Lab 7: Measuring latent variables in the social world

DATA5207: Data Analysis in the Social Sciences

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Contents

Introduction

In Week 7 and 8, you will be working with your groups on the first assessable group exercise. You will have these two labs to finish and upload your work (see the *Group assignment 1* assessment on canvas). Your goal in this project is to come up with a theory that explains quality of life. You are required to work out what might best predict these quality of life scores.

To do this we will give you a survey and corresponding data (*The World Values Survey*). You will use these data to identify predictors for quality of life. **We will create the dependent variable in this lab**. This will be a measure of quality of life created with a combination of five questions from the survey using factor analysis. These variables are listed below. ***Since they will form part of your dependent variable, they should not be included as predictors for this exercise***. However, if you want to check out whether your predictors have reasonable explanatory power, you can test them using these variables.

This week, you will work on developing theories for what might predict higher/lower quality of life. Think about what drives life quality. Look at questionnaire and codebook. Identify possible predictors. Write up the descriptive analysis (means, sd, or histograms, tables).

Next week you will test your ideas on the dependent variable we create today. Further details are available below.

More details on the group project

This task, which counts towards your group work grade, should not require each group member to spend more than four hours to complete. The three group projects in this semester combined are worth 25% of your total grade for the unit and will be conducted in your groups for the assessable group projects, which should have no more than five members.

In the lecture, we explored the use of different methodologies to understand measures of similarities used in the social sciences (also known as data reduction techniques). These methods are usually adopted in social science research to reduce the number of variables included in a model, or to detect structure in the associations between different variables. In this lab, we will primarily focus on the first of these. This strategy is particularly important for measuring characteristics of individuals for which a single question would often not provide an accurate result; due to measurement error, social desirability bias, or because what we are trying to measure is a latent trait where no one question could possibly capture the true picture.

The most common method used to do this in the social sciences is factor analysis. While factor analysis expresses the underlying common factors for an entire group of variables, it also helps researchers differentiate these factors by grouping variables into different dimensions or factors, each of which is ideally uncorrelated with the others.

During this lab, we will walk through the process of fitting a factor analysis to survey data on quality of life. We will look at factor analysis as a tool to understand quality of life. This is an appropriate method for this kind of research, as there are a number of variables in our dataset that provide information on the outcome we are interested in, and we can better understand the problem if we decompose the information they contain into a single measure, which we can then study further. The assessable component of the two labs over Week 7 and 8 will require you to undertake an analysis of the measure we create using the other methods you have learned in this subject.

You should submit your final written document as a *RMarkdown* file through a link that will be provided in this module. **Submit the RMD in a zipped folder with your data**. Make sure your RMD is knittable without any errors. Only one member of your group needs to submit your work. As long as the groups are properly registered on canvas, all members of the group will receive the full grades awarded.

Lab 7 Agenda

Your work in this lab consists of two parts. First we will walk you through the use of *factor analysis* in R. Then you will be familiarising yourself with the survey data, and examining possible predictors, or independent variables, for this project.

1. DLD and review
2. Creating the dependent variable
3. Interpreting factor analysis
4. Overview of FA
5. Assessable group work Part 1

In next week's lab you will use the output from the factor analysis model we create today to complete your assessable group project.

DLD

In your DATA5207 local folder, create a new *R Markdown* file and save it with a descriptive name (i.e., Lab7) that will make sense to you when you come back to it in the future.

Add and edit appropriate YAML headers into the *R Markdown* file. Use the console or other short hand commands to **set your working directory**.

We start by **loading in our libraries**:

```
library(ggplot2)
# install.packages("psych")
library(psych)
library(tidyverse)
```

Note: To run our factor analysis, we use the `psych` package, which we need to download from CRAN using the `install.packages` function before loading the psych package.

