Analyzing Intensive Longitudinal Data (with DSEM)

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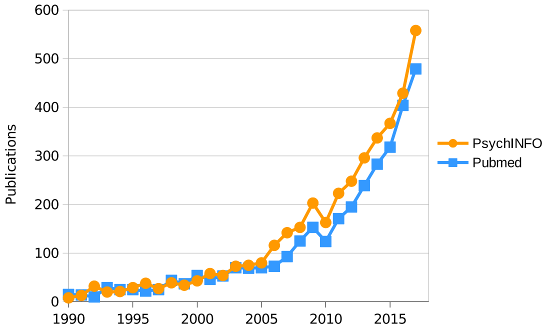
Times are changing



- Annual number of publications with "daily diary", "experience sampling", "ambulatory assessment", or "ecological momentary assessment" in the title, abstract, or keywords. Adapted from Hamaker & Wichers (2017).

Overview

- Intensive Longitudinal Data
- Single Subject Univariate Autoregressive Modeling
- Single Subject Multivariate (Vector) Autoregressive Modeling
- Multiple Subjects: Separating within and between person variance
- Multiple Subjects: Multilevel Autoregressive Modeling
- Caveats/Advanced Issues/State of the Art/Work in Progress

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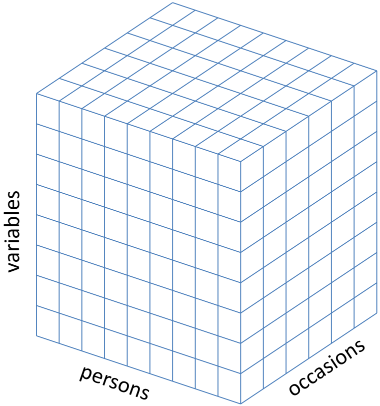
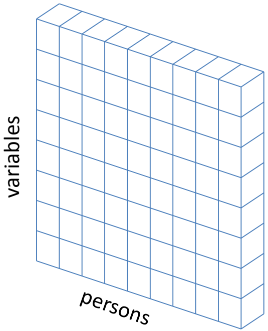
Cattell's data box



Cross-sectional research: N is large, T=1



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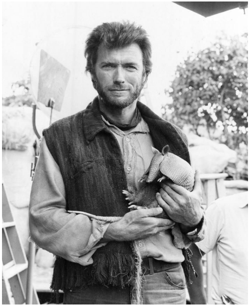
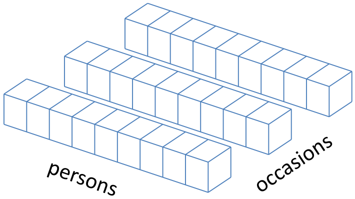
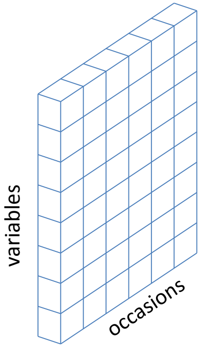


Panel research: N is large, T is small

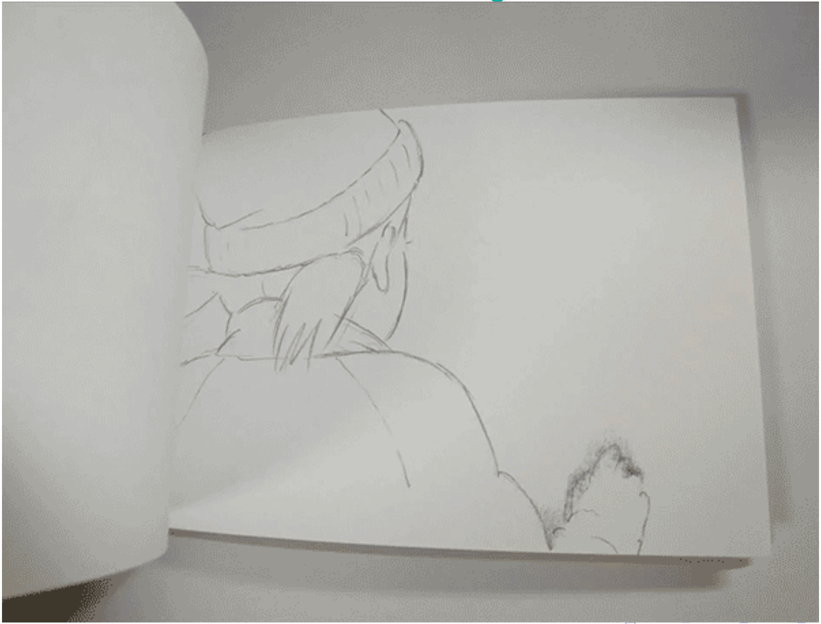


Panel research: N is large, T is small

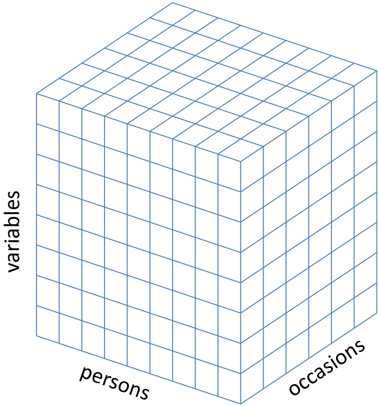
Time series data: N=1 and T is large



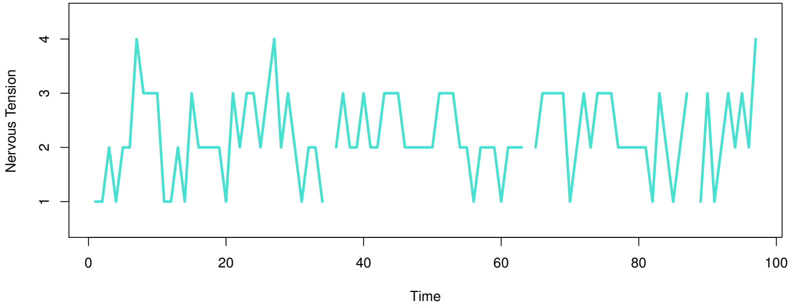
Time series data: N=1 and T is large



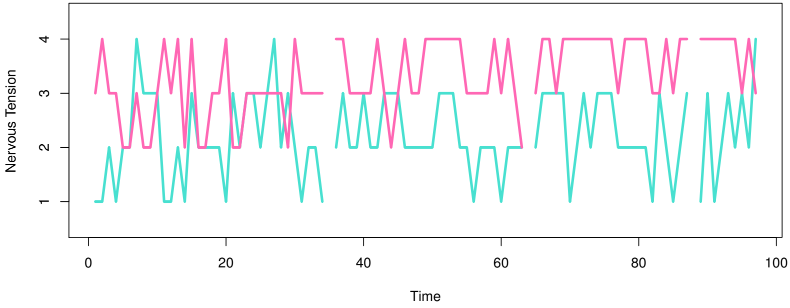
Intensive Longitudinal Data



Time Series



Multivariate Time Series



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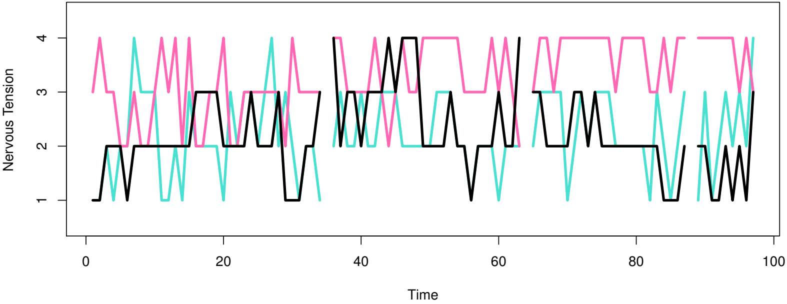
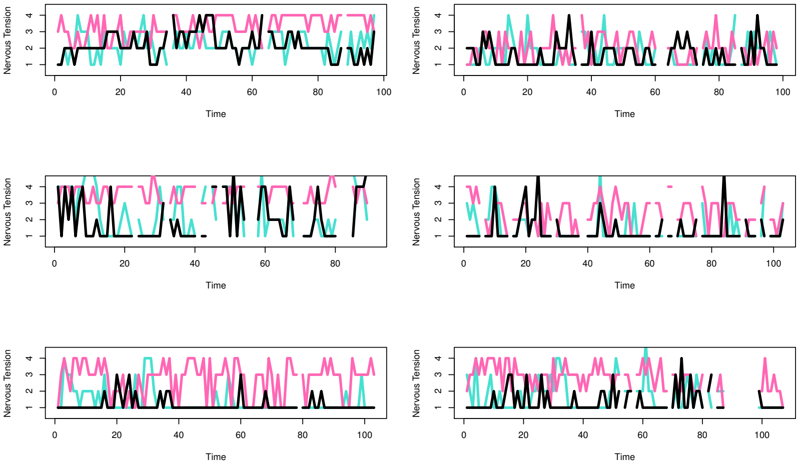


Intensive Longitudinal Data



Collecting Intensive Longitudinal Data

Ambulatory Assessment or Ecological Momentary Assessment

Experience Sampling, Daily diary, Tracking apps...See work by Timothy Trull and Ulrich Ebner-PriemerSociety of Ambulatory AssessmentLifedata, Ethica, Movisens, Expimetrics, ...

Collecting Daily Diary Data

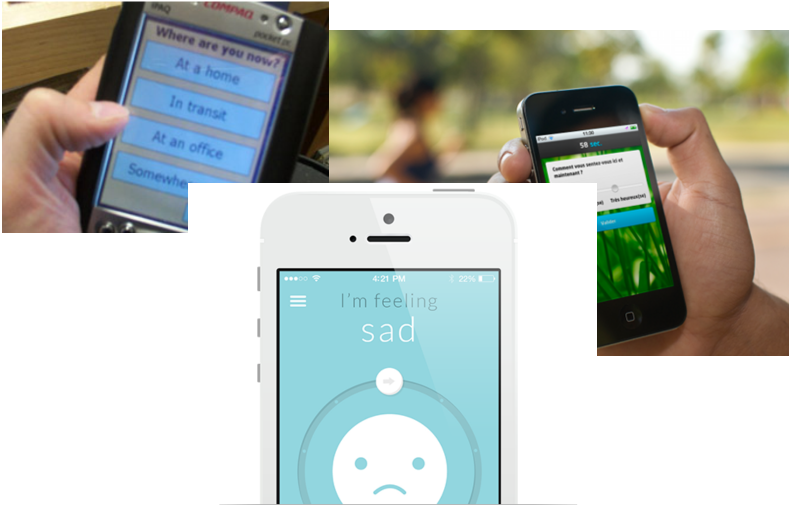
usually once at the end of the a day

Collecting Daily Diary Data

usually once at the end of the a day

Collecting Experience Sampling Data

Alert people randomly throughout the day



Tamlin Conner: https://www.youtube.com/watch?v=nQBBVp9vBIQ

Collection: Monitoring or Tracking Technology

Collection: Monitoring or Tracking Technology

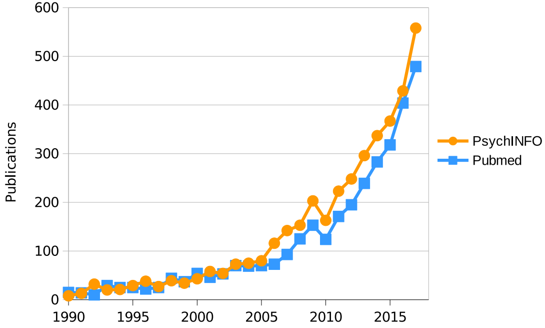
Collection: Monitoring or Tracking Technology

Collection: Ambulatory/Ecological Momentary Assessment

Advantages

- limited recall bias
- high ecological validity
- allows for consistent monotoring, with new possibilities for feedback and intervention
- window into the dynamics of processes

Times are changing



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How to Analyze This Stuff?

- Fairly young methodological area
- Not part of basic curriculum
- Huge development
- Already many options: discrete or continuous variables, latent variables, linear models, nonlinear models, and so on (Hamaker et al. 2015).

Dynamic SEM "SEM" (in Mplus v8)

- Designed for modeling intensive longitudinally measured continuous, normal variables
- N=1 or n=Many (via multilevel modeling; all parameters can be allowed to vary across persons)
- Similar to the State Space modeling framework (but even more general!)
- Allows for specifying many different time series models, including classic AR, ARMA, ARIMA models
- Explicit separation of within/between (using the multilevel context)
- Allows for adding predictors or outcome variables on between level and the within level (with a one-step-procedure)
- Can deal with categorical items via a probit link function (I believe dynamic IRT models are possible)
- **Bayesian estimation**

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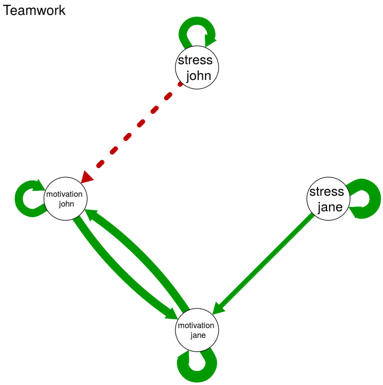
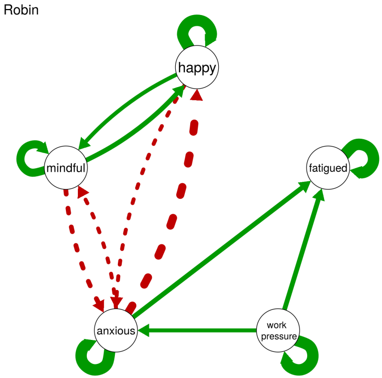
Simple models: Autoregressive Modeling



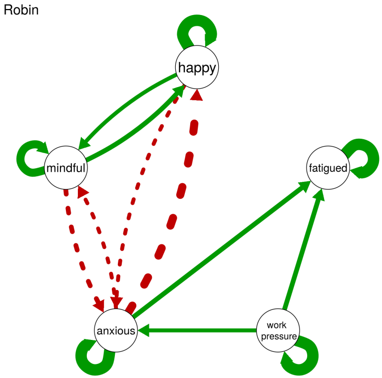
Why?

