Discovering Psychological Dynamics

Part 2: Time-series Analysis

Sacha Epskamp

11-10-2016

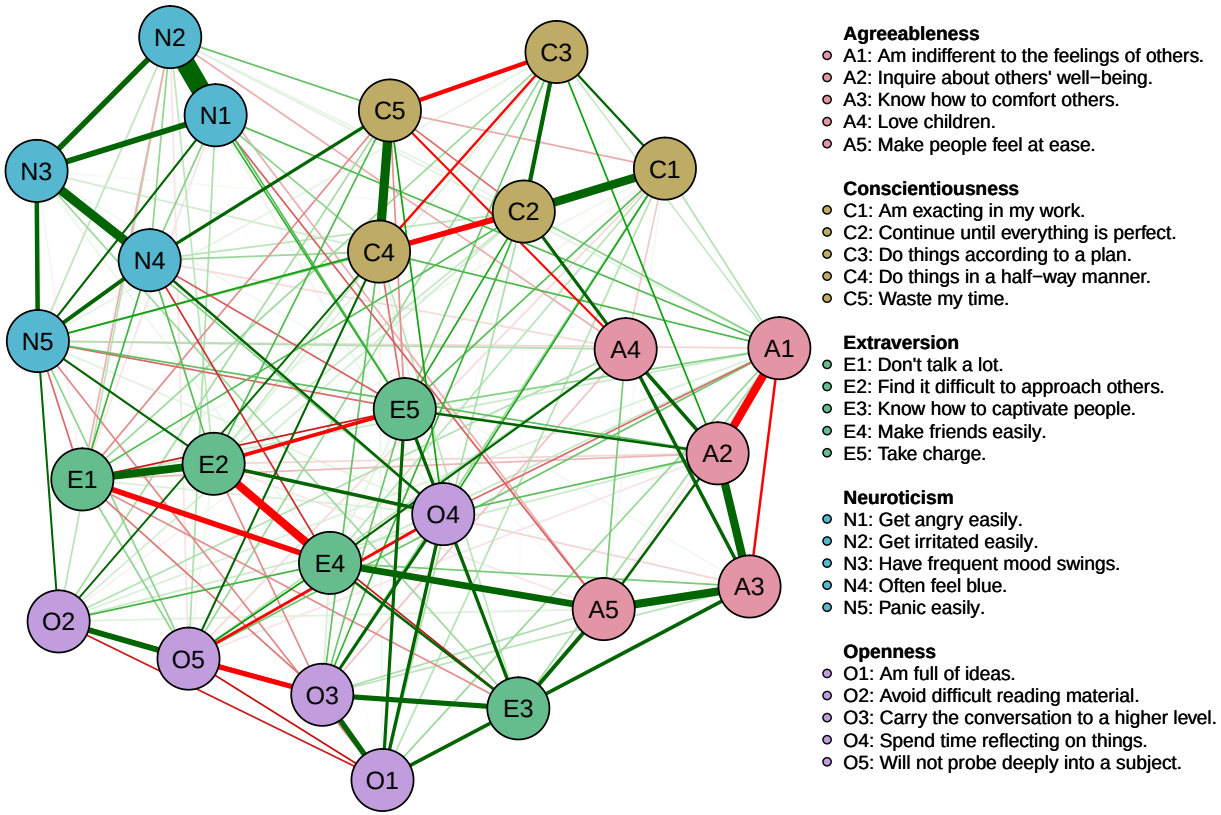
Three Types of Psychological Networks

Network	Gaussian	Binary	Mixed
Concentration	GGM	Ising	MGM
Contemporaneous	GGM	?	?
Temporal	VAR	Logistic VAR	MGM
Between-subjects	GGM	?	?

GGM = Gaussian graphical model; VAR = Vector Autoregression; MGM = Mixed graphical models

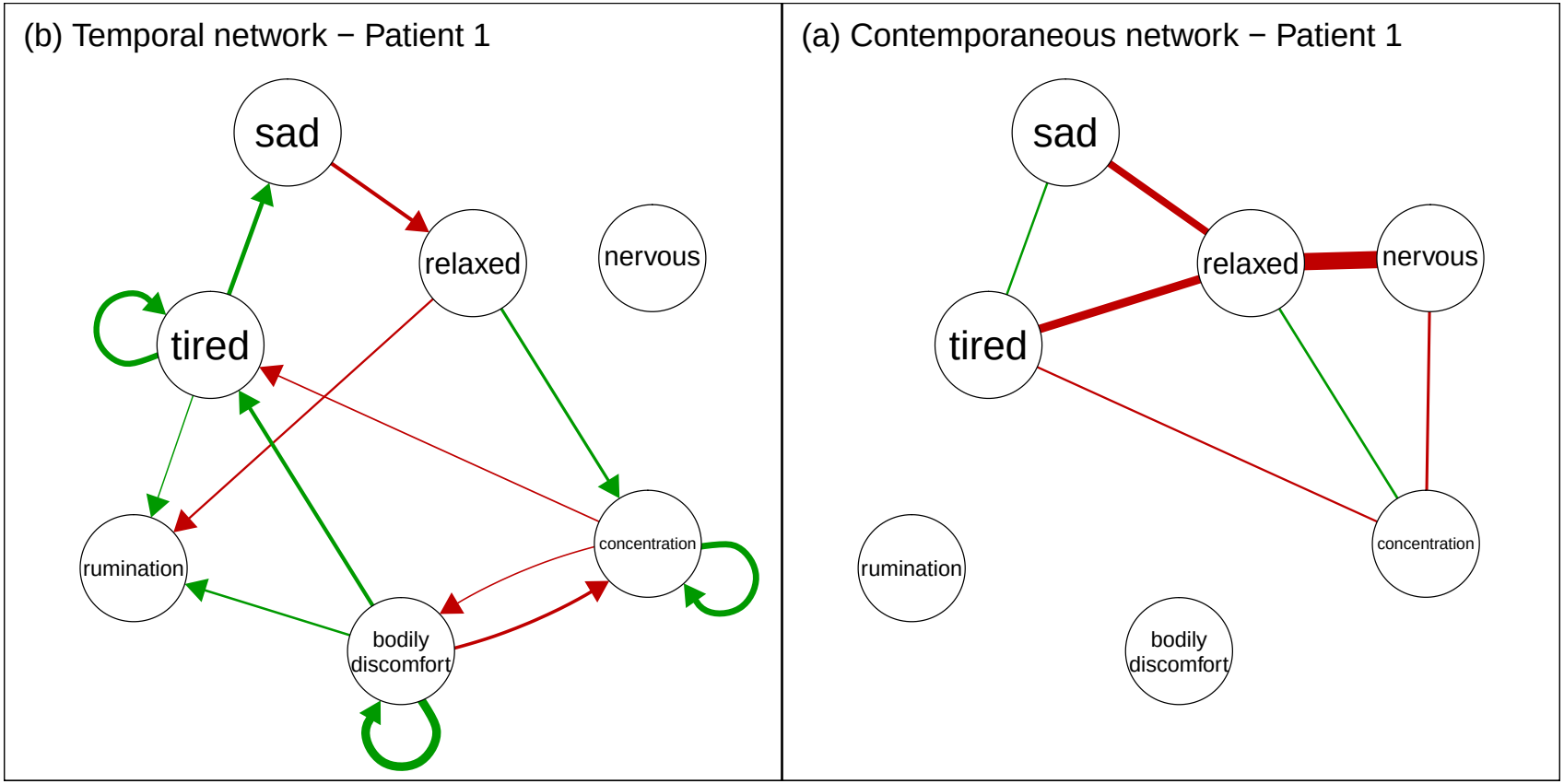
- Cross-sectional: concentration network
- $N = 1$ time-series: contemporaneous and temporal networks
  - The concentration network is the same as the contemporaneous network in time-series analysis
- $N > 1$ time-series: contemporaneous, temporal and between-subject networks

Cross-sectional Analysis



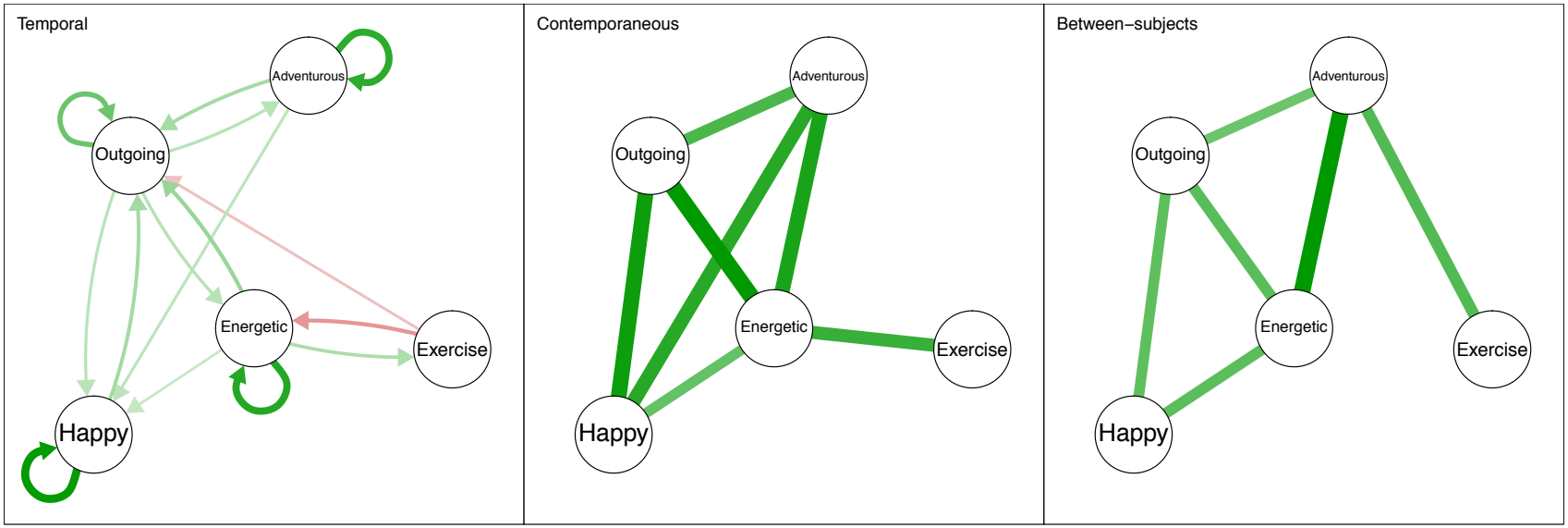
- Concentration network: unique variance between two variables

$N = 1$ Time-series Analysis



- Contemporaneous network: conditional concentration given $t - 1$
- Temporal network: regression coefficients between $t - 1$ and t

$N > 1$ Time-series Analysis

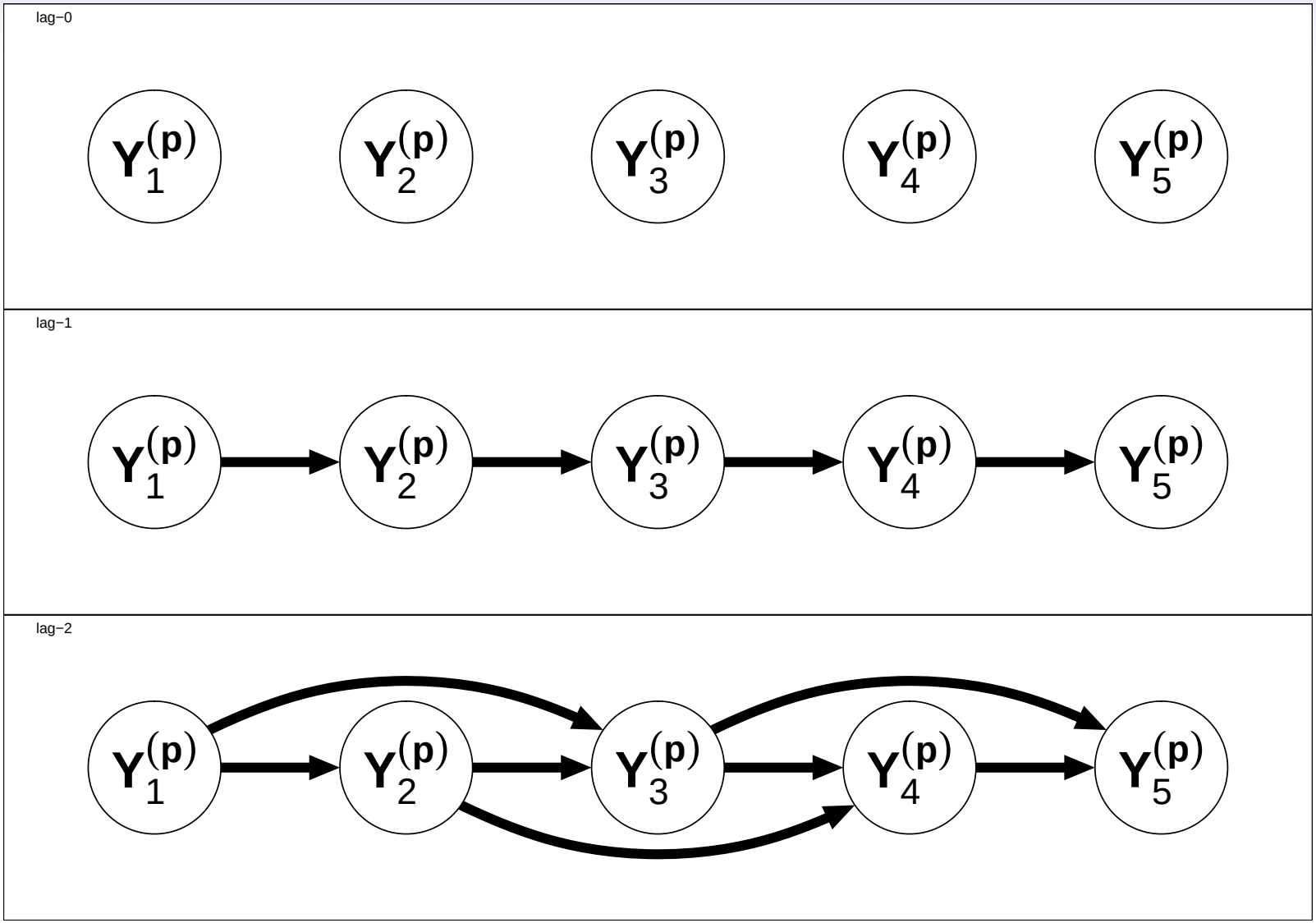


- Between-subjects network: concentration network between stationary means
- Two-step multilevel VAR