We are using the 2018 Australian World Values Survey for this research. This is a survey of Australians, run in conjunction with other similar surveys conducted around the world. It asks respondents more questions than most other surveys, and therefore provides a useful data source for researchers. A copy of the dataset, code book and questionnaire is available in the zipped folder in the module for this class on canvas. These data come from the Australian Data Archive.

```
wvs.dat <- read.csv("Data/wvs_data.csv")
```

YOUR TASK #1

1. What are latent variables?
   Insert answer here.
2. What is factor analysis?
   Insert answer here.
3. What are the assumptions of factor analysis?
   Insert answer here.

Creating the dependent varaible

For this project, you will conduct an analysis on life quality using survey data.

Quality of life is a latent variable. We cannot directly measure it. But, we can use other variables to create a measure for quality of life. Using the survey data we've loaded, we will examine how different personal characteristics might be associated with higher and lower quality of life. We will do this by fitting a factor analysis to five variables which cover reported happiness, life satisfaction, health, and financial situation. These variables are:

- *Q46.* Taking all things together, would you say you are… (variable V10)
- *Q47.* All in all, how would you describe your state of health these days? Would you say it is… (variable V11)
- *Q48.* Some people feel they have completely free choice and control over their lives, while other people feel that what they do has no real effect on what happens to them. Please use this scale where 1 means "no choice at all" and 10 means "a great deal of choice" to indicate how much freedom of choice and control you feel you have over the way your life turns out. (variable V55)

- *Q49.* All things considered, how satisfied are you with your life as a whole these days? (variable V23)
- *Q50.* How satisfied are you with the financial situation of your household? (variable V59)

Using a factor analysis, we will create out dependent variable, a measure for quality of life.

Standardise variables

We begin by making sure these are coded the correct way (greater quality of life being the positive score), and we standardise the scores.

We need to recode our variables. As we do this we provide the variables with more intuitive names, to make our work easier. This can be done with the code:

```
wvs.dat <- wvs.dat %>%
  dplyr::mutate(happiness = dplyr::recode(V10,
                                   '1' = 4,
                                   '2' = 3,
                                   '3' = 2,
                                   '4' = 1,
                                   '-2' = NULL),

         health = dplyr::recode(V11,
                                '1' = 5,
                                '2' = 4,
                                '3' = 3,
                                '4' = 2,
                                '5' = 1,
                                '-2' = NULL),

         finances = dplyr::recode(V59,
                                  '-2' = NULL,
                                  .default = V59),

         satisfaction = dplyr::recode(V23,
                                      '-2' = NULL,
                                      .default = V23),

         freedom = dplyr::recode(V55,
                                 '-2' = NULL,
                                 .default = V55))
```

We use the `recode` function from `dplyr` to both switch around those variables that are coded incorrectly (where the higher value is associated with lower quality of life) and where missing values are included as a numeric value (such as -2 for `V10`), which will result in these values being included in our factor analysis and adding misleading information into our model. Here we are using the `recode()` function from `dplyr`.

Fitting the factor analysis

We use the `fa` function, from the `psych` package, to run our factor analysis. More information on this function can be found here. We fit the model with this syntax:

```
fa.fit <- fa(wvs.dat[,c("happiness",
                         "health",
                         "finances",
                         "satisfaction",
                         "freedom")],
             nfactors=1)
```

Within this function we specify our variables, the number of factors we wish to calculate (in our case, just one).

It is not shown here, but there are several rotation methods available with factor analysis. These can be characterised as orthogonal, which do not allow the latent dimensions to be correlated, and oblique, which do allow correlation. Varimax is a popular method (especially in the social sciences) for orthogonal rotation in factor and principal components analysis, so in instances where you have multiple dimensions, they will remain uncorrelated. We have not included this here, as we have a single dimensional factor analysis, but good to know for future work you might do where there are two or more factors. If we had wanted to include a Varimax rotation, we could do so by adding `rotate="varimax"` after the `nfactors` command (separated by a comma, of course).

