Multivariate Statistics

Assignment 1

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# Question A

We load the data and rename the variables following the factors. There are concepts measuring well-being that have opposite scaling, but since they are consistent with the concept well-being, we decided to keep them as original and not inverting them. We then center the data, compute the covariance matrix, fit a CFA model with three correlated factors (one for each attitude concept), and assuming each item only has a loading on the concept it aims to measure. We print fit measures, the standardized solution and we compute, for each latent variable, the composite reliability, the average variance extracted and the maximum shared variance with other latent variables.

> load("ess.Rdata")

> names(ess)[2:14]<-c("sotru1","sotru2","sotru3","truin1","truin2","truin3","truin4",

+ "webe1","webe2","webe3","webe4","webe5","webe6")

>

> centered\_ess <- ess %>%

+ mutate(across(2:14, ~ . - mean(., na.rm = TRUE)))

> covmat<-cov(centered\_ess[-1])

##specify model with 3 correlated factors

cfa1<-'sotru =~NA\*+sotru1+sotru2+sotru3

truin =~NA\*truin1+truin2+truin3+truin4

webe =~NA\*webe1+webe2+webe3+webe4+webe5+webe6

sotru ~~1\*sotru

truin ~~1\*truin

webe ~~1\*webe'

#fit model on covariance matrix

fitcfa1<-cfa(cfa1,sample.cov=covmat,sample.nobs=4046)

> #standardized solution

> d<-standardizedSolution(fitcfa1)

> d

lhs op rhs est.std se z pvalue ci.lower ci.upper

1 sotru =~ sotru1 0.684 0.013 52.036 0 0.658 0.709

2 sotru =~ sotru2 0.648 0.013 48.322 0 0.622 0.674

3 sotru =~ sotru3 0.626 0.014 46.031 0 0.600 0.653

4 truin =~ truin1 0.789 0.008 93.956 0 0.773 0.805

5 truin =~ truin2 0.718 0.010 74.774 0 0.699 0.737

6 truin =~ truin3 0.581 0.012 48.194 0 0.557 0.605

7 truin =~ truin4 0.802 0.008 97.758 0 0.786 0.818

8 webe =~ webe1 0.661 0.011 60.710 0 0.640 0.683

9 webe =~ webe2 0.670 0.011 62.343 0 0.649 0.691

10 webe =~ webe3 0.589 0.012 48.379 0 0.565 0.612

11 webe =~ webe4 0.718 0.010 72.725 0 0.699 0.738

12 webe =~ webe5 0.677 0.011 63.729 0 0.656 0.698

13 webe =~ webe6 0.595 0.012 49.291 0 0.571 0.618

14 sotru ~~ sotru 1.000 0.000 NA NA 1.000 1.000

15 truin ~~ truin 1.000 0.000 NA NA 1.000 1.000

16 webe ~~ webe 1.000 0.000 NA NA 1.000 1.000

17 sotru1 ~~ sotru1 0.533 0.018 29.674 0 0.498 0.568

18 sotru2 ~~ sotru2 0.580 0.017 33.355 0 0.546 0.614

19 sotru3 ~~ sotru3 0.608 0.017 35.629 0 0.574 0.641

20 truin1 ~~ truin1 0.377 0.013 28.488 0 0.352 0.403

21 truin2 ~~ truin2 0.485 0.014 35.192 0 0.458 0.512

22 truin3 ~~ truin3 0.662 0.014 47.280 0 0.635 0.690

23 truin4 ~~ truin4 0.357 0.013 27.162 0 0.331 0.383

24 webe1 ~~ webe1 0.562 0.014 39.020 0 0.534 0.591

25 webe2 ~~ webe2 0.551 0.014 38.292 0 0.523 0.579

26 webe3 ~~ webe3 0.654 0.014 45.641 0 0.626 0.682

27 webe4 ~~ webe4 0.484 0.014 34.112 0 0.456 0.512

28 webe5 ~~ webe5 0.542 0.014 37.693 0 0.514 0.570

29 webe6 ~~ webe6 0.646 0.014 45.059 0 0.618 0.675

30 sotru ~~ truin 0.555 0.016 34.183 0 0.524 0.587

31 sotru ~~ webe 0.287 0.020 14.604 0 0.248 0.326

32 truin ~~ webe 0.185 0.018 10.022 0 0.149 0.221

#print fit measures

> fitmeasures(fitcfa1,c("chisq","df","pvalue","cfi","tli","rmsea","srmr"))

