

HUDM6122 Homework_09

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0.0 Github Address

All my latest homework can be found on Github: https://github.com/cgpan/hudm6122_homeworks . Thanks for checking if interested.

1.0 Exercise 1

The matrix below shows the correlations between ratings on nine statements about pain made by 123 people suffering from extreme pain. Each statement was scored on a scale from 1 to 6, ranging from agreement to disagreement. The nine pain statements were as follows:

MY SOLUTION:

To solve the question, I chose to use the package `lavaan`. This question only provides the correlation matrix, we **have to make a assumption that all variables are standardized**. Then, the covariance's value equals to the correlation and the variance of a centered and standardized variable is equal to one.

```
> # import the correlation matrix first
> corr <- '
+ 1
+ -0.04 1
+ 0.61 -0.07 1
+ 0.45 -0.12 0.59 1
+ 0.03 0.49 0.03 -0.08 1
+ -0.29 0.43 -0.13 -0.21 0.47 1
+ -0.3 0.3 -0.24 -0.19 0.41 0.63 1
+ 0.45 -0.31 0.59 0.63 -0.14 -0.13 -0.26 1
+ 0.30 -0.17 0.32 0.37 -0.24 -0.15 -0.29 0.4 1
+ '
>
> cov_stded <- getCov(corr,
+                      names = c("Q1", "Q2", "Q3", "Q4", "Q5",
+                                "Q6", "Q7", "Q8", "Q9"))
> head(cov_stded)
      Q1    Q2    Q3    Q4    Q5    Q6    Q7    Q8    Q9
Q1  1.00 -0.04  0.61  0.45  0.03 -0.29 -0.30  0.45  0.30
Q2 -0.04  1.00 -0.07 -0.12  0.49  0.43  0.30 -0.31 -0.17
Q3  0.61 -0.07  1.00  0.59  0.03 -0.13 -0.24  0.59  0.32
Q4  0.45 -0.12  0.59  1.00 -0.08 -0.21 -0.19  0.63  0.37
Q5  0.03  0.49  0.03 -0.08  1.00  0.47  0.41 -0.14 -0.24
Q6 -0.29  0.43 -0.13 -0.21  0.47  1.00  0.63 -0.13 -0.15
```

The complete correlation matrix looks good. Next, I fitted the SEM model.

```

> library(lavaan)
> model_01 <- 'DocRes =~ Q1 + Q3 + Q4 + Q8
+             PatRes =~ Q2 + Q5 + Q6 + Q7
+             DocRes ~~ PatRes'
> model_01_fit <- sem(model_01, sample.cov = cov_stded, sample.nobs = 123)
> summary(model_01_fit)
lavaan 0.6.15 ended normally after 28 iterations

```

Estimator	ML
Optimization method	NLMINB
Number of model parameters	17

Number of observations	123
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Model Test User Model:

Test statistic	63.749
Degrees of freedom	19
P-value (Chi-square)	0.000

Parameter Estimates:

Standard errors	Standard
Information	Expected
Information saturated (h1) model	Structured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
DocRes =~				
Q1	1.000			
Q3	1.209	0.169	7.158	0.000
Q4	1.131	0.165	6.873	0.000
Q8	1.134	0.165	6.884	0.000
PatRes =~				
Q2	1.000			
Q5	1.116	0.240	4.649	0.000
Q6	1.572	0.296	5.304	0.000
Q7	1.381	0.266	5.198	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
DocRes ~~				
PatRes	-0.107	0.044	-2.409	0.016

Variances:

	Estimate	Std.Err	z-value	P(> z)
.Q1	0.551	0.083	6.640	0.000
.Q3	0.347	0.070	4.990	0.000
.Q4	0.427	0.073	5.812	0.000
.Q8	0.425	0.073	5.790	0.000
.Q2	0.714	0.100	7.114	0.000
.Q5	0.645	0.095	6.816	0.000
.Q6	0.305	0.087	3.521	0.000

.Q7	0.461	0.086	5.394	0.000
DocRes	0.441	0.114	3.868	0.000
PatRes	0.278	0.097	2.854	0.004

The results show that the correlation between the two latent variables is $-.107$, $p = .016$. The standard error is $.044$. Therefore, the 95% confidence interval of this correlation is $-.107 \pm 1.96 \times .044 = [-.193, -.021]$.

2.0 Exercise 2

For the stability of alienation example, fit the model in which the measurement errors for anomia in 1967 and anomia in 1971 are allowed to be correlated.

