

A single-factor Confirmatory Factor Analysis Model (starting simply)

Standardized

$$\begin{aligned}
 Z_1 &= \lambda_1 F + e_1 \\
 Z_2 &= \lambda_2 F + e_2 \\
 Z_3 &= \lambda_3 F + e_3
 \end{aligned}$$

$$\begin{aligned}
 V(F) = V(Z_1) = V(Z_2) = V(Z_3) = 1 \\
 F, e_1, e_2, e_3 \text{ ind.}
 \end{aligned}$$

← Covariance

$$\Sigma = \begin{matrix} & \begin{matrix} Z_1 & Z_2 & Z_3 \end{matrix} \\ \begin{matrix} Z_1 \\ Z_2 \\ Z_3 \end{matrix} & \begin{bmatrix} 1 & \lambda_1 \lambda_2 & \lambda_1 \lambda_3 \\ & 1 & \lambda_2 \lambda_3 \\ & & 1 \end{bmatrix} \end{matrix}$$

$$\begin{aligned}
 V(Z_1) = 1 &= \lambda_1^2 + V(e_1) \\
 \Rightarrow V(e_1) &= 1 - \lambda_1^2 \\
 &\text{etc}
 \end{aligned}$$

$$\Theta = (\lambda_1, \lambda_2, \lambda_3)$$

• What does the parameter space Θ look like? It's a cube.

Are the parameters identifiable?

- If only one is given, you can tell. For ex if $\lambda_1 = 0$ but not λ_2 or λ_3 , then λ_1 is ident but $\sigma_{23} = \lambda_2 \lambda_3 \neq$ they are not.

λ_1 is identifiable on $\{\Theta \in \Theta : \lambda_1 = 0, \lambda_2 \neq 0, \lambda_3 \neq 0\}$

- Clearly we must examine identifiability at different points, regions of the

Suppose none of the factor loadings = 0

$$\frac{\sigma_{12} \sigma_{13}}{\sigma_{23}} = \frac{\lambda_1 \lambda_2 \lambda_1 \lambda_3}{\lambda_2 \lambda_3} = \lambda_1^2$$

$$\frac{\sigma_{12} \sigma_{23}}{\sigma_{13}} = \lambda_2^2, \quad \frac{\sigma_{13} \sigma_{23}}{\sigma_{12}} = \lambda_3^2$$

The squared factor loadings are identifiable, but not the factor loadings. Look at Σ . Replace λ_j by $-\lambda_j$ for $j=1, 2, 3$ & get the same Σ .

Solution: Decide on the sign of one factor loading (What if Z_1, Z_2, Z_3 are all math tests? Is F math ability or math inability? You decide)

For ex, if $\lambda_1 > 0$, you can tell the signs of λ_2 & λ_3 right away from Σ .

Additional points

- How many equality constraints? Zero
- How many inequality constraints; I say one

$\sigma_{12} \sigma_{13} \sigma_{23} = 0$ These guys are slippery. No, there are more! If $\sigma_{23} \neq 0, \sigma_{12} \sigma_{13} / \sigma_{23}^2 \neq 1$ etc.

- Expect 2 maxima of the likelihood function. Which one you find depends on where you start.

(C)