- Simple model (linear regression relationships, continuous variables)
- Appealing interpretation
- Basis for or related to many other dynamic models
- Can use coefficients to make pretty dynamic networks
- ***Hence, popular***

Intermezzo: Dynamic Networks/Intraindividual Networks



Intermezzo: Dynamic Networks/Intraindividual Networks



Intermezzo: Dynamic Networks/Intraindividual Networks

- Visualize how psychological variables are associated with themselves, and each other over time
- Conceptual models, or based on statistical estimates from (intensive longitudinal) data
- Currently, such statistical estimates are typically based on Vector Autoregressive Models

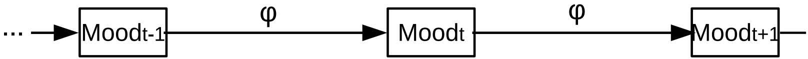
Read more: Borsboom (2017), Bringmann et al (2013), Cramer et al (2010).

Autoregressive Modeling: The Basic Idea

> "The best predictor of future behavior is past behavior"

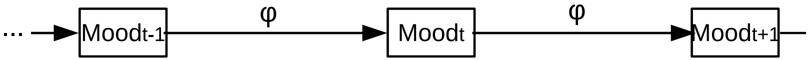
The N=1 Univariate Model (AR Model)

- Model for the time series of a specific person (N=1, T=many)
- Variable is regressed on itself at (a) previous occasion(s)
- AR(1) model: on the nearest previous occasion

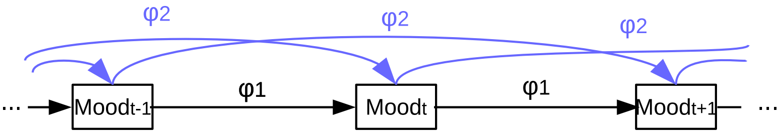


The N=1 Univariate Model (AR Model)

- AR(1) model: on the nearest previous occasion

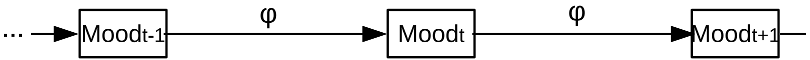


- AR(2) model: on the nearest previous occasion, and the occasion before that



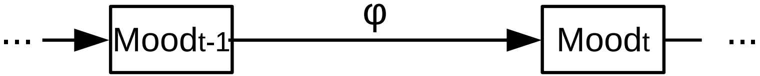
- AR(3) model: on the nearest previous occasion, and the occasion before that, and the one before that
- etc

The N=1 AR(1) Model



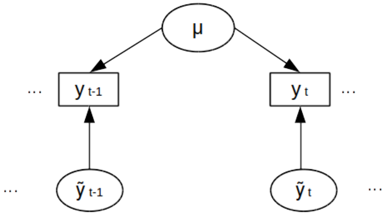
Mood t	Mood t-1
5	.
3	5
3	3
4	3
2	4
3	2
1	3
1	1
2	1
.	2

The N=1 AR(1) Model

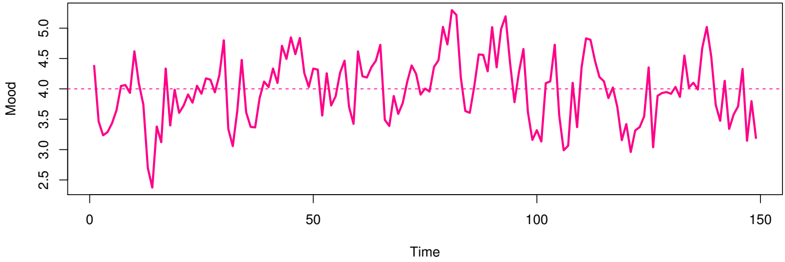


- What does the process look like?
- What about model assumptions?

The N=1 AR(1) Model: Delving Deeper



$$y_t = \mu + \tilde{y}_t$$



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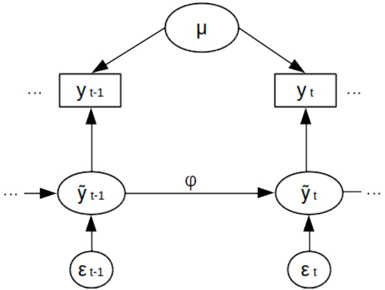
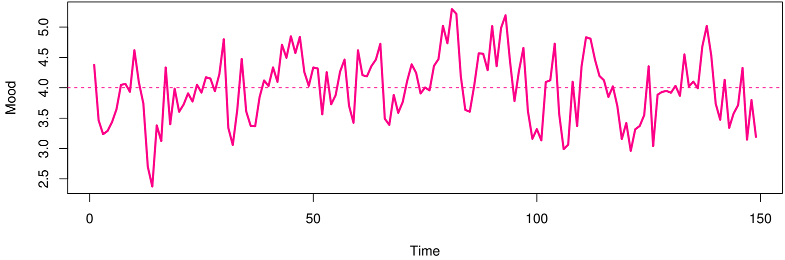


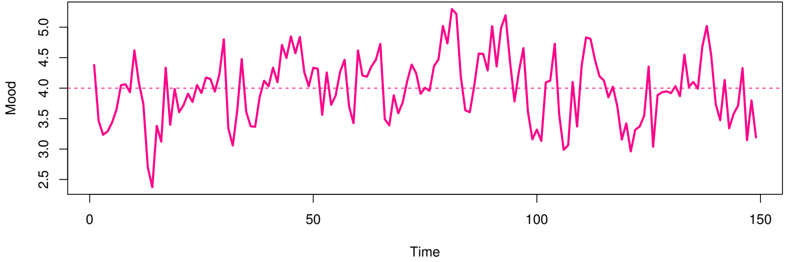
$$y_t = \mu + \tilde{y}_t$$
$$\tilde{y}_t = \phi \tilde{y}_{t-1} + \epsilon_t$$

$$\epsilon_t \sim Normal\left(0, \sigma^2\right)$$



The N=1 AR(1) Model: Delving Deeper

- In the AR(1) model ϕ lies between -1 and 1



AR(1) with ϕ = .5

The N=1 AR(1) Model: Delving Deeper

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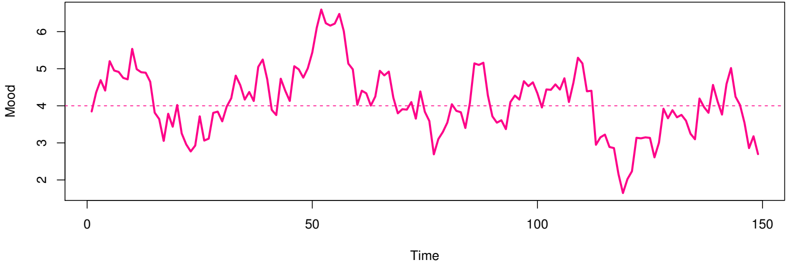

AR(1) with $\phi = .8$

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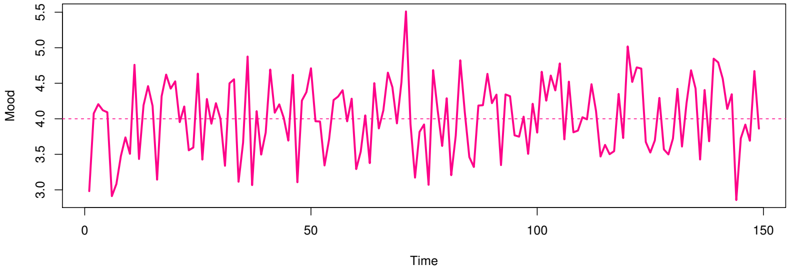

AR(1) with $\phi = 0$

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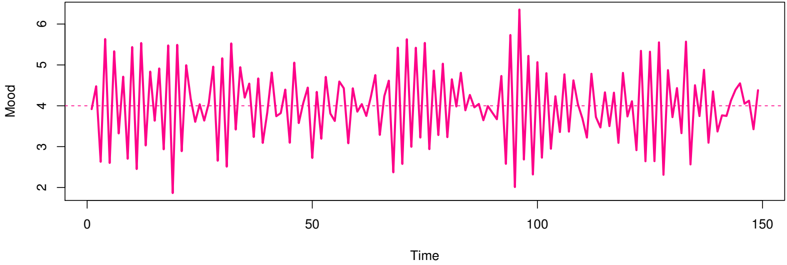

AR(1) with ϕ = -.8

The N=1 AR(1) Model: Psychological Practice?

- The autoregressive effect as resilience
- emotional inertia positively related with psychological maladjustment (Kuppens et al. 2011)
- emotional inertia positively related with rumination and depression severity (Koval, 2012)
- emotional inertia predicts the onset of depressive disorder in adolescence (Kuppens et al. 2015)

The N=1 AR(1) Model: Software?

	N=1	multilevel
uni-variate	- any regression software - arima in R - State Space Modeling software - Openmx - Bayesian modeling software (Including WinBUGS, STAN, JAGS and Mplus v8!)	
some-what multi-variate		
multi-variate		

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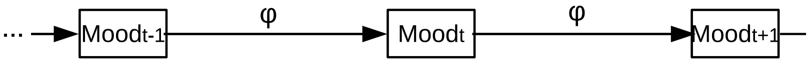

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The N=1 AR(1) Model: DEMO

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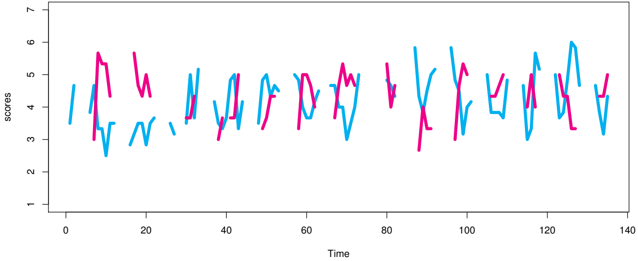
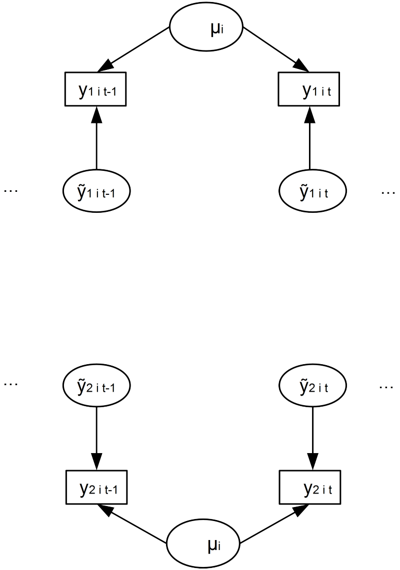
VAR modeling: Example

Competence and Exhaustion of people diagnosed with burnout

- Experience Sampling study by Sonnenschein et al. (2006)
- 54 persons diagnosed with burnout
- On average 80 repeated measures for exhaustion and 40 for feeling competent



Bivariate autoregressive model



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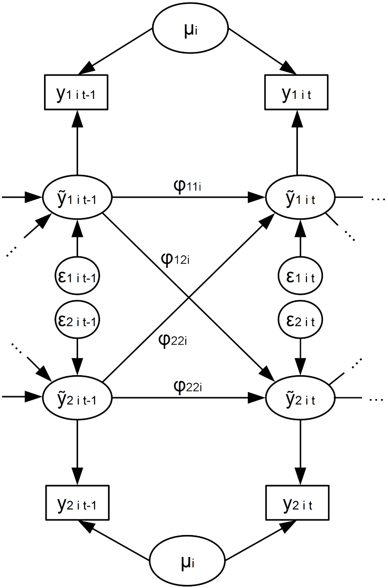
Bivariate autoregressive model



$$y_t = \mu + \tilde{y}_t$$
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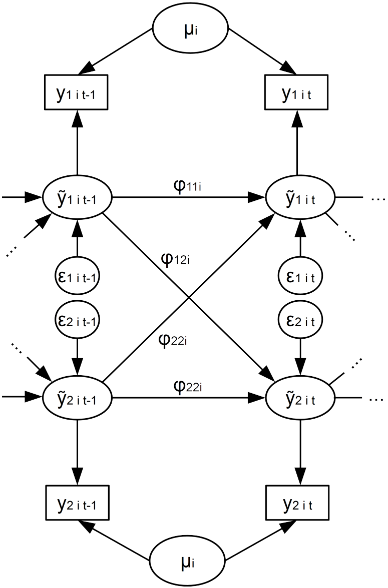