We can take the factor scores from this analysis — the latent quality of life estimated by our factor analysis — and save this back into our existing dataset using the code:

```
wvs.dat$life.quality <- as.numeric(fa.fit$scores)
```

This saves the factor scores as a new variable called `life.quality`. We can view a sample of these using the `head` function:

```
head(wvs.dat$life.quality, 10)
```

```
##  [1]  0.72256548 -0.74706729          NA  0.26937731  1.28122093  0.12100610
##  [7]          NA  0.08338665          NA -1.25791923
```

Interpreting factor analysis

The output from your model should look like this:

```
## Factor Analysis using method =  minres
## Call: fa(r = wvs.dat[, c("happiness", "health", "finances", "satisfaction",
##     "freedom")], nfactors = 1)
## Standardized loadings (pattern matrix) based upon correlation matrix
##               MR1   h2   u2 com
## happiness    0.64 0.41 0.59   1
## health       0.52 0.28 0.72   1
## finances     0.63 0.39 0.61   1
## satisfaction 0.93 0.86 0.14   1
## freedom      0.71 0.50 0.50   1
##
##                 MR1
## SS loadings    2.43
## Proportion Var 0.49
##
```

```
## Mean item complexity =  1
## Test of the hypothesis that 1 factor is sufficient.
##
## df null model =  10  with the objective function =  1.73 with Chi Square =  3136.16
## df of  the model are 5  and the objective function was  0.02
##
## The root mean square of the residuals (RMSR) is  0.02
## The df corrected root mean square of the residuals is  0.04
##
## The harmonic n.obs is  1788 with the empirical chi square  22.35  with prob <  0.00045
## The total n.obs was  1813  with Likelihood Chi Square =  33.28  with prob <  3.3e-06
##
## Tucker Lewis Index of factoring reliability =  0.982
## RMSEA index =  0.056  and the 90 % confidence intervals are  0.039 0.075
## BIC =  -4.23
## Fit based upon off diagonal values = 1
## Measures of factor score adequacy
##                                                    MR1
## Correlation of (regression) scores with factors   0.95
## Multiple R square of scores with factors          0.90
## Minimum correlation of possible factor scores     0.79
```

There is a lot here, and we do not expect you to understand it all straight away. For this exercise, we will focus on the first table.

The first column of the top table in our output, labelled `MR1`, shows how each item loads onto the latent trait for quality of life. 'MR' here stands for minimum residual, and its name reflects the fitting method (if we had used a different method we would get a different column name; `ML` for maximum likelihood, for instance). A positive loading means that a higher response on this variable indicates a higher score on the combined measure of life quality created by this analysis. A negative loading (if there was one) would suggest that a higher response predicts lower quality of life.

It is only this simple to interpret the finding because we recoded our variables. If we had not, we would need to remember the way each variable was coded to infer the meaning of these results. You can see what I mean by replacing `happiness` and `health` with the original variables and re-running the factor analysis.

Once you have done this, return to the original model. There are three other columns. The second column, `h2`, represents the communalities of the variables. These communalities are the total amount of common variance between the variable and the factor(s). Higher communalities are better. If communalities for a particular variable are low, then that variable may struggle to load significantly on any factor.

The communalities for the ith variable are computed by taking the sum of the squared loadings for that variable. To compute the communality for `happiness`, for instance, we square the factor loading for this variable (if there was more than one dimension, we would square the loading for each then sum the results). This gives us 0.41. You can think of these values as the equivalent of multiple *R^2* values from regression models, predicting the variables of interest for your factors. The communality for a given variable can be interpreted as the proportion of variation in that variable explained by the factor(s). If we perform multiple regression of `happiness` against the factor score, we obtain an *R^2* of 0.41, indicating that about 41 per cent of the variation in happiness (as measured by this variable) is explained by the factor score.