Time-series: $n = 1$

Time-series Data

- One person measured several times in a short period
- Cases can **not** reasonably be assumed to be *independent*
  - Knowing someone's level of fatigue at a time point helps predict his or her level of fatigue at the next time point.
- Likelihood not easy to compute without three assumptions:
  - The time-series factorize according to a graph
  - The model does not change over time
  - The first measurement is exogenous

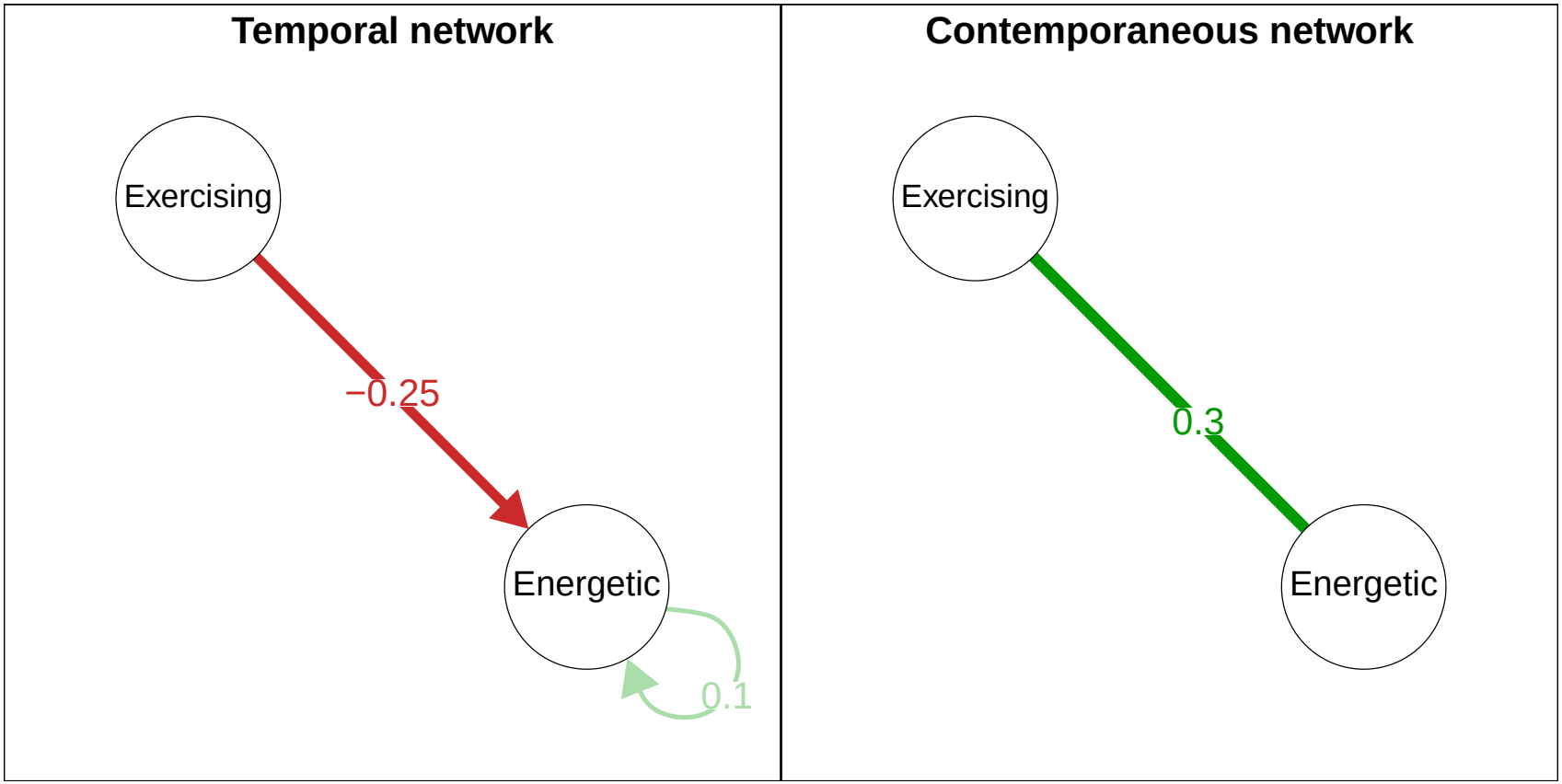


- We will use the lag-1 factorization

Vector Auto-regression

$$\boldsymbol{Y}_t \mid \boldsymbol{y}_{t-1} \sim N\left(\boldsymbol{\mu} + \boldsymbol{B}\left(\boldsymbol{y}_{t-1} - \boldsymbol{\mu}\right), \boldsymbol{\Theta}\right)$$

- $\boldsymbol{B}$ encodes the *temporal network*
  - Granger causality
- $\boldsymbol{\Theta}^{-1}$ encodes the *contemporaneous network*
  - GGM
- The sample means can be used as plugin to center the predictors


Temporal network
Exercising
−0.25
Energetic
0.1
Contemporaneous network
Exercising
0.3
Energetic

Contemporaneous Causation

- Many causal effects likely faster than the time-window of measurement
  - Somatic arousal $\rightarrow$ anticipation of panic attack $\rightarrow$ anxiety
- These can be caught in a contemporaneous network of **partial correlations**
- Thus, the contemporaneous network can also be seen to highlight potential causal relationships
- As the contemporaneous network is the GGM, the temporal network can be seen as a correction for dependent measurements in estimating the GGM

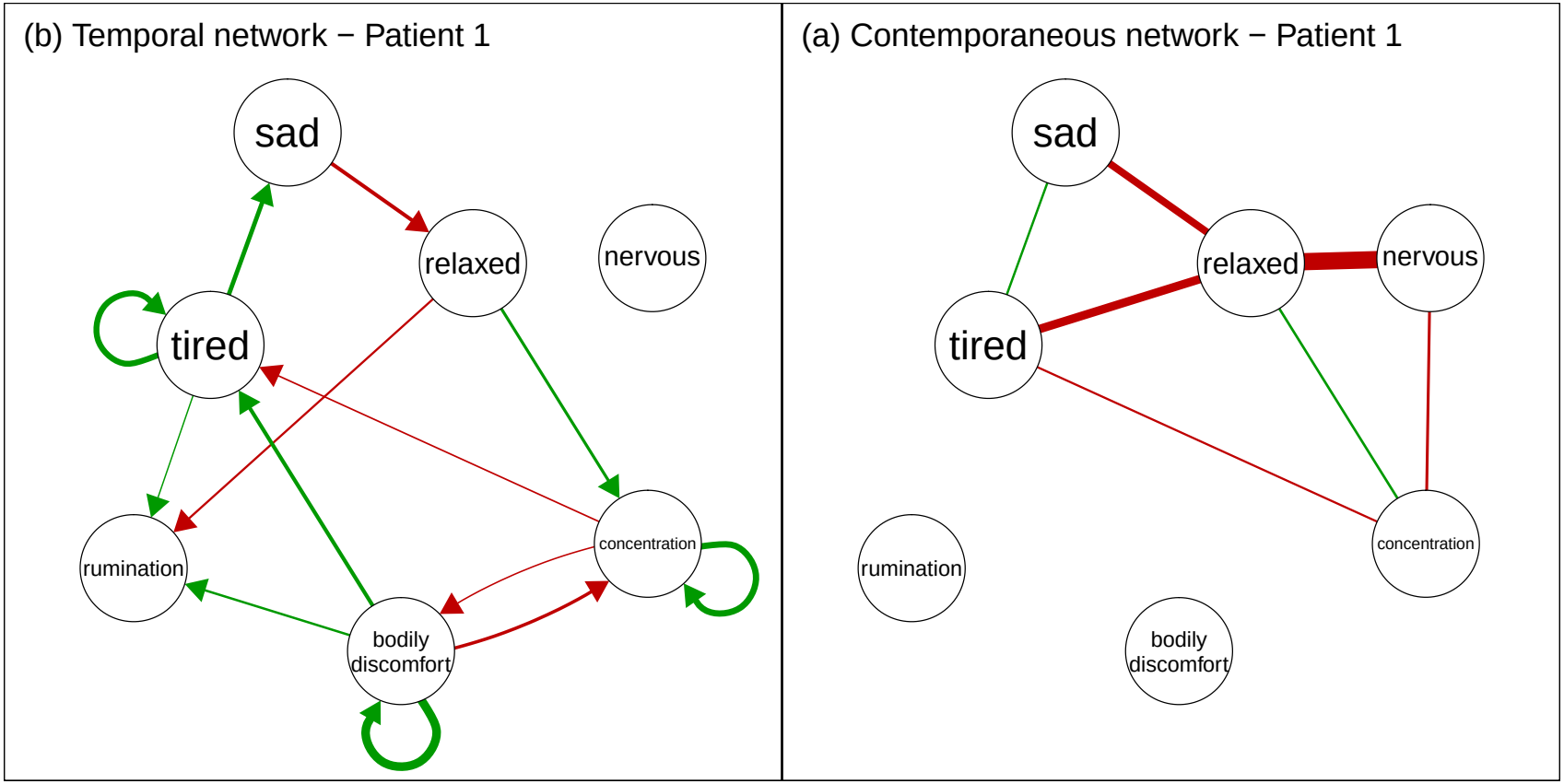
- Estimation straightforward using multiple regression
- For model selection, we use the graphical VAR model
  - Wild et al. (2010). A graphical vector autoregressive modelling approach to the analysis of electronic diary data. *BMC Medical Research Methodology 10 (1):* 28.
- Estimation via LASSO regularization, using EBIC to select optimal tuning parameter
  - Abegaz & Wit (2013). Sparse Time Series Chain Graphical Models for Reconstructing Genetic Networks. *Biostatistics*: kxt005.
  - Rothman, Elizaveta, & Zhu (2010). Sparse Multivariate Regression with Covariance Estimation. *Journal of Computational and Graphical Statistics 19 (4)*: 947–62.
- We implemented these methods in the R package `graphicalVAR`
- Also implemented in `sparseTSCGM`

Personalized Network Modeling in Psychopathology: The Importance of Contemporaneous and Temporal Connections

Sacha Epskamp[1], Claudia D. van Borkulo[1], Date C. van der Veen[2], Michelle N. Servaas[2], Adela-Maria Isvoranu[1], Harriëtte Riese[2], Angelique O.J. Cramer[1]

1. University of Amsterdam, Department of Psychological Methods
2. University of Groningen, University Medical Center Groningen, Department of Psychiatry, Interdisciplinary Center for Psychopathology and Emotion Regulation

Personalized Networks in Clinical Practice

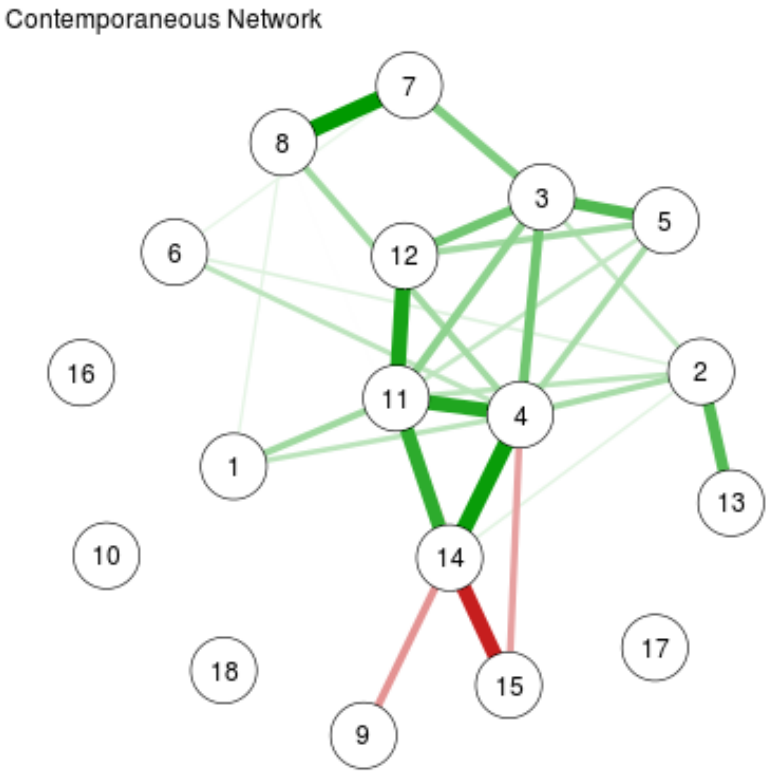


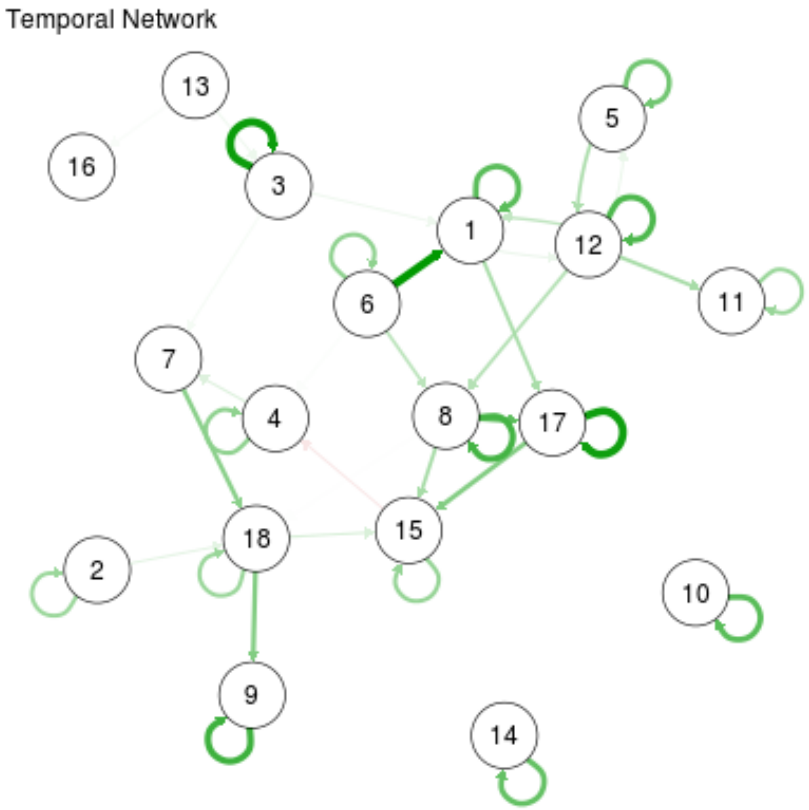
- Contemporaneous network: conditional concentration given $t - 1$
- Temporal network: regression coefficients between $t - 1$ and t

