

Matching Criterion for Identifiability in Sparse Factor Analysis

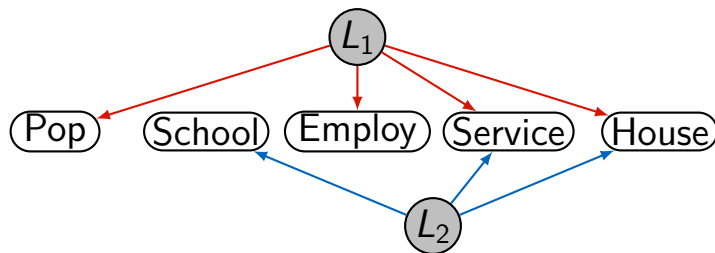
Nils Sturma

Institute of Mathematics

EPFL

(joint work with Mathias Drton, Miriam Kranzlmüller, Irem Portakal)

Socio-Economic Example from Harmann (1976), Modern Factor Analysis



Linear structural equations:

$$X_1 = \lambda_{10} + \lambda_{11}L_1 + \varepsilon_1,$$

$$X_2 = \lambda_{20} + \lambda_{22}L_2 + \varepsilon_2,$$

$$X_3 = \lambda_{30} + \lambda_{31}L_1 + \varepsilon_3,$$

$$X_4 = \lambda_{40} + \lambda_{41}L_1 + \lambda_{42}L_2 + \varepsilon_4.$$

$$X_5 = \lambda_{50} + \lambda_{51}L_1 + \lambda_{52}L_2 + \varepsilon_5.$$

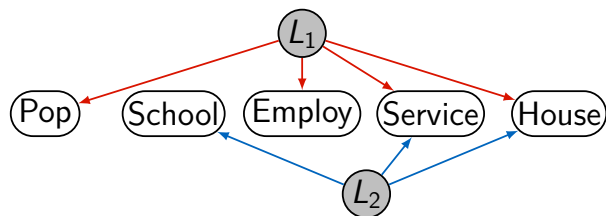
Jointly independent

errors: $\varepsilon_1, \dots, \varepsilon_5$.

$$\text{Var}[\varepsilon_v] = \omega_{vv} < \infty, \text{Var}[L_i] = 1.$$

Topic: Can we recover the “factor loadings” $\lambda_{v1}, \lambda_{v2}$ and the “error variances” ω_{vv} from $\Sigma = \text{Var}[X]$?

Example: Identifiability of Factor Loadings



$$X = \Lambda L + \varepsilon, \quad \text{where } \Lambda = \begin{pmatrix} \lambda_{11} & 0 \\ 0 & \lambda_{22} \\ \lambda_{31} & 0 \\ \lambda_{41} & \lambda_{42} \\ \lambda_{51} & \lambda_{52} \end{pmatrix}.$$

Observed covariance matrix:

$$\Sigma = \Lambda \Lambda^\top + \Omega = \begin{pmatrix} \omega_{11} + \lambda_{11}^2 & 0 & \boxed{\lambda_{11}\lambda_{31}} & \boxed{\lambda_{11}\lambda_{41}} & \lambda_{11}\lambda_{51} \\ 0 & \omega_{22} + \lambda_{22}^2 & 0 & \lambda_{22}\lambda_{42} & \lambda_{22}\lambda_{52} \\ \lambda_{11}\lambda_{31} & 0 & \omega_{33} + \lambda_{31}^2 & \boxed{\lambda_{31}\lambda_{41}} & \lambda_{31}\lambda_{51} \\ \lambda_{11}\lambda_{41} & \lambda_{22}\lambda_{42} & \lambda_{31}\lambda_{41} & \omega_{44} + \lambda_{41}^2 + \lambda_{42}^2 & \lambda_{41}\lambda_{51} + \lambda_{42}\lambda_{52} \\ \lambda_{11}\lambda_{51} & \lambda_{22}\lambda_{52} & \lambda_{31}\lambda_{51} & \lambda_{41}\lambda_{51} + \lambda_{42}\lambda_{52} & \omega_{55} + \lambda_{51}^2 + \lambda_{52}^2 \end{pmatrix}.$$

