MUNI
FSS

The nets meet the latent trait.

Introduction to Network Analysis, L4

Edita Chvojková

edita.chvojkova@mail.muni.cz

psychometrics

Universiteit van Amsterdam

PRE-CHRISTMAS NETWORK GATHERING

DECEMBER 9, 4 PM
FSS U35/ONLINE

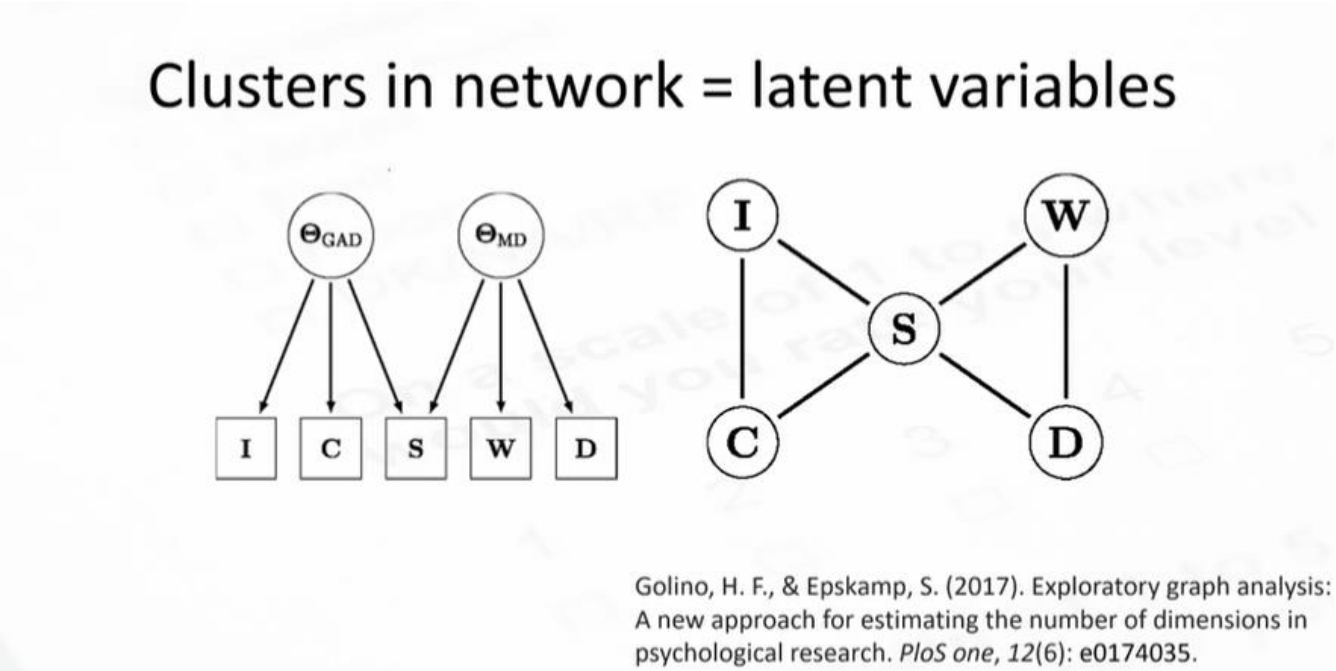
The students of the Introduction to network analysis class will present their final projects. You can look forward to interesting network insights to:

- left vs. right-wing radicalization
- development of the Generalized Anxiety Disorder
- the structure of attachment

Streaming at
https://meet.google.com/isq-ncyi-cbj

Networks and latent variables

- psychology data – the model must be good at allowing everything to correlate – **that's why the factor model works so well**
- latent variable model is equivalent to a network model, **where every cluster is defined by a latent variable**



Current trends in *psychonetrics:*

- networks and LVM are (near) equivalent
- Golino & Epskamp (part 2)
- pseudo EFA approach – better results than EFA – why?
- even when a factor model fits, the data didn't need to be generated under a factor-model structure
- for that, we need a different type of research

SEM

- latent variables – measurement error
- fit indices
- modification indices
- robust estimators
- multi-group – invariance
- FIML for missing data

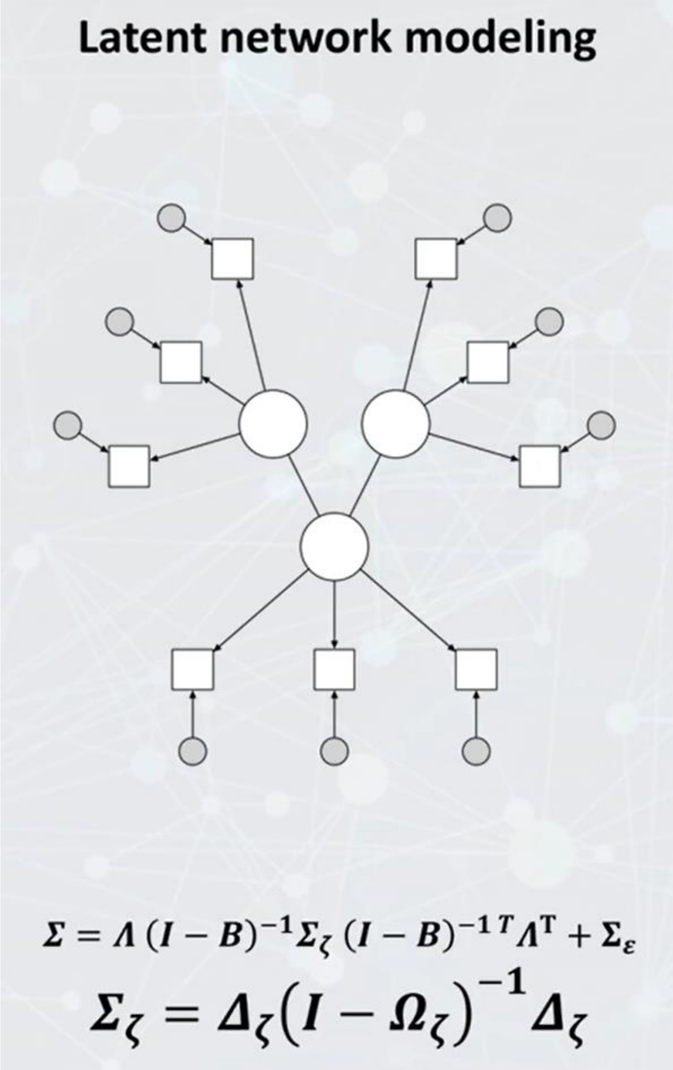
- *BUT! Restrictive*
- *BUT! acyclicity assumption*

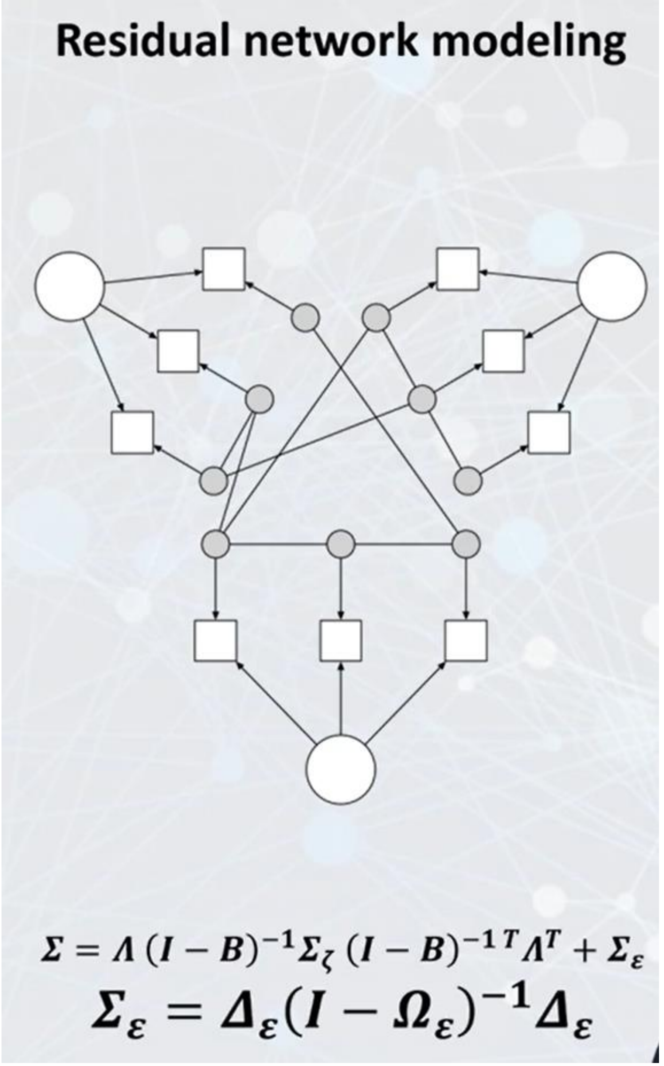
network analysis - GGM

- uniquely identified
- strong exploration component – careful about that
- no acyclicity assumption
- often "sparse" models

- *BUT! no measurement error*
- *BUT! no fit indices*
- *group comparison limited*
- *exploration too wild*
- *poor handling of missing data*