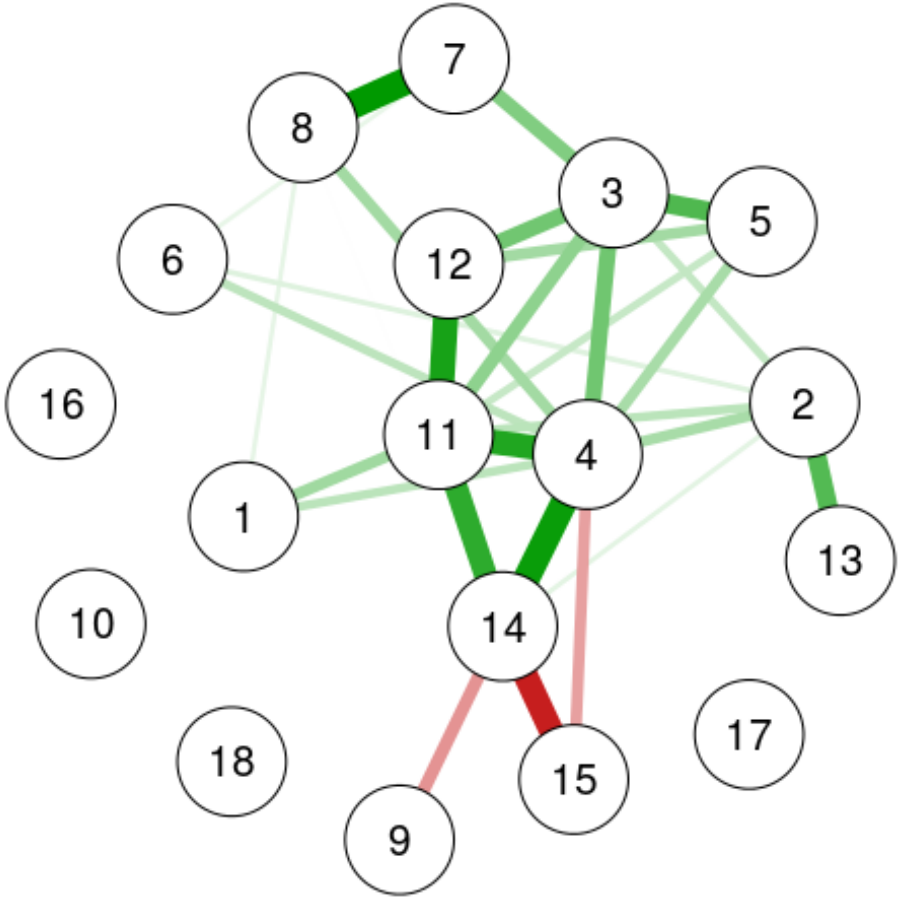
Empirical Example 2

Data collected by Date C. Van der Veen, in collaboration with Harriette Riese en Renske Kroeze.

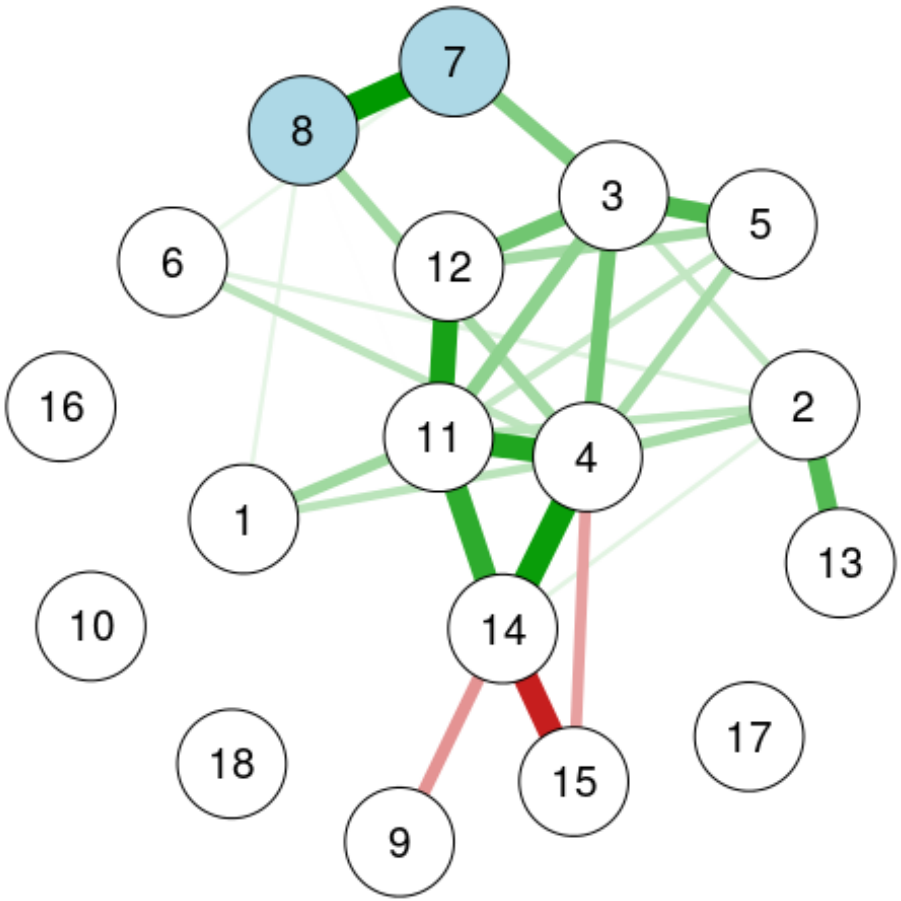
- Patient suffering from panic disorder and depressive symptoms
  - Perfectionist
- Measured over a period of two weeks
- Five times per day
- Items were chosen after intake together with therapist


Contemporaneous Network
7
8
3
5
6
12
16
11
4
2
1
13
10
14
17
18
15
9


Temporal Network
13
5
16
3
1
12
6
11
7
4
8
17
18
15
2
10
9
14



1: I feel anxious
2: I feel stressed
3: I feel angry
4: I feel sad
5: I feel guilty
6: I feel weak
7: I feel worthless
8: I feel helpless
9: I feel full of Energy
10: I am afraid of a panic attack
11: I am afraid I am going to cry
12: I am afraid of appearing angry
13: I have 'had to do things'
14: I am experiencing bodily discomfort
15: I am enjoying myself
16: I let something pass I find important
17: I experienced my social environment as pleasurable
18: I was physically active



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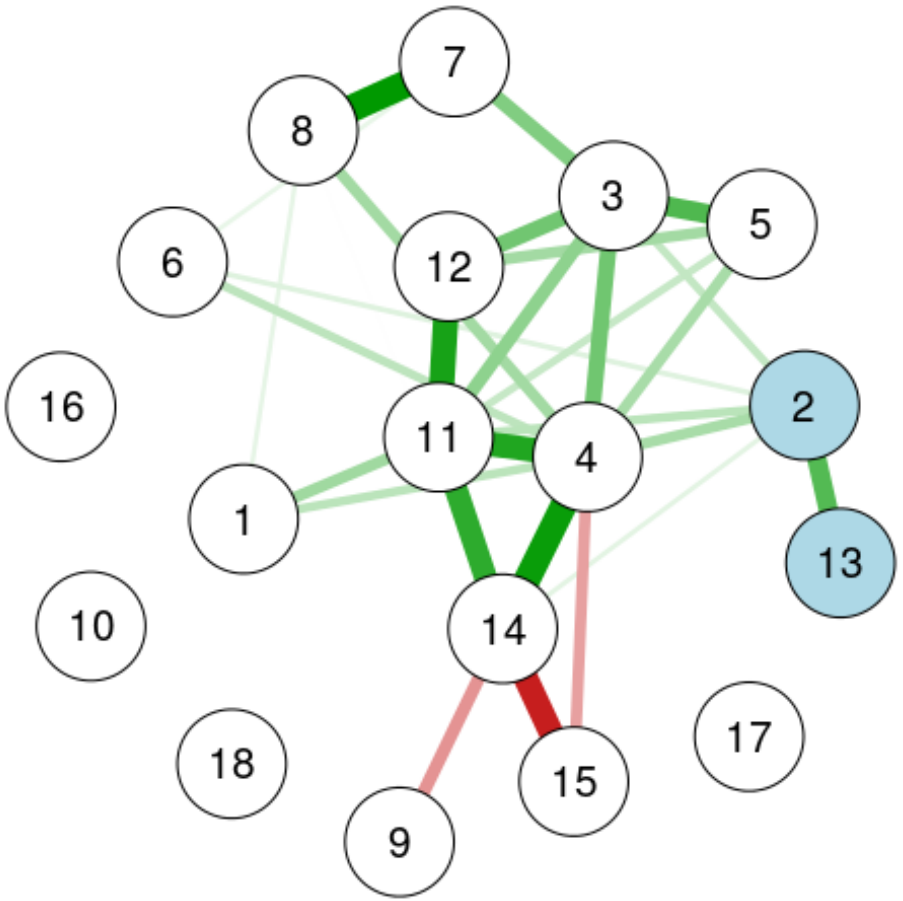
Feeling worthless interacts with feeling helpless



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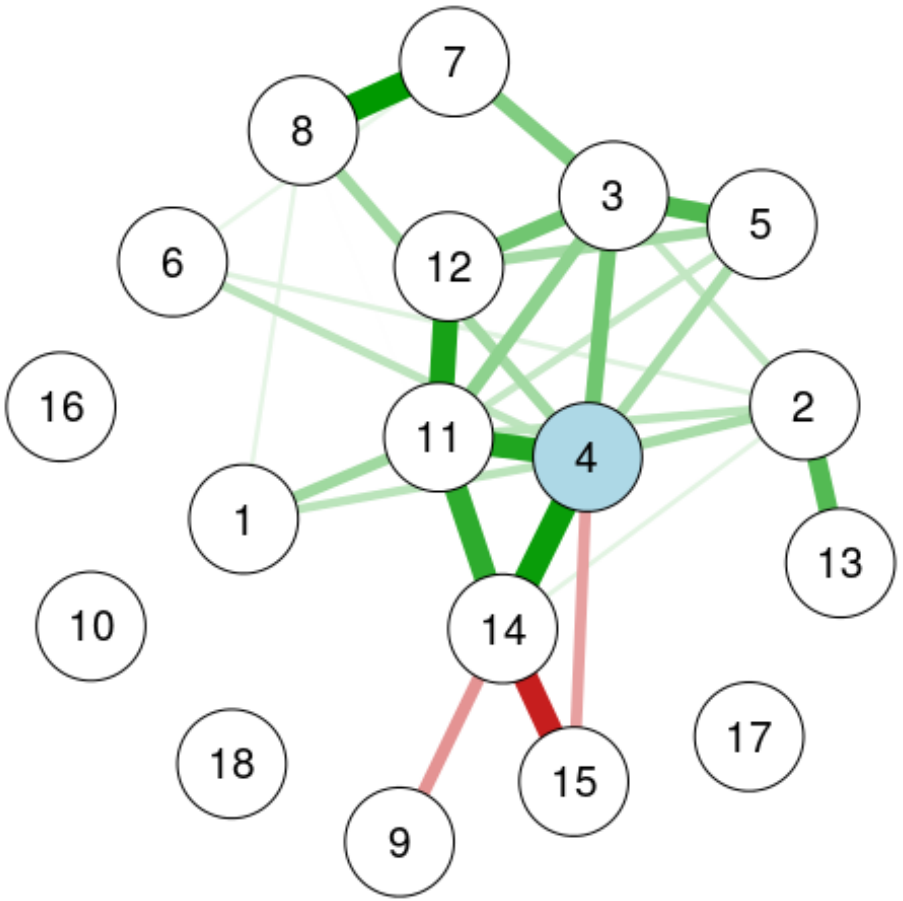
Feeling stressed interacts with feeling the need to do things



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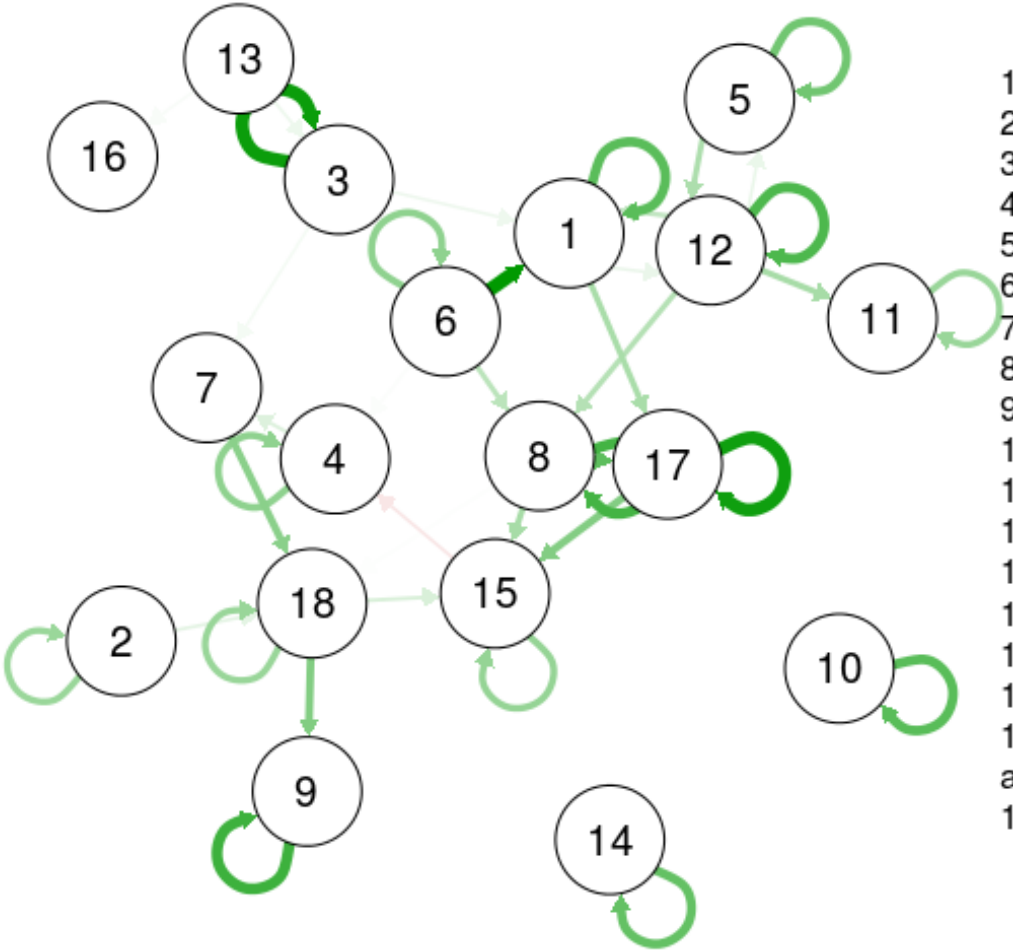
Central node: Feeling sad