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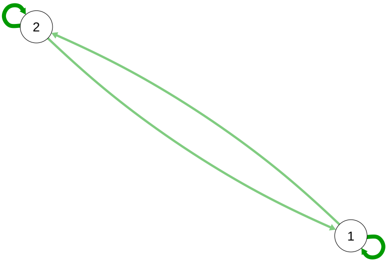
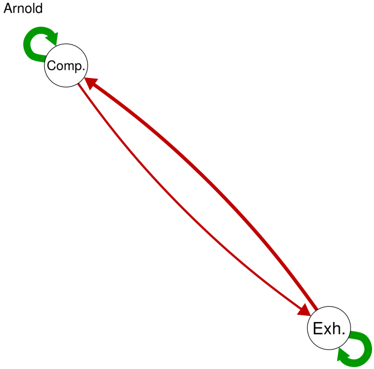
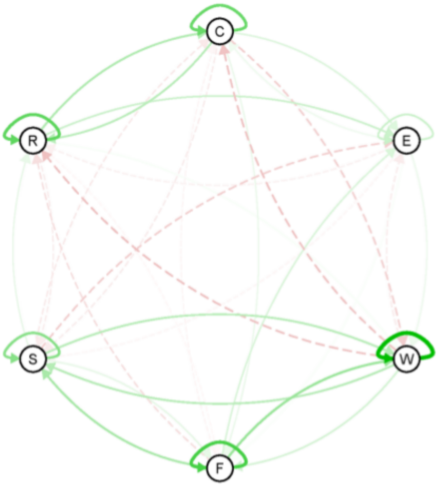


Vector Autoregressive Modeling: Multiple Variables



Based on results from Schuurman et al. 2016

Dynamic Network Examples



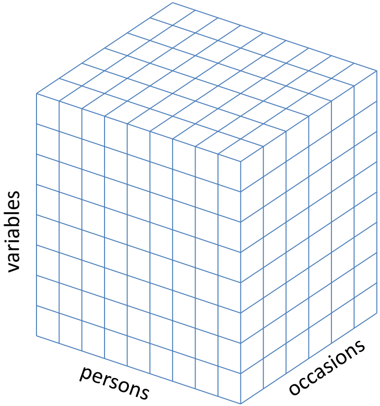
C=Cheerful; E=Event; W=Worried; F=Fear; S=Sad; R=Relaxed.
Image from Bringmann et al. (2013)

The N=1 VAR(1) Model: Software?

	N=1	multilevel
uni-variate	- any regression software - arima in R - State Space Modeling software - Openmx - Bayesian modeling software	
some-what multi-variate	- any regression software - VARS package in R - State Space Modeling Software - Bayesian software	
multi-variate	- State Space Modeling Software (mkfm6; Ox; fkf, dlm, KFAS, and MARSS in R) - Bayesian software (Winbugs, Openbugs, JAGS, STAN, Mplus v8)	

The N=1 VAR(1) Model: DEMO

Intensive Longitudinal Data: N=many, t=many



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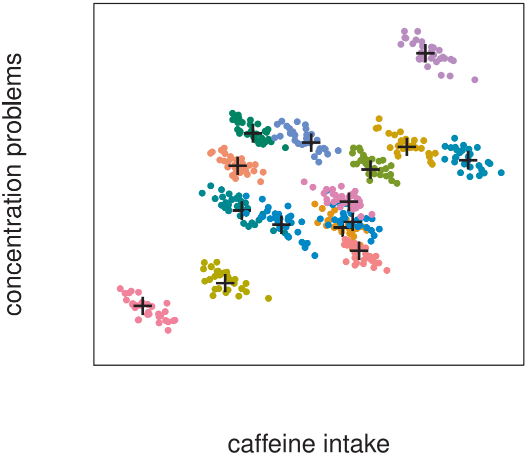
Multiple subjects: Separating Within-variance from Between-variance

- Whatever method you end up with....
- Separate **stable between person differences** from within person differences.
- and take into account that there may be between person differences in the within person dynamics.

Within vs Between vs Cross-sectional

Within vs Between vs Cross-sectional



Taken from Schuurman (2016).

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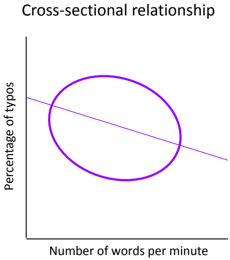

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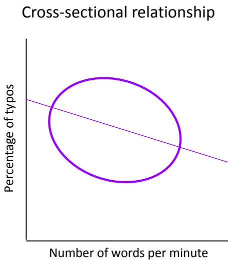
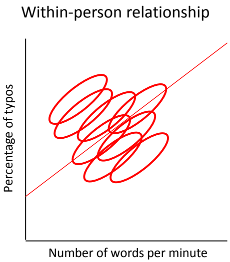
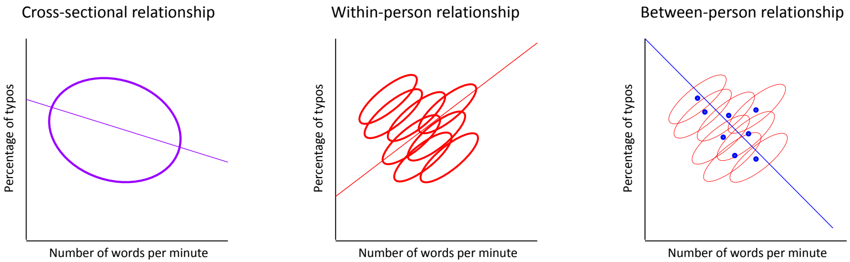




Within vs Between vs Cross-sectional



Taken from Hamaker (2012).

Separating within person differences from stable between person differences:

Without Repeated Measurements

- Design measurements such that they measure only within person variation or only between person variation
- Filter out between person variation using control variables that reflect these between person differences
- Make use of random assignment:
  "[...] note that, in true experimental designs, between-group (treatment) differences on the dependent variables appear as interindividual differences in the data, but that these differences actually imply intraindividual change" (Baltes, Reese and Nesselroade, 1977, p.101-103)

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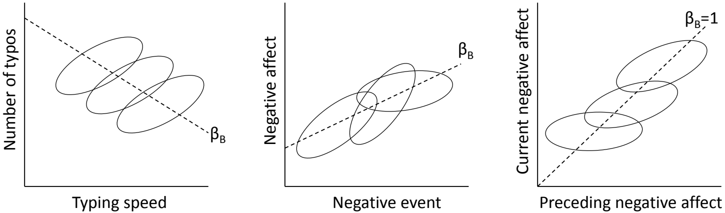
With Repeated Measurements

- Go for n=1. Then there are no between person differences
- Separate the two during the analyses, making use of techniques such as within person centering or multilevel modeling

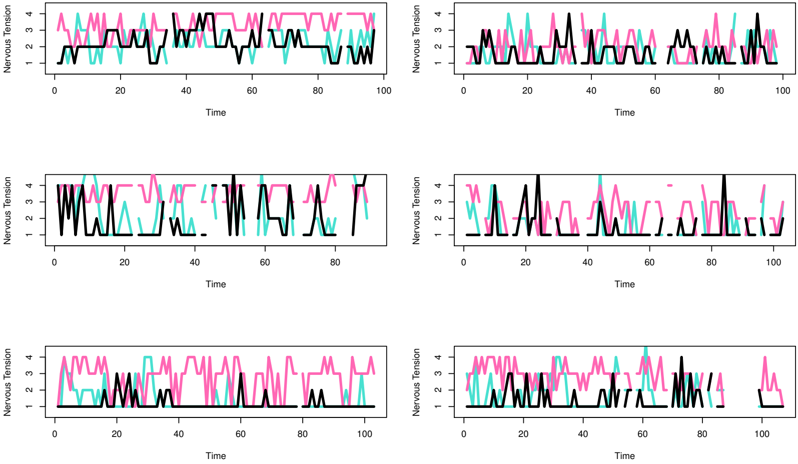
Within-person processes may differ from person to person

Interindividual differences in within person variation over time / processes



Taken from Hamaker and Grasman (2014).

Within-person processes may differ from person to person



Separate within and between, and account for differences in people's processes

In conclusion: To study within-person processes we need

- to **decompose** observed variance into within and between person variance
- to consider **individual differences** in within-person dynamics
- –> (intensive) **longitudinal** data

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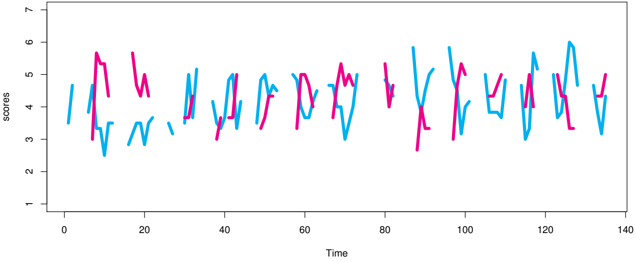
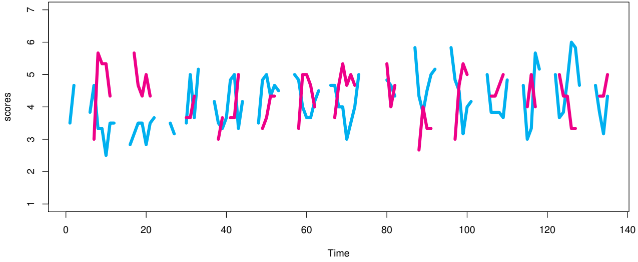
N=1 Models...



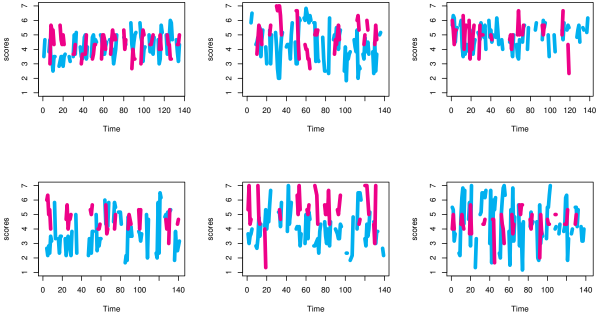
- Tailored to the person, but...

N=1 Models...



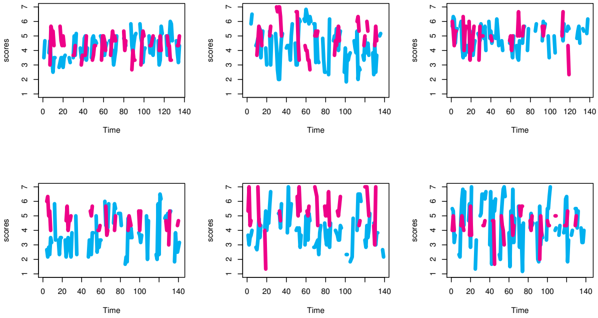
- Tailored to the person, but...
- difficult to generalize
- need many repeated measures

Use Multilevel VAR modeling



Because...

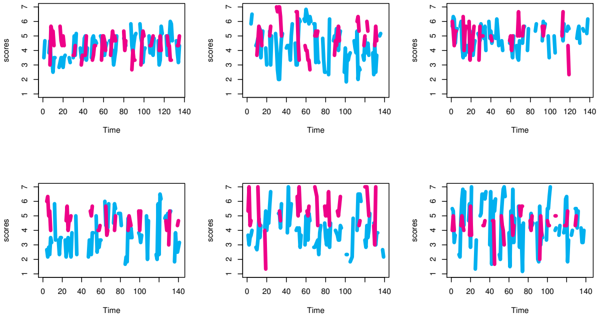
Use Multilevel VAR modeling



Because...

- People are similar

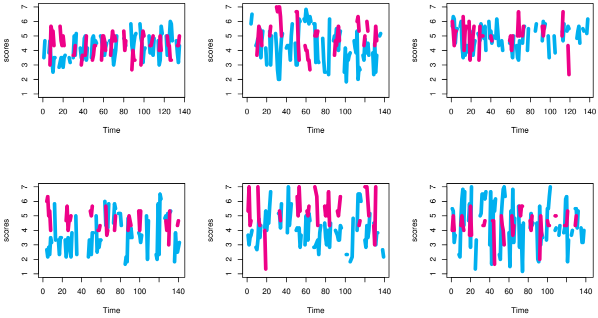
Use Multilevel VAR modeling



Because...

- People are similar
- People are different

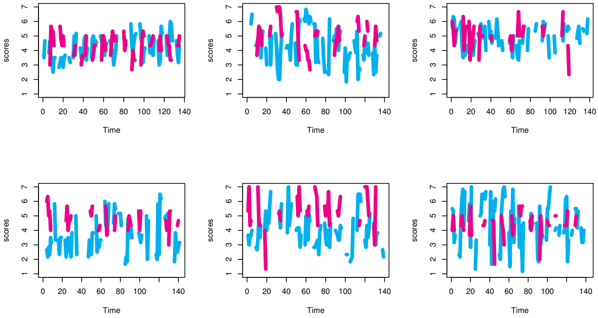
Use Multilevel VAR modeling



Because...

- People are similar
- People are different
- Easier to generalize

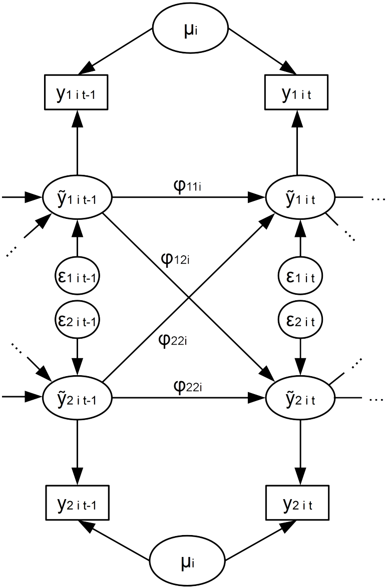
Use Multilevel VAR modeling



Because...