Latentní a reziduální network modely

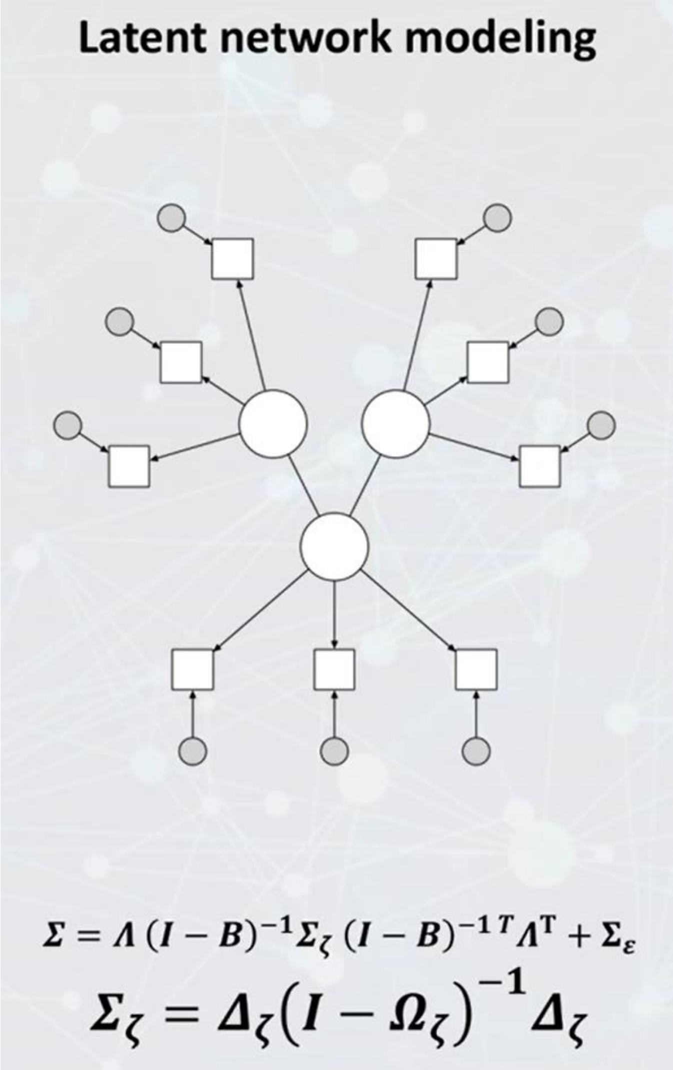


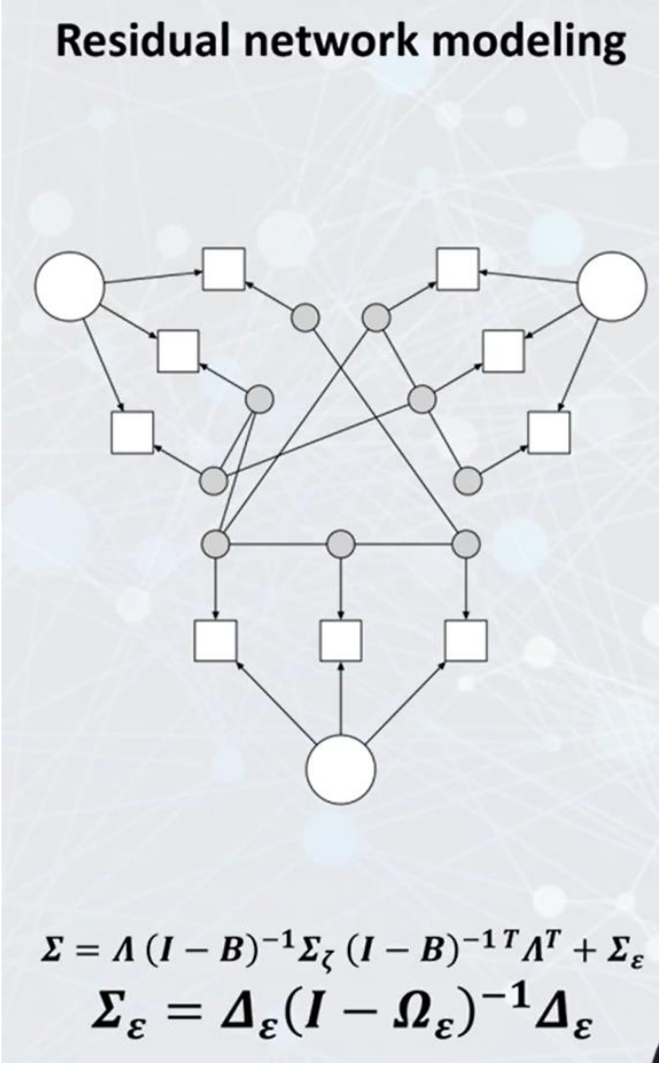


The *psychonetrics* package

- Sacha claims, that it is similar to *lavaan*
- but the model definition is stagerringly different
- first we plug in matrices that via matrix multiplication allow us to create $\boldsymbol{\Sigma}$
- these matrices are arguments for the estimation function
- *ggm* – maximum likelihood exploratory model search

Latentní a reziduální network modely





But what is it good for?

But what is it good for?

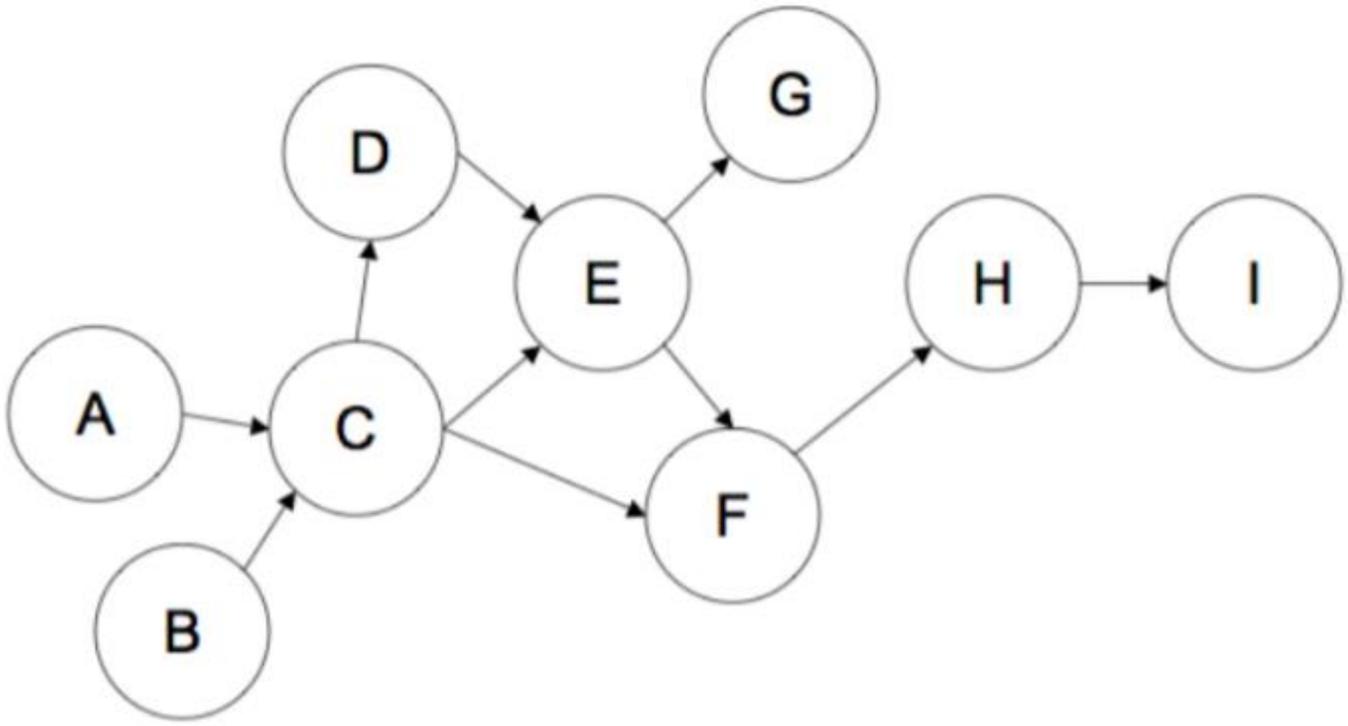
With SEM, I can test causality!

But what is it good for?

With SEM, I can test causality!

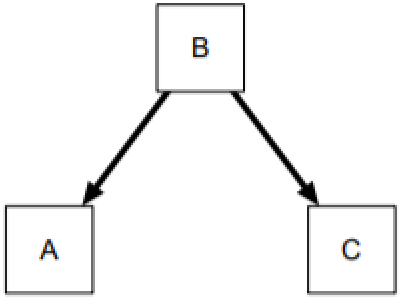
Can you?