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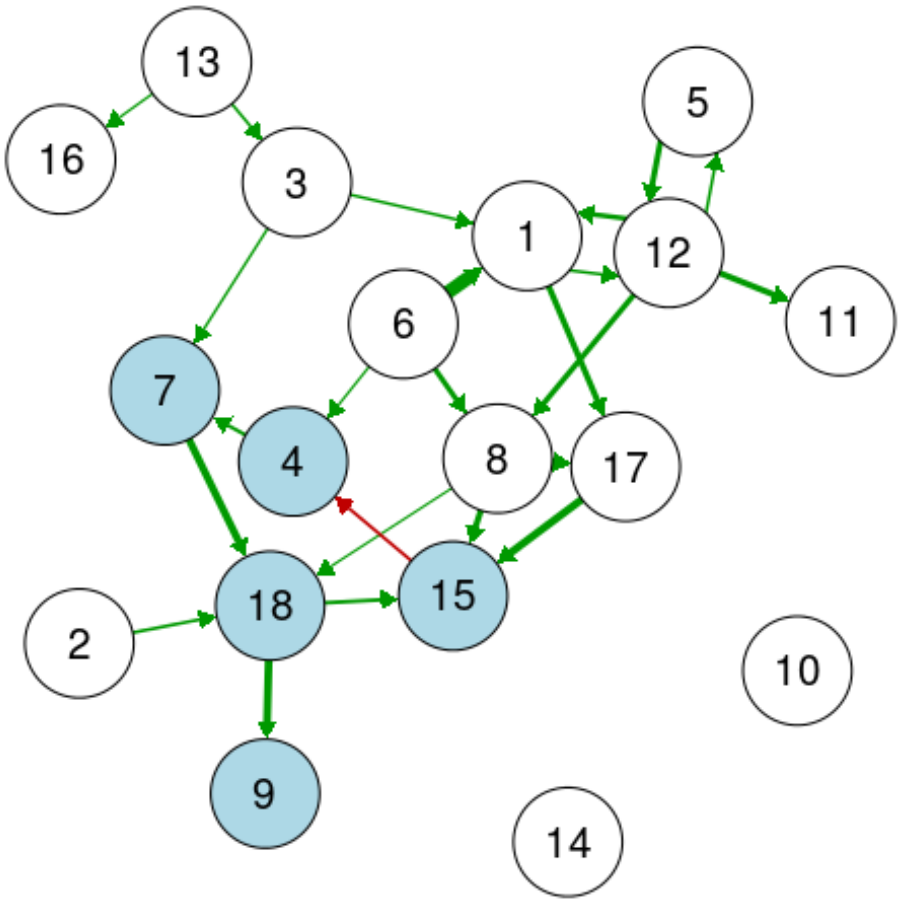

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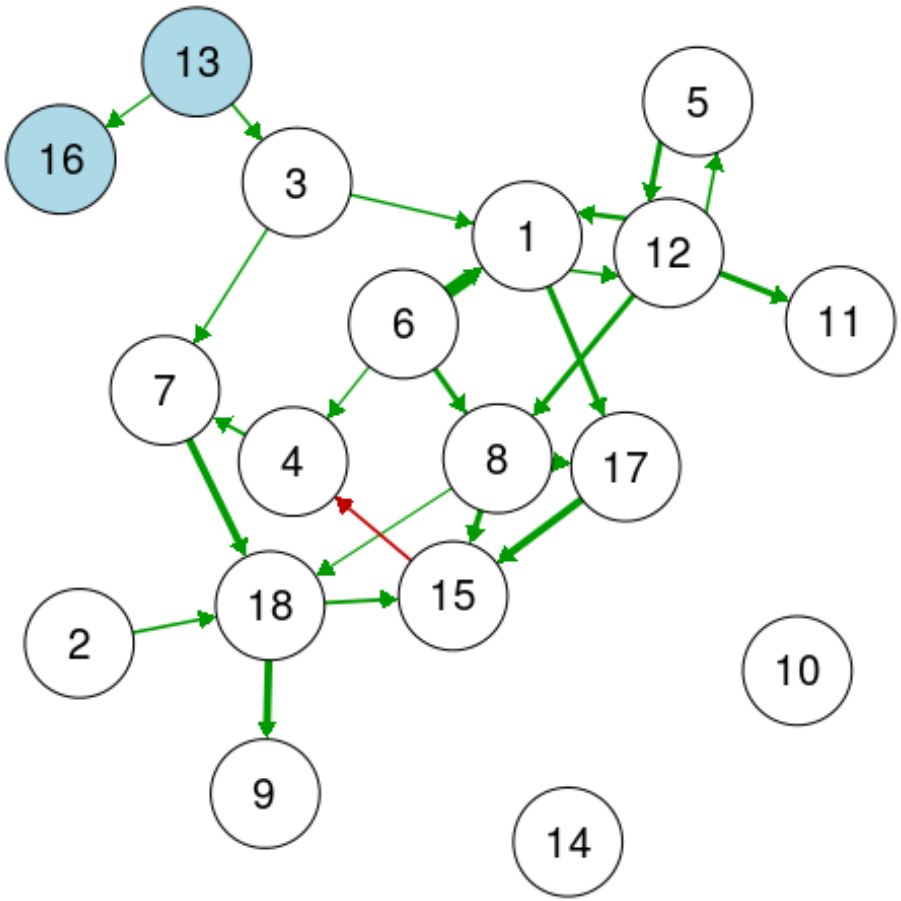
Cycle of enjoyment, feeling sad, feeling worthless and being active



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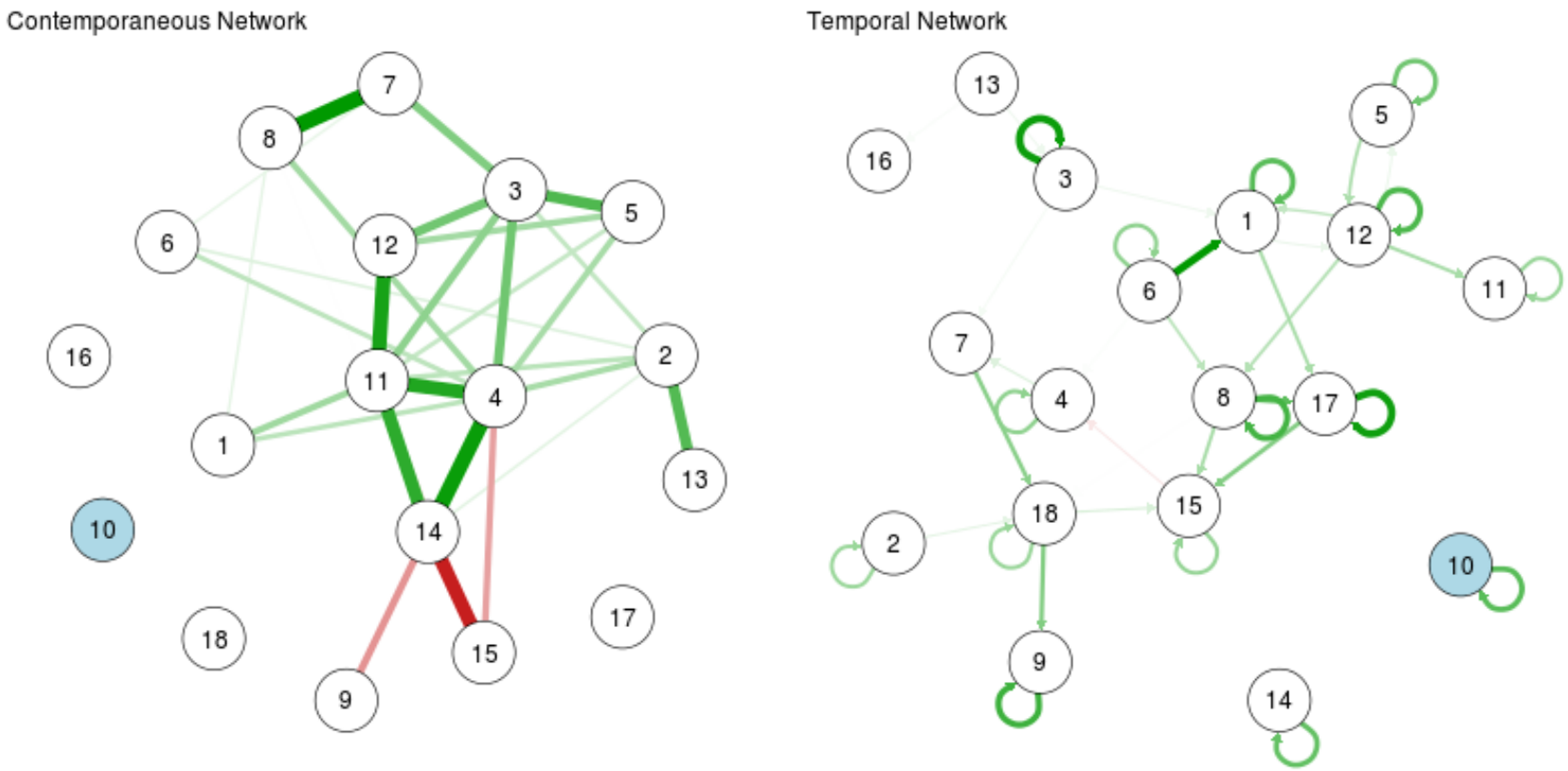
Having to had to do things leads to letting important things pass



Fear of panic attack is not connected

Time-series: $n > 1$

A Network Approach to Psychopathology: New Insights into Clinical Longitudinal Data

Laura F. Bringmann[1]*, Nathalie Vissers[1], Marieke Wichers[2], Nicole Geschwind[3], Peter Kuppens[1], Frenk Peeters[2], Denny Borsboom[4], Francis Tuerlinckx[1]

1 Department of Psychology, University of Leuven, Leuven, Belgium, **2** Department of Psychiatry and Neuropsychology, Maastricht University, Maastricht, The Netherlands, **3** Department of Clinical Psychological Science, Maastricht University, Maastricht, The Netherlands, **4** Department of Psychology, University of Amsterdam, Amsterdam, The Netherlands

Abstract

In the network approach to psychopathology, disorders are conceptualized as networks of mutually interacting symptoms (e.g., depressed mood) and transdiagnostic factors (e.g., rumination). This suggests that it is necessary to study how symptoms dynamically interact over time in a network architecture. In the present paper, we show how such an architecture can be constructed on the basis of time-series data obtained through Experience Sampling Methodology (ESM). The proposed methodology determines the parameters for the interaction between nodes in the network by estimating a multilevel vector autoregression (VAR) model on the data. The methodology allows combining between-subject and within-subject information in a multilevel framework. The resulting network architecture can subsequently be analyzed through network analysis techniques. In the present study, we apply the method to a set of items that assess mood-related factors. We show that the analysis generates a plausible and replicable network architecture, the structure of which is related to variables such as neuroticism; that is, for subjects who score high on neuroticism, worrying plays a more central role in the network. Implications and extensions of the methodology are discussed.