chisq df pvalue cfi tli rmsea srmr

1526.049 62.000 0.000 0.912 0.889 0.076 0.040

> factorscore<-c("sotru","truin","webe")

> #composite reliability

> reliability<-round(c(compositerel(d[1:3,4]),compositerel(d[4:6,4]),compositerel(d[7:9,4])),3)

> #average variance extracted

> average\_var\_extracted<-round(c(mean(d[1:3,4]^2),mean(d[4:6,4]^2),mean(d[7:9,4]^2)),3)

> #maximum shared variance

> max\_shared\_var<-round(c(max(d[c(22,23),4]^2),max(d[c(22,24),4]^2),max(d[c(23,24),4]^2)),3)

> data.frame(factorscore,reliability,average\_var\_extracted,max\_shared\_var)

factorscore reliability average\_var\_extracted max\_shared\_var

1 sotru 0.690 0.427 0.308

2 truin 0.816 0.530 0.308

3 webe 0.816 0.427 0.082

The fit measures indicate that the model is rejected by an absolute goodness of fit test, i.e. the fit of the model is significantly lower than for a perfectly fitting model (chisquare= 1526.049, df=62, p<.001). Furthermore, descriptive fit measures also indicate that the model cannot reproduce the observed covariance matrix well: CFI (.912) and TLI (.889) both are lower than .95 and hence do not meet the cutoff of good fit. RMSEA (.076) and SRMR (.04) indicate a good fit as they are below 0.08. Given these results, it can be argued that further modifications to the model are needed.

As can be seen in the standardized solution, all variables have significant and positive standardized loadings. Note that there are only 4 variables having loadings which exceed 0.7. Hence, the square of these loadings i.e. the individual reliabilities are larger than 0.5 only for these 4 variables. This indicates that the other variables do not have sufficient reliability and therefore convergent validity is not satisfied for these other variables in the model. Correlations between the factors (.555, .287, .185) show that they are poorly correlated. Furthermore, divergent validity is satisfied for all latent variables. Using the criterion of Fornell and Lanker to assess divergent validity, it is also confirmed as for each latent variable, the average variance extracted in the observed indicator variables is larger than the maximum variance that is shared with other latent variables except social trust factor since the scores are almost the same.

Finally, we see that composite reliability of the factor scores is not good, but still acceptable as they are .690 and .816.

## Question B

To improve our model, we can use the ‘modificationIndices()’ function to get an idea of which error terms correlation we can add to improve our model.

> modificationindices(fitcfa1)