SEM & Dags



Causal patterns as identified by Pearl

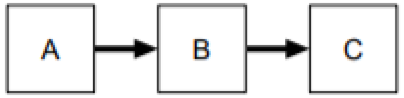
Common Cause



Example: Disease (B) causes two symptoms (A and C).

$$A \not\!\perp\!\!\!\perp C$$
$$A \perp\!\!\!\perp C \mid B$$

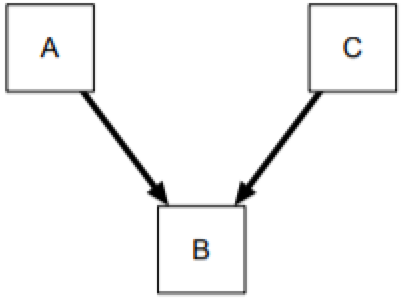
Chain



Example: Insomnia (A) causes fatigue (B), which in turn causes concentration problems (C)

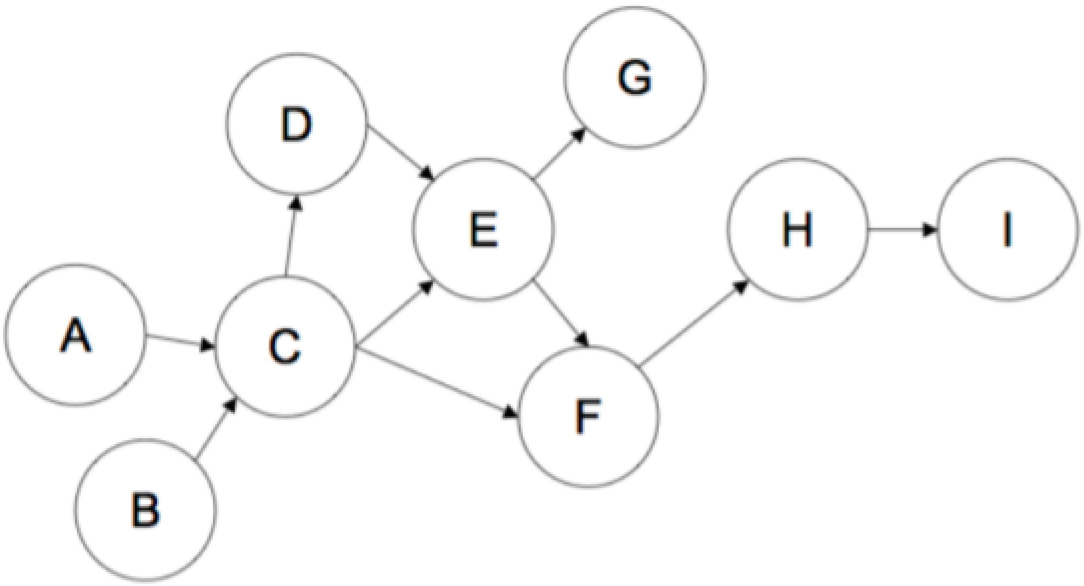
$$A \not\!\perp\!\!\!\perp C$$
$$A \perp\!\!\!\perp C \mid B$$

Collider



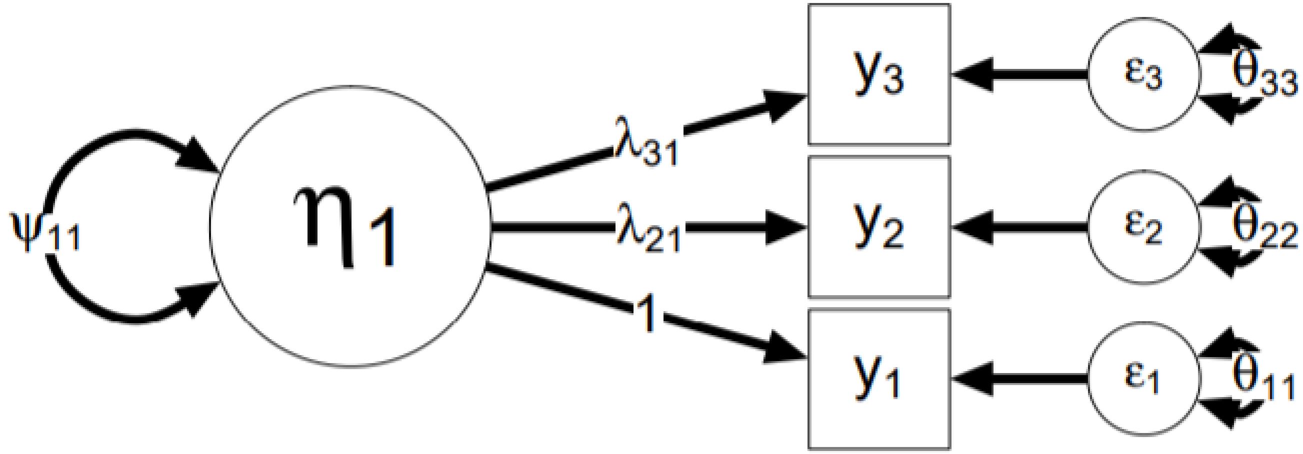
Example: Difficulty of class (A) and motivation of student (C) cause grade on a test (B)

$$A \perp\!\!\!\perp C$$
$$A \not\!\perp\!\!\!\perp C \mid B$$



- $A \perp\!\!\!\perp B$
- $A \perp\!\!\!\perp D \mid C$
- $B \perp\!\!\!\perp G \mid C, E$
- ...

Testing this causal model involves testing if all these conditional independence relations hold



$$y_1 \perp\!\!\!\perp y_2 \mid \eta_1$$

Local independence

The issue of equivalent models

However, if this model fits:

- $A \rightarrow B \rightarrow C$

Then so do these:

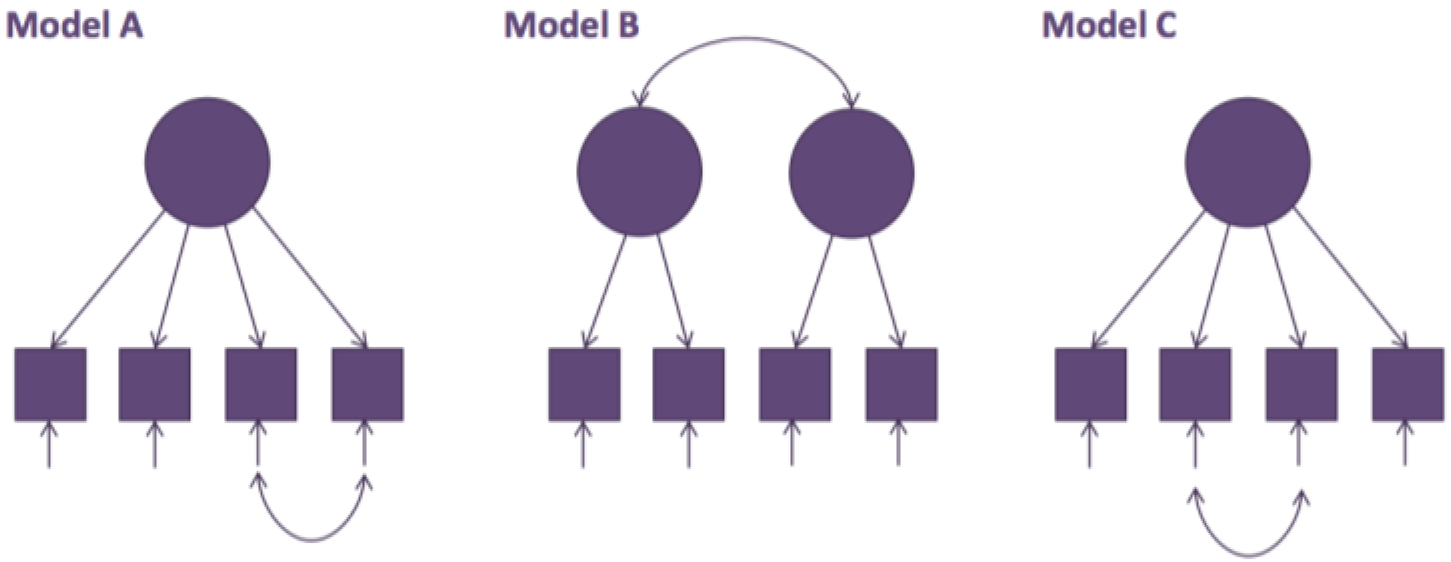
- $A \leftarrow B \rightarrow C$
- $A \leftarrow B \leftarrow C$