Citation: Bringmann LF, Vissers N, Wichers M, Geschwind N, Kuppens P, et al. (2013) A Network Approach to Psychopathology: New Insights into Clinical Longitudinal Data. PLoS ONE 8(4): e60188. doi:10.1371/journal.pone.0060188

Multi-level VAR

- Each subject is assumed to have their own temporal and contemporaneous VAR model
- VAR parameters come from distribution
  - Fixed effect
  - Random effect

Multi-level VAR

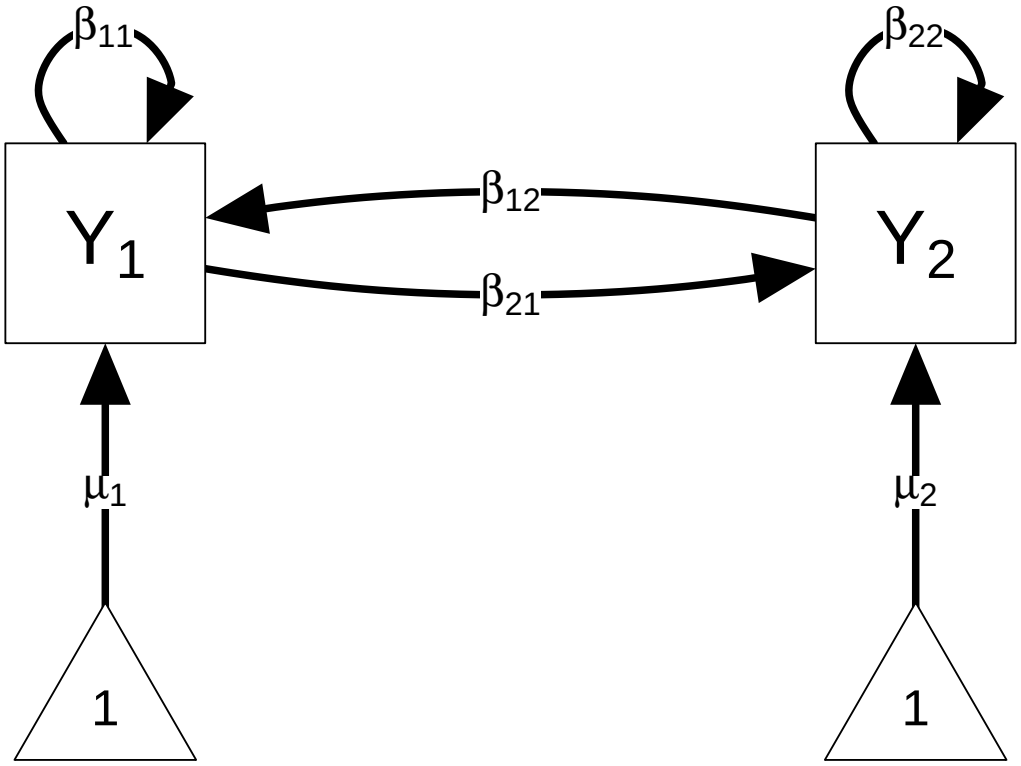
Adding superscript p for subject. Level 1 model:

$$\boldsymbol{Y}_t^{(p)} \mid \boldsymbol{y}_t^{(p)} = N\left(\boldsymbol{\mu}^{(p)} + \boldsymbol{B}^{(p)}\boldsymbol{y}_{t-1}^{(p)}, \boldsymbol{\Theta}^{(p)}\right)$$

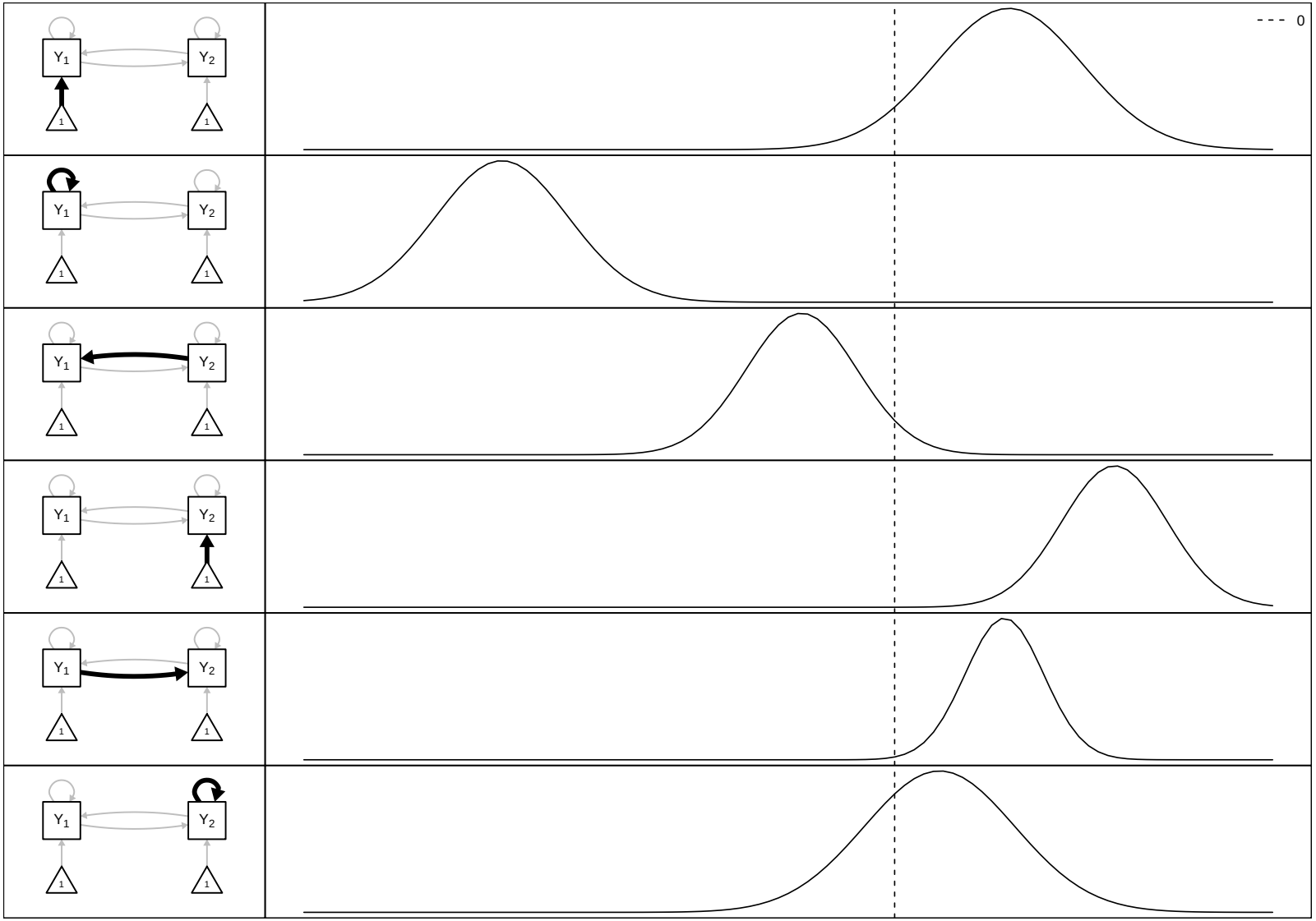
Level 2 model:

$$\begin{bmatrix} \boldsymbol{\mu}^{(p)} \\ \mathrm{Vec}\left(\boldsymbol{B}^{(p)}\right) \end{bmatrix} \sim N\left(\boldsymbol{f}, \boldsymbol{\Omega}\right).$$

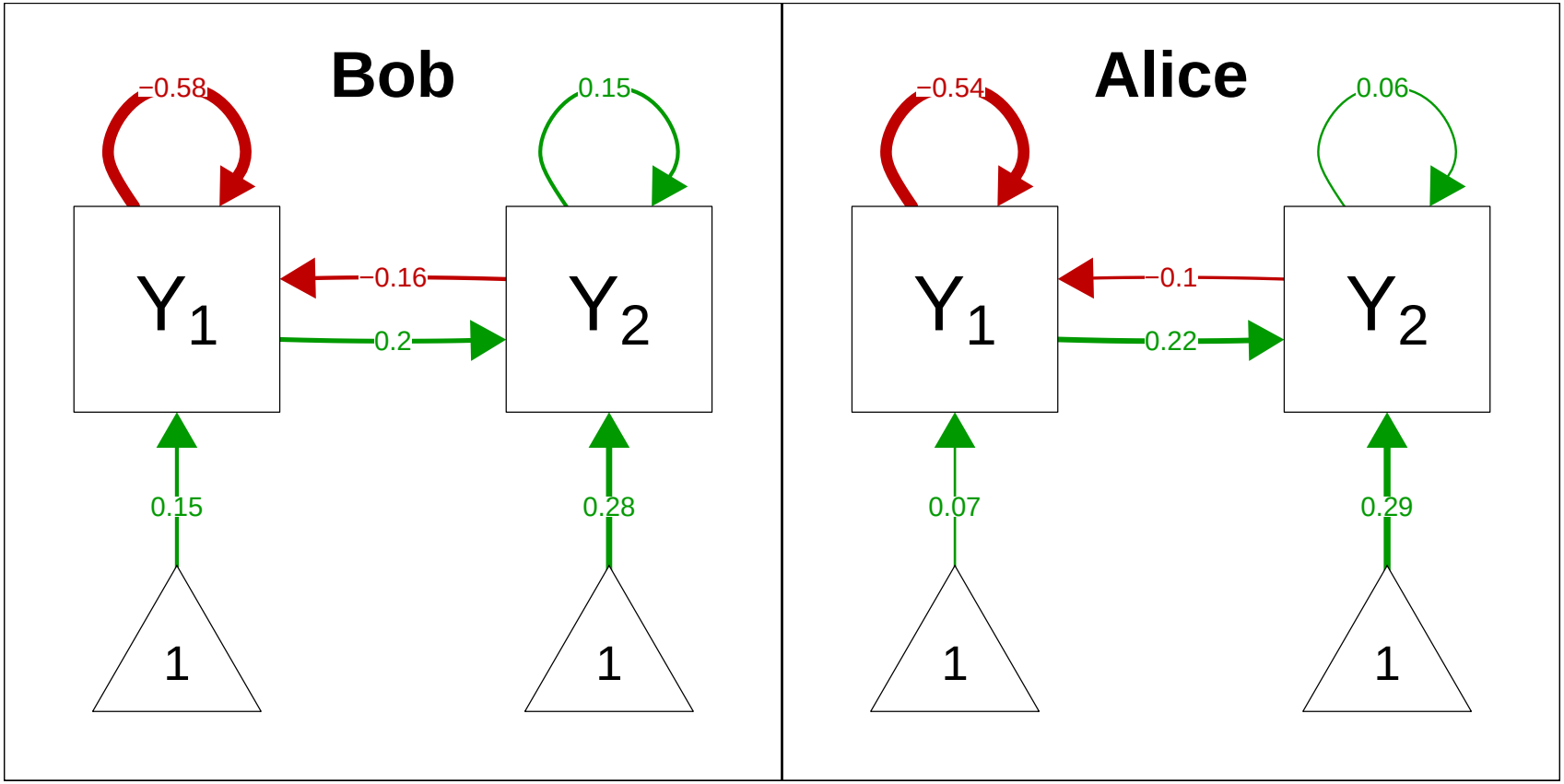
$\boldsymbol{f}$ encodes fixed effects and $\boldsymbol{\Omega}$ the distribution of random effects.