We see that

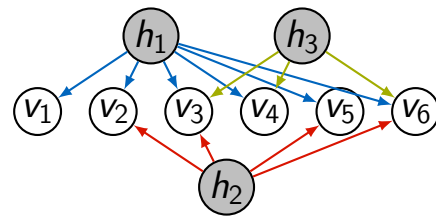
$$\begin{aligned} 1) \quad & \sqrt{\frac{\sigma_{13}\sigma_{14}}{\sigma_{34}}} = \sqrt{\frac{\lambda_{11}\lambda_{31}\lambda_{11}\lambda_{41}}{\lambda_{31}\lambda_{41}}} = \sqrt{\lambda_{11}^2} = a_1\lambda_{11} \quad \text{with } a_1 \in \{\pm 1\} \text{ and } \sigma_{34} = \lambda_{31}\lambda_{41} \neq 0 \text{ 'almost surely'}, \\ 2) \quad & \frac{\sigma_{13}}{\sqrt{\sigma_{13}\sigma_{14}/\sigma_{34}}} = \frac{\lambda_{11}\lambda_{31}}{a_1\lambda_{11}} = a_1\lambda_{31} \quad \text{with } \lambda_{11} \neq 0 \text{ 'almost surely'}. \end{aligned}$$

$\implies$ Can identify $\Lambda_{\text{ch}(L_1), L_1}$ up to column-sign, similarly $\Lambda_{\text{ch}(L_2), L_2}$.

Identifiability of Factor Loadings

Setup

- $X = (X_v)_{v \in V}$ observed and $L = (L_h)_{h \in \mathcal{H}}$ latent variables.
- **Bipartite** Graph $G = (V \dot{\cup} \mathcal{H}, D)$ with $D \subseteq \mathcal{H} \times V$.
- Model: $X = \Lambda L + \varepsilon$ with Λ **sparse** according to G .



Identifiability Problem

Given a graph G and the covariance matrix $\Sigma = \Lambda \Lambda^\top + \Omega$, can we solve for Λ ? Up to column-sign?

Main Contributions

- **Necessary** conditions: Algebraic Sparse Factor Analysis [SIAGA, 2025].
- **Sufficient** condition: Matching Criterion for Identifiability in Sparse Factor Analysis [arXiv:2502.02986].

Combinatorial condition based on graph structure, efficient algorithm.

Key Idea

Determinantal approach: Fix $v \in V$. Find disjoint $U, W \subseteq V \setminus \{v\}$ with $|W| = |U|$ and ensure that

$$\det([\Lambda\Lambda^\top]_{U,W}) \neq 0 \quad \text{and that} \quad \det([\Lambda\Lambda^\top]_{\{v\} \cup U, \{v\} \cup W}) = 0.$$

Solve for $[\Lambda\Lambda^\top]_{vv}$: Observe that

$$[\Lambda\Lambda^\top]_{\{v\} \cup U, \{v\} \cup W} = \left(\begin{array}{c|c} [\Lambda\Lambda^\top]_{vv} & [\Lambda\Lambda^\top]_{v,W} \\ \hline [\Lambda\Lambda^\top]_{U,v} & [\Lambda\Lambda^\top]_{W,U} \end{array} \right) = \left(\begin{array}{c|c} [\Lambda\Lambda^\top]_{vv} & \Sigma_{v,W} \\ \hline \Sigma_{U,v} & \Sigma_{U,W} \end{array} \right).$$

It follows by Laplace expansion:

$$0 = \det([\Lambda\Lambda^\top]_{\{v\} \cup U, \{v\} \cup W}) = [\Lambda\Lambda^\top]_{vv} \underbrace{\det(\Sigma_{U,W})}_{\neq 0} - \sum_{w \in W} \text{sign}(w) \sigma_{vw} \det(\Sigma_{U, \{v\} \cup W \setminus \{w\}}).$$

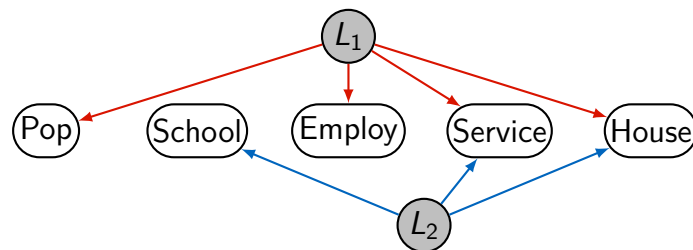
Solve column-wise: If $[\Lambda\Lambda^\top]_{vv} = (\Lambda_{v,h})^2$, then we recovered $\Lambda_{v,h}$ up to sign ... other entries “easy”.

Need characterization: When is $\det([\Lambda\Lambda^\top]_{A,B}) = 0$ if Λ is sparse?

$\rightsquigarrow$ “Intersection-free matchings.”

Our Software

```
# Define graph
> L = matrix(c(1, 0,
+             0, 1,
+             1, 0,
+             1, 1,
+             1, 1), 5, 2, byrow=TRUE)
> g = FactorGraph(L)
>
> # Check identifiability
> res = mID(g)
Generic Sign-Identifiability Summary
# nr. of latent nodes that are gen. sign-identifiable: 2
# gen. sign-identifiable nodes: 1, 2
```



Available at <https://github.com/MiriamKranzlmueeller/id-factor-analysis>.