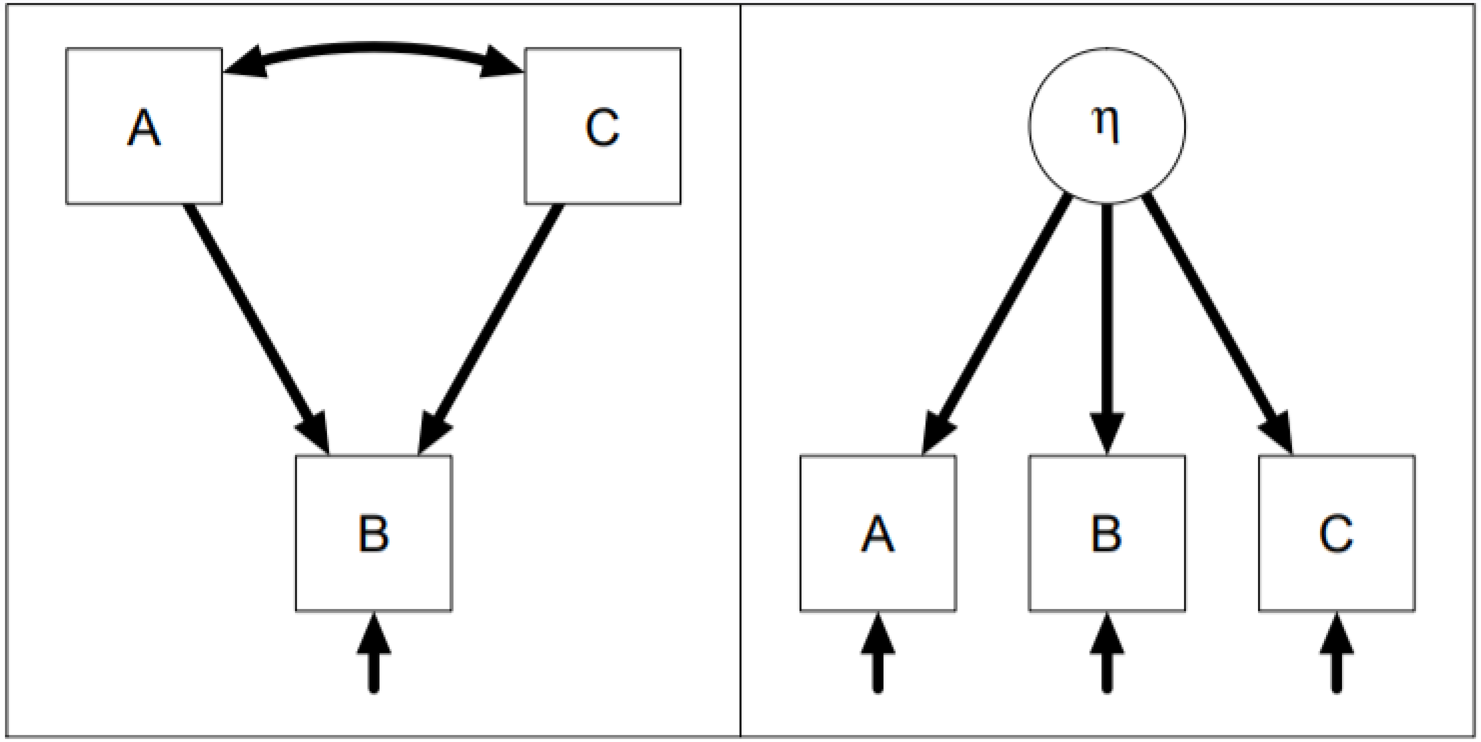
Because these models imply the **same conditional independence** relationships and are therefore **equivalent**.

The issue of equivalent models

Two models, with the same (observed/latent) variables are equivalent if:

- The models imply **exactly the same conditional independence relationships**
- The models **fit exactly equally well** on all datasets
- The models have **the same number of degrees of freedom**
- Equivalent models **can not be distinguished in statistical ways**
- **All identified saturated models are equivalent!**
- Adding more latent variables can lead to an infinite number of equivalent models


Model A
Model B
Model C



Equivalent models or not?

Determinants of Radicalization of Islamic Youth in the Netherlands: Personal Uncertainty, Perceived Injustice, and Perceived Group Threat

Bertjan Doosje*
University of Amsterdam

Annemarie Loseman and Kees van den Bos
Utrecht University

In this study among Dutch Muslim youth ($N = 131$), we focus on the process of radicalization. We hypothesize that this process is driven by three main factors: (a) personal uncertainty, (b) perceived injustice, and (c) perceived group threat. Using structural equation modeling, we demonstrate that personal uncertainty, perceived injustice, and group-threat factors are important determinants of a radical belief system (e.g., perceived superiority of Muslims, perceived illegitimacy of Dutch authorities, perceived distance to others, and a feeling of being disconnected from society). This radical belief system in turn predicts attitudes toward violence by other Muslims, which is a determinant of own violent intentions. Results are discussed in terms of the role of individual and group-based determinants of radicalization.