β11
β22
Y1
Y2
β12
β21
μ1
μ2
1
1

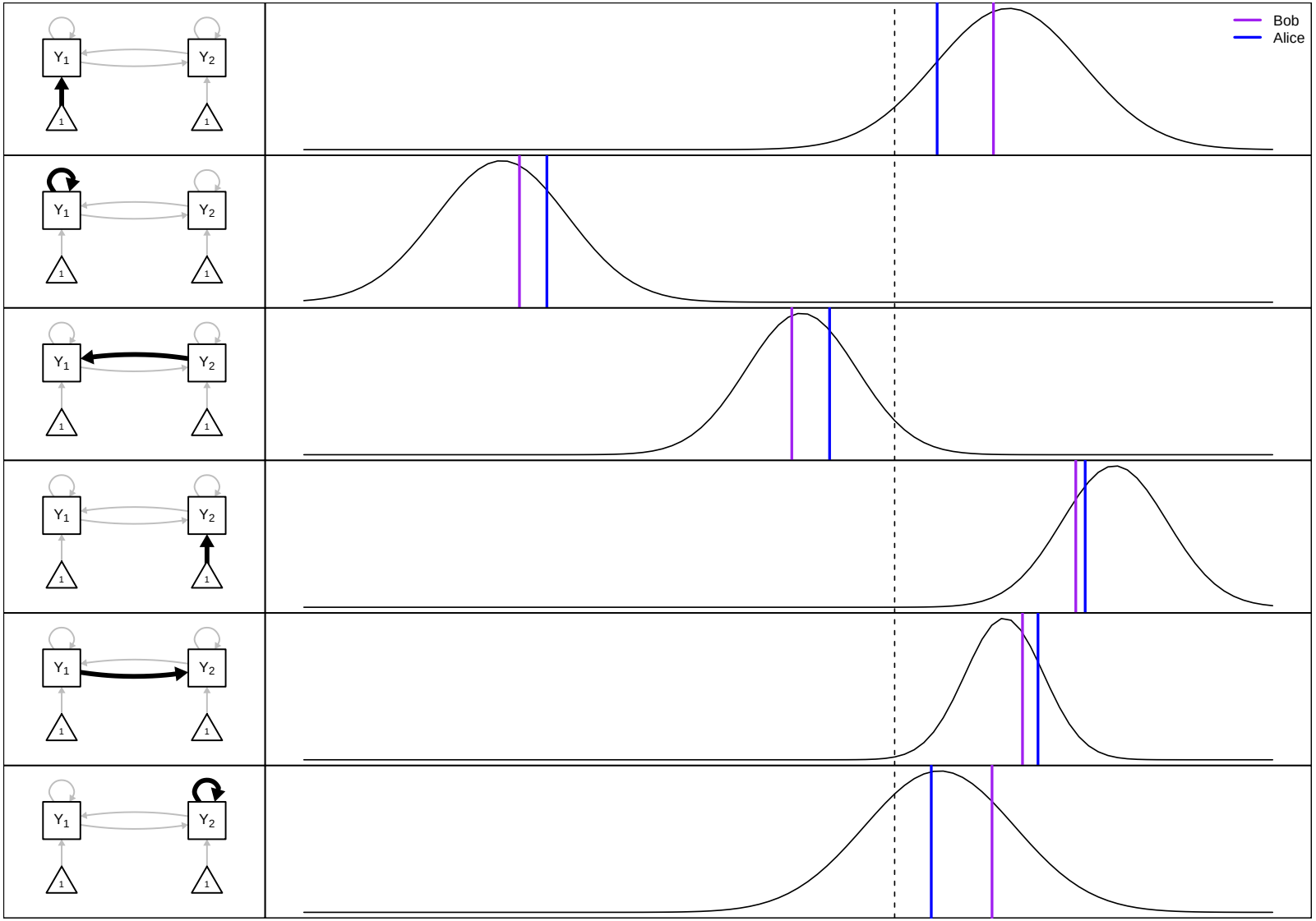
Each Parameter has a Distribution



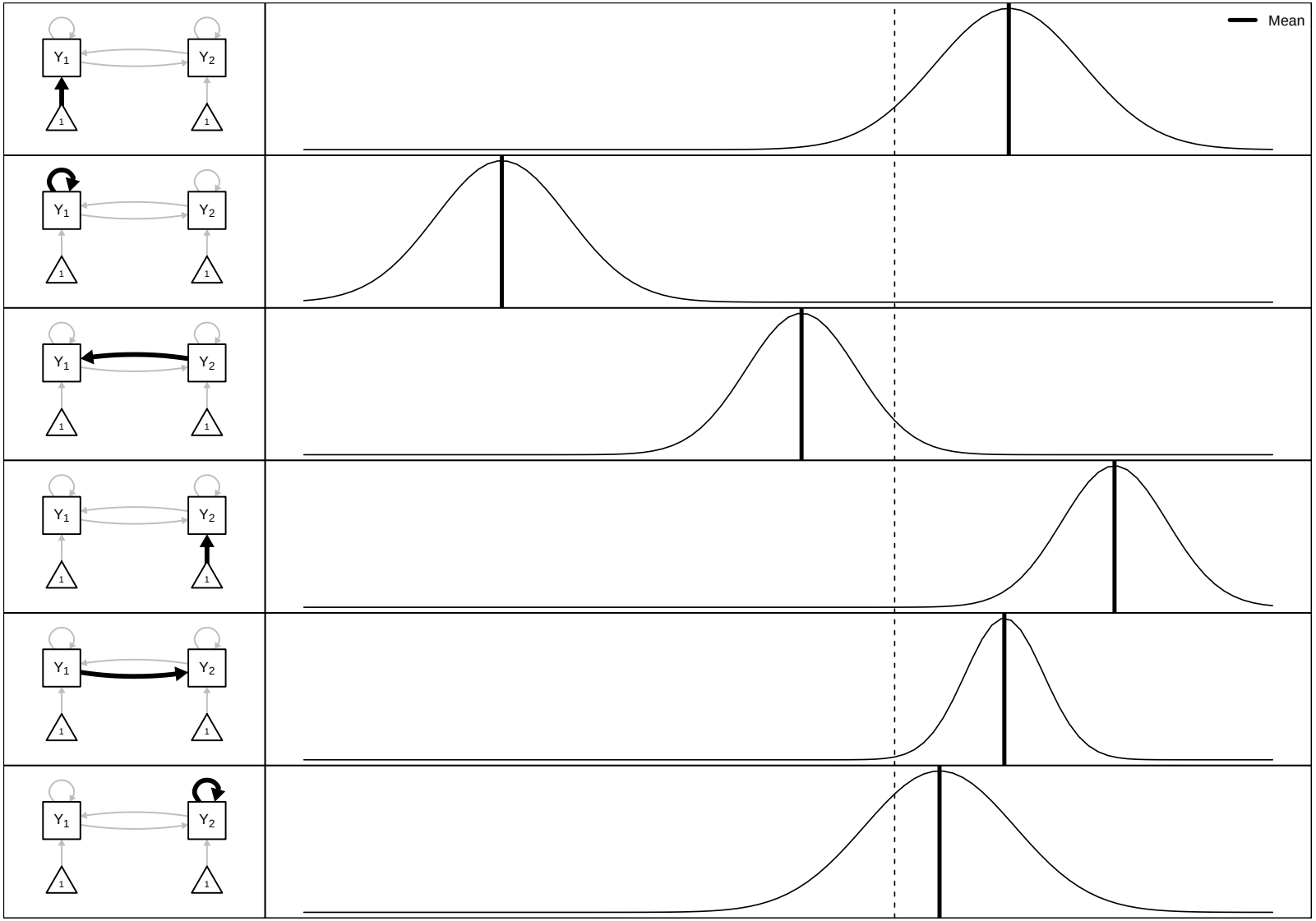
Individual Networks



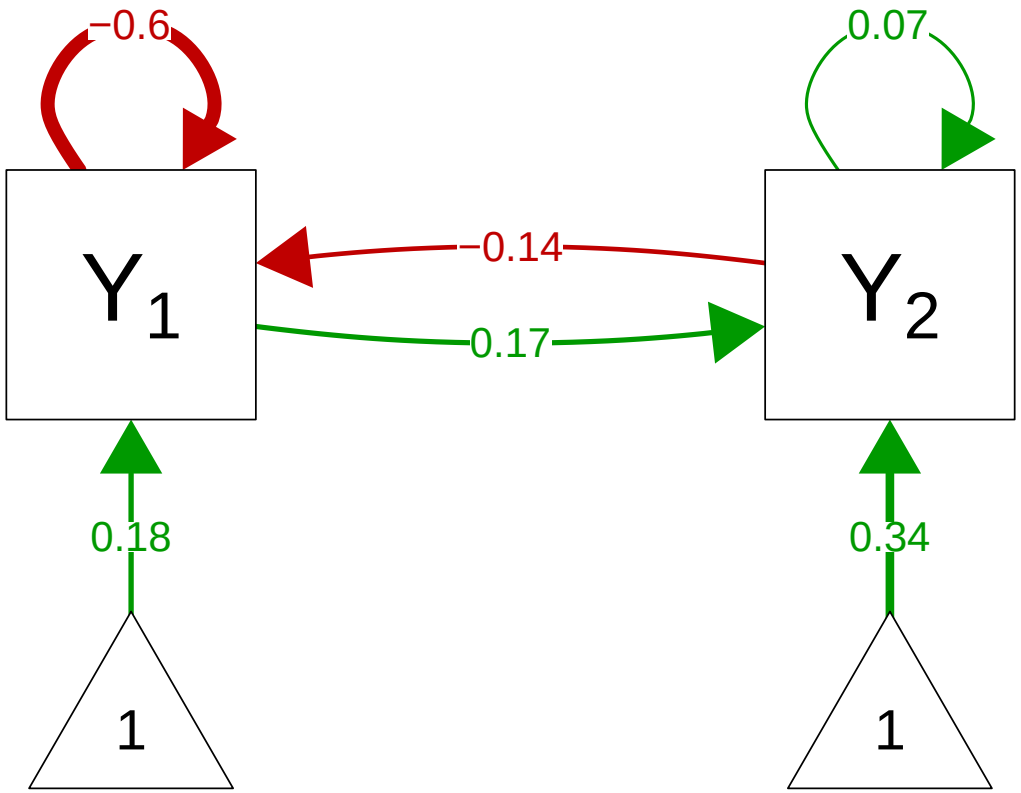
Random Effects



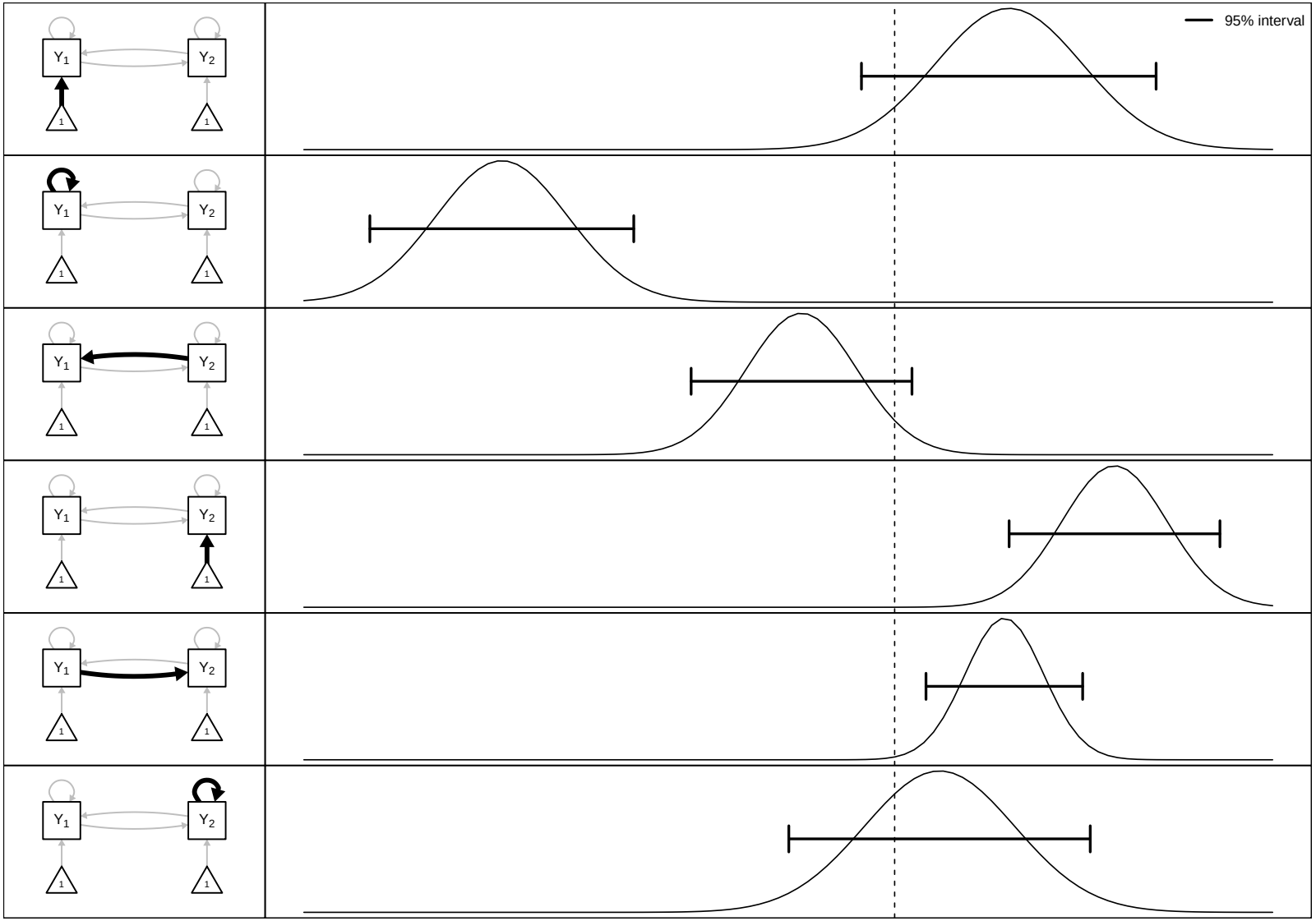
Fixed Effects



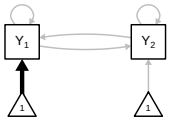
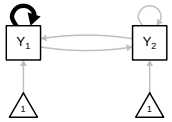
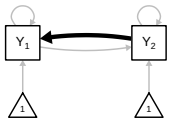
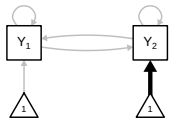
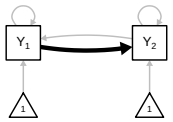
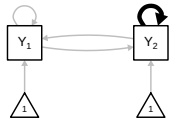
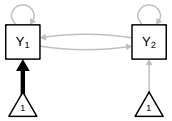
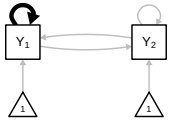
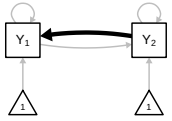
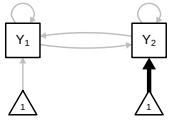
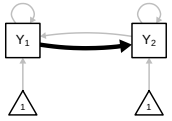
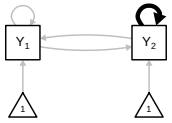
Fixed Effects



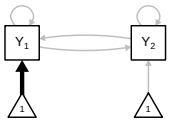
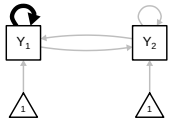
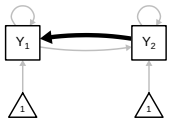
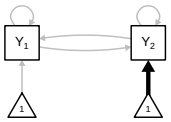
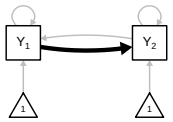
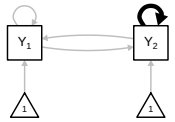
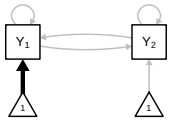
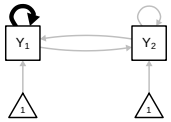
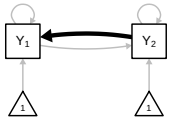
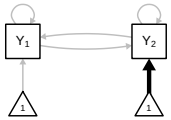
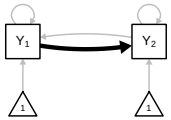
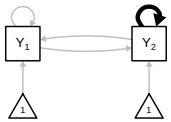
Individual Differences



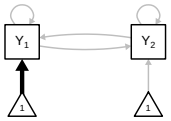
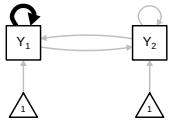
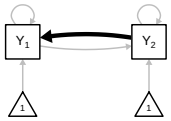
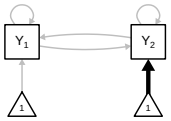
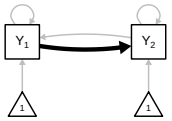
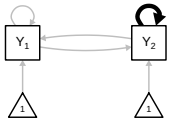
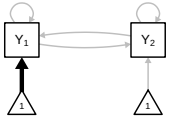
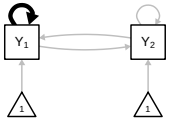
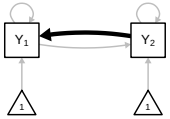
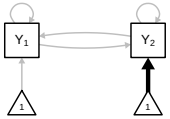
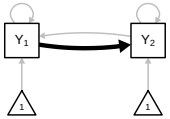
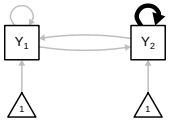
Parameter correlation Matrix

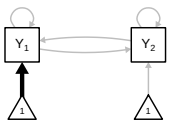
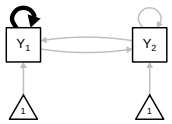
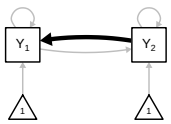
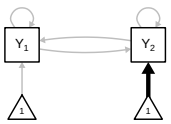
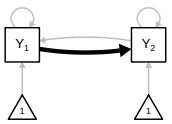
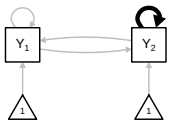
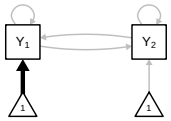
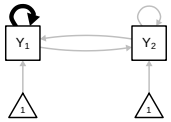
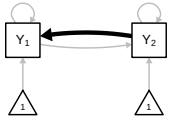
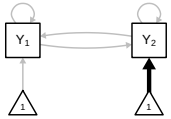
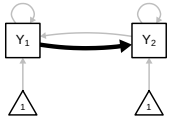
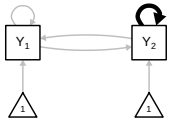
Parameter Correlation Matrix