- People are similar
- People are different
- Easier to generalize
- Balance T with N

Bivariate multilevel autoregressive model



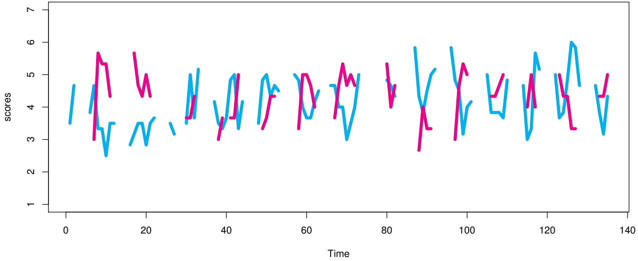
$$y_{it} = \mu_i + \tilde{y}_{it}$$
$$\tilde{y}_{it} = \Phi_i \tilde{y}_{it-1} + \epsilon_{it}$$

$$\epsilon_{it} \sim MvN(0, \Sigma)$$
$$\mu_i, \Phi_i \sim MvN(\gamma, \Psi)$$

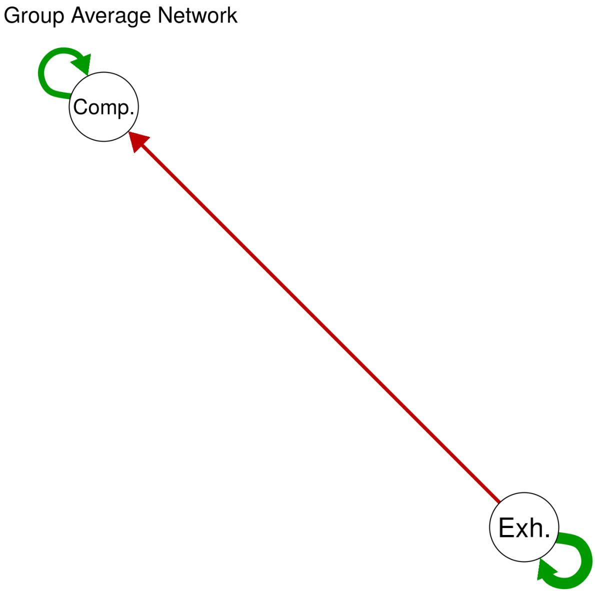
Multilevel VAR modeling: Example

Competence and Exhaustion of people diagnosed with burnout

- Experience Sampling study by Sonnenschein et al. (2006)
- 54 persons diagnosed with burnout
- On average 80 repeated measures for exhaustion and 40 for feeling competent



Average Within-person Competence and Exhaustion network



Multilevel VAR modeling:

Worrying and PA regulation

- Experience Sampling study by Geschwind et al. (2011)
- 129 persons, about 45 measures per person for PA and Worrying scores.

Multilevel VAR modeling:

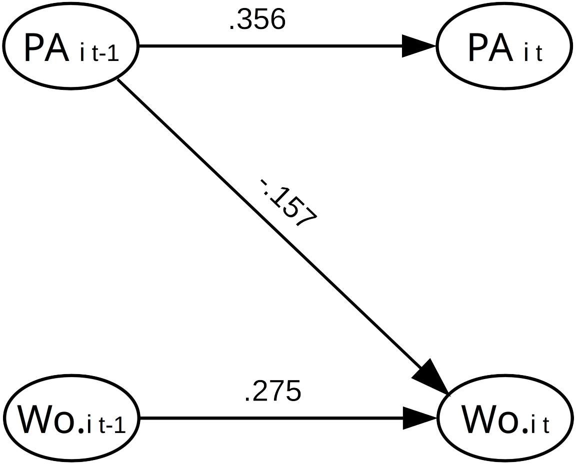
Worrying and PA regulation

- Experience Sampling study by Geschwind et al. (2011)
- 129 persons, about 45 measures per person for PA and Worrying scores.

- Worrying may be adaptive for regulating emotions (including PA) or maladaptive
- A strong autoregression coefficient for worrying may indicate maladaptive worrying
- We explore the reciprocal effects of worrying and PA on each other
- and the associations between the person-specific autoregressive effects, cross-lagged effects, and mean levels.

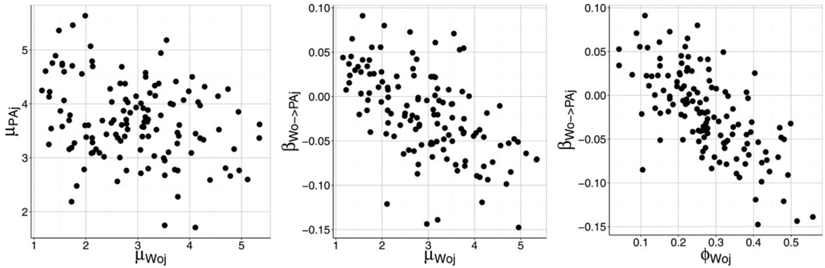
Worrying and PA

Average within-person effects



Worrying and PA

Between-person Associations between person-specific coefficients



Read more: Schuurman, Grasman & Hamaker (2016)

In sum: Multilevel VAR

- Good first step in exploring how variables affect themselves and each other over a time lag
- Get an impression of the dynamics involved
- Take into account individual differences, and (multilevel) model them!

(Multilevel V)AR: Software

	N=1	multilevel
uni-variate	- any regression software - arima in R - State Space Modeling software - Openmx - Bayesian modeling software	- any multilevel software - MLvar package in R - Bayesian modeling software
some-what multi-variate	- any regression software - VARS package in R - State Space Modeling Software - Openmx - Bayesian modeling software	- any multilevel software - MLVar package in R - Bayesian modeling software
multi-variate	- State Space Modeling Software (mkfm6; Ox; fkf, dlm, KFAS, and MARSS in R) - Bayesian software (Winbugs, Openbugs, JAGS, STAN)	- Bayesian software (Winbugs, Openbugs, JAGS, STAN)

(Multilevel V)AR: Software

	N=1	multilevel
uni-variate	M	P
some-what multi-variate	l	u
multi-variate	s	v8

DSEM in Mplus v8

- Designed for continuous, normal variables
- N=1 or multilevel (all parameters can be allowed to vary across persons
- Explicit separation of within/between (so a multilevel context)
- Similar to the State Space modeling framework (but even more general!).
- Allows for specifying many different time series models, including classic AR, ARMA, ARIMA models
- Allows for adding predictors or outcome variables on between level and the within level in one step
- Can deal with categorical variables via a probit link function (I believe dynamic IRT models are possible)
- **Bayesian estimation**

DSEM Software

Mplus v8

- Specifically developed for DSEM
- –> tailored to DSEM specific issues, time saving features
- –> fast, stable
- –> less flexible
- Not free (aside from student version), not open source
- Support from Mplus
- Probably more user friendly

Bugs, Stan, Jags

- Not specifically developed for DSEM, very general
- –> dealing with specific DSEM issues requires (much) more work
- –> less fast, can be less stable (depending on your implementation)
- –> more flexible
- Free, open source
- Tips/advice everywhere, but you are basically on your own
- Probably less user friendly

Overview

- Dynamic Networks
- Intensive Longitudinal Data
- Univariate Autoregressive Modeling (N=1)
- Multivariate Autoregressive Modeling (N=1)
- Multilevel Autoregressive Modeling (N=Many)
- **Caveats/Advanced Issues/State of the Art/Work in Progress**

Caveats/Advanced Issues/State of the Art/Work in Progress

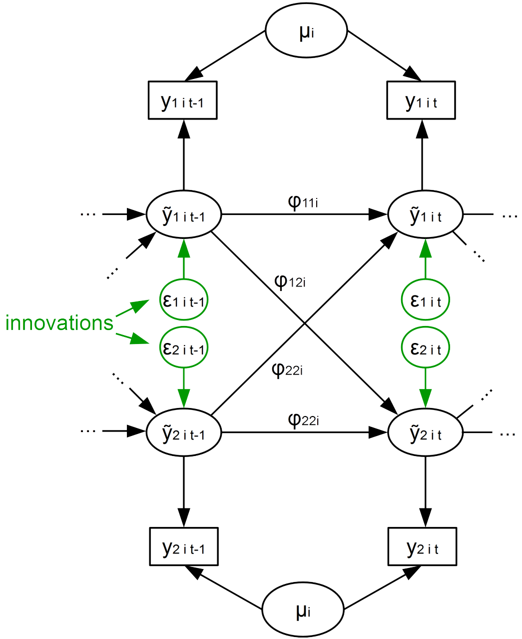
- Measurement error
- Standardizing coefficients
- Non-stationarity
- Non-equidistant measurements/Differential Equations/Continuous Time Modeling
- Missing data (Pay attention to what your software is doing - listwise deletion makes no sense for these data)
- Variable selection/model selection
- Mediation, Interventions and Causality
- Modeling processes on that take place at different time scales
- Linear vs Non-linear models
- Categorical models (multilevel) markov models
- Models with other distributional assumptions
- Clustering rather than multilevel (e.g., Gimme by Gates & Molenaar)
- ...

Two limitations of many AR applications

(Multilevel) VAR models are getting applied more frequently in psychology, but...

- The model usually disregards measurement error
- The multilevel models usually disregard that residual variances may be different from person to person

Innovations =/= Measurement errors



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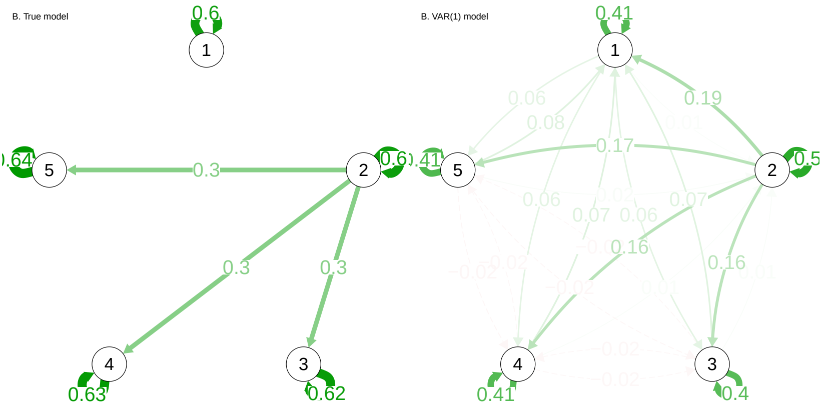
Disregarding Measurement Error...



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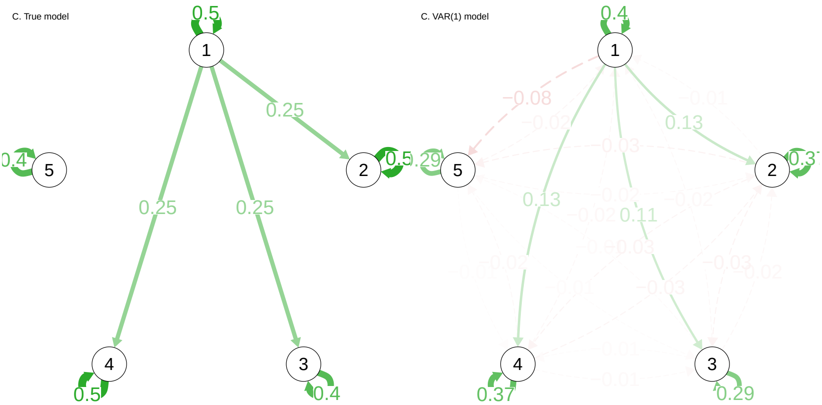

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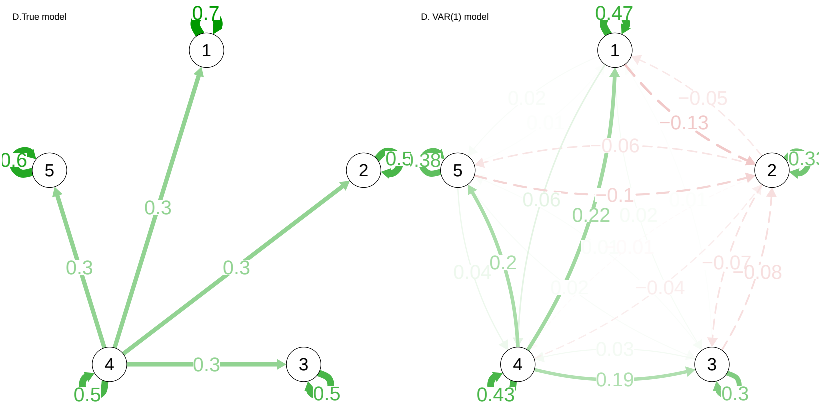
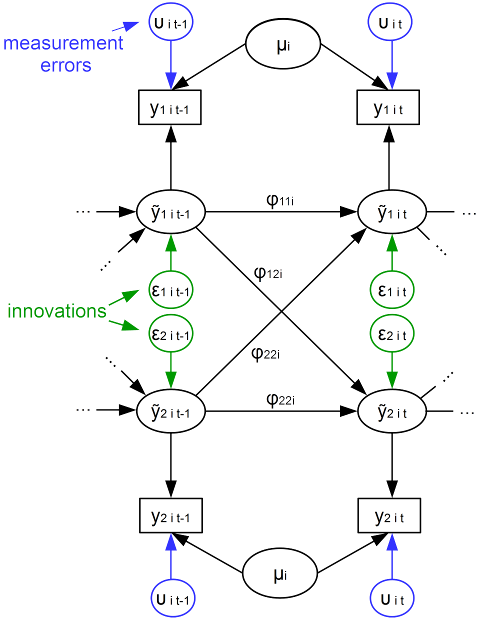


Innovations =/= Measurement errors



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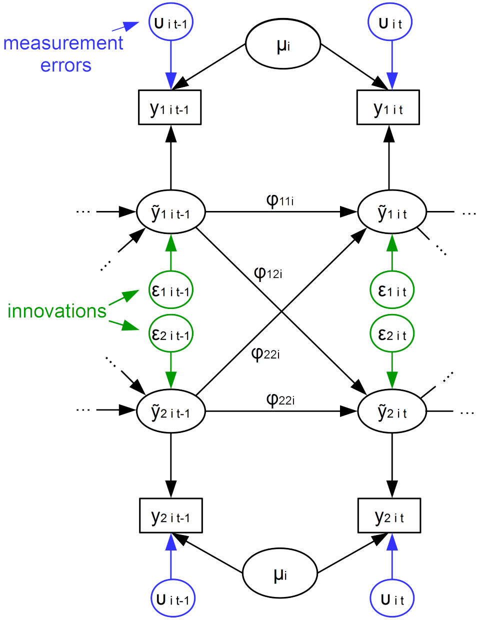
Innovations =/= Measurement errors



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Measurement error variance may be different for each person!