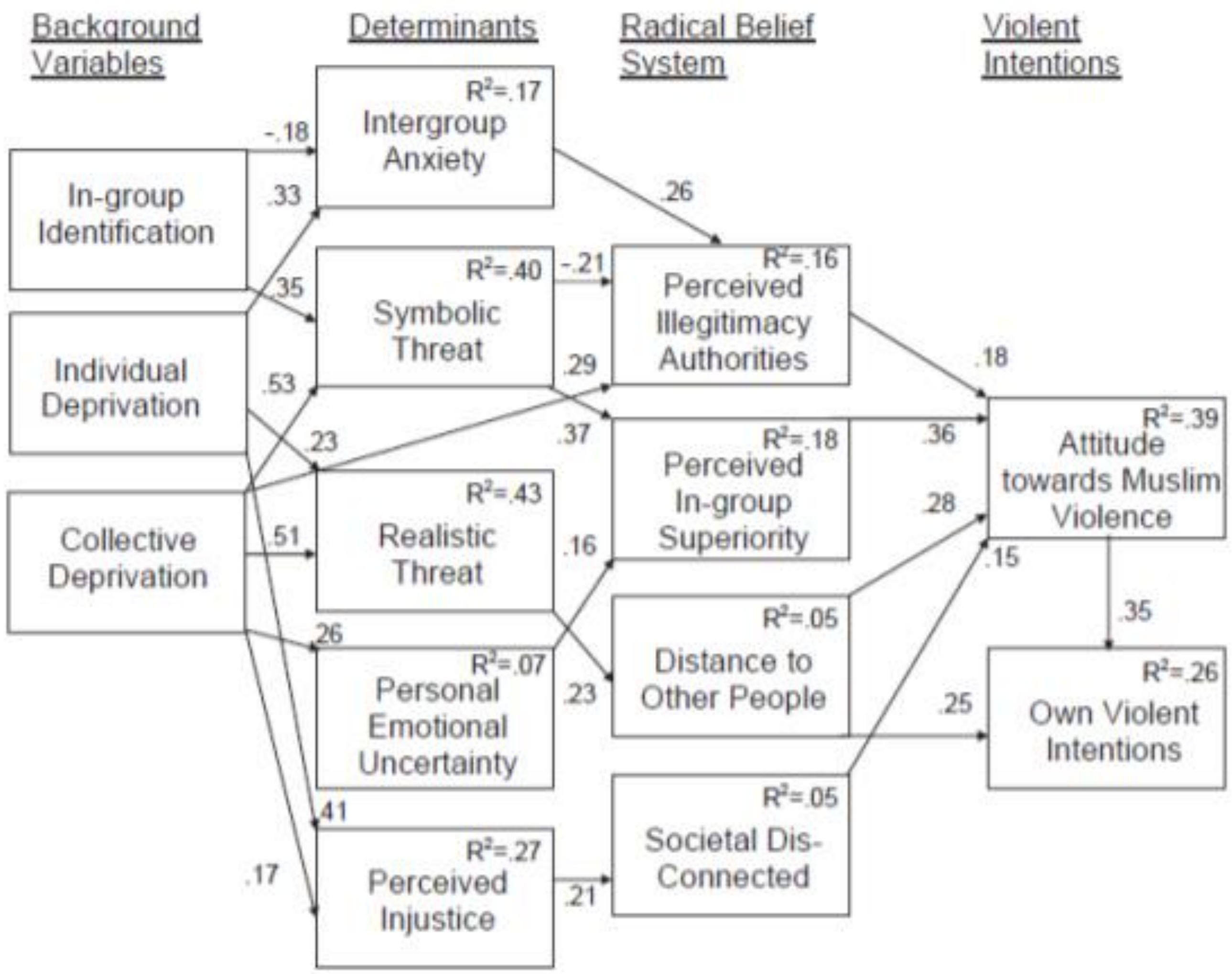
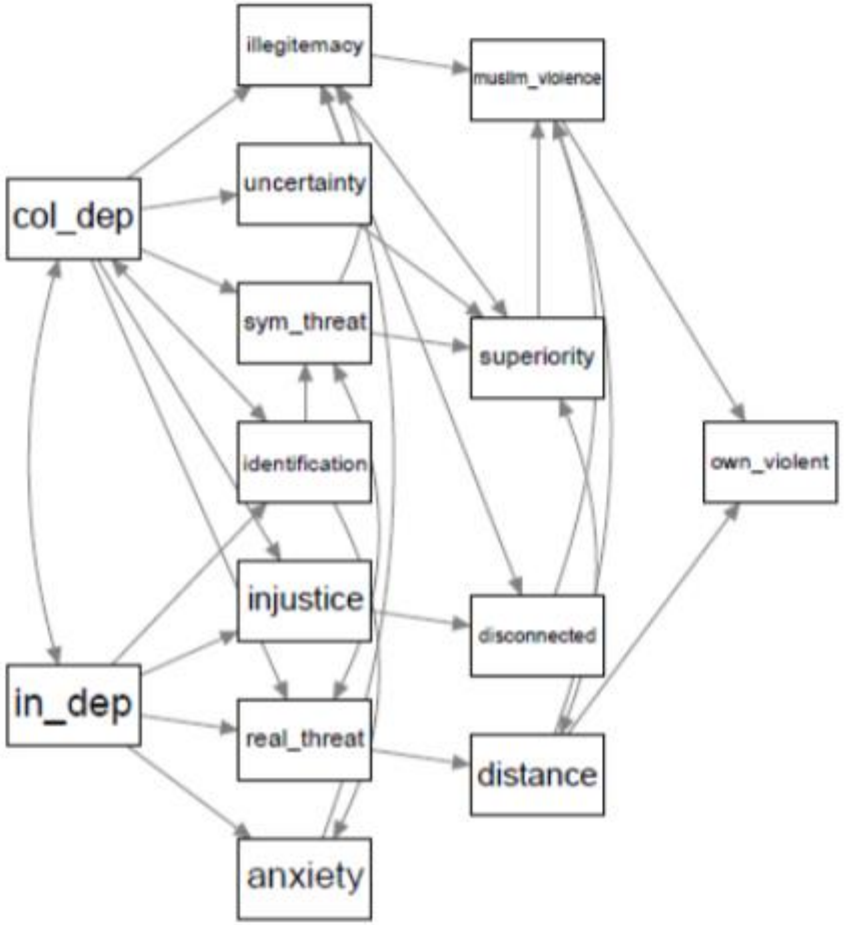
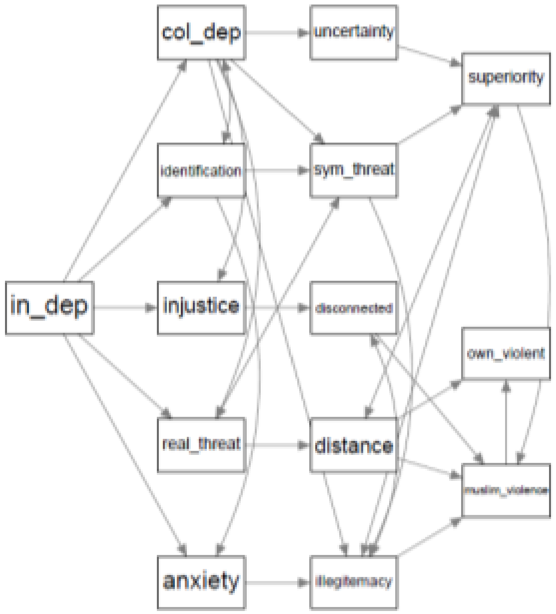
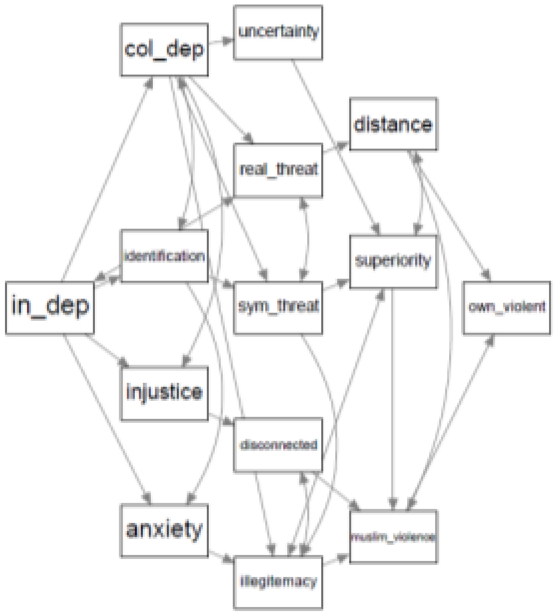
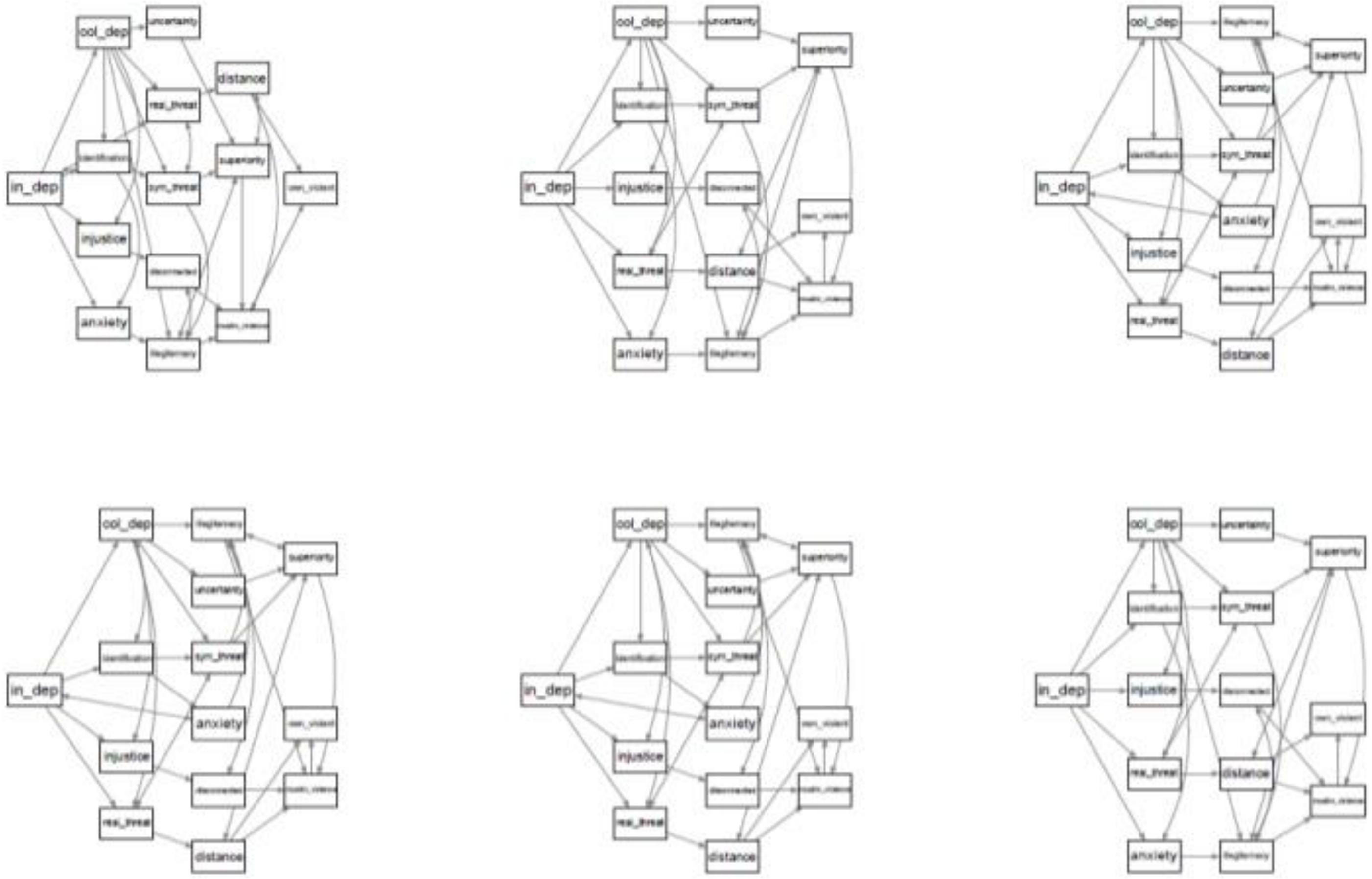


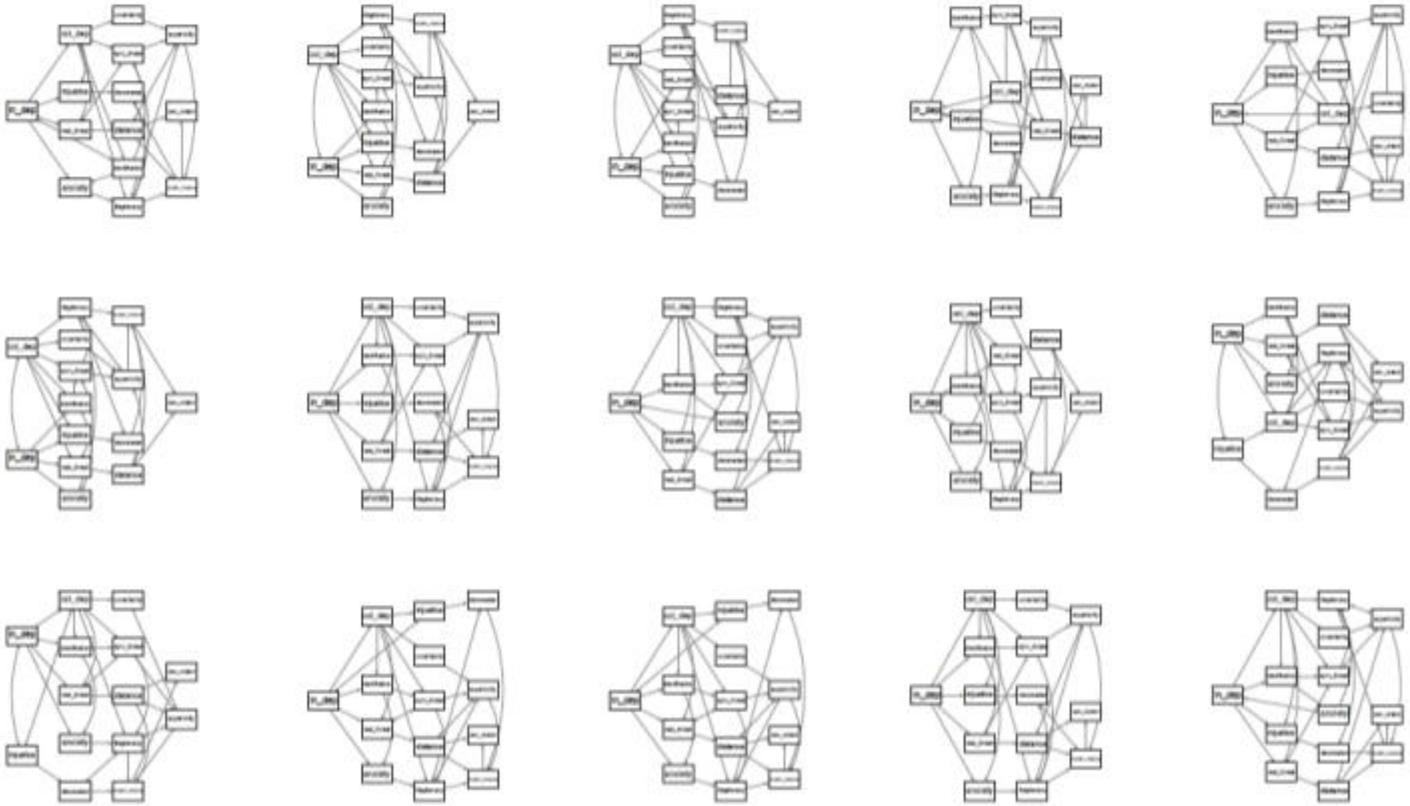
Fig. 1. Final structural equation model. All paths are significant. R^2 = % variance explained.