						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Stability

						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Connectivity

						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Brief Empirical Report

Clinical Psychological Science
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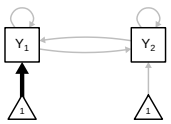
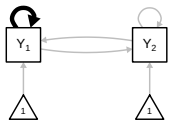
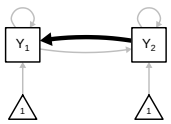
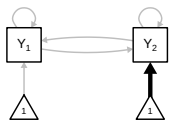
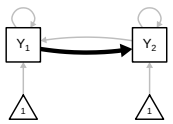
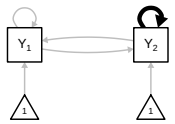
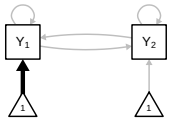
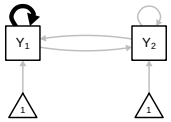
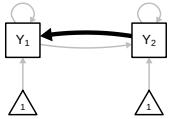
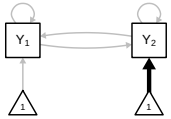
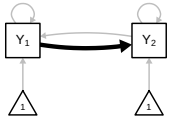
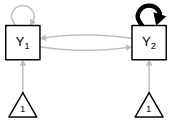
Emotion-Network Density in Major Depressive Disorder

Madeline Lee Pe[1], Katharina Kircanski[2], Renee J. Thompson[3], Laura F. Bringmann[1], Francis Tuerlinckx[1], Merijn Mestdagh[1], Jutta Mata[4], Susanne M. Jaeggi[5], Martin Buschkuehl[6], John Jonides[7], Peter Kuppens[1], and Ian H. Gotlib[2]

[1]Department of Psychology, KU Leuven; [2]Department of Psychology, Stanford University; [3]Department of Psychology, Washington University in St. Louis; [4]Max Planck Institute for Human Development; [5]School of Education, University of California, Irvine; [6]MIND Research Institute, Irvine, California; and [7]Department of Psychology, University of Michigan, Ann Arbor

Between-subject Effects

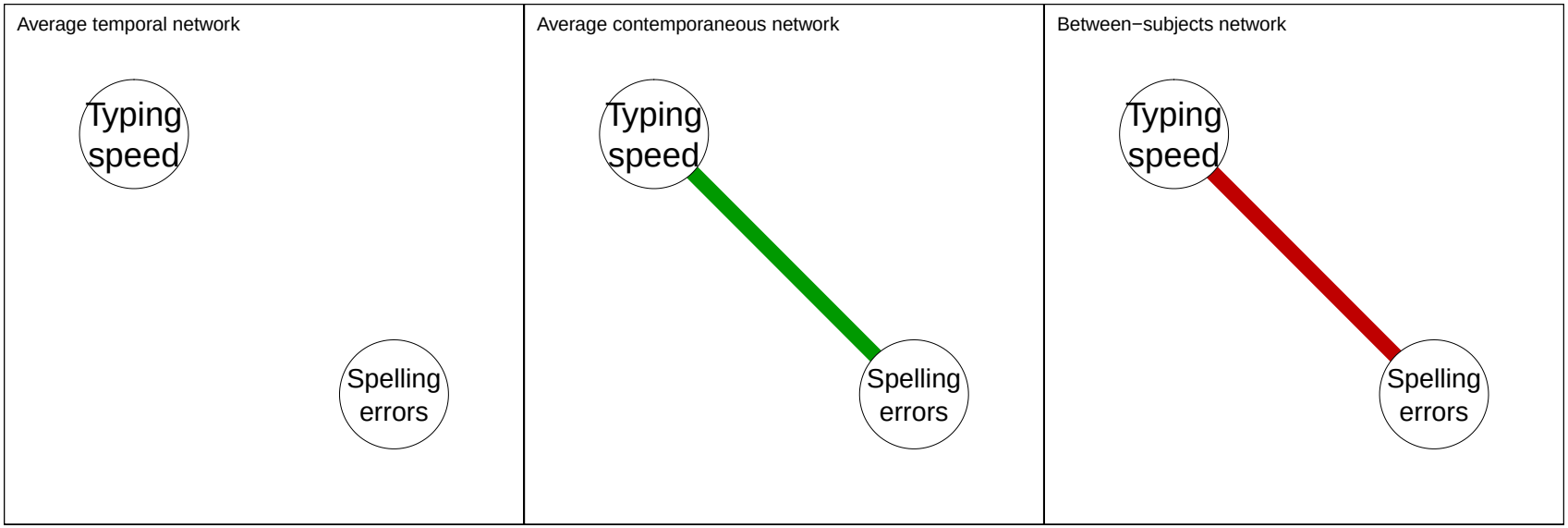
						
	1	0.01	−0.54	0.21	−0.18	0.46
	0.01	1	−0.24	−0.66	0.77	0.06
	−0.54	−0.24	1	−0.12	0.34	−0.75
	0.21	−0.66	−0.12	1	−0.76	0.1
	−0.18	0.77	0.34	−0.76	1	−0.18
	0.46	0.06	−0.75	0.1	−0.18	1

Between-subjects Network

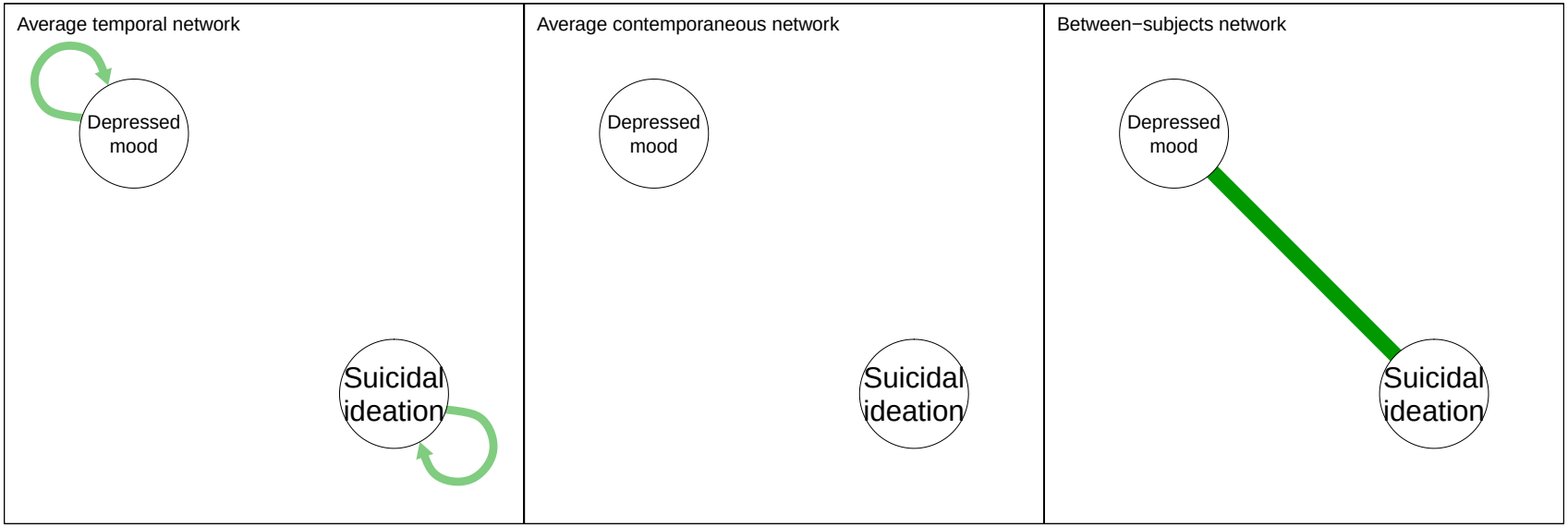
The random effects variance-covariance matrix can be divided in four blocks:

$$\begin{bmatrix} \boldsymbol{R_\mu} \\ \boldsymbol{R_B} \end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} \boldsymbol{\Omega_\mu} & \boldsymbol{\Omega_{\mu B}} \\ \boldsymbol{\Omega_{B\mu}} & \boldsymbol{\Omega_B} \end{bmatrix}\right).$$

- Block $\boldsymbol{\Omega_\mu}$ encodes the between-subject relationships between *means*
- These can be used to estimate a GGM
  - Between-subjects network of **partial correlations**



Example based on Hamaker, E. L. (2012). Why Researchers Should Think 'Within-Person': A Paradigmatic Rationale. *Handbook of Research Methods for Studying Daily Life*. The Guilford Press New York, NY, 43–61.

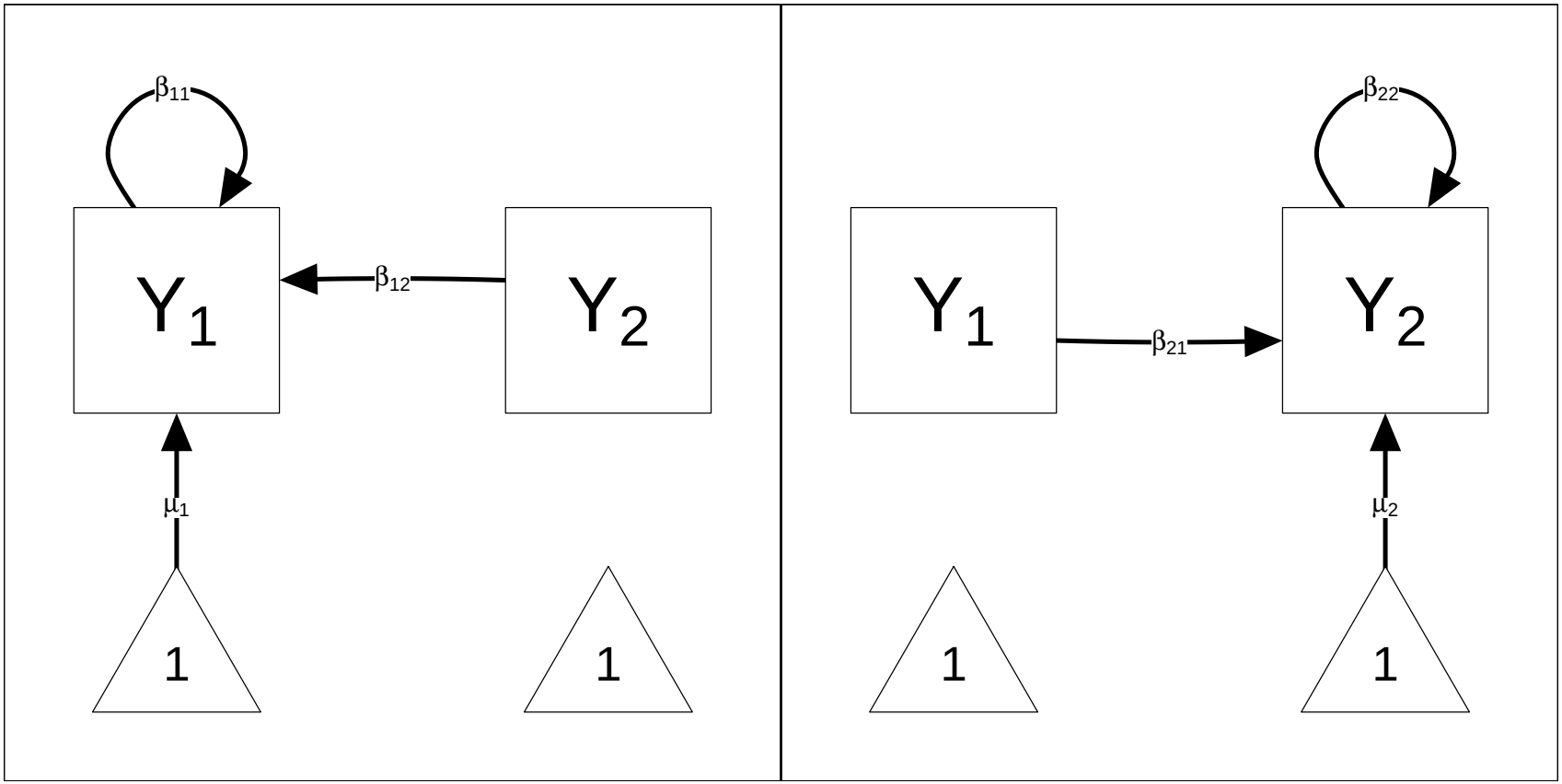


Hypothetical example of networks based on two persons:

- Clinically depressed person constantly scoring high on both
- Healthy person constantly scoring low on both