lhs op rhs mi epc sepc.lv sepc.all sepc.nox

...  
sotru3 ~~ webe5 5.836 -0.044 -0.044 -0.046 -0.04691   
sotru3 ~~ webe6 1.311 -0.024 -0.024 -0.021 -0.02192   
truin1 ~~ truin2 52.242 -0.492 -0.492 -0.210 -0.21093   
truin1 ~~ truin3 211.717 -0.854 -0.854 -0.326 -0.32694   
truin1 ~~ truin4 559.300 1.707 1.707 0.914 0.91495   
truin1 ~~ webe1 0.319 0.008 0.008 0.011 0.01196   
truin1 ~~ webe2 2.238 0.021 0.021 0.030 0.03097   
truin1 ~~ webe3 2.379 -0.026 -0.026 -0.030 -0.03098   
truin1 ~~ webe4 2.427 -0.025 -0.025 -0.032 -0.03299   
truin1 ~~ webe5 1.698 0.022 0.022 0.026 0.026100   
truin1 ~~ webe6 0.003 0.001 0.001 0.001 0.001101   
truin2 ~~ truin3 478.146 1.275 1.275 0.430 0.430102   
truin2 ~~ truin4 168.787 -0.834 -0.834 -0.395 -0.395103   
truin2 ~~ webe1 0.000 0.000 0.000 0.000 0.000104   
truin2 ~~ webe2 0.671 0.013 0.013 0.015 0.015105   
truin2 ~~ webe3 1.245 0.020 0.020 0.020 0.020106   
truin2 ~~ webe4 0.004 0.001 0.001 0.001 0.001107   
truin2 ~~ webe5 0.006 0.001 0.001 0.001 0.001108   
truin2 ~~ webe6 0.196 0.009 0.009 0.008 0.008109   
truin3 ~~ truin4 73.909 -0.471 -0.471 -0.199 -0.199110   
truin3 ~~ webe1 2.761 -0.028 -0.028 -0.029 -0.029111   
truin3 ~~ webe2 0.001 0.000 0.000 0.000 0.000112   
truin3 ~~ webe3 1.206 0.021 0.021 0.019 0.019113   
truin3 ~~ webe4 3.041 0.032 0.032 0.032 0.032114   
truin3 ~~ webe5 0.204 0.009 0.009 0.008 0.008115   
truin3 ~~ webe6 0.967 0.021 0.021 0.017 0.017116   
truin4 ~~ webe1 1.231 0.015 0.015 0.022 0.022117   
truin4 ~~ webe2 0.493 -0.009 -0.009 -0.014 -0.014118   
truin4 ~~ webe3 0.022 0.002 0.002 0.003 0.003119   
truin4 ~~ webe4 3.942 -0.030 -0.030 -0.041 -0.041120   
truin4 ~~ webe5 3.947 -0.031 -0.031 -0.040 -0.040121   
truin4 ~~ webe6 0.012 -0.002 -0.002 -0.002 -0.002122   
webe1 ~~ webe2 153.517 0.068 0.068 0.255 0.255123   
webe1 ~~ webe3 50.754 0.045 0.045 0.137 0.137124   
webe1 ~~ webe4 62.404 -0.051 -0.051 -0.173 -0.173125   
webe1 ~~ webe5 68.018 -0.054 -0.054 -0.171 -0.171126   
webe1 ~~ webe6 5.876 -0.017 -0.017 -0.047 -0.047127   
webe2 ~~ webe3 128.133 0.068 0.068 0.219 0.219128   
webe2 ~~ webe4 57.439 -0.047 -0.047 -0.168 -0.168129   
webe2 ~~ webe5 86.209 -0.058 -0.058 -0.194 -0.194130   
webe2 ~~ webe6 23.523 -0.033 -0.033 -0.094 -0.094131   
webe3 ~~ webe4 114.875 -0.075 -0.075 -0.219 -0.219132   
webe3 ~~ webe5 150.356 -0.088 -0.088 -0.239 -0.239133   
webe3 ~~ webe6 33.002 0.045 0.045 0.105 0.105134   
webe4 ~~ webe5 612.318 0.182 0.182 0.553 0.553135   
webe4 ~~ webe6 0.199 0.004 0.004 0.009 0.009136   
webe5 ~~ webe6 3.493 0.015 0.015 0.037 0.037

Based on this output we included every error term correlation that lowers the chi square by at least 100, since this is a relatively large improvement in comparison to chisq = 1526.049. This yields the following model:

> cfa2<-'sotru =~NA\*sotru1+sotru2+sotru3

+ truin =~NA\*truin1+truin2+truin3+truin4

+ webe =~NA\*webe1+webe2+webe3+webe4+webe5+webe6

+ sotru ~~1\*sotru

+ truin ~~1\*truin

+ webe ~~1\*webe

+ truin1 ~~ truin3

+ truin1 ~~ truin4

+ truin2 ~~ truin3

+ truin2 ~~ truin4

+ webe1 ~~ webe2

+ webe2 ~~ webe3

+ webe3 ~~ webe4

+ webe3 ~~ webe5

+ webe4 ~~ webe5'