Random innovation variances and measurement error variances

Reasons to assume **individual differences** for these variances:

- individuals may differ with respect to the **variability in exposure** to external factors
- individuals may differ with respect to their **reactivity** to external influences (see reward experience and stress sensitivity research)

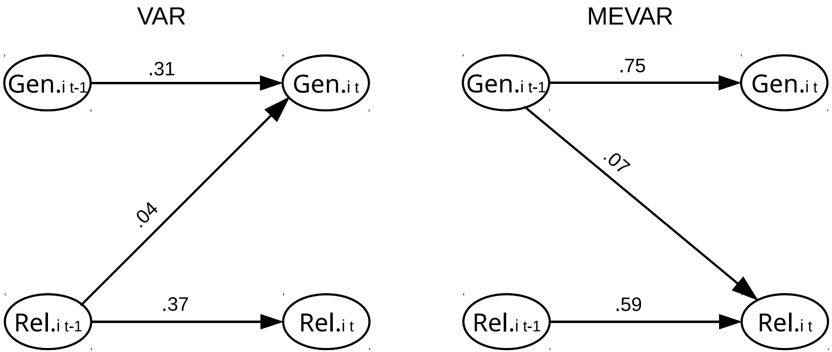
Empirical Example: General PA and Relationship PA

Multilevel VAR modeling: Example

Positive affect of women in a heterosexual relationship

- Data from study by Ferrer, Steele, and Hsieh (2012)
- 190 women filled out a diary every evening
- about 60 to 90 repeated measures on daily General Positive Affect and Relationship Positive Affect

Empirical Example: General PA and Relationship PA



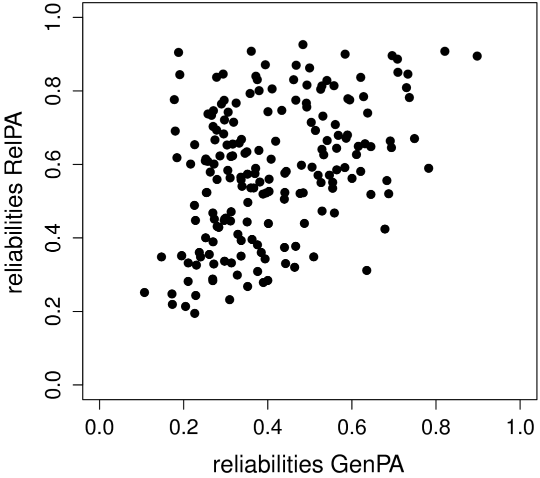
mean ϕ_{geni}: .31 (.28, .34)
mean ϕ_{reli}: .37 (.34, .40)
mean $\phi_{gen->reli}$: .04 (.02, .07)
mean $\phi_{rel->geni}$: .02 (.00, .04)

mean ϕ_{geni}:.75 (.69, .80)
mean ϕ_{reli}: .59 (.53, .64)
mean $\phi_{gen->reli}$: -.03 (-.07, .00)
mean $\phi_{rel->geni}$: .07 (.02, .13)

Person-specific reliabilities

- Unique measurement error variances per person (and variable) also implies unique reliabilities!
- For each person: Calculate the proportion of that person's total variance and the part of the variance which is not due to measurement errors

Person-specific reliabilities



Read more:

Schuurman & Hamaker (2018)

Comparing cross-lagged parameters

To compare the strength of the cross-lagged effects, the coefficients should be standardized.
However, Standardization in multilevel models is a **tricky issue**.

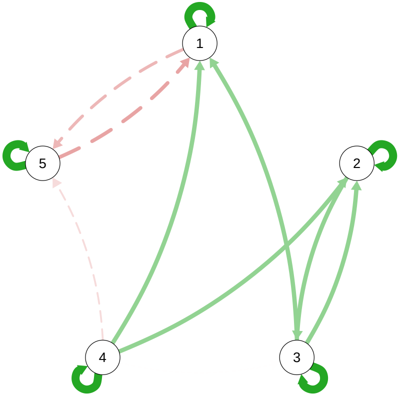
Comparing cross-lagged parameters

To compare the strength of the cross-lagged effects, the coefficients should be standardized.
However, Standardization in multilevel models is a **tricky issue**.
Four forms of **standardization in multilevel models**, using:

- total variance (i.e., grand standardization)
- between-person variance (i.e., between standardization)
- average within-person variance
- within-person variance (i.e., within standardization)

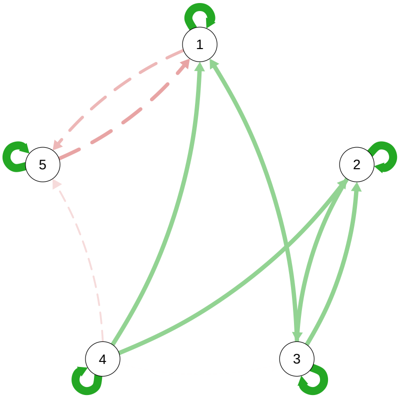
Why standardized coefficients

Unstandardized coefficients are sensitive to the measurement unit



Why standardized coefficients

Unstandardized coefficients are sensitive to the measurement unit (variable 1 multiplied by 2)



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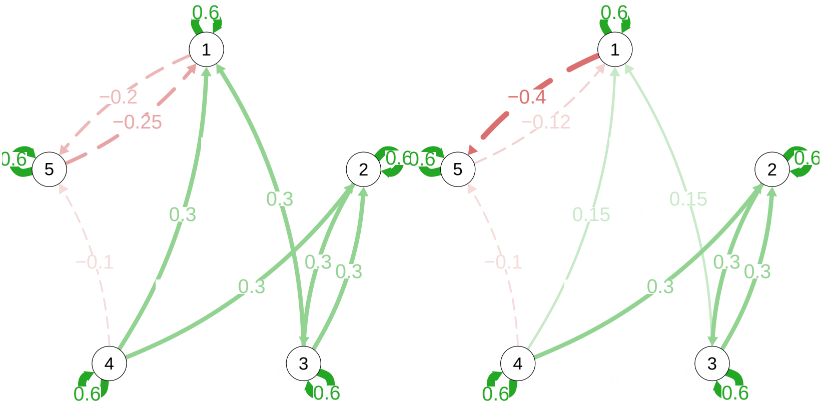

Multilevel Standardization

$$\beta = b\frac{\sigma_x}{\sigma_y}$$

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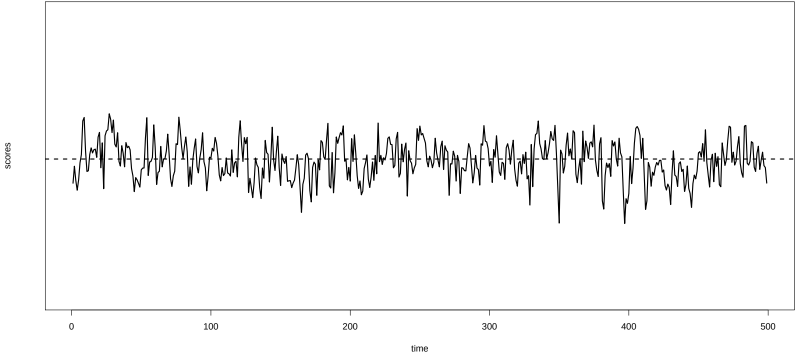
Different variances in the multilevel model: within-person, between-person, grand



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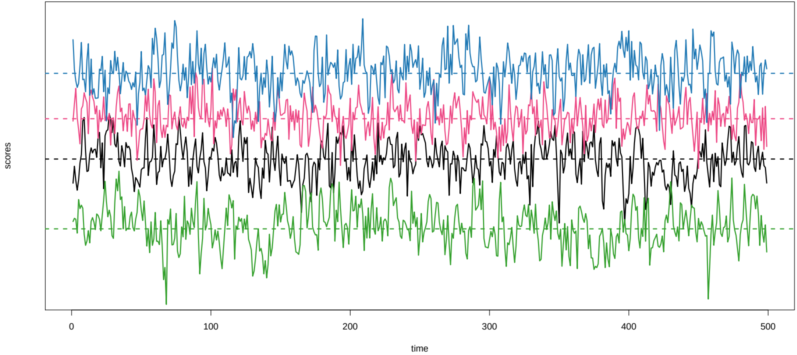

Multilevel Standardization

Within-person, between-person or grand?

- Always standardize on the level on which the predictor explains variance.

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Multilevel Standardization

Within-person, between-person or grand?

- Always standardize on the level on which the predictor explains variance.
- The cross-lagged coefficients are about within person effects, and explain within-unit variance.
- Different individuals have different parameters, take this into account in the standardization!
- **So: Standardize each person's coefficients, using within person standardization.**

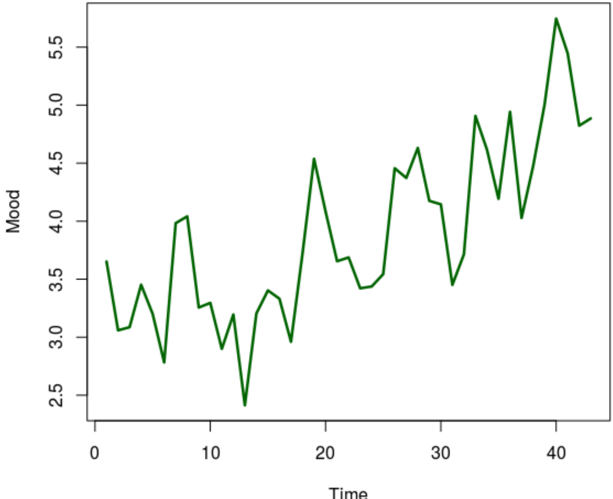
Read more: Schuurman, Ferrer, Boer-Sonnenschein & Hamaker (2016)

Mplus standardized results

STDYX Standardization	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within-Level Standardized Estimates Averaged Over Clusters						
P_PP | DAYPA ON						
DAYPA&1	0.335	0.011	0.000	0.312	0.358	*
P_PN | DAYPA ON						
DAYNA&1	0.034	0.013	0.006	0.008	0.059	*
P_NP | DAYNA ON						
DAYPA&1	0.038	0.011	0.000	0.017	0.059	*
P_NN | DAYNA ON						
DAYNA&1	0.370	0.012	0.000	0.347	0.394	*
DAYNA WITH						
DAYPA	-0.194	0.010	0.000	-0.213	-0.175	*
Residual Variances						
DAYPA	0.816	0.008	0.000	0.799	0.832	*
DAYNA	0.792	0.008	0.000	0.775	0.808	*

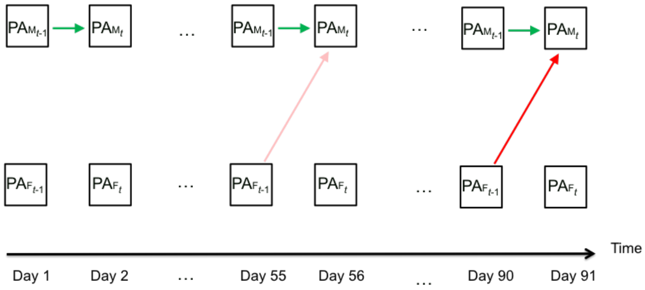
Stationarity Assumption

Parameters must not change over time (means, regression coefficients, variances, and so on).