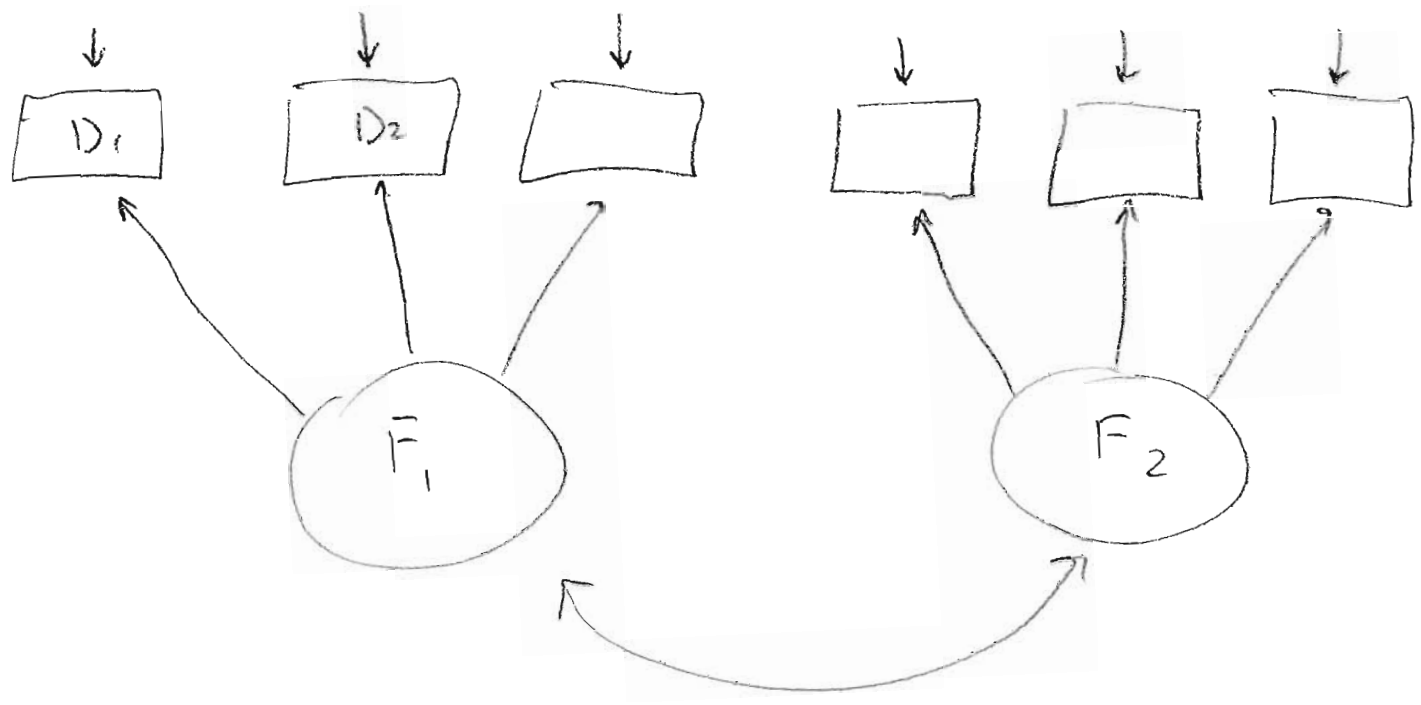
Add another variable: $X_4 = \lambda_4 F + e_4$

$$\Sigma =$$

1	$\lambda_1 \lambda_2$	$\lambda_1 \lambda_3$	$\lambda_1 \lambda_4$
	1	$\lambda_2 \lambda_3$	$\lambda_2 \lambda_4$
		1	$\lambda_3 \lambda_4$
			1

- Parameters will all be identifiable as long as 3 out of 4 loadings are non-zero (and sign of one is known)
- For ex, if $\lambda_1 = 0$, top row = 0 and you can get $\lambda_2 \lambda_3 \lambda_4$ as before
- For 5 vars, two can be zero, etc.
- How many equality restrictions? $6 - 4 = 2$
- Inequality restrictions? It's like an Easter egg hunt.

Now add another Factor



$$D_1 = \lambda_1 F_1 + e_1$$

$$\vdots$$

$$D_6 = \lambda_6 F_2 + e_6$$

$\Sigma =$

	D_1	D_2	D_3	D_4	D_5	D_6
D_1	1	$\lambda_1 \lambda_2$	$\lambda_1 \lambda_3$	$\lambda_1 \lambda_4 \rho_{12}$		
D_2		1	$\lambda_2 \lambda_3$		etc	
D_3			1			
D_4				1	$\lambda_4 \lambda_5$	$\lambda_4 \lambda_6$
D_5					1	$\lambda_5 \lambda_6$
D_6						1