> #fit model on covariance matrix

> fitcfa2<-cfa(cfa2,sample.cov=covmat,sample.nobs=4046)

> fitmeasures(fitcfa2,c("chisq","df","pvalue","cfi","tli","rmsea","srmr"))

chisq df pvalue cfi tli rmsea srmr

169.929 53.000 0.000 0.993 0.990 0.023 0.017

Looking at the fit measurements we see indeed an improvement. CFI and TLI are above 0.95 and RMSEA and SRMR are below 0.08. The chi-square test is still significantly different from the perfectly fitted model (chi-square= 169.929, df=53, p<.001). This is probably due to the large number of observations in the dataset. We can therefore conclude that these additions add enough value to be included in the final model. This is also confirmed with the LR test below (LR= 1356.1, df=9, p<.001).

> anova(fitcfa1,fitcfa2)

Chi-Squared Difference Test

Df AIC BIC Chisq Chisq diff RMSEA Df diff Pr(>Chisq)

fitcfa2 53 164265 164504 169.93

fitcfa1 62 165603 165786 1526.05 1356.1 0.19234 9 < 2.2e-16 \*\*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Comparing the standardized estimates of cfa2 and cfa1. Overall, we can see some differences between the two models but what stands out the most is that only three estimates are above 0.7. This is also reflected in the difference in composite reliability as this is decreased for Trust institution and wellbeing. However, the reliability is above 0.7 for Trust institution and well-being and almost 0.7 social trust.

|  |  |  |
| --- | --- | --- |
|  | **cfa2 (est.std)** | **cfa1 (est.std)** |
| sotru =~ sotru1 | 0.681 | 0.648 |
| sotru =~ sotru2 | 0.648 | 0.626 |
| sotru =~ sotru3 | 0.629 | 0.626 |
| truin =~ truin1 | 0.713 | 0.789 |
| truin =~ truin2 | 0.750 | 0.718 |
| truin =~ truin3 | 0.628 | 0.581 |
| truin =~ truin4 | 0.689 | 0.802 |
| webe =~ webe1 | 0.623 | 0.661 |
| webe =~ webe2 | 0.613 | 0.670 |
| webe =~ webe3 | 0.691 | 0.589 |
| webe =~ webe4 | 0.703 | 0.718 |
| webe =~ webe5 | 0.657 | 0.677 |
| webe =~ webe6 | 0.602 | 0.595 |
|  |  |  |
| truin1 ~~ truin3 | -0.121 |  |
| truin1 ~~ truin4 | 0.386 |  |
| truin2 ~~ truin3 | 0.200 |  |
| truin2 ~~ truin4 | 0.030 |  |
|  |  |  |
| webe1 ~~ webe2 | 0.232 |  |
| webe2 ~~ webe3 | 0.096 |  |
| webe3 ~~ webe4 | -0.266 |  |
| webe3 ~~ webe5 | -0.270 |  |
| webe4 ~~ webe5 | 0.307 |  |

|  |  |  |
| --- | --- | --- |
| **Factorscore** | **Composite reliability cfa2** | **Composite reliability cfa1** |
| sotru | 0.690 | 0.690 |
| truin | 0.789 | 0.816 |
| webe | 0.813 | 0.816 |

Looking at the correlations between the error terms they are all significant (p<0.001). Overall, the correlations between the different variables are positively correlated except for truin1 (Trust in the country's parliament) and truin3 (Trust in the police) are negatively correlated. This value ranges from 0.030 to 0.386. For well-being, all terms have a positive correlation ranging from 0.096 to 0.307.

# Question C

For this question we use the same model from the previous question (cfa2) and transform it to four multi-group structural equation models using sem1 (which lets the coefficient of the regressions range freely) and sem2 (which constraints the coefficients to be equal across groups (countries: FR and GB)).