Stationarity Assumption

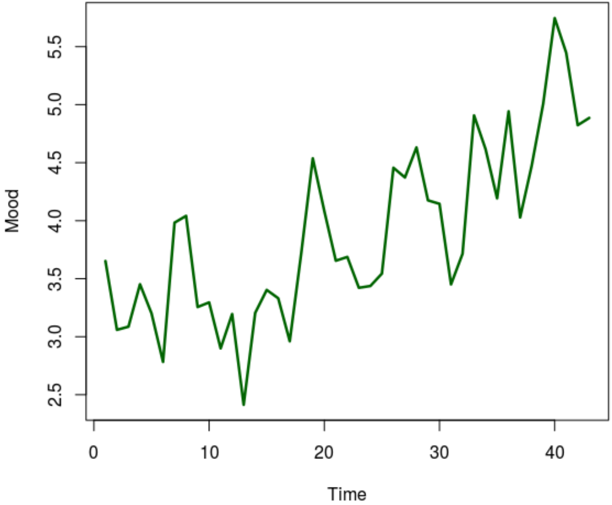
Time Varying VAR Read more: Bringmann, Hamaker, Vigo, Aubert, Borsboom, & Tuerlinckx (2016; only n=1)



More sudden changes?: Regime switching models, change point analysis, Threshold-AR models,... Read more: de Haan-Rietdijk et al. (2016), Hamaker, Grasman & Kamphuis (2016).

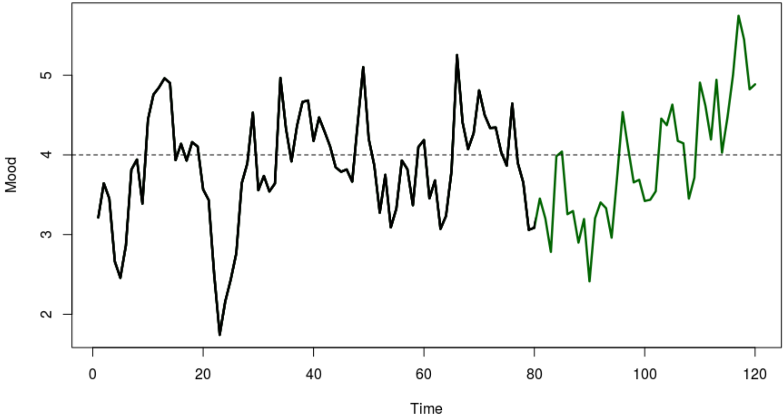
Stationarity Assumption

Trend...?

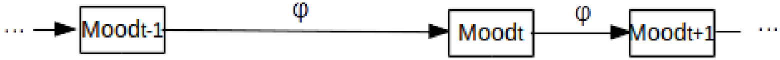


Stationarity Assumption

Trend...? No! Autoregressive process.



Equal Spacing Between Measurements



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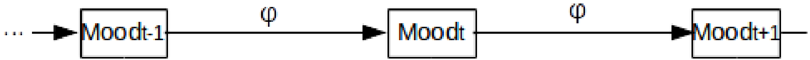

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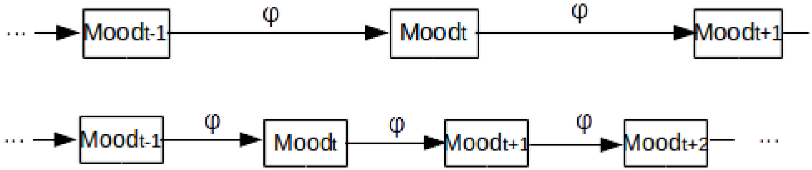

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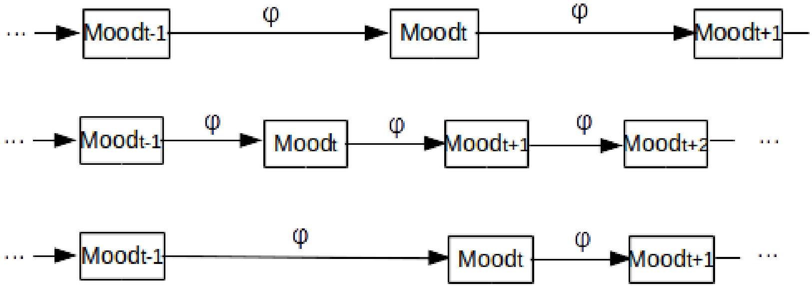

Different measurement spacing, Different results

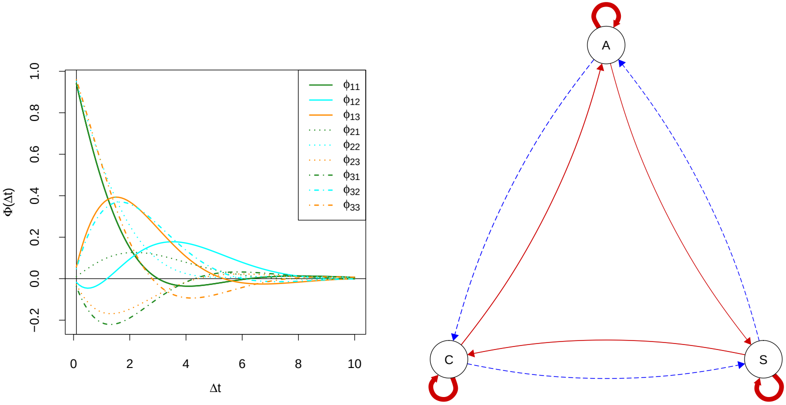

Image made by Oisin Ryan (Utrecht University)

Discrete Time vs Continuous Time

- Mplus possible to specify time grid and will add in missing observations to equally space measurements
- Continuous time models can directly take the length of the time intervals into account
- Based on differential equations

Recent developments:

- ctsem (Driver, Voelkle and Oud)
- DynR (Ou, Hunter and Chow)
- BOUM (Oravecz, Tuerlinckx and Vanderkerckhove)
- ...

Caveats/Advanced Issues/State of the Art/Work in Progress

- Measurement error
- Standardizing coefficients
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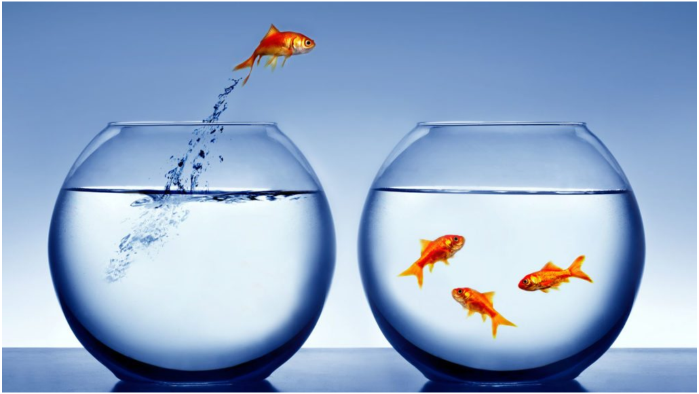
- Categorical models (multilevel) markov models
- Models with other distributional assumptions
- Clustering rather than multilevel (e.g., Gimme by Gates & Molenaar)
- ...

Going forward...

Resources for joining in

- Workshop slides and references here
- Practice exercises/code for Mplus or R + JAGS here
- Mplus DSEM workshops and webinars here
- Ellen Hamaker, Laura Bringmann, Rebecca Kuiper, Oisin Ryan and me also developed a 5-day course.
- At Utrecht University in august, winter course is in the making.



Applications Overview

- **1. Multilevel VAR model for PA and NA**
- 2. Multilevel VAR model with mediation
- 3. Intervention Study

Data: Daily measurements affect

Data come from the **COGITO study** of the MPI in Berlin; goal is to study aging using a younger and older sample. Analyses here are

based on Hamaker et al. (2018, Multivariate Behavioral Research).

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Data come from the **COGITO study** of the MPI in Berlin; goal is to study aging using a younger and older sample. Analyses here are

based on Hamaker et al. (2018, Multivariate Behavioral Research). Characteristics of the **younger** and **older sample**:

- aged 20-31; aged 65-80
- 101 individuals; 103 individuals
- about 100 daily measurements of positive affect (PA) and negative affect (NA)

Decomposition

Decomposition into a between part and a within part

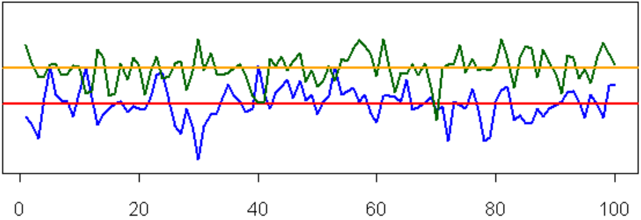
$$PA_{it} = \mu_{PA,i} + PA_{it}^{(w)}$$
$$NA_{it} = \mu_{NA,i} + NA_{it}^{(w)}$$

Decomposition into a between part and a within part

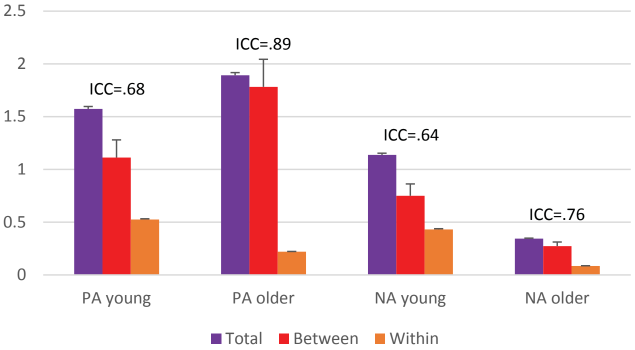
$$PA_{it} = \mu_{PA,i} + PA_{it}^{(w)}$$
$$NA_{it} = \mu_{NA,i} + NA_{it}^{(w)}$$

where

- $\mu_{PA,i}$ and $\mu_{NA,i}$ are the individual's **means** on PA and NA (i.e., baseline, trait, or equilibrium scores) $\Rightarrow$ between-person part
- $PA_{it}^{(w)}$ and $NA_{it}^{(w)}$ are the **within-person centered** (cluster-mean centered) scores $\Rightarrow$ within-person part



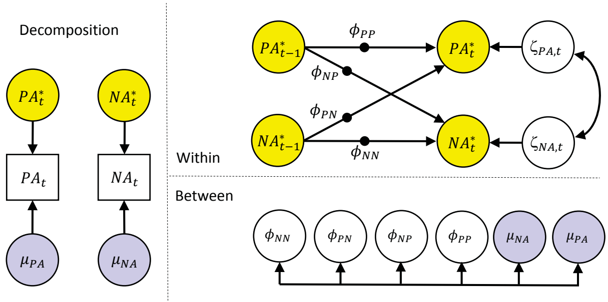
Total, between-, and within-person variance



Intraclass correlation:

$$\frac{\sigma^2_{between}}{\sigma^2_{between}+\sigma^2_{within}} = \frac{\sigma^2_{between}}{\sigma^2_{total}}$$

Bivariate model: Multilevel vector AR(1) model



Within-person level model

Lagged within-person model:

$$PA_{it}^{(w)} = \phi_{PP,i} PA_{i,t-1}^{(w)} + \phi_{PN,i} NA_{i,t-1}^{(w)} + \zeta_{PA,it}$$
$$NA_{it}^{(w)} = \phi_{NN,i} NA_{i,t-1}^{(w)} + \phi_{NP,i} PA_{i,t-1}^{(w)} + \zeta_{NA,it}$$

where

- $\phi_{PP,i}$ is the **autoregressive parameter** for PA (i.e., inertia, carry-over)
- $\phi_{NN,i}$ is the **autoregressive parameter** for NA (i.e., inertia, carry-over)

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where

- $\phi_{PP,i}$ is the **autoregressive parameter** for PA (i.e., inertia, carry-over)
- $\phi_{NN,i}$ is the **autoregressive parameter** for NA (i.e., inertia, carry-over)
- $\phi_{PN,i}$ is the **cross-lagged parameter** for NA to PA (i.e., spill-over)
- $\phi_{NP,i}$ is the **cross-lagged parameter** for PA to NA (i.e., spill-over)

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- $\phi_{NP,i}$ is the **cross-lagged parameter** for PA to NA (i.e., spill-over)
- $\zeta_{PA,it}$ is the **innovation** for PA (residual, disturbance, dynamic error)
- $\zeta_{NA,it}$ is the **innovation** for NA (residual, disturbance, dynamic error)

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where

- $\phi_{PP,i}$ is the **autoregressive parameter** for PA (i.e., inertia, carry-over)
- $\phi_{NN,i}$ is the **autoregressive parameter** for NA (i.e., inertia, carry-over)
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- $\zeta_{PA,it}$ is the **innovation** for PA (residual, disturbance, dynamic error)
- $\zeta_{NA,it}$ is the **innovation** for NA (residual, disturbance, dynamic error)

Parameters estimated at this level are the residual variances and covariance:

$$\begin{bmatrix} \zeta_{PA,it} \\ \zeta_{NA,it} \end{bmatrix} \sim MN\left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \theta_{11} & \\ \theta_{21} & \theta_{22} \end{bmatrix}\right]$$

Between-person level model

Between level: fixed and random effects

$$\mu_{PA,i} = \gamma_P + u_{P,i}$$
$$\mu_{NA,i} = \gamma_N + u_{N,i}$$
$$\phi_{PP,i} = \gamma_{PP} + u_{PP,i}$$
$$\phi_{PN,i} = \gamma_{PN} + u_{PN,i}$$
$$\phi_{NP,i} = \gamma_{NP} + u_{NP,i}$$
$$\phi_{NN,i} = \gamma_{NN} + u_{NN,i}$$

The u's are assumed to be **multivariate normally distributed** (i.e., $u \sim MN(0, \Psi)$).

