Latent Growth Curve Modeling With lavaan

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Rationales of Longitudinal Research ¹

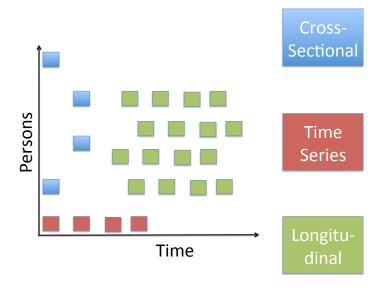
- 1. Direct identification of intraindividual change
- 2. Direct identification of interindividual differences (similarity) in intraindividual change
- 3. Analysis of interrelationships in behavioral change
- 4. Analysis of causes (determinants) of intraindividual change
- 5. Analysis of causes (determinants) of interindividual differences in intraindividual change

¹Baltes and Nesselroade (1979). *History and rationale of longitudinal research*.

Goals of Longitudinal Research

- 1. Within person change?
- 2. Between person differences in change?
- 3. Variables change together?
- 4. Causes of within person change?
- 5. Causes of between person differences in change?

Types of Data



Core Ingredients for Measuring Change

- Longitudinal data: multiple persons measured at multiple time points
- (Statistical) models:
 - Mathematical description of our assumptions (often derived from a theory) before seeing the data
 - At least: How do people change and how do they differ in their change (rationales 1,2).
- "...all repeated measures analyses should start with the question,"What is your model for change"
- One popular class of models for longitudinal data are latent growth curve models
- ► Goal: Introduction of the Latent Growth Curve Modelling and it's implementation in lavaan

²McArdle (2009). Latent Variable Modeling of Differences and Changes with Longitudinal Data.

Outline

Introduction

Latent Growth Curve Models

Advanced Latent Growth Curve Models

Further Readings

Some Terminology

- ▶ Given a variable of interest, for example, fluid intelligence
- ▶ We observed it for multiple persons on multiple occasions.
- y_{i,t} is our observation for this variable for person i at time point t.
- In statistical modeling we assume that $y_{i,t}$ is a realization of a corresponding random variable $Y_{i,t}$.
- A longitudinal model describes possible distributions for $Y_{i,t}$ for all time points t and persons i.

Latent Growth Curve Models

Constant Model

- A very easy (unrealistic) longitudinal model is the constant model.
- For every random variable $Y_{i,t}$ the same distribution is assumed.

$$Y_{i,t} = I + \epsilon_{i,t}$$

with $\epsilon_{I,t} \sim \mathcal{N}(0,\sigma_{\epsilon}^2)$ and $I \in \mathbb{R}$

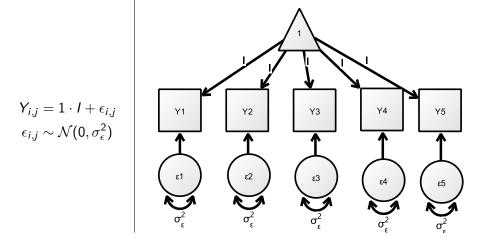
Alternatively,

$$Y_{i,t} \sim \mathcal{N}(I, \sigma_{\epsilon}^2)$$

- ► This encodes the assumption that the variable of interest is the same across all persons and time points.
- ▶ All observed differences are caused by measurement error.

SEM: Constant Model

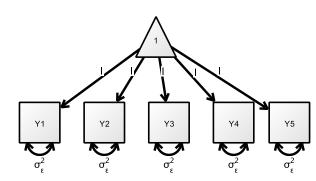
For five measurement occasions $t_j \in \{t_1, \ldots, t_5\}$:



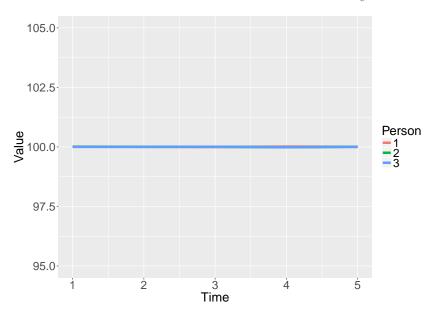
Example: Constant Model Compact Representation

For five measurement occasions $t_i \in \{t_1, \dots, t_5\}$:

$$Y_{i,j} = 1 \cdot I + \epsilon_{i,j}$$
 $\epsilon_{i,j} \sim \mathcal{N}(0, \sigma_{\epsilon}^2)$