> sem1<-'sotru =~NA\*sotru1+sotru2+sotru3

+ truin =~NA\*truin1+truin2+truin3+truin4

+ webe =~NA\*webe1+webe2+webe3+webe4+webe5+webe6

+ sotru ~~1\*sotru

+ truin ~~1\*truin

+ webe ~~1\*webe

+ truin1 ~~ truin3

+ truin1 ~~ truin4

+ truin2 ~~ truin3

+ truin2 ~~ truin4

+ webe1 ~~ webe2

+ webe2 ~~ webe3

+ webe3 ~~ webe4

+ webe3 ~~ webe5

+ webe4 ~~ webe5

+ webe ~ sotru + truin'

>

> sem2<-'sotru =~NA\*sotru1+sotru2+sotru3

+ truin =~NA\*truin1+truin2+truin3+truin4

+ webe =~NA\*webe1+webe2+webe3+webe4+webe5+webe6

+ sotru ~~1\*sotru

+ truin ~~1\*truin

+ webe ~~1\*webe

+ truin1 ~~ a\*truin3

+ truin1 ~~ b\*truin4

+ truin2 ~~ c\*truin3

+ truin2 ~~ d\*truin4

+ webe1 ~~ e\*webe2

+ webe2 ~~ f\*webe3

+ webe3 ~~ g\*webe4

+ webe3 ~~ h\*webe5

+ webe4 ~~ i\*webe5

+ webe ~ j\*sotru + k\*truin'

> # Configural measurement invariance model with country-specific regression

> config1 <- sem(sem1, data = ess, group = "cntry")

> # Configural measurement invariance model with country-specific regression and equality constraints

> config2 <- sem(sem2, data = ess, group = "cntry")

> # Metric measurement invariance model with country-specific regression

> metric1 <- sem(sem1, data = ess, group = "cntry", group.equal="loadings")

> # Metric measurement invariance model with country-specific regression and equality constraints

> metric2 <- sem(sem2, data = ess, group = "cntry", group.equal="loadings")

> # Fit measures

> fitconfig1 <- fitmeasures(config1,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fitconfig2 <- fitmeasures(config2,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fitmetric1 <- fitmeasures(metric1,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fitmetric2 <- fitmeasures(metric2,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fit<-rbind(fitconfig1,fitconfig2,fitmetric1,fitmetric2)

> rownames(fit)<-c("config1","config2","metric1","metric2")

> round(fit,3)

chisq df pvalue cfi tli rmsea srmr aic bic

config1 218.858 106 0 0.993 0.990 0.023 0.020 163211.0 163854.2

config2 259.497 117 0 0.991 0.989 0.025 0.022 163229.6 163803.4

metric1 261.703 119 0 0.991 0.989 0.024 0.027 163227.9 163789.0

metric2 311.430 130 0 0.989 0.987 0.026 0.031 163255.6 163747.4

Looking at the fitmeasures we can conclude that the best model to fit the data is config1. This model has the lowest chi-square, this is still different from the perfectly, fitted model, both CFI and TLI are the highest and RMSEA and SRMR are the lowest. Looking at the AIC and BIC again config1 yields the lowest value, indicating this is the best fitting model. ever, the results are remarkably close and overall, the models could be a fit for our data (CFI and TLI >0.95, RMSEA and SRMR< 0.08).   
Using The LR test we can conclude that all models are significantly different (p<0.001) except for config2 and metric1 (LR: 2.2057, df=2, p=0.03319). Given the fact that config1 is the best model, we can say that it is best not to constrain the coefficient to be equal across the two countries.