One assessment of how well this model is doing can be obtained from the communalities. What you want to see is values that are close to one. This would indicate that the model explains most of the variation for those variables. In this case, the model does better for some variables than it does for others. Our results suggest the factor analysis does the best job of explaining variation in `satisfaction`. This makes sense, as we're trying to measure quality of life, and self-reported life satisfaction is likely the closest variable to this in the model.

The third column, u2, has nothing to do with the band, but is rather the measure of uniqueness. This is the proportion of a variable's variance that is not shared with a factor structure. Unique variance is composed of specific and error variance. The existence of uniquenesses is what distinguishes factor analysis from principal components analysis. If the variables in the model are thought to represent a 'true' or latent part of some phenomena, then factor analysis provides an estimate of the correlations with the latent factor(s) representing the data. If we believe them to be measured without error, then principal components provides the most parsimonious description of the data. When we look at our table factor loading table, the output in the third column is the direct inverse of the second; the more the variance of a item is explained by the factor score(s), the less the proportion a variable's variance will not shared with a factor structure.

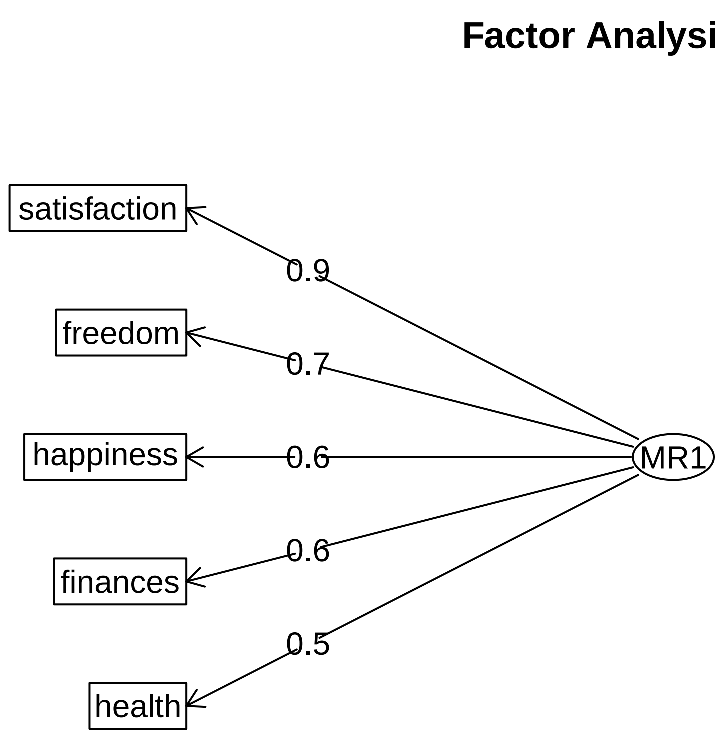
The last column, com, is the complexity of the factor loadings for that variable (see below). This will be '1' when you only have a single dimension, but will (usually) increase as you increase the number of dimensions in your model.

Just below the first table, we can see that our latent dimension accounted for around 49 per cent of the variance in responses. If we had multiple dimensions we would be provided with a statistic for each dimension and the cumultive variance explained.

Visualising

To visualise the loadings of the factor analysis, you can use this code:

```
fa.diagram(fa.fit)
```



See: https://rstudio-pubs-static.s3.amazonaws.com/498796_05b4e23682d54da387499507495c7ef6.html for more details and examples on using fa.

Our created QoL measure is approximately standardised, with a mean of zero and standard deviation of (almost) one. We can then use this to analyse the association between quality of life and different individual characteristics that are also available in this dataset.