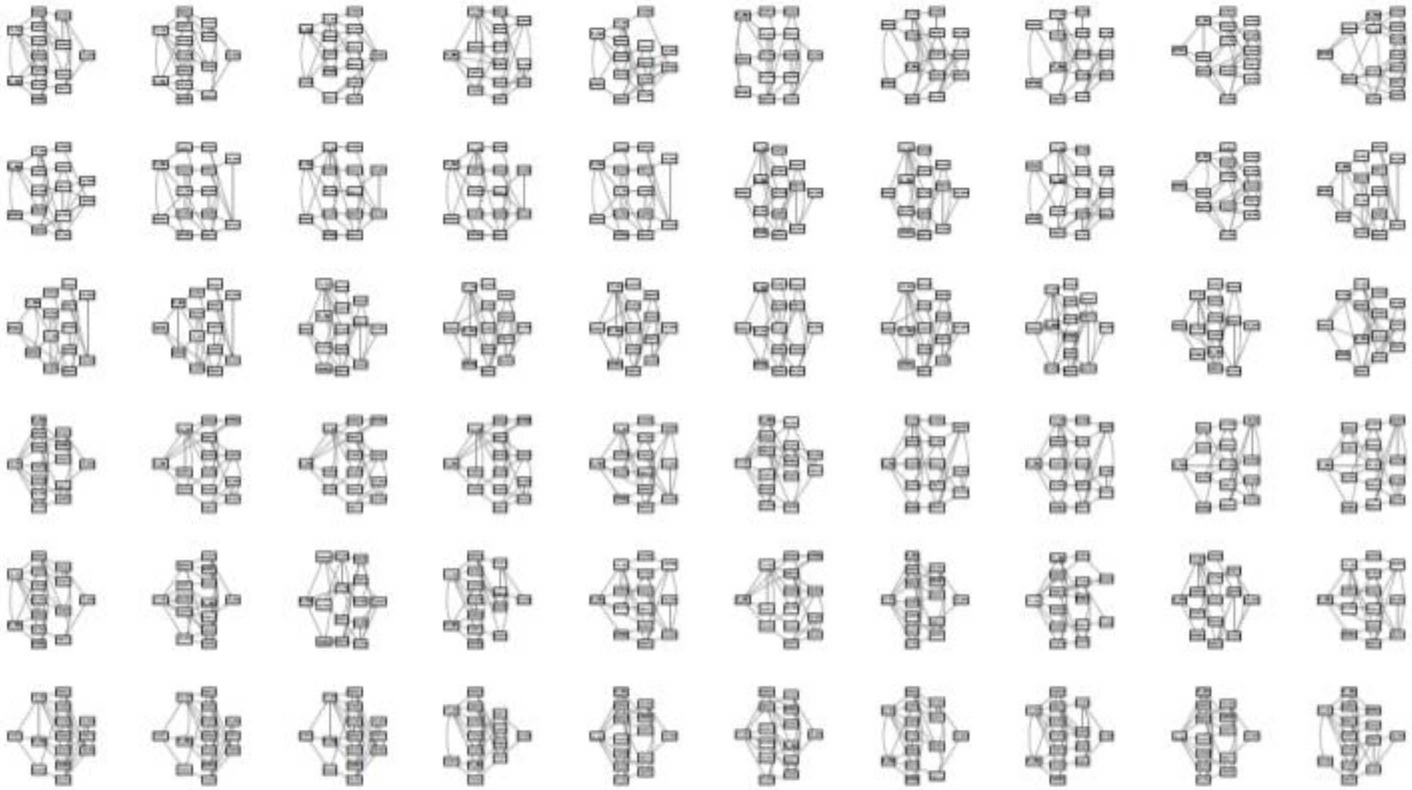

illegitemacy
muslim_violence
col_dep
uncertainty
sym_threat
superiority
identification
own_violent
injustice
disconnected
in_dep
real_threat
distance
anxiety

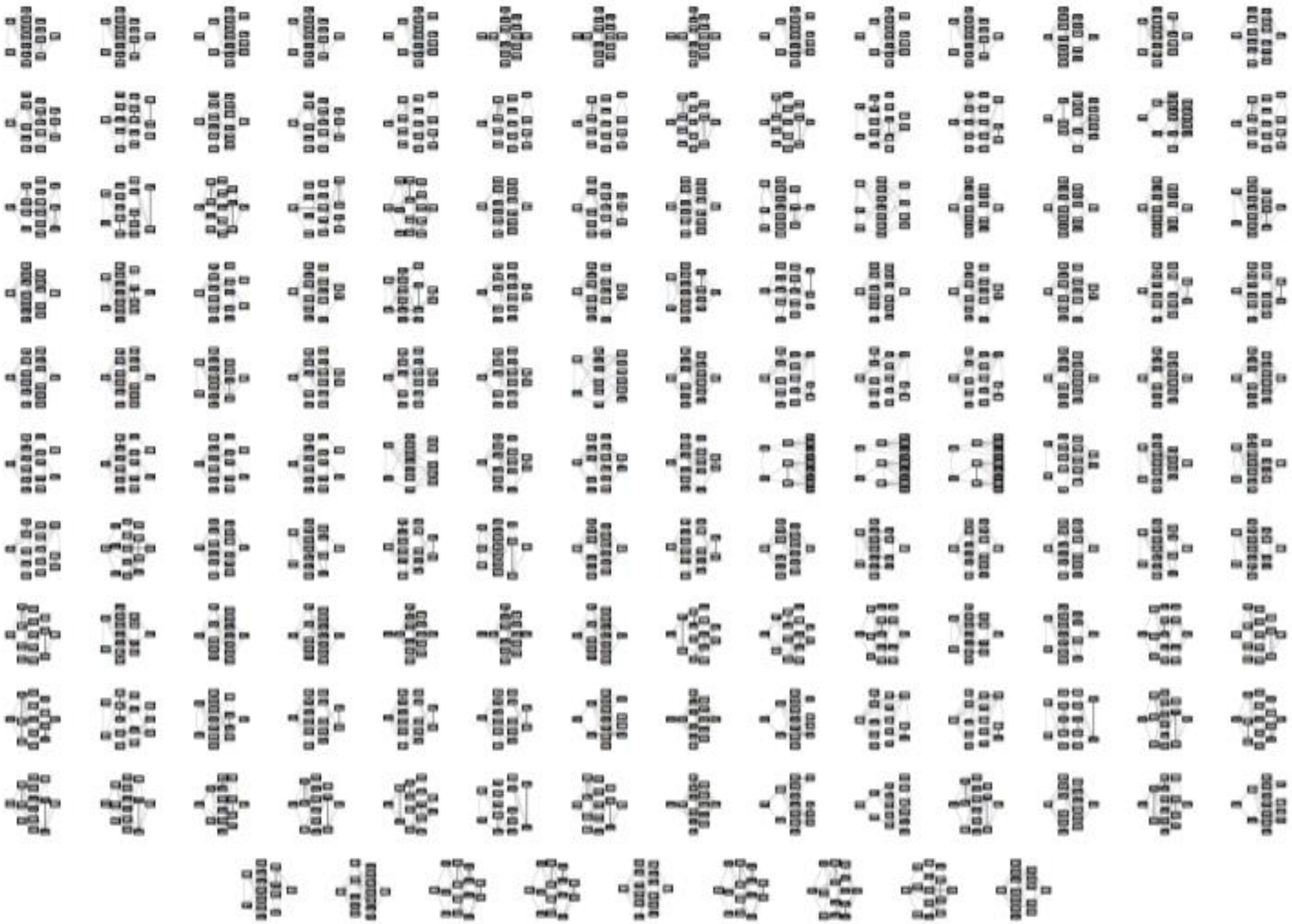

col_dep
uncertainty
superiority
identification
sym_threat
in_dep
injustice
disconnected
own_violent
real_threat
distance
muslim_violence
anxiety
illegitemacy


col_dep
uncertainty
distance
real_threat
identification
superiority
in_dep
sym_threat
own_violent
injustice
disconnected
anxiety
muslim_violence
illegitemacy


col_dep
uncertainty
distance
real_threat
identification
superiority
in_dep
sym_threat
injustice
disconnected
anxiety
illegitimacy
own_violent