Looking at the standardized solution of config1:

> standardizedSolution(config1)

lhs op rhs group est.std se z pvalue ci.lower ci.upper

1 sotru =~ sotru1 1 0.611 0.021 29.231 0.000 0.570 0.652

2 sotru =~ sotru2 1 0.686 0.020 33.767 0.000 0.646 0.726

3 sotru =~ sotru3 1 0.570 0.021 26.608 0.000 0.528 0.612

4 truin =~ truin1 1 0.688 0.024 28.458 0.000 0.640 0.735

5 truin =~ truin2 1 0.737 0.024 30.183 0.000 0.689 0.785

6 truin =~ truin3 1 0.603 0.028 21.815 0.000 0.549 0.657

7 truin =~ truin4 1 0.666 0.028 24.182 0.000 0.612 0.720

8 webe =~ webe1 1 0.639 0.018 34.716 0.000 0.603 0.675

9 webe =~ webe2 1 0.656 0.020 33.221 0.000 0.617 0.694

10 webe =~ webe3 1 0.692 0.021 32.594 0.000 0.650 0.734

11 webe =~ webe4 1 0.656 0.020 32.239 0.000 0.616 0.696

12 webe =~ webe5 1 0.616 0.021 29.024 0.000 0.575 0.658

13 webe =~ webe6 1 0.608 0.018 33.498 0.000 0.573 0.644

Overall, all the correlations with the latent variables are significant however all but one (truin =~ truin2) are below 0,7.

Looking at the coefficients of social trust and trust institution we see that in the first group, FR, social trust has a significant effect on well-being while this is not the case for trust institution. In the second group, GB, however, both predictors are significant in explaining well-being but here social trust has a bigger impact than trust institution.

> standardizedSolution(config1)

lhs op rhs group est.std se z pvalue ci.lower ci.upper

26 webe ~ sotru 1 0.263 0.043 6.191 0.000 0.180 0.347

27 webe ~ truin 1 0.040 0.042 0.955 0.340 -0.042 0.121

83 webe ~ sotru 2 0.218 0.036 6.120 0.000 0.148 0.288

84 webe ~ truin 2 0.070 0.035 1.996 0.046 0.001 0.139

> # Fit measures

> fitconfig1 <- fitmeasures(config1,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fitconfig2 <- fitmeasures(config2,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fitmetric1 <- fitmeasures(metric1,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fitmetric2 <- fitmeasures(metric2,c("chisq","df","pvalue","cfi","tli","rmsea","srmr","aic","bic"))

> fit<-rbind(fitconfig1,fitconfig2,fitmetric1,fitmetric2)

> rownames(fit)<-c("config1","config2","metric1","metric2")

> round(fit,3)

chisq df pvalue cfi tli rmsea srmr aic bic

config1 218.858 106 0 0.993 0.990 0.023 0.020 163211.0 163854.2

config2 259.497 117 0 0.991 0.989 0.025 0.022 163229.6 163803.4

metric1 261.703 119 0 0.991 0.989 0.024 0.027 163227.9 163789.0

metric2 311.430 130 0 0.989 0.987 0.026 0.031 163255.6 163747.4

# Question D

We load the data with the original variable names, standardize the variables, use the candisc() procedure to conduct canonical correlation analysis and print a summary of the results and compute redundancies.

> load("ess.Rdata")

> sess<- ess

> sess[,2:14]<-scale(ess[,2:14],center=TRUE,scale=FALSE)

> cancor.out<-cancor(cbind(fltdpr, fltsd, fltanx, wrhpp, enjlf, fltpcfl)

+ ~ppltrst+ pplfair+ pplhlp+ trstprl+ trstlgl+ trstplc+ trstplt, data=sess)

> summary(cancor.out)

Canonical correlation analysis of:

7 X variables: ppltrst, pplfair, pplhlp, trstprl, trstlgl, trstplc, trstplt

with 6 Y variables: fltdpr, fltsd, fltanx, wrhpp, enjlf, fltpcfl

CanR CanRSQ Eigen percent cum scree

1 0.242629 5.887e-02 6.255e-02 77.37503 77.38 \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

2 0.110279 1.216e-02 1.231e-02 15.22875 92.60 \*\*\*\*\*\*

3 0.063206 3.995e-03 4.011e-03 4.96159 97.57 \*\*

4 0.041142 1.693e-03 1.696e-03 2.09741 99.66 \*

5 0.016167 2.614e-04 2.614e-04 0.32339 99.99

6 0.003343 1.118e-05 1.118e-05 0.01383 100.00

Test of H0: The canonical correlations in the

current row and all that follow are zero

CanR LR test stat approx F numDF denDF Pr(> F)