Supposing you know one sign in each set,

- Identify λ_1 from set 1
- Ident λ_2 2
- Solve σ_{12} for ρ_{12}

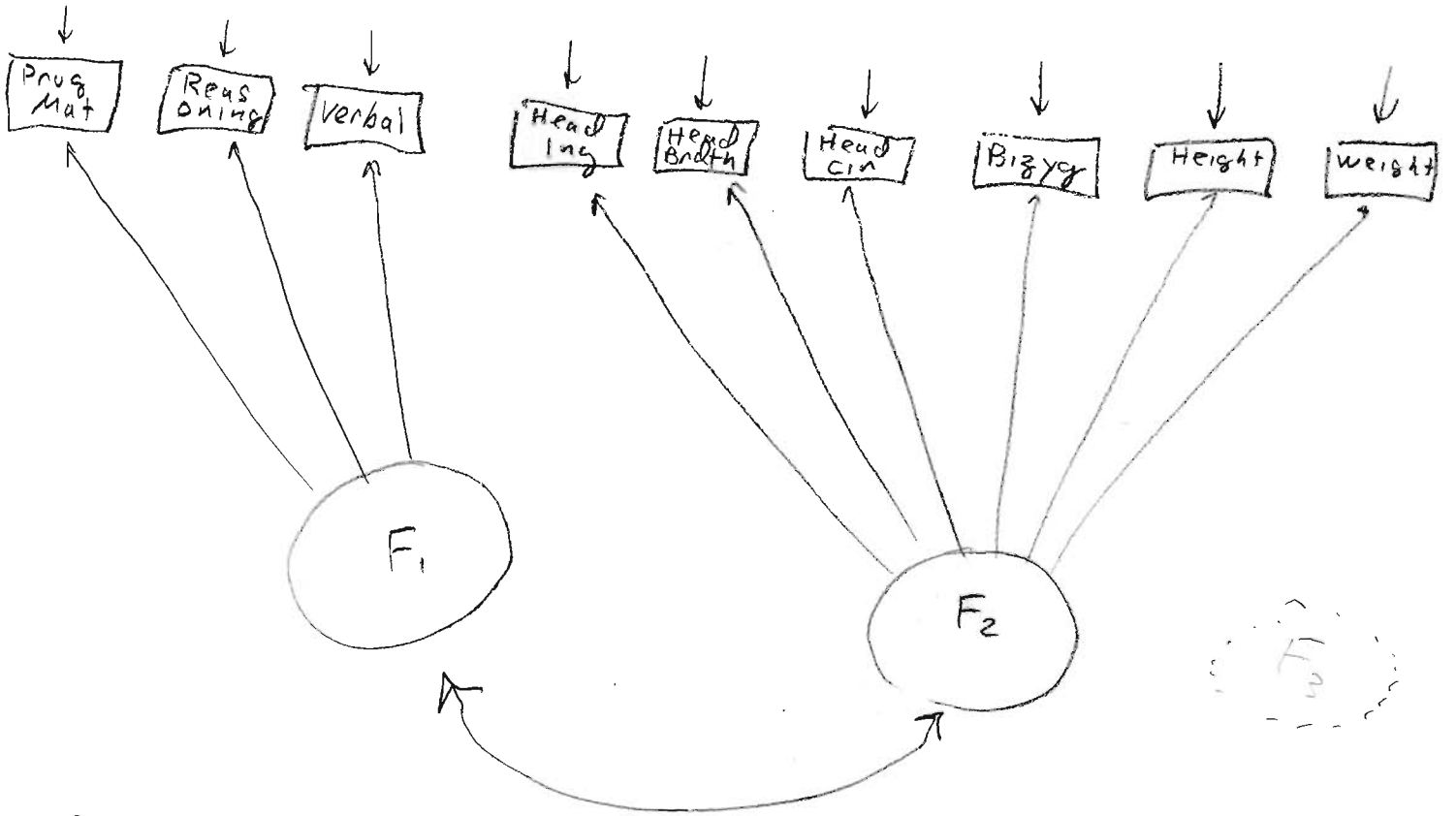
What if you added more vars?
" " " " " Factors?

What if the obs vars were just centered, not standardized?
Rule

For a factor analysis model ~~with standardized~~
~~observed variables (classical)~~ the parameters will
be identifiable if

- Errors are independent of one another & of the factors
- $V(\text{Factors}) = 1$
- Each obs var is a function of only one factor
- There are at least 3 vars with non-zero loadings per factor
- Sign of one non-zero loading per factor is known.

Tried a 2-factor confirmatory FA on the twin data



But it did not fit. Separate factor for height and weight is attractive, but there are only 2 variables

Just 2 variables for two second factor

Both have non-zero factor loadings, and the sign of one is known.

$$D_1 = \lambda_1 F_1 + e_1$$

$$D_2 = \lambda_2 F_1 + e_2$$

$$D_3 = \lambda_3 F_1 + e_3$$

$$D_4 = \lambda_4 F_2 + e_4$$

$$D_5 = \lambda_5 F_2 + e_5$$

$$V(F_1) = V(F_2) = 1$$

$$\text{Cov}(F_1, F_2) = \rho_{12} \neq 0$$

e_1, \dots, e_5 iid & ind of F_1, F_2

Say $\lambda_1 > 0, \lambda_4 > 0$

$\Sigma =$

	1	2	3	4	5
1	✓	λ_1, λ_2	λ_1, λ_3	$\lambda_1, \lambda_4, \rho_{12}$	$\lambda_1, \lambda_5, \rho_{12}$
2		✓	λ_2, λ_3	$\lambda_2, \lambda_4, \rho_{12}$	$\lambda_2, \lambda_5, \rho_{12}$
3			✓	$\lambda_3, \lambda_4, \rho_{12}$	$\lambda_3, \lambda_5, \rho_{12}$
4				✓	λ_4, λ_5
5					✓

$\lambda_1, \lambda_2, \lambda_3$ ident.

$$\frac{\sigma_{24} \sigma_{25}}{\sigma_{45}} = \frac{\lambda_2 \lambda_4 \rho_{12} \lambda_2 \lambda_5 \rho_{12}}{\lambda_4 \lambda_5} = \lambda_2^2 \rho_{12}^2$$

Since λ_2 is identifiable, this means ρ_{12}^2 is ident.