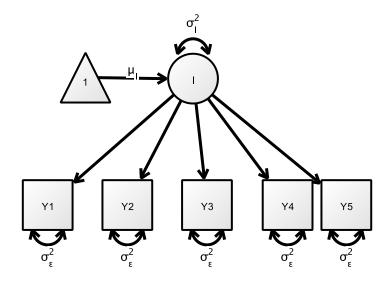


Constant Model Implied Trajectories I = 100, $\sigma_{\epsilon}^2 = 0$



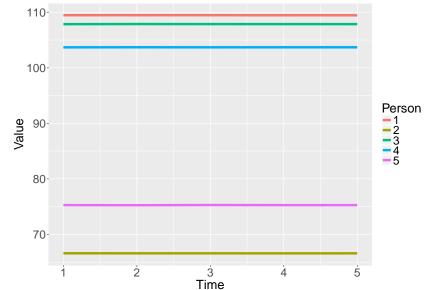
First Extension: Random Intercept

- ► Each person may have their own intercept I
- ► Results in random intercept model

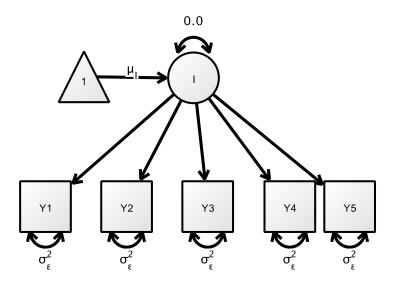


Trajectories: Random Intercept Model

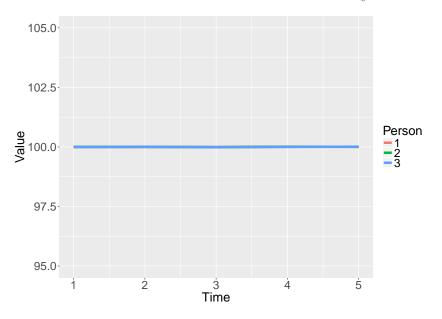
$$\mu_I=100, \sigma_I^2=400, \sigma_\epsilon^2=0$$



Constant as Special Case of Random Intercept

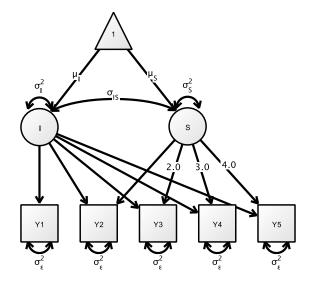


Constant Model Implied Trajectories I = 100, $\sigma_{\epsilon}^2 = 0$



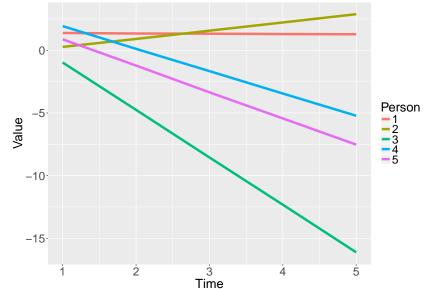
Next Extension: Random Slope

- ► Allow every person to have a different linear trend
- Results in latent growth curve model



Trajectories: Latent Growth Curve Model

$$\mu_I = 1, \sigma_I^2 = 5, \mu_S = 0, \sigma_S^2 = 10, \sigma_\epsilon^2 = 0$$



Which Model To Trust?

- ► Plot
- ► Fit Indices

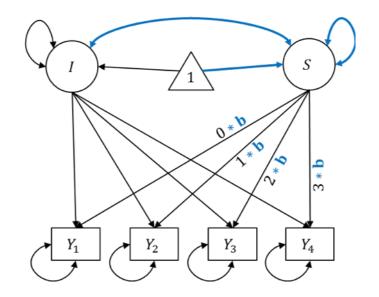
Identification

- ► For a regular LGCM, we need at least 3 time points
- ▶ We estimate 4 (μ_I , σ_I^2 , μ_S , σ_S^2 , σ_ϵ^2) parameters -> Need at least 4 unique covariance matrix entries -> Need at least 3 time points
- ► For more complex models, we typically need more time points

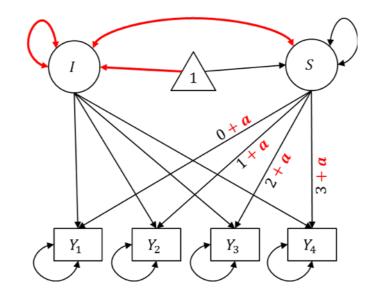
Choosing Time

- We use the time variable t as predictor
- Scaling time i.e. $t^* = a + bt$, will not change the fit but the parameters \rightarrow conclusions
- ▶ a shifts the origin of time
- b changes the unit of time (seconds vs minutes)