1 0.242629 0.92415 7.6396 42 18920 < 2.2e-16 \*\*\*

2 0.110279 0.98196 2.4539 30 16138 1.618e-05 \*\*\*

3 0.063206 0.99405 1.2056 20 13384 0.2378

4 0.041142 0.99804 0.6617 12 10678 0.7897

5 0.016167 0.99973 0.1834 6 8074 0.9815

6 0.003343 0.99999 NaN 2 NaN NaN

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> #redundancies

> redu<-redundancy(cancor.out)

> round(redu$Xcan,3)

Xcan1 Xcan2 Xcan3 Xcan4 Xcan5 Xcan6

0.023 0.001 0.001 0.000 0.000 0.000

> round(redu$Ycan,3)

Ycan1 Ycan2 Ycan3 Ycan4 Ycan5 Ycan6

0.030 0.002 0.000 0.000 0.000 0.000

> #computation redundancies from output

> R2tu<-cancor.out$cancor^2

> VAFYbyt<-apply(cancor.out$structure$Y.yscores^2,2,sum)/4

> redund<-R2tu\*VAFYbyt

> round(cbind(R2tu,VAFYbyt,redund,total=cumsum(redund)),3)

R2tu VAFYbyt redund total

Ycan1 0.059 0.770 0.045 0.045

Ycan2 0.012 0.192 0.002 0.048

Ycan3 0.004 0.132 0.001 0.048

Ycan4 0.002 0.131 0.000 0.048

Ycan5 0.000 0.154 0.000 0.048

Ycan6 0.000 0.122 0.000 0.048

The canonical correlation analysis extracts 6 pairs of canonical variances. Hypotheses tests indicate that only the first two correlations are significant i.e., H0: corr(u3,t3)=0 cannot be rejected at the 5% level (p= 0.2378).

The first canonical correlation equals 0.24. This means that the canonical variate u1 accounts for 5.89% of the variance in the canonical variate t1. The second canonical correlation equals 0.11. This means that the canonical variate u2 accounts for 1.21% of the variance in the canonical variate t2.

Looking at redundancies, we observe that u1 accounts for 3% variance in Y and u2 accounts for 0.2% variance in Y. Since only the first two correlations are significant, we can say that X variables account for 3.2% of variance in the Y variables. The u2 barely contributed. Only a small portion of variance in Y is explained by X.

In addition, we make a scatter plot of the first pair of canonical variates and indicate a different color for observations of each country.

A red and blue dots

Description automatically generated

# Question E

To assess the validity of the analysis, we used a split-half approach.

samplesize<-dim(ess)[1]

train<-ess[seq(2,samplesize,by=2),2:14]

valid<-ess[seq(1,samplesize,by=2),2:14]

train<-as.data.frame(scale(train,center=TRUE,scale=TRUE))

valid<-as.data.frame(scale(valid,center=TRUE,scale=TRUE))

#conduct CCA on training data

cancor.train<-cancor(cbind(fltdpr, fltsd, fltanx, wrhpp, enjlf, fltpcfl)

~ppltrst+ pplfair+ pplhlp+ trstprl+ trstlgl+ trstplc+ trstplt, data=train)

#summary(cancor.train)

round(cancor.train$structure$X.xscores,3)

round(cancor.train$structure$Y.yscores,3)

#conduct CCA on validation data

cancor.valid<-cancor(cbind(fltdpr, fltsd, fltanx, wrhpp, enjlf, fltpcfl)

~ppltrst+ pplfair+ pplhlp+ trstprl+ trstlgl+ trstplc+ trstplt, data=valid)

#summary(cancor.valid)

round(cancor.valid$structure$X.xscores,3)

round(cancor.valid$structure$Y.yscores,3)