Between-person level model

Between level: fixed and random effects

$$\mu_{PA,i} = \gamma_P + u_{P,i}$$
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$$\phi_{PP,i} = \gamma_{PP} + u_{PP,i}$$
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$$\phi_{NP,i} = \gamma_{NP} + u_{NP,i}$$
$$\phi_{NN,i} = \gamma_{NN} + u_{NN,i}$$

The u's are assumed to be **multivariate normally distributed** (i.e., $u \sim MN(0, \Psi)$). **Parameters estimated at this level** are:

- 6 fixed effects (i.e., γ's)
- 6 variances for random effects (i.e., diagonal elements of Ψ: variances of the u's)
- 15 covariances between the random effects (i.e., off-diagonal elements in Ψ)

Bivariate model: Mplus code

Data are in **long format** (i.e., each record is an occasion within a person; multiple records per person).

Lagged variables are **created in Mplus** (using the LAGGED command).

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Lagged variables are **created in Mplus** (using the LAGGED command).

```
VARIABLE:      NAMES = id sessdate
               na1 na2 na3 na4 na5 na6 na7 na8 na9 na10
               pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10
               sessionNr age_pre sex CESDpre CESDpost dayNA dayPA older;

               CLUSTER = id; ! Specify the person id variable
               USEVAR = dayPA dayNA; ! Specify which variables are used in the model
               MISSING = ALL(-999);
               LAGGED = dayPA(1) dayNA(1); ! This creates lagged variables
               TINTERVAL = sessdate(1); ! This is to account for unequal intervals

ANALYSIS:      TYPE = TWOLEVEL RANDOM; ! This allows for random slopes
               ESTIMATOR = BAYES; ! DSEM requires Bayesian estimation
               PROC = 2; ! Using 2 processors makes it faster
               BITER = (5000); ! This implies at least 5000 iterations are used
               THIN = 10; ! Thinning helps with getting more stable results
```

Bivariate model: Mplus code

```
MODEL:      %WITHIN% ! Specify the random lagged relationships
            p_pp | dayPA ON dayPA&1;
            p_pn | dayPA ON dayNA&1;
            p_np | dayNA ON dayPA&1;
            p_nn | dayNA ON dayNA&1;

            %BETWEEN% ! Allow all 6 random effects to be correlated
            p_pp WITH p_pn-p_nn dayPA dayNA;
            p_pn WITH p_np-p_nn dayPA dayNA;
            p_np WITH p_nn dayPA dayNA;
            p_nn WITH dayPA dayNA;
            dayPA WITH dayNA;

OUTPUT:     TECH1 TECH8 STDYX;

PLOT:       TYPE = PLOT3;
            FACTORS = ALL;
```

Mplus results: Within-person (younger sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within Level						
DAYNA WITH						
DAYPA	-0.069	0.004	0.000	-0.076	-0.061	*
Residual Variances						
DAYPA	0.414	0.006	0.000	0.403	0.426	*
DAYNA	0.302	0.004	0.000	0.294	0.311	*

Mplus results: Between-person (younger sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
Between Level						
...						
Means						
DAYPA	3.090	0.110	0.000	2.875	3.308	*
DAYNA	0.977	0.077	0.000	0.826	1.128	*
P_PP	0.334	0.026	0.000	0.283	0.387	*
P_PN	0.050	0.022	0.016	0.006	0.093	*
P_NP	0.038	0.015	0.006	0.008	0.068	*
P_NN	0.370	0.027	0.000	0.315	0.423	*
Variances						
DAYPA	1.178	0.189	0.000	0.886	1.618	*
DAYNA	0.595	0.101	0.000	0.443	0.832	*
P_PP	0.055	0.010	0.000	0.039	0.079	*
P_PN	0.024	0.006	0.000	0.014	0.039	*
P_NP	0.013	0.003	0.000	0.008	0.021	*
P_NN	0.062	0.012	0.000	0.044	0.089	*

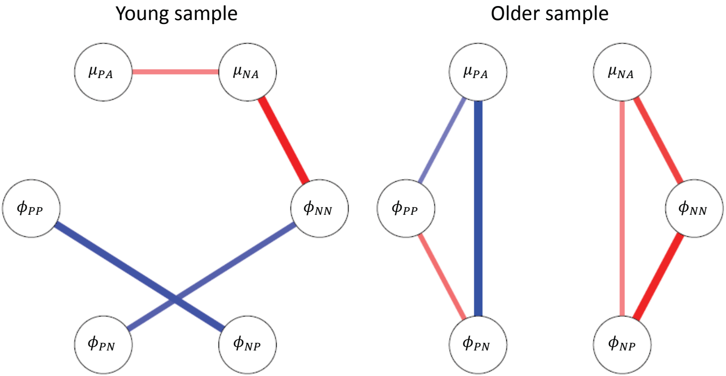
Mplus standardized results (younger sample)

Within-Level R-Square Averaged Across Clusters

Variable	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%
DAYPA	0.184	0.008	0.000	0.168	0.201
DAYNA	0.208	0.008	0.000	0.192	0.225

Between-person level: Correlated random effects

To **represent the correlation matrices** of the 6 random effects in each group, we can use the network representation (with qgraph from Sacha Epskamp in R):



Applications Overview

- 1. Multilevel VAR model for PA and NA
- **2. Multilevel VAR model with mediation**
- 3. Random (co)Variances and Measurement Error
- 4. Intervention Study

Including level 2 predictor and outcome

Depression was measured prior to the ILD phase and afterwards, using the CESD; we include these measures at the between-person level as a **predictor** and an **outcome**.

Between level: Including a level 2 predictor

$$\mu_{PA,i} = \gamma_{00} + \gamma_{01}\,CESDpre_i + u_{0i}$$
$$\mu_{NA,i} = \gamma_{10} + \gamma_{11}\,CESDpre_i + u_{1i}$$
$$\phi_{PP,i} = \gamma_{20} + \gamma_{21}\,CESDpre_i + u_{2i}$$
$$\phi_{PN,i} = \gamma_{30} + \gamma_{31}\,CESDpre_i + u_{3i}$$
$$\phi_{NN,i} = \gamma_{40} + \gamma_{41}\,CESDpre_i + u_{4i}$$
$$\phi_{NP,i} = \gamma_{50} + \gamma_{51}\,CESDpre_i + u_{5i}$$

Including level 2 predictor and outcome

Depression was measured prior to the ILD phase and afterwards, using the CESD; we include these measures at the between-person level as a **predictor** and an **outcome**.

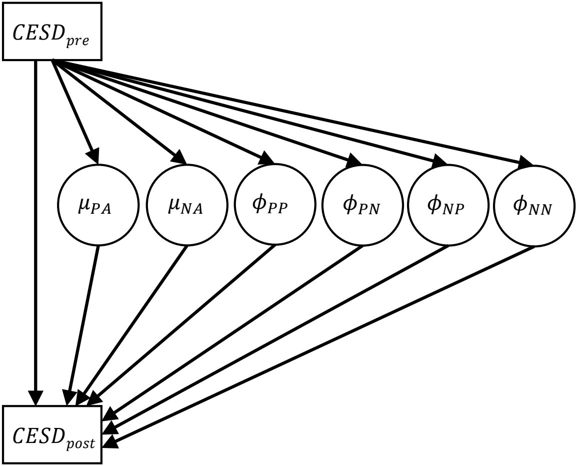
Between level: Including a level 2 predictor

$$
\begin{aligned}
\mu_{PA,i} &= \gamma_{00} + \gamma_{01}\,CESDpre_i + u_{0i} \\
\mu_{NA,i} &= \gamma_{10} + \gamma_{11}\,CESDpre_i + u_{1i} \\
\phi_{PP,i} &= \gamma_{20} + \gamma_{21}\,CESDpre_i + u_{2i} \\
\phi_{PN,i} &= \gamma_{30} + \gamma_{31}\,CESDpre_i + u_{3i} \\
\phi_{NN,i} &= \gamma_{40} + \gamma_{41}\,CESDpre_i + u_{4i} \\
\phi_{NP,i} &= \gamma_{50} + \gamma_{51}\,CESDpre_i + u_{5i}
\end{aligned}
$$

Between level: Including a level 2 outcome

$$
\begin{aligned}
CESDpost_i = \gamma_{60} &+ \gamma_{61}\,CESDpre_i + \gamma_{62}\mu_{PA,i} + \gamma_{63}\mu_{NA,i} \\
&+ \gamma_{64}\phi_{PP,i} + \gamma_{65}\phi_{PN,i} + \gamma_{66}\phi_{NN,i} + \gamma_{67}\phi_{NP,i} + u_{6i}
\end{aligned}
$$

Dynamic mediation model



Mplus input mediation model

```
VARIABLE:    NAMES = id sessdate
             na1 na2 na3 na4 na5 na6 na7 na8 na9 na10
             pa1 pa2 pa3 pa4 pa5 pa6 pa7 pa8 pa9 pa10
             sessionNr age_pre sex CESDpre CESDpost dayNA dayPA older;
             CLUSTER = id;
             USEVAR = dayPA dayNA CESDpre CESDpost; ! Plus level 2 variables
             BETWEEN = CESDpre CESDpost; ! Specify these as level 2 variables
             LAGGED = dayPA(1) dayNA(1);
             TINTERVAL = sessdate(1);
             MISSING = ALL(-999);

DEFINE:      CENTER CESDpre CESDpost (GRANDMEAN);! Grand mean centering

ANALYSIS:    TYPE = TWOLEVEL RANDOM;
             ESTIMATOR = BAYES;
             PROCESSORS = 2;
             BITER = (5000);
             THIN = 10;
```

Bivariate model: Mplus code

```
MODEL:               %WITHIN% ! Same as before
                     p_pp | dayPA ON dayPA&1;
                     p_pn | dayPA ON dayNA&1;
                     p_np | dayNA ON dayPA&1;
                     p_nn | dayNA ON dayNA&1;

                     %BETWEEN% ! Mediation model with parameter names
                     p_pp-p_nn dayPA dayNA ON CESDpre (a1-a6);
                     CESDpost ON p_pp-p_nn dayPA dayNA CESDpre (b1-b7);

MODEL CONSTRAINT:    ! Compute the indirect effects
                     new (ab_p_pp); ab_p_pp=a1*b1;
                     new (ab_p_pn); ab_p_pn=a2*b2;
                     new (ab_p_np); ab_p_np=a3*b3;
                     new (ab_p_nn); ab_p_nn=a4*b4;
                     new (ab_dayPA); ab_dayPA=a5*b5;
                     new (ab_dayNA); ab_dayNA=a6*b6;

OUTPUT:              TECH1 TECH8 STDYX;

PLOT:                TYPE = PLOT3;
                     FACTOR =ALL;
```

Mplus output mediation model (younger sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
New/Additional Parameters						
AB_P_PP	0.010	0.025	0.266	-0.028	0.076	
AB_P_PN	-0.002	0.032	0.439	-0.074	0.062	
AB_P_NP	-0.004	0.037	0.401	-0.089	0.067	
AB_P_NN	0.195	0.070	0.000	0.081	0.359	*
AB_DAYPA	0.049	0.035	0.029	-0.001	0.135	
AB_DAYNA	0.028	0.043	0.234	-0.052	0.119	

Mplus output mediation model (older sample)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
New/Additional Parameters						
AB_P_PP	0.005	0.016	0.302	-0.018	0.049	
AB_P_PN	-0.004	0.025	0.396	-0.061	0.045	
AB_P_NP	0.012	0.027	0.268	-0.035	0.076	
AB_P_NN	-0.036	0.038	0.112	-0.130	0.025	
AB_DAYPA	0.028	0.038	0.209	-0.042	0.110	
AB_DAYNA	0.027	0.036	0.194	-0.040	0.108	

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- **3. Random (co)Variances and Measurement Error**
- 4. Intervention Study

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Intervention study with ESM

When **ESM** is used in a **randomized controlled trial**, we can investigate whether treatment affects symptoms through changing:

- means
- dynamics (e.g., autoregression)
- variability

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- dynamics (e.g., autoregression)
- variability

Here we use negative affect (NA) from individuals with a **history of depression** and current residual depressive symptoms (Geschwind et al., 2011).

Each ESM period consisted of 6 days, 10 beeps per day.

We analyze data from 117 participants; 56 received a **mindfulness training** between the two phases, and 61 served as **controls**.

Data setup

Phase	Meas	Y
1	1	31
1	2	45
1	3	42
1	4	38
1	5	51
1	6	34
2	1	16
2	2	31
2	3	34
2	4	28
2	5	19
2	6	22

Data setup

Phase	Meas	Y
1	1	31
1	2	45
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2	2	31
2	3	34
2	4	28
2	5	19
2	6	22

Phase	Meas	Y1	Y2
1	1	31	
1	2	45	
1	3	42	
1	4	38	
1	5	51	
1	6	34	
2	1		16
2	2		31
2	3		34
2	4		28
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Treatment effect on the within-person mean

We use $NA1_{it}$ and $NA2_{it}$ as **two separate variables**!

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We use $NA1_{it}$ and $NA2_{it}$ as **two separate variables**!