Effect of Changing Units



Effect of Changing Origin



Solution

- Always interpret results conditional on scaling
- $ightharpoonup \mu_I$ the mean at time point 0
- ho μ_S average change if 1 time unit (seconds, hours, months) elapses
- $ightharpoonup \sigma_I^2$ the variance at time point 0
- $ightharpoonup \sigma_S^2$ the variance in change if 1 time unit elapses
- $ightharpoonup \sigma_{\it IS}$ the covariance between intercept and slope

Practical Advise

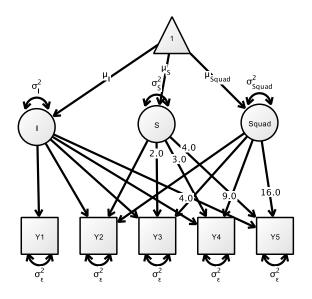
- Unit change is not so drammatic but keep in mind for interpretation.
- ► Is there a natural origin?



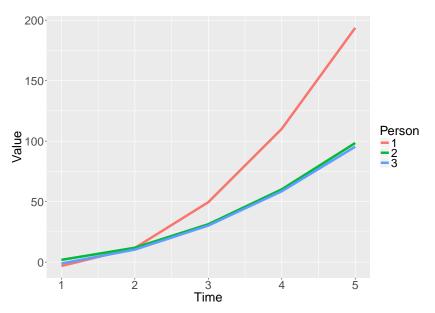
Other Growth Forms

- Real growth is probably not linear
- ► LGCM allows modeling of nonlinear trajectories
- ▶ Polynomials of arbitrary degree are in principal possible

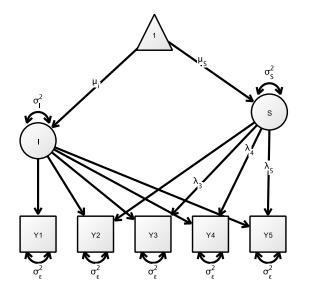
Example: Quadratic + Linear Growth



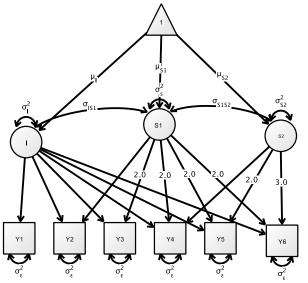
Trajectories: Quadtratic LGCM



Estimating the Form of Change



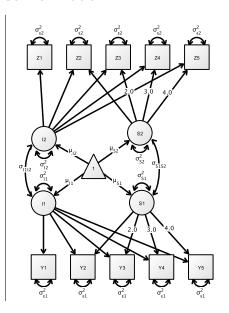
Piecewise Slopes Model



► Demonstrate: Trajectories

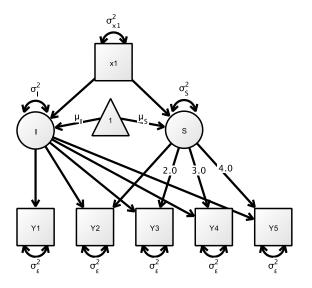
Bivariate Latent Growth Curve Model

- Model both variables using a LGCM
- Allow intercepts and slopes to covary
- Captures interrelationships in behavioral change (3)

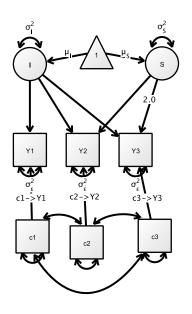


LGCM with time-invariant covariates

Use time-invariant covariates (for example, parents education) to predict intercept and slope



LGCM with time-variant covariates



Exercise

- ► Read Example
- Do Exercises
- ► All at https://github.com/marjoleinF/LVMbasic

Further Readings

Longitudinal Structural Equation Modeling

- ▶ Bollen and Curran (2006). Latent Curve Models: A Structural Equation Perspective.
- ▶ Duncan, Duncan, and Stycker (2006). *Introduction to Latent Variable Growth Curve Modeling: Concepts, Issues, and Applications.*
- ► Todd D. Little (2006). Longitudinal Structural Equation Modeling.
- ▶ Jason T. Newsom (2015). Longitudinal Structural Equation Modeling: A Comprehensive Introduction.