And $\lambda_1 > 0, \lambda_4 > 0$, so sign of $\rho_{12} = \text{sign of } \sigma_{14}$

And ρ_{12} is ident.

Then
$$\frac{\sigma_{45}}{\sigma_{34}} = \frac{\lambda_4 \lambda_5}{\lambda_3 \lambda_4 \rho_{12}} = \frac{\lambda_5}{\lambda_3 \rho_{12}}$$
 Denom is ident, so λ_5 is ident. So λ_4 is ident.

Solving for w_1, \dots, w_5 is easy now.

So we have a two-variables rule (For standardized Factors)

We can add a factor that has only 2 vars provided

- Both loadings are non-zero
- Sign of one loading is known
- Has a non-zero covariance with a factor ~~that~~ with 3 variables.

~~So in the~~

So in the confirmatory factor analysis of the twin data, it is possible to have a 3rd factor for height and weight

Why should we say that factors have variance one? "Because it's arbitrary" but saying it does not make it so. It's a re-parameterization, a semi-arbitrary restriction (reduction of two parameter space) to buy identifiability.

Truth

$$D_1 = \lambda_1 F + e_1$$

$$D_2 = \lambda_2 F + e_2$$

$$D_3 = \lambda_3 F + e_3$$

$$D_4 = \lambda_4 F + e_4$$

F, e_1, \dots, e_4 ind

$$V(e_i) = \omega_i$$

$$V(F) = \sigma^2$$

$\Sigma =$

$\lambda_1^2 \sigma^2 + \omega_1$	$\lambda_1 \lambda_2 \sigma^2$		
			$\lambda_4^2 \sigma^2 + \omega_4$

10 eq, in 9 unknowns, $\theta = (\sigma^2, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \omega_1, \dots, \omega_4)$

Passes the test of the counting rule

But

(j)

	ϕ	λ_1	λ_2	λ_3	λ_4	w_1	w_2	w_3	w_4
Θ_1	ϕ	λ_1	λ_2	λ_3	λ_4	w_1	w_2	w_3	w_4
Θ_2	1	$\lambda_1 \phi^{\frac{1}{2}}$	$\lambda_2 \phi^{\frac{1}{2}}$	$\lambda_3 \phi^{\frac{1}{2}}$	$\lambda_4 \phi^{\frac{1}{2}}$	w_1	w_2	w_3	w_4

Yield the same covariance matrix

That's two Θ s yielding the same Σ , but there are ∞ many. Set $c > 0$

ϕ	λ_1	λ_2	λ_3	λ_4	w_1	w_2	w_3	w_4
c^2	$\frac{\lambda_1}{c}$	$\frac{\lambda_2}{c}$	$\frac{\lambda_3}{c}$	$\frac{\lambda_4}{c}$	w_1	w_2	w_3	w_4

ALL Yield

$\Sigma =$

$\lambda_1^2 + w_1$	$\lambda_1 \lambda_2$	etc	
	$\lambda_2^2 + w_2$		
		$\lambda_3^2 + w_3$	
			$\lambda_4^2 + w_4$

The choice $\phi = 1$ just sets $c = 1$: Convenient

You should be concerned!

Because the value of c is arbitrary except for $c > 0$, it would seem that the factor loadings could be anything. But it's not as bad as that

- Because $c > 0$, you can tell the ^{two} signs $+ - 0$ of the factor loadings (if you know one of them) with the arbitrary choice $\phi = 1$
- Same will be true of the σ_{ij} covariances
- Hypothesis testing is still on, but "estimation" is just a technical device

Testing the model

- Note that all the equality constraints must involve the covariances σ_{ij} $i \neq j$
- In the true model, they are all multiplied by the same ^{nonzero} constant.
- So the equality constraints of the true model and the pretend model with $\phi = 1$ are the SAME.
- χ^2 test for goodness of fit applies to the true model. A great relief!