Decomposition into a between part and a within part

$$\begin{aligned}\text{Pre-treatment phase:} \quad & NA1_{it} = \mu_{1i} + NA1_{it}^{(w)} \\ \text{Post-treatment phase:} \quad & NA2_{it} = \mu_{2i} + NA2_{it}^{(w)}\end{aligned}$$

Treatment effect on the within-person mean

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Decomposition into a between part and a within part

$$\text{Pre-treatment phase:} \quad NA1_{it} = \mu_{1i} + NA1_{it}^{(w)}$$
$$\text{Post-treatment phase:} \quad NA2_{it} = \mu_{2i} + NA2_{it}^{(w)}$$

Between level

$$\mu_{1i} = \gamma_{00} + \gamma_{01} Group_i + u_{1i}$$
$$\mu_{2i} = \gamma_{10} + \mu_{1i} + \gamma_{11} Group_i + u_{2i}$$

- γ_{01} is the **initial difference** between the groups
- γ_{10} is the **effect of time**
- γ_{11} is the **effect of treatment**

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$$\text{Pre-treatment phase:} \quad NA1_{it} = \mu_{1i} + NA1_{it}^{(w)}$$
$$\text{Post-treatment phase:} \quad NA2_{it} = \mu_{2i} + NA2_{it}^{(w)}$$

Between level

$$\mu_{1i} = \gamma_{00} + \gamma_{01} Group_i + u_{1i}$$
$$\mu_{2i} = \gamma_{10} + \mu_{1i} + \gamma_{11} Group_i + u_{2i}$$

- γ_{01} is the **initial difference** between the groups
- γ_{10} is the **effect of time**
- γ_{11} is the **effect of treatment**

Note: $\mu_{2i} - \mu_{1i} = \gamma_{10} + \gamma_{11} Group_i + u_{2i}$.

Mplus input

```
MODEL:    %WITHIN%
          NA1 WITH NA2@0;

          %BETWEEN%
          NA1 ON Group;
          NA2 ON NA1@1 Group;
          NA1 WITH NA2;
```

Note: When $NA1_{it}$ is observed, $NA2_{it}$ is missing, and vice versa; hence, we fix their within-person **covariance to zero**.

Mplus results: Within

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within Level						
NA1 WITH						
NA2	0.000	0.000	1.000	0.000	0.000	
Variances						
NA1	0.631	0.012	0.000	0.607	0.656	*
NA2	0.472	0.009	0.000	0.454	0.490	*

Mplus results: Between

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
NA1 ON						
GROUP	-0.031	0.136	0.408	-0.304	0.234	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.280	0.110	0.003	-0.500	-0.074	*
Intercepts						
NA1	2.028	0.093	0.000	1.849	2.213	*
NA2	-0.027	0.076	0.345	-0.175	0.122	
Residual Variances						
NA1	0.520	0.074	0.000	0.398	0.683	*
NA2	0.316	0.049	0.000	0.237	0.431	*

Conclusion:

- No initial differences between the groups
- Significant (negative) change in NA due to treatment
- No change due to time

Treatment and time effects on autoregression

Within level: AR(1) processes

$$\text{Pre-treatment phase:} \quad NA1_{it}^{(w)} = \phi_{1i} NA1_{it-1}^{(w)} + \zeta1_{it}$$
$$\text{Post-treatment phase:} \quad NA2_{it}^{(w)} = \phi_{2i} NA2_{it-1}^{(w)} + \zeta2_{it}$$

Treatment and time effects on autoregression

Within level: AR(1) processes

$$\text{Pre-treatment phase:} \quad NA1_{it}^{(w)} = \phi_{1i} NA1_{it-1}^{(w)} + \zeta 1_{it}$$
$$\text{Post-treatment phase:} \quad NA2_{it}^{(w)} = \phi_{2i} NA2_{it-1}^{(w)} + \zeta 2_{it}$$

Between level: Pre-treatment phase

$$\mu_{1i} = \gamma_{00} + \gamma_{01} Group_i + u_{0i}$$
$$\phi_{1i} = \gamma_{10} + \gamma_{11} Group_i + u_{1i}$$

We expect γ_{01} and γ_{11} to be zero.

Treatment and time effects on autoregression

Within level: AR(1) processes

$$\text{Pre-treatment phase:} \quad NA1_{it}^{(w)} = \phi_{1i} NA1_{it-1}^{(w)} + \zeta 1_{it}$$
$$\text{Post-treatment phase:} \quad NA2_{it}^{(w)} = \phi_{2i} NA2_{it-1}^{(w)} + \zeta 2_{it}$$

Between level: Pre-treatment phase

$$\mu_{1i} = \gamma_{00} + \gamma_{01}\, Group_i + u_{0i}$$
$$\phi_{1i} = \gamma_{10} + \gamma_{11}\, Group_i + u_{1i}$$

We expect γ_{01} and γ_{11} to be zero.

Between level: Post-treatment phase

$$\mu_{2i} = \gamma_{20} + \mu_{1i} + \gamma_{21}\, Group_i + u_{2i} \quad \text{or:}$$
$$\Delta\mu_i = \gamma_{20} + \gamma_{21}\, Group_i + u_{2i}$$
$$\phi_{2i} = \gamma_{30} + \phi_{1i} + \gamma_{31}\, Group_i + u_{3i} \quad \text{or:}$$
$$\Delta\phi_i = \gamma_{30} + \gamma_{31}\, Group_i + u_{3i}$$

Where: γ_{20} and γ_{30} represent the **effects of time** and: γ_{21} and γ_{31} represent the **effects of treatment**

Mplus results (all effects random)

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
PHI2 ON						
PHI1	1.000	0.000	0.000	1.000	1.000	
PHI1 ON						
GROUP	0.052	0.047	0.130	-0.039	0.142	
PHI2 ON						
GROUP	-0.077	0.066	0.119	-0.209	0.057	
NA1 ON						
GROUP	-0.079	0.134	0.284	-0.340	0.183	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.246	0.105	0.010	-0.457	-0.038	*
Intercepts						
NA1	2.008	0.092	0.000	1.831	2.190	*
NA2	-0.005	0.071	0.470	-0.148	0.136	
PHI1	0.454	0.034	0.000	0.390	0.522	*
PHI2	-0.092	0.047	0.022	-0.185	-0.004	*

Mplus results with: phi2@0;

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
PHI2 ON						
PHI1	1.000	0.000	0.000	1.000	1.000	
PHI1 ON						
GROUP	0.075	0.049	0.053	-0.014	0.174	
PHI2 ON						
GROUP	-0.070	0.033	0.014	-0.137	-0.005	*
NA1 ON						
GROUP	-0.071	0.132	0.302	-0.327	0.192	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.247	0.105	0.010	-0.454	-0.043	*
Intercepts						
NA1	2.012	0.090	0.000	1.837	2.194	*
NA2	-0.010	0.071	0.442	-0.152	0.133	
PHI1	0.425	0.034	0.000	0.356	0.491	*
PHI2	-0.019	0.022	0.199	-0.062	0.026	

Now: No effect of time on the change in ϕ, but instead a treatment

Including a level 1 predictor

Let $UP1_{it}$ and $UP2_{it}$ be variables for phases 1 and 2, that indicate whether something emotionally charged happened **since the previous beep** (positive scores is Pleasant event, negative score is Unpleasant event).

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Within level

Pre-treatment phase: $NA1_{it}^{(w)} = \phi_{1i} NA1_{it-1}^{(w)} + \beta_{1i} UP1_{it}^{(w)} + \zeta_{1it}$

Post-treatment phase: $NA2_{it}^{(w)} = \phi_{2i} NA2_{it-1}^{(w)} + \beta_{2i} UP2_{it}^{(w)} + \zeta_{2it}$

where:

- ϕ_{1i} and ϕ_{2i} represent carry-over
- β_{1i} and β_{2i} represent reactivity/sensitivity

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- ϕ_{1i} and ϕ_{2i} represent carry-over
- β_{1i} and β_{2i} represent reactivity/sensitivity

Note that we have **concurrent regressions** in this model (i.e., β_{1i} and β_{2i}).

Including a level 1 predictor

Group is a predictor at the between level:

Between level: Pre-treatment phase

$$\mu_{1i} = \gamma_{00} + \gamma_{01} Group_i + u_{0i}$$
$$\phi_{1i} = \gamma_{10} + \gamma_{11} Group_i + u_{1i}$$
$$\beta_{1i} = \gamma_{20} + \gamma_{21} Group_i + u_{2i}$$

where γ_{01}, γ_{11}, and γ_{21} are expected to be zero.

Including a level 1 predictor

Group is a predictor at the between level:

Between level: Pre-treatment phase

$$\mu_{1i} = \gamma_{00} + \gamma_{01}\,Group_i + u_{0i}$$
$$\phi_{1i} = \gamma_{10} + \gamma_{11}\,Group_i + u_{1i}$$
$$\beta_{1i} = \gamma_{20} + \gamma_{21}\,Group_i + u_{2i}$$

where γ_{01}, γ_{11}, and γ_{21} are expected to be zero.

The **change** in mean, carry-over, and reactivity is modeled as:

Between level: Post-treatment phase

$\mu_{2i} = \gamma_{30} + \mu_{1i} + \gamma_{31}\,Group_i + u_{3i}$ or:
$\Delta\mu_i = \gamma_{30} + \gamma_{31}\,Group_i + u_{3i}$
$\phi_{2i} = \gamma_{40} + \phi_{1i} + \gamma_{41}\,Group_i + u_{4i}$ or:
$\Delta\phi_i = \gamma_{40} + \gamma_{41}\,Group_i + u_{4i}$
$\beta_{2i} = \gamma_{50} + \beta_{1i} + \gamma_{51}\,Group_i + u_{5i}$ or:
$\Delta\beta_i = \gamma_{50} + \gamma_{51}\,Group_i + u_{5i}$

where

- γ_{30}, γ_{40}, and γ_{50} represent **change due to time**

Mplus input: Centering within predictors

```
VARIABLE:   NAMES = ID Time PrePost Group pa1 pa2 na1 na2
            PDLA1 PDLA2 up1 up2 ham1 ham2;
            CLUSTER = ID;
            USEVAR = na1 na2 up1 up2 Group;
            LAGGED = na1(1) na2(1);
            BETWEEN = Group;
            WITHIN = up1 up2;
            TINTERVAL = Time(1);
            MISSING = ALL(-999);

DEFINE:     CENTER up1 up2 (GROUPMEAN);
```

Note that the **concurrent predictors** UP1 and UP2 are:

- defined as **within-level variables**
- centered per person (i.e., group mean centering using **sample means** rather than latent means)

This is to allow for **lag zero (concurrent) regressions** when the **predictor has missings**.

Mplus input: Within and between model

Note: The within-person predictor has missings; by asking for the variances, Mplus treats it as a y-variable, which is allowed to have missings.

```
MODEL:
        %WITHIN%
        phi1 | na1 ON na1&1;
        beta1 | na1 ON up1;
        phi2 | na2 ON na2&1;
        beta2 | na2 ON up2;

        na1-up1 WITH na2-up2@0;
        up1; up2;

        %BETWEEN%
        na1 phi1 beta1 ON Group;
        na2 ON na1@1 Group;
        phi2 ON phi1@1 Group;
        beta2 ON beta1@1 Group;
```

Mplus output: Regressions at Between level

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	Upper 2.5%	Significance
Between Level						
PHI2 ON						
PHI1	1.000	0.000	0.000	1.000	1.000	
BETA2 ON						
BETA1	1.000	0.000	0.000	1.000	1.000	
PHI1 ON						
GROUP	0.050	0.046	0.119	-0.035	0.144	
BETA1 ON						
GROUP	0.001	0.019	0.470	-0.034	0.041	
PHI2 ON						
GROUP	-0.077	0.068	0.123	-0.214	0.053	
BETA2 ON						
GROUP	-0.016	0.026	0.264	-0.069	0.032	
NA1 ON						
GROUP	-0.070	0.134	0.297	-0.340	0.180	
NA2 ON						
NA1	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.255	0.105	0.007	-0.463	-0.059	*

Mplus output: Intercepts and random effects

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Between Level						
Intercepts						
NA1	2.012	0.091	0.000	1.835	2.189	*
NA2	-0.014	0.071	0.422	-0.155	0.126	
PHI1	0.423	0.033	0.000	0.357	0.487	*
BETA1	-0.123	0.013	0.000	-0.150	-0.097	*
PHI2	-0.082	0.047	0.039	-0.173	0.011	
BETA2	0.005	0.018	0.388	-0.027	0.041	
Residual Variances						
NA1	0.466	0.070	0.000	0.355	0.632	*
NA2	0.268	0.042	0.000	0.199	0.359	*
PHI1	0.038	0.008	0.000	0.026	0.056	*
BETA1	0.006	0.001	0.000	0.004	0.009	*
PHI2	0.078	0.016	0.000	0.051	0.114	*
BETA2	0.008	0.003	0.000	0.005	0.015	*

Conclusion:

- means of μ_{1i}, ϕ_{1i}, and β_{1i} deviate from zero
- no change due to time (intercepts for μ_{2i}, ϕ_{2i}, and β_{2i} are zero)

Mplus output: Standardized regressions

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within-Level Standardized Estimates Averaged Over Clusters						
PHI1 | NA1 ON						
NA1&1	0.449	0.014	0.000	0.419	0.475	*
BETA1 | NA1 ON						
UP1	-0.254	0.013	0.000	-0.279	-0.229	*
PHI2 | NA2 ON						
NA2&1	0.328	0.016	0.000	0.297	0.358	*
BETA2 | NA2 ON						
UP2	-0.259	0.015	0.000	-0.287	-0.230	*

Conclusion:

- the standardized parameters are standardized per person first
- the standardized parameters for the post treatment phase are for the "total" parameter (e.g., $\phi_{2i} = \gamma_{40} + \phi_{1i} + \gamma_{41} Group_i + u_{4i}$)