Psychology 350: An introduction to R for Psychological Research Week 3 Multidimensional analysis

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https://personality-project.org/courses/350



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Fitting models and fit statistics 0000000000

Outline

Fitting models and fit statistics Iterative fit



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Fitting functions as way of testing theory

- 1. Closed form versus open form
- 2. Much of classical statistics is "closed form". That is, it is a matter of solving some equations using basic algebra.
 - Examples include the
 - t.test
 - F. test
 - basic linear regression
- 3. However, other functions are "open form" and have to be estimated using the process of iteration.
- 4. Although computers are useful for solving closed form equations, they are particularly useful for solving open forms.



The basic concept of fitting

- Given some fit statistic, try to find the optimal values for that fit
 - Consider the case of the square root of 47
 - Guess X
 - find 47/Guess
 - try a new *Guess* = 47/*Guess*
 - do it again
- The next example is a baby function to do this
- It is the concept, not the programming that is important



Iterative fitting to find a square root

```
iterative.sqrt <- function(X, quess) {</pre>
if (missing (quess)) quess <- 1 #a dumb quess
iterate <- function(X, quess) {
    low <- quess
    high <- X/guess
    guess <-((high+low)/2)
                                                             iterative solution
    quess}
Iter <- matrix(NA, ncol=2, nrow=10)</pre>
for (i in 1:10) {
                                             ຊ
Iter[i,1] <- quess
Iter[i,2] <- guess <- iterate(X, guess)</pre>
                                             40
      #this returns the value
Tter}
                                           Guesses
> X <- 47
                                             0
> iter <- iterative.sgrt(47)
> iter
            [,1]
                      [,2]
                                             ю
     1.000000 24.000000
 [1,]
      24.000000 12.979167
 [2, ]
 [3,] 12.979167 8.300177
 [4.] 8.300177 6.981353
                                                     2
                                                                    6
                                                                           8
                                                                                   10
 [5,] 6.981353 6.856786
                                                                Iteration
 [6,] 6.856786 6.855655
 [7.] 6.855655 6.855655
 [8,] 6.855655 6.855655
 [9,] 6.855655 6.855655
[10,] 6.855655
                 6.855655
```



Iterative fitting to find a square root – a better guess





The optim function is one way to fit complex models

optim() minimising 'wild function'





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Iterative fitting has several steps

- Specifying a model and loss function
 - Ideally supplying a first derivative to the loss function
 - Can be done empirically
- Some way to evaluate the quality of the fit
- Minimization of function, but then how good is this minimum



Fitting models and fit statistics 0 0000000000 Iterative fit

Multivariate analysis

- Many procedures use this concept of iterative fitting
- Some, such as principal components are "closed form" and can just be solved directly
- Others, such as "factor analysis" need to find solutions by successive approximations
- The issue of factor or component rotation is an iterative procedure.
- Principal Components and Factor analysis are all the result of some basic matrix equations to approximate a matrix
- Conceptually, we are just taking the square root of a correlation matrix:
- $R \approx CC'$ or $R \approx FF' + U2$
- For any given correlation matrix, R, can we find a C or an F matrix which approximates it?



Consider the following matrix

What would be its "square root"? That is to say, what simpler matrix, times itself is equal to R?

R V1 V2 V3 V4 V1 1.00 0.56 0.48 0.40 V2 0.56 1.00 0.42 0.35 V3 0.48 0.42 1.00 0.30 V4 0.40 0.35 0.30 1.00



Fitting models and fit statistics

We create this matrix using the sim.congeneric function

```
R code
"sim.congeneric" <- function{
 (loads = c(0.8, 0.7, 0.6, 0.5), ...)
n <- length(loads)</pre>
 loading <- matrix(loads, nrow = n)</pre>
error <- diag(1, nrow = n)
diag(error) <- sqrt(1 - loading<sup>2</sup>)
model <- pattern %*% t(pattern)
 result <- model
 return (result)
```

- 1. Give some default values
- 2. Create a correlation matrix using matrix algebra
- 3. Return the value



A congeneric matrix is one with just one factor

R code
R <- sim.congeneric()
R
f1 <- fa(R)
> R
V1 V2 V3 V4
V1 1.00 0.56 0.48 0.40
V2 0.56 1.00 0.42 0.35
V3 0.48 0.42 1.00 0.30
V4 0.40 0.35 0.30 1.00
> f1 <- fa(R)
> f1
Factor Analysis using method = minres
Call: $fa(r = R)$
Standardized loadings (pattern matrix) based upon correlation matrix
MR1 h2 u2 com
V1 0.8 0.64 0.36 1
V2 0.7 0.49 0.51 1
V3 0.6 0.36 0.64 1
V4 0.5 0.25 0.75 1
MR1
SS loadings 1.74
Proportion Var 0.43



But does this really fit?

```
Think about the residuals (Data - model)
```

R round(f1\$model,2) residuals(f1)	
> R	
V1 V2 V3 V4	
V1 1.00 0.56 0.48 0.40	
V2 0.56 1.00 0.42 0.35	
V3 0.48 0.42 1.00 0.30	
V4 0.40 0.35 0.30 1.00	
<pre>> round(f1\$mode1,2)</pre>	
V1 V2 V3 V4	
V1 0.64 0.56 0.48 0.40	
V2 0.56 0.49 0.42 0.35	
V3 0.48 0.42 0.36 0.30	
V4 0.40 0.35 0.30 0.25	
<pre>> residuals(f1)</pre>	
V1 V2 V3 V4	
V1 0.36	
V2 0.00 0.51	
V3 0.00 0.00 0.64	
V4 0.00 0.00 0.00 0.75	
Hence we add the fudge fa	actor $U2 = diagonal of residuals and say ($
$\kappa = FF' + U^2$	