# canonical variates calibration set

train.X1<-cancor.train$score$X

train.Y1<-cancor.train$score$Y

# compute canonical variates using data of calibration set and coefficients estimated on validation set

train.X2<-as.matrix(train[,1:7])%\*%cancor.valid$coef$X

train.Y2<-as.matrix(train[,8:13])%\*%cancor.valid$coef$Y

> #R(T,T\*) and R(U,U\*) for t1,t2,u1,u2

> round(cor(train.Y1,train.Y2)[1:2,1:2],3)

Ycan1 Ycan2

Ycan1 0.989 -0.111

Ycan2 0.101 0.817

> round(cor(train.X1,train.X2)[1:2,1:2],3)

Xcan1 Xcan2

Xcan1 0.982 -0.042

Xcan2 0.029 0.514

The absolute value of the diagonal elements of R(T,T\*) and R(U,U\*) represent the reliabilities of the canonical variates for Y and X variables. The reliabilities of t1, t2 equal .989, .817. And the reliabilities of u1, u2 equal .982, .514. In other words, the first pairs of canonical variates have excellent reliability, but the reliability of u2 is unacceptable. The off-diagonal correlations are low.

> #R(U,T) and R(U\*,T\*)

> round(cor(train.X1,train.Y1)[1:2,1:2],3)

Ycan1 Ycan2

Xcan1 0.253 0.000

Xcan2 0.000 0.129

> round(cor(train.X2,train.Y2)[1:2,1:2],3)

Ycan1 Ycan2

Xcan1 0.246 -0.028

Xcan2 -0.002 0.044

A comparison of R(U\*,T\*) and R(U,T) shows that R(u1, t1) 0.253 is only a little higher than R(u1\*, t1\*) 0.246. In other words, overestimation of the first canonical correlation due to the maximization involved is not an issue. Yet, the overestimation in the second canonical correlation is rather large (.129 versus .044).

> #R(T\*,T\*) and R(U\*,U\*)

> round(cor(train.Y2,train.Y2)[1:2,1:2],3)

Ycan1 Ycan2

Ycan1 1.000 -0.019

Ycan2 -0.019 1.000

> round(cor(train.X2,train.X2)[1:2,1:2],3)

Xcan1 Xcan2

Xcan1 1.000 -0.007

Xcan2 -0.007 1.000

The off-diagonal elements of R(T\*,T\*) and R(U\*,U\*) are close to 0, which indicates that canonical variates of Y variables and of X variables computed on calibration data but based on the coefficients from validation data have as expected correlations that are close to 0 (canonical variates are independent).

Question F

From the redundancies in previous results, we can conclude that the first two pairs of canonical variates have very good reliabilities. The redundancy analysis has shown that u1 accounts for 4.5% of the variance in the Y variables, and that u2 accounts only for an additional 0.2% of the variance in the Y variables. As the second pair of canonical variates is not practically important, we focus for the interpretation on the first pair of canonical variates.

> as.matrix(round(cancor.out$structure$X.xscores[,1],3))

[,1]

ppltrst -0.676

pplfair -0.842

pplhlp -0.609

trstprl -0.544

trstlgl -0.599

trstplc -0.554

trstplt -0.441

These canonical loadings show u1 has negative associations with variables related to social trust and trust in institutions (correlations for ppltrst, pplfair, pplhlp, trstprl, trstlgl, trstplc, trstplt are all negative, with social trust variables have higher correlations). This indicates that people who score lower on u1 have more trust in society and institutions.

> as.matrix(round(cancor.out$structure$Y.yscores[,1],3))

[,1]

fltdpr -0.740

fltsd -0.687

fltanx -0.677

wrhpp -0.749

enjlf -0.793

fltpcfl -0.644

These canonical loadings show t1 has negative associations with variables related to well-being, including positive emotions and inverted negative emotions (correlations for fltdpr, fltsd, fltanx, wrhpp, enjlf, fltpcfl are all highly negative). This indicates that people who score lower on t1 have more negative emotions.

Hence, the positive correlation between u1 and t1 means that persons who are experiencing more positive emotions and less negative emotions would also have higher trust in institutions and on society.