.0001 0.11597	0.0001 1.00000 0.37688 0.0401	0.541 0.3768 0.040 1.0000	7 0.0025 8 0.57419 1 0.0009 0 0.28334 0.1292 4 1.00000	<.0001 0.71812 <.0001 0.12230	0.002 0.77138 <.000 0.50894 0.004
NEWLEARI RAISES CRITICAL	0.00( 0.590 0.00( 0.156- 0.40( 0.155)	0.0005 0.66920 0.66920 0.6001 0.18771 0.3205 0.900 0.22458 0.2328 0.95614	0	0.0056 .44548 0.0136 .14723 0.4375	0.64031 0.0001 0.11597 0.5417 0.53162	0.0001 1.00000 0.37688 0.0401 0.57418	0.541 0.3768 0.040 1.0000 0.2833 0.129	7 0.0025 8 0.57419 1 0.0009 0 0.28334 0.1292 4 1.00000 2 0.29183	<.0001 0.71812 <.0001 0.12230 0.5197 0.29183 0.1176	0.002° 0.77138′ <.000° 0.5089⁴ 0.004° 0.88390 <.000° 0.2904° 0.1198

#### a

Looking at the summary statistics, the means for the factors matches the standardized assumption in that they are both 0. However, the standard deviation for both factors are not 1 which violates our assumption of standardization. Additionally when looking at the Pearson correlation coefficient matrix, we can see that the two factors are correlated with each other which also violates another assumption.

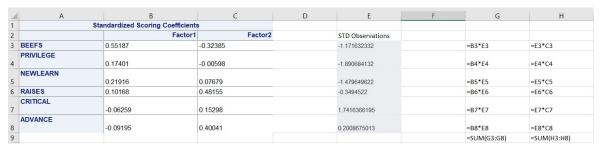
## b

From the SAS output, The first supervisor has  $F_1 = -1.462881996$  and  $F_2 = 0.4556968621$ . Next, I had to standardize the data via:

#### \*Problem 9 b.;

Proc STDIZE Data = Work.evaluatesupervisors\_scores out = evaluatesupervisors\_scores\_STD; Var BEEFS PRIVILEGE NEWLEARN RAISES CRITICAL ADVANCE; RUN;

Then referencing the standardized scores from the code in 8 and the standardized observations, I did the following calculations in excel. First, I elect to show the formulas. Then I show the results.



1	Α	В	C	D	E	F	G	Н
1	Standardiz	ed Scoring Coe	fficients					
2		Factor1	Factor2		STD Observ	ations		
3	BEEFS	0.55187	-0.32385		-1.171632		-0.64659	0.379433
4	PRIVILEGE	0.17401	-0.00598		-1.890684		-0.329	0.011306
5	NEWLEARN	0.21916	0.07679		-1.47965		-0.32428	-0.11362
6	RAISES	0.10168	0.48155		-0.349452		-0.03553	-0.16828
7	CRITICAL	-0.06259	0.15298		1.7416366		-0.10901	0.266436
8	ADVANCE	-0.09195	0.40041		0.2008675		-0.01847	0.080429
9							-1.46288	0.455703

As seen from the excel calculation, the SAS calculated scores more or less match with the manually calculated ones with minute differences mostly due to rounding.

# Problem 10

The SAS code is as follows

\*Problem 10;

PROC FACTOR DATA = WORK.Evaluatesupervisors METHOD = ML PRIORS = SMC HEYWOOD; VAR BEEFS PRIVILEGE NEWLEARN RAISES CRITICAL ADVANCE; RUN;

The hypothesis test results are:

Significance Tests Based	on 30	Observations	•
Test	DF	Chi-Square	Pr > ChiSq
H0: No common factors	15	65.5127	<.0001
HA: At least one common factor			
H0: 2 Factors are sufficient	4	2.9161	0.5720
HA: More factors are needed			

#### $\mathbf{a}$

For the first test, we can see that the p-value for the chi-square test is very low meaning that we can reject the null hypothesis of there being no common factors. Thus, it provides support that common factors exist.

# $\mathbf{b}$

For the second test, the chi-square p-value is rather large implying that we cannot reject the null hypothesis. This provides support that the default number of factors extracted by SAS was not sufficient.