MY SOLUTION:

This dataset shown in the 7.4.1 section is included in the package MVA. I do not know why the authors did not provide an easier way to find the data rather than hiding it in the package!! I found the covariance data and save it as an csv file.

```
> # import the data
> cov_df <- read.csv("alien_cov_size932.csv")
> cov_m <- as.matrix(cov_df)
> # convert the covariance matrix into correlation matrix
> cor_m <- cov2cor(cov_m)
> round(cor_m,2)
      Anomia67 Powles67 Anomia71 Powles71 Educ SEI
[1,]      1.00      0.66      0.56      0.44 -0.36 -0.30
[2,]      0.66      1.00      0.47      0.52 -0.41 -0.29
[3,]      0.56      0.47      1.00      0.67 -0.35 -0.29
[4,]      0.44      0.52      0.67      1.00 -0.37 -0.28
[5,]     -0.36     -0.41     -0.35     -0.37  1.00  0.54
[6,]     -0.30     -0.29     -0.29     -0.28  0.54  1.00
```

Based on the description from the book, the sample size is 932. Next, I specified the model.

```
> # specify the model
> model_alien <- '## measurement models
+               SES =~ 1*Educ + SEI
+               Alienation67 =~ 1*Anomia67 + Powles67
+               Alienation71 =~ 1*Anomia71 + Powles71
+
+               # structural model
+               Alienation67 ~ SES
+               Alienation71 ~ Alienation67 + SES
+
+               # add correlation
+               Anomia67 ~~ Anomia71
+               '
> # fit the model
> model_alien_fit <- sem(model_alien,
+               sample.cov = cov_m,
+               sample.nobs = 932)
> # check the result
> summary(model_alien_fit, fit.measure = T)
```

lavaan 0.6.15 ended normally after 78 iterations

Estimator	ML
Optimization method	NLMINB
Number of model parameters	16
Number of observations	932

Model Test User Model:

Test statistic	6.366
Degrees of freedom	5
P-value (Chi-square)	0.272

Model Test Baseline Model:

Test statistic	2133.833
Degrees of freedom	15
P-value	0.000

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.999
Tucker-Lewis Index (TLI)	0.998

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-15213.740
Loglikelihood unrestricted model (H1)	-15210.558
Akaike (AIC)	30459.481
Bayesian (BIC)	30536.878
Sample-size adjusted Bayesian (SABIC)	30486.063

Root Mean Square Error of Approximation:

RMSEA	0.017
90 Percent confidence interval - lower	0.000
90 Percent confidence interval - upper	0.051
P-value H ₀ : RMSEA ≤ 0.050	0.943
P-value H ₀ : RMSEA ≥ 0.080	0.000

Standardized Root Mean Square Residual:

SRMR	0.011
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Parameter Estimates:

Standard errors	Standard
Information	Expected
Information saturated (h1) model	Structured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
SES =~				
Educ	1.000			
SEI	5.163	0.421	12.263	0.000
Alienation67 =~				
Anomia67	1.000			
Powles67	1.027	0.053	19.319	0.000
Alienation71 =~				
Anomia71	1.000			
Powles71	0.971	0.049	19.660	0.000
Regressions:				
	Estimate	Std.Err	z-value	P(> z)
Alienation67 ~				
SES	-0.549	0.053	-10.296	0.000
Alienation71 ~				
Alienation67	0.617	0.050	12.428	0.000
SES	-0.212	0.049	-4.302	0.000
Covariances:				
	Estimate	Std.Err	z-value	P(> z)
.Anomia67 ~~				
.Anomia71	1.886	0.240	7.869	0.000
Variances:				
	Estimate	Std.Err	z-value	P(> z)
.Educ	2.718	0.515	5.276	0.000
.SEI	266.579	18.160	14.679	0.000
.Anomia67	5.067	0.371	13.669	0.000
.Powles67	2.209	0.317	6.962	0.000
.Anomia71	4.807	0.395	12.184	0.000
.Powles71	2.681	0.329	8.141	0.000
.SES	6.872	0.656	10.469	0.000
.Alienation67	4.700	0.432	10.868	0.000
.Alienation71	3.862	0.343	11.262	0.000

This model looks good. Please note, here I use the variance covariance matrix to fit the model. If we standardize everything in this model, the loadings will become correlation coefficients.

3.0 Exercise 3

Meyer and Bendig (1961) administered the five Thurstone Primary Mental Ability tests, verbal meaning (V), space (S), reasoning (R), numerical (N), and word fluency (W), to 49 boys and 61 girls in grade 8 and again three and a half years later in grade 11. The observed correlation matrix is shown below. Fit a single-factor model to the correlations that allows the factor at time one to be correlated with the factor at time two.