Causal models imply a set of conditional independence relationships that can be tested…

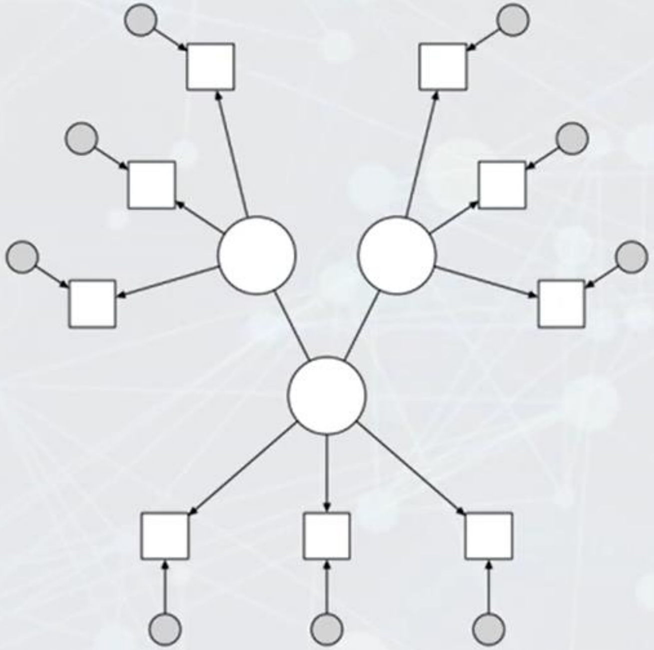
SEM

- a powerful technique to test such a causal model in one step
- many equivalent models can fit the data equally well
- be careful in explorative model modification!
- near saturated models do not "prove" a causal theory!

GGM

- the poor identification of directed graphical models led recent researchers (e.g. Sacha Epskamp) to use undirected graphical models instead
- A – B – C indicates $A \perp\!\!\!\perp C \mid B$ without troublesome causal interpretation and equivalent models

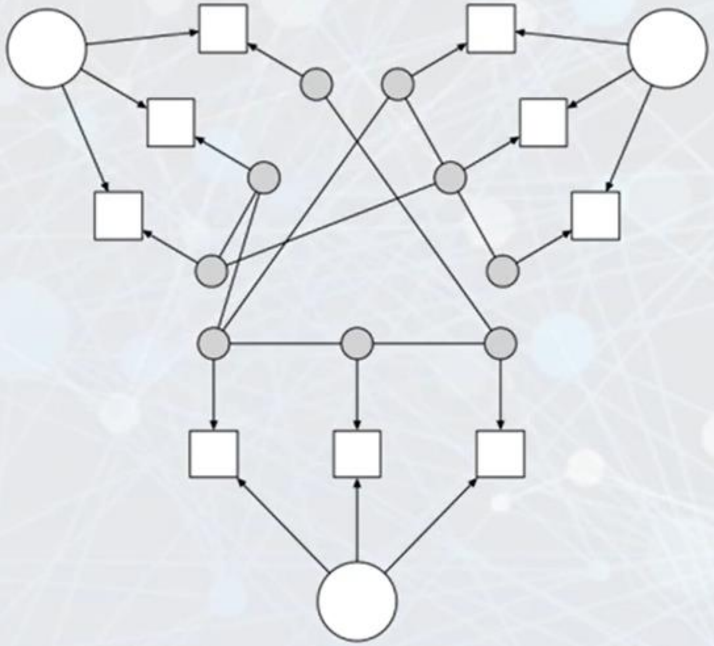
Latent network modeling



$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}\,(\boldsymbol{I} - \boldsymbol{B})^{-1}\boldsymbol{\Sigma}_{\zeta}\,(\boldsymbol{I} - \boldsymbol{B})^{-1\,T}\boldsymbol{\Lambda}^{\mathrm{T}} + \boldsymbol{\Sigma}_{\varepsilon}$$

$$\boldsymbol{\Sigma}_{\zeta} = \boldsymbol{\Delta}_{\zeta}\left(\boldsymbol{I} - \boldsymbol{\Omega}_{\zeta}\right)^{-1}\boldsymbol{\Delta}_{\zeta}$$

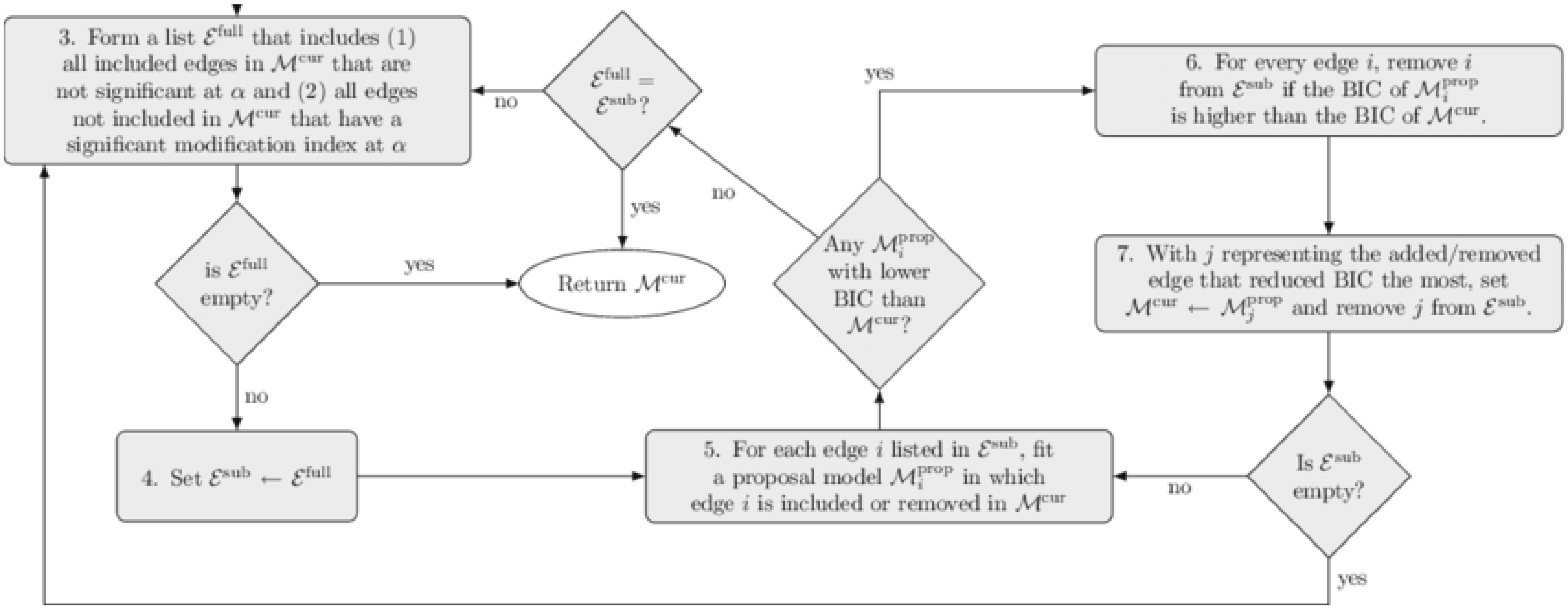
Residual network modeling



$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}\,(\boldsymbol{I} - \boldsymbol{B})^{-1}\boldsymbol{\Sigma}_{\zeta}\,(\boldsymbol{I} - \boldsymbol{B})^{-1\,T}\boldsymbol{\Lambda}^{T} + \boldsymbol{\Sigma}_{\varepsilon}$$

$$\boldsymbol{\Sigma}_{\varepsilon} = \boldsymbol{\Delta}_{\varepsilon}(\boldsymbol{I} - \boldsymbol{\Omega}_{\varepsilon})^{-1}\boldsymbol{\Delta}_{\varepsilon}$$

Exploratory model search - *psychonetrics*



Estimating the dimensionality of intelligence like data using Exploratory Graph Analysis

Hudson F. Golino [a], Andreas Demetriou [b,*]

[a] Universidade Salgado de Oliveira, Brazil
[b] University of Nicosia, Cyprus

ABSTRACT

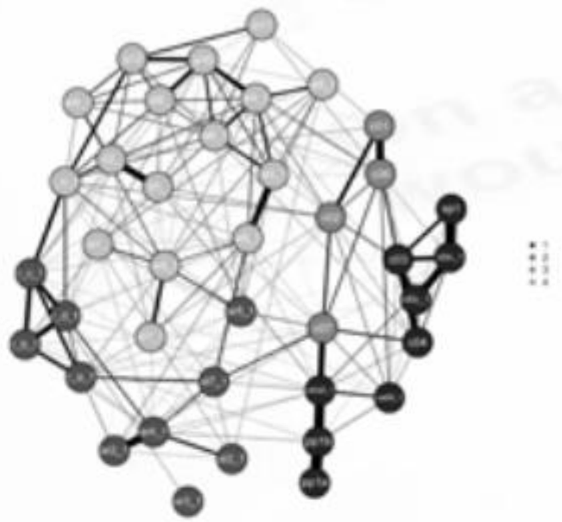
This study compared various exploratory and confirmatory factor methods for recovering factors of cognit test-like data. We first note the problems encountered by several widely used methods, such as parallel analy minimum average partial procedure, and confirmatory factor analysis, in estimating the number of dimensio underlying performance on test batteries. We then argue that a new method, Exploratory Graph Analy (EGA), can more accurately uncover underlying dimensions or factors and demonstrate how this method outp forms the other methods. We use several published data sets to demonstrate the advantages of EGA. We concl that a combination of EGA and confirmatory factor analysis or structural equation modeling may be the ideal precisely specifying latent factors and their relations.