This is showing the distribution of quaity of life within the sample.

```
ggplot(wvs.dat, aes(life.quality)) +
  geom_histogram(fill = 'black') +
  theme_minimal()
```

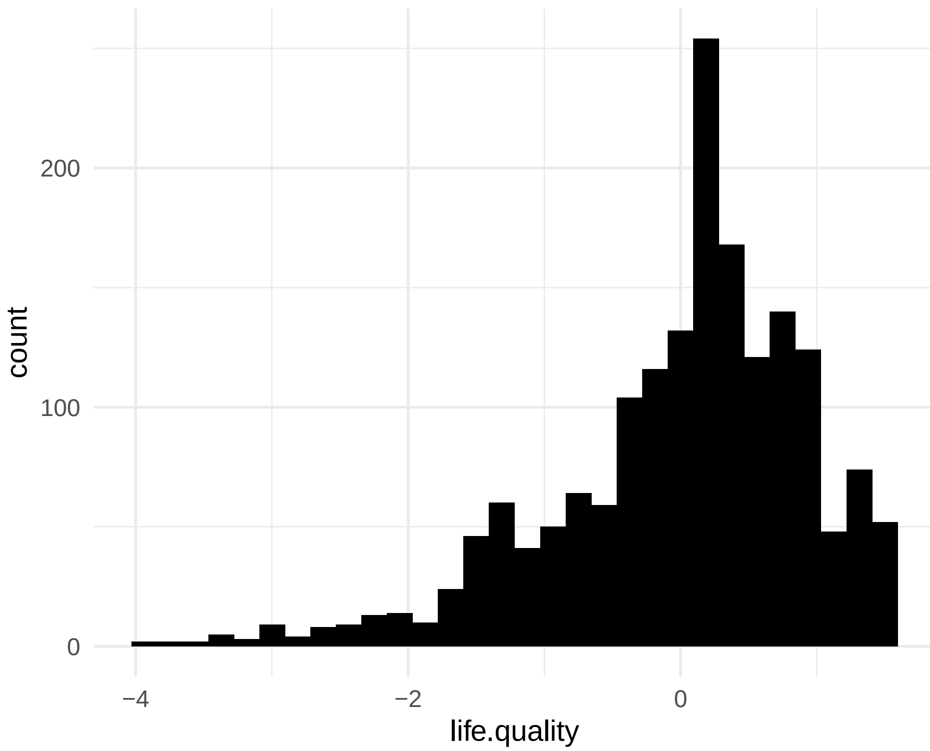


Figure 1: Distribution of quality of life measure produced by factor analysis.

Overview of factor analysis steps

1. Data cleaning and recoding
2. Running factor analysis
3. Saving the factor scores
4. Plotting factor scores
5. Interpreting factor analysis
6. Analysing the association between quality of life and other variables (part of your assessable group work!)
7. Assessing the reliability of your model (part of your assessable group work!)

Assessable group work

Now you are ready to start the assessable group exercise.

Part 1 (lab 7): Understanding your survey data

In this lab, you will be familiarising yourself with the survey data, and examining possible predictors, or independent variables, for this project.

As a class, we will first go over creating the dependent variable using factor analysis (above).

Then, in your groups, you will undertake three main steps:

1. Develop a theory or theories of what factors might influence quality of life, and why. This will inform your selection of independent variables (predictors). This does not need to be sophisticated or complicated. A few simple ideas will suffice. Write this up in the Markdown file you will be submitting.
2. Take the time to familiarise yourself with the survey and data. Using the theory you have developed, select what you believe to be appropriate predictors to explain quality of life from the provided survey data. There should be at least five of these. Examine these predictors in R. Look at their mean, standard deviation, distribution, etc. Do they need to be recoded in any way? Write up your data cleaning decisions in the Markdown file, and include any descriptive analysis you do.

Some code to help you get started:

```
library(tidyverse)
library(psych)
library(ggpubr)

data <- read.csv("Data/wvs_data.csv")

glimpse(data)

data %>%
  ggpubr::get_summary_stats()
```

3. Finally, properly write up the Introduction, Theory, and Data and Methods section of your report.

Each step in your Markdown file should be clearly labelled.

Make sure you SAVE your work so you can continue on it in next week's lab.