MY SOLUTION:

```
> # import the data
> corr <- '
+ 1
+ 0.37 1
+ 0.42 0.33 1
```

```

+ 0.53 0.14 0.38 1
+ 0.38 0.10 0.20 0.24 1
+ 0.81 0.34 0.49 0.58 0.32 1
+ 0.35 0.65 0.20 -0.04 0.11 0.34 1
+ 0.42 0.32 0.75 0.46 0.26 0.46 0.18 1
+ 0.40 0.14 0.39 0.73 0.19 0.55 0.06 0.54 1
+ 0.24 0.15 0.17 0.15 0.43 0.24 0.15 0.20 0.16 1
+ '
>
> cov_stded <- getCov(corr,
+                      names = c("V1","S1","R1","N1","W1",
+                                "V2","S2","R2","N2","W2"))
> cov_stded
      V1  S1  R1   N1  W1  V2   S2  R2  N2  W2
V1 1.00 0.37 0.42 0.53 0.38 0.81 0.35 0.42 0.40 0.24
S1 0.37 1.00 0.33 0.14 0.10 0.34 0.65 0.32 0.14 0.15
R1 0.42 0.33 1.00 0.38 0.20 0.49 0.20 0.75 0.39 0.17
N1 0.53 0.14 0.38 1.00 0.24 0.58 -0.04 0.46 0.73 0.15
W1 0.38 0.10 0.20 0.24 1.00 0.32 0.11 0.26 0.19 0.43
V2 0.81 0.34 0.49 0.58 0.32 1.00 0.34 0.46 0.55 0.24
S2 0.35 0.65 0.20 -0.04 0.11 0.34 1.00 0.18 0.06 0.15
R2 0.42 0.32 0.75 0.46 0.26 0.46 0.18 1.00 0.54 0.20
N2 0.40 0.14 0.39 0.73 0.19 0.55 0.06 0.54 1.00 0.16
W2 0.24 0.15 0.17 0.15 0.43 0.24 0.15 0.20 0.16 1.00

```

Correlation matrix looks good. Next, I specified the model.

```

> # specify the model
> model_spe <- '# the measurement model
+              LV1 =~ V1 + S1 + R1 + N1 + W1
+              LV2 =~ V2 + S2 + R2 + N2 + W2
+
+              # add the correlation
+              LV1 ~~ LV2 '
> # fit the model
> model_fit <- sem(model_spe, sample.cov = cov_stded, sample.nobs = 110)
>
> # extract the results
> summary(model_fit, fit.measure=T)
lavaan 0.6.15 ended normally after 26 iterations

```

Estimator	ML
Optimization method	NLMINB
Number of model parameters	21
Number of observations	110

Model Test User Model:

Test statistic	211.828
Degrees of freedom	34
P-value (Chi-square)	0.000

Model Test Baseline Model:

Test statistic	553.443
Degrees of freedom	45
P-value	0.000

User Model versus Baseline Model:

Comparative Fit Index (CFI)	0.650
Tucker-Lewis Index (TLI)	0.537

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-1385.002
Loglikelihood unrestricted model (H1)	-1279.088
Akaike (AIC)	2812.004
Bayesian (BIC)	2868.714
Sample-size adjusted Bayesian (SABIC)	2802.353

Root Mean Square Error of Approximation:

RMSEA	0.218
90 Percent confidence interval - lower	0.190
90 Percent confidence interval - upper	0.247
P-value H ₀ : RMSEA ≤ 0.050	0.000
P-value H ₀ : RMSEA ≥ 0.080	1.000

Standardized Root Mean Square Residual:

SRMR	0.120
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Parameter Estimates:

Standard errors	Standard
Information	Expected
Information saturated (h1) model	Structured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
LV1 = ~				
V1	1.000			
S1	0.523	0.122	4.270	0.000
R1	0.827	0.118	6.991	0.000
N1	0.871	0.118	7.414	0.000
W1	0.466	0.123	3.793	0.000
LV2 = ~				
V2	1.000			
S2	0.390	0.113	3.451	0.001
R2	0.790	0.102	7.759	0.000
N2	0.735	0.104	7.078	0.000
W2	0.351	0.114	3.086	0.002

Covariances:

Estimate	Std.Err	z-value	P(> z)
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LV1 ~				
LV2	0.706	0.115	6.146	0.000
Variances:				
	Estimate	Std.Err	z-value	P(> z)
.V1	0.419	0.063	6.604	0.000
.S1	0.835	0.113	7.405	0.000
.R1	0.600	0.083	7.215	0.000
.N1	0.557	0.078	7.128	0.000
.W1	0.866	0.117	7.411	0.000
.V2	0.305	0.054	5.629	0.000
.S2	0.886	0.120	7.382	0.000
.R2	0.563	0.080	7.054	0.000
.N2	0.620	0.087	7.159	0.000
.W2	0.906	0.123	7.390	0.000
LV1	0.572	0.124	4.596	0.000
LV2	0.686	0.132	5.198	0.000

Since we inputted the correlation matrix here, the **covariance** shown in the result is actually the correlation coefficient between the the factor at two time points, which is .706, $p < .001$.