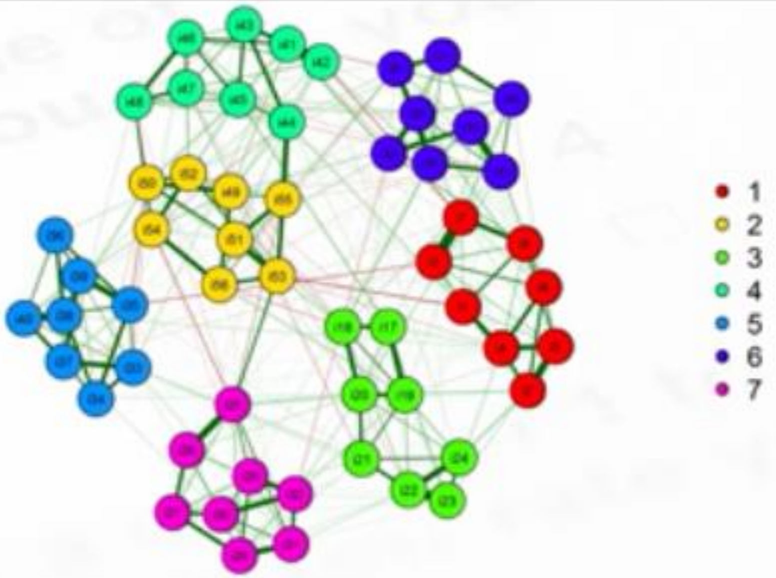
Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research

Hudson F. Golino[1,2*], Sacha Epskamp[3]

1 Department of Psychology, University of Virginia, Charlottesville, VA, United States of America, 2 Graduate School of Psychology, Universidade Salgado de Oliveira, Rio de Janeiro, Brasil, 3 University of Amsterdam, Amsterdam, Netherlands

* hfgolino@gmail.com





But what is it good for?

But what is it good for?

With FA, I can get the factor scores!

But what is it good for?

With FA, I can get the factor scores!

Do you need them?

Implications

- network loadings – node strength used formerly, but replaced
- relatively (agnostic) to the data generating model
- although **if a latent variable underlies the data, we can expect firm clustering**
- to the best fitting network model – there is an equivalent latent variable model
- the network architecture can help the psychometric craft via item selection, measurement invariance, "factor" scores

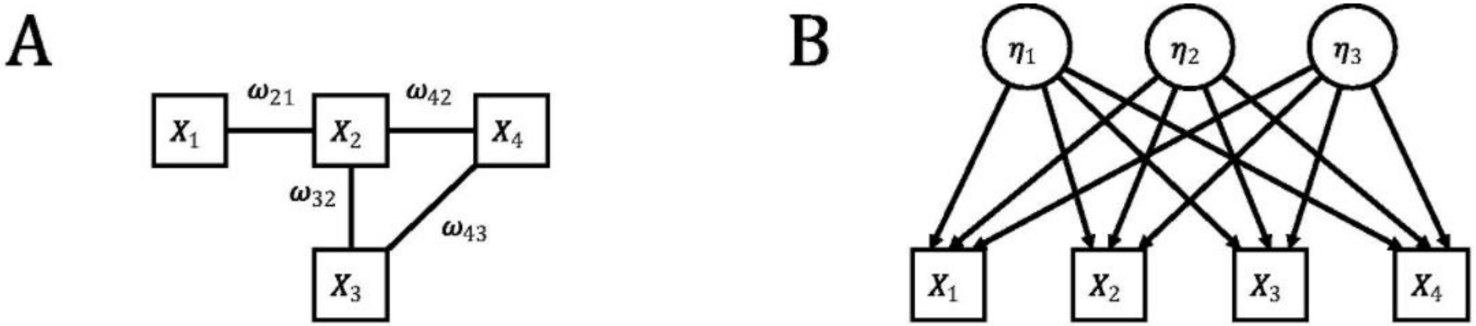
How do I know whether I am dealing with a factor, or a network model? Promising new developments.

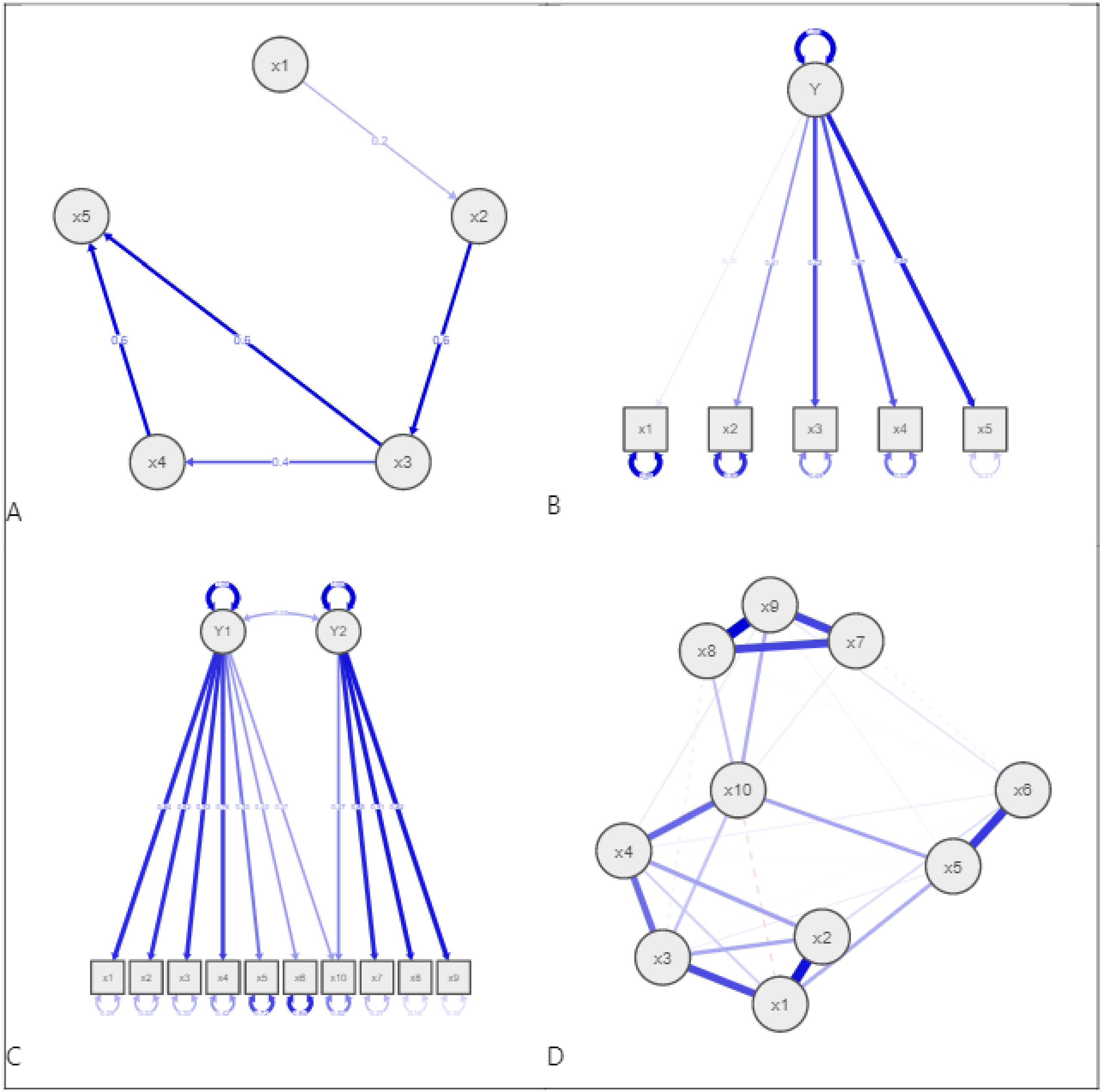
Philosophical – Riet van Bork

- does it make sense to find a realist emergent entity (a latent variable) when a network model seems more plausible?

Machine Learning – Hudson Golino

- we can train neural networks on typical psychological data and predict, which structure has most likely generated the data




x1
0.2
x5
x2
0.6
0.5
0.5
x4
0.4
x3
A
Y
x1
x2
x3
x4
x5
B
Y1
Y2
x1
x2
x3
x4
x5
x6
x10
x7
x8
x9
C
x9
x8
x7
x10
x6
x4
x5
x2
x3
x1
D

Thank you for your attention and good luck with the tutorial!