Temporal Estimation

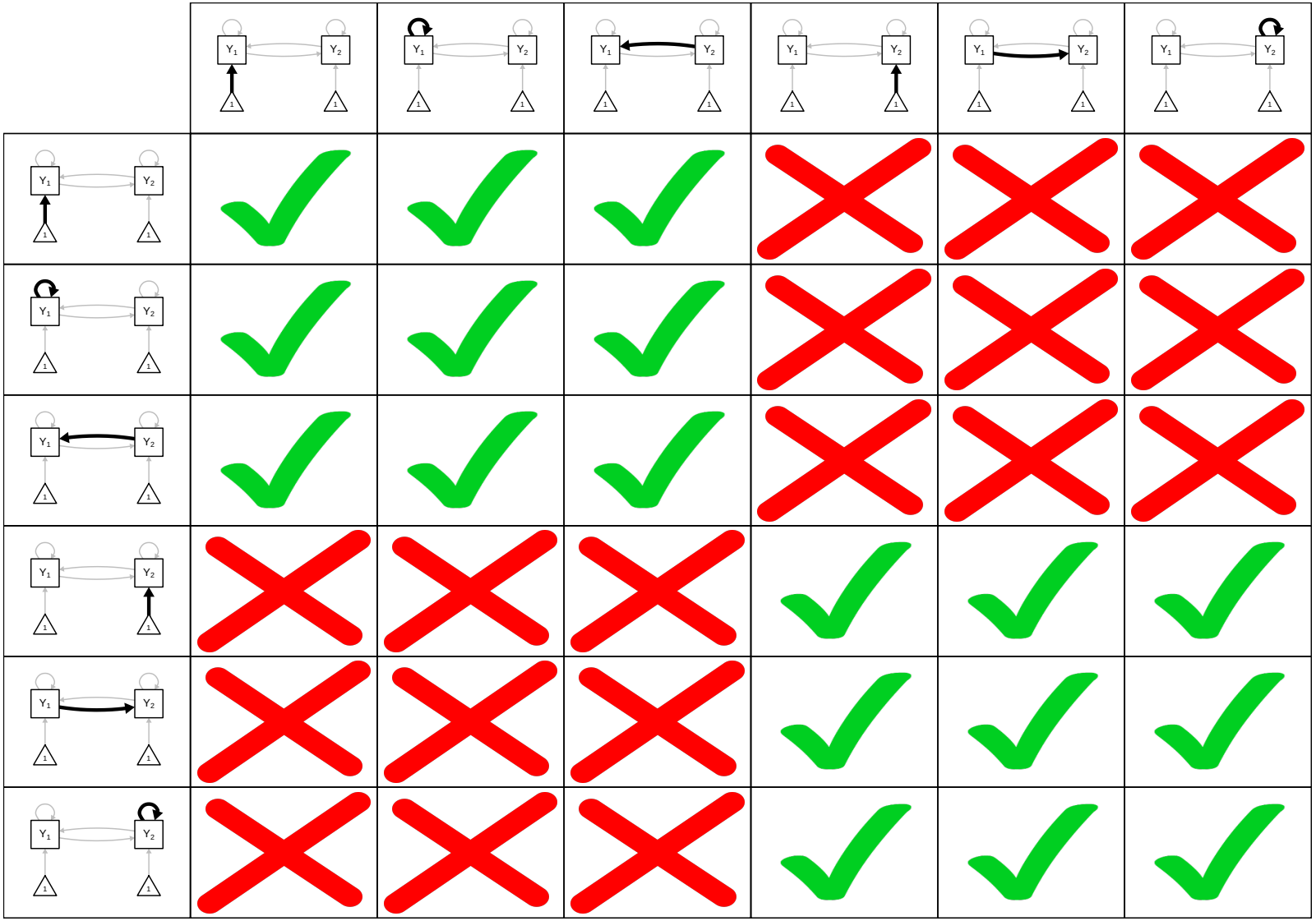
- Multi-variate multi-level MLE regression estimation is complicated and not yet well implemented in open source software
- `lme4` packages implements univariate multi-level regression
  - Douglas Bates, Martin Maechler, Ben Bolker, Steve Walker (2015). Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software, 67(1), 1-48. `doi:10.18637/jss.v067.i01`
  - `lmer` function
- A multi-level VAR model can be estimated by sequentially estimating univariate models
  - Estimate all incoming edges per node
  - Bringmann et al. (2013). A network approach to psychopathology: new insights into clinical time-series data. PloS one, 8(4), e60188.


β11
Y1
β12
Y2
μ1
1
1
β22
Y1
β21
Y2
μ2
1
1

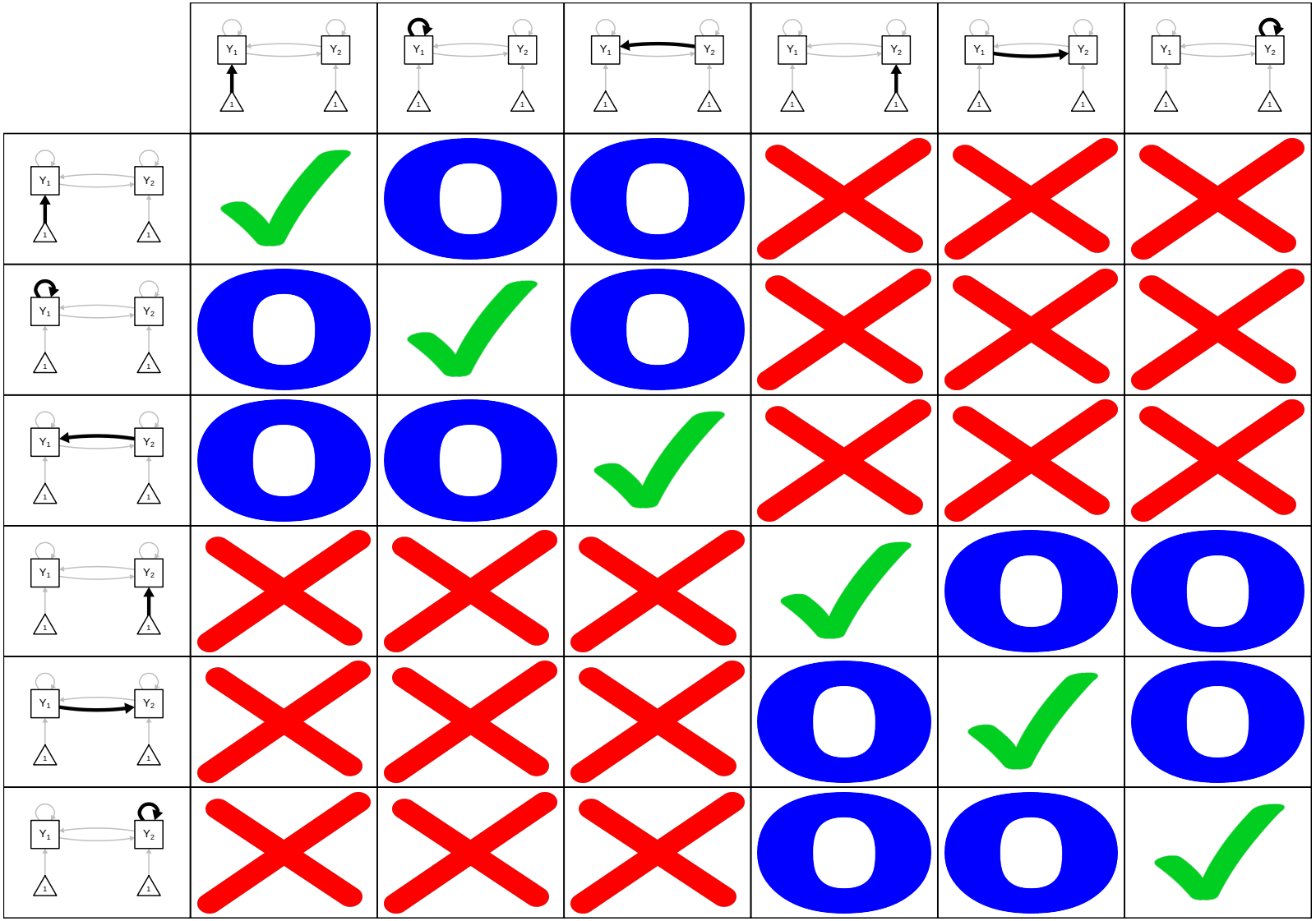
Temporal Estimation

- Correlated estimation:
  - Needs to integrate out a high-dimensional distribution over parameters
  - Only feasible for up to ~6 nodes
  - Does not estimate all parameter covariances
    - Not all parameters together in the same model
- Orthogonal estimation
  - Alternatively, parameter covariances can be fixed to zero
  - Fast, and works for high dimensions (e.g., 20 nodes)
  - But, does not return *any* parameter correlation

Correlated Estimation



Orthogonal Estimation



Between-subject Estimation

- Between subject effects can be obtained by centering predictors and adding the person-means as level 2 predictors
  - Hamaker, E. L., & Grasman, R. P. (2015). To center or not to center? Investigating inertia with a multilevel autoregressive model. Frontiers in psychology, 5, 1492.
- This can be seen as node-wise estimation of a GGM
- Thus, an estimate for the between-subjects GGM can be obtained by averaging the level-2 predictive effects standardized with the residual variances

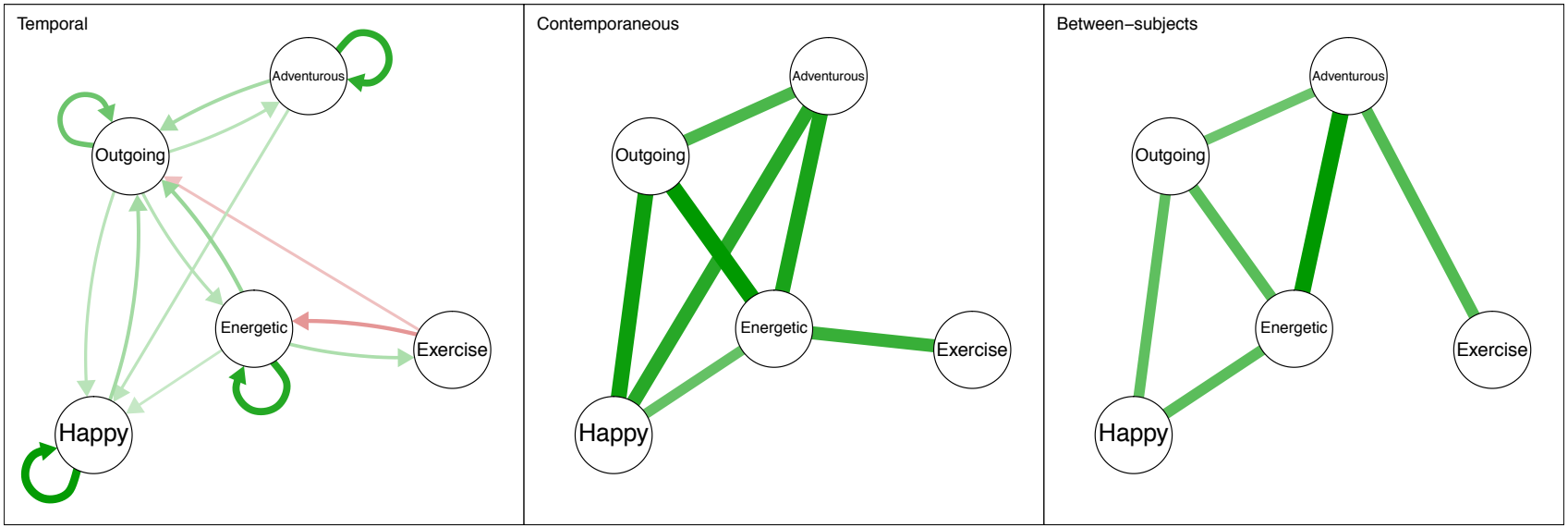
Contemporaneous Estimation

- Contemporaneous networks need to be estimated post-hoc by investigating the residuals
- Either inverting the sample variance-covariance matrix of residuals:
  - Fixed
  - Unique
- Or as a second multi-level model using nodewise estimation of a GGM:
  - Correlated
  - Orthogonal

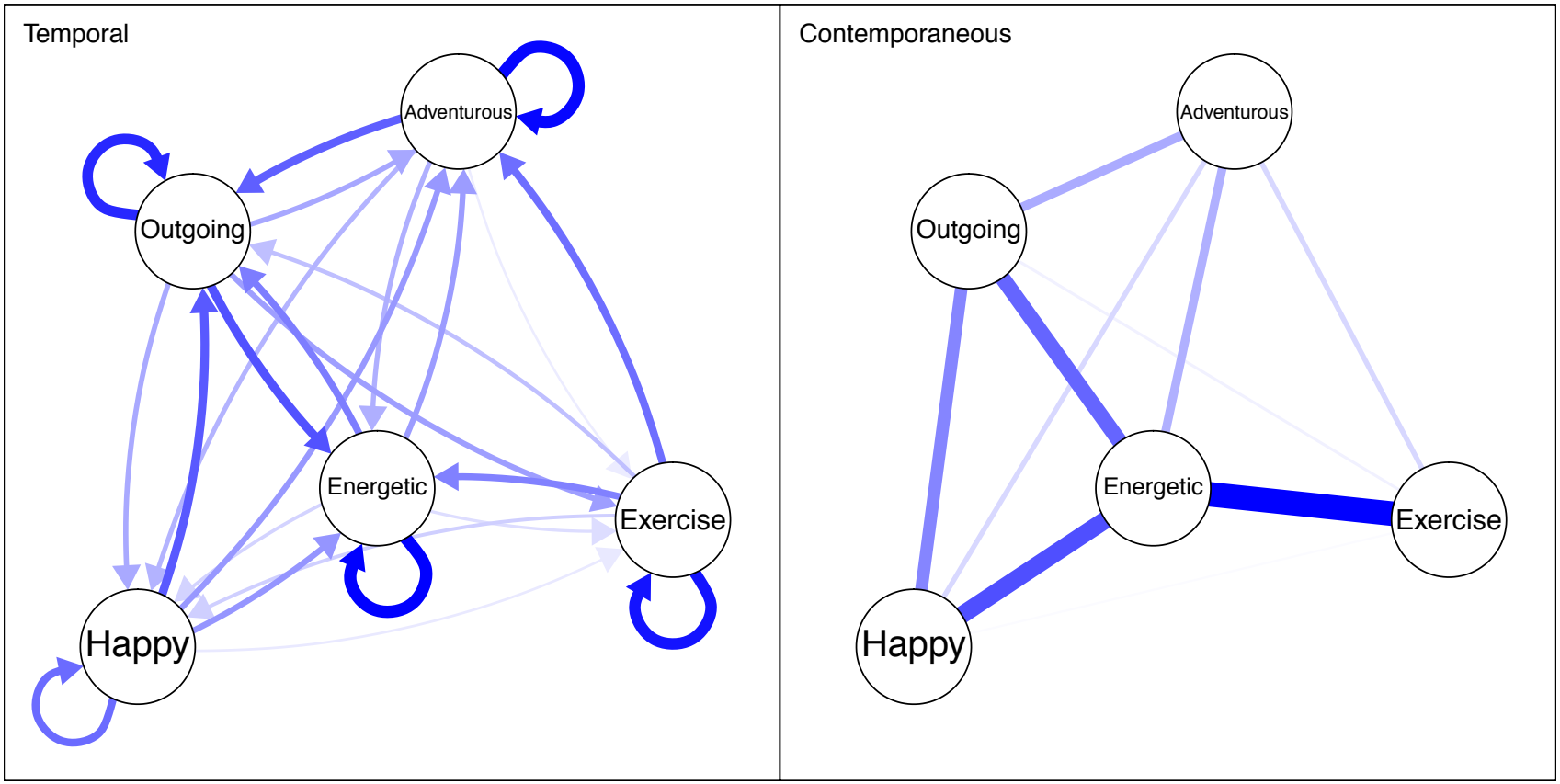
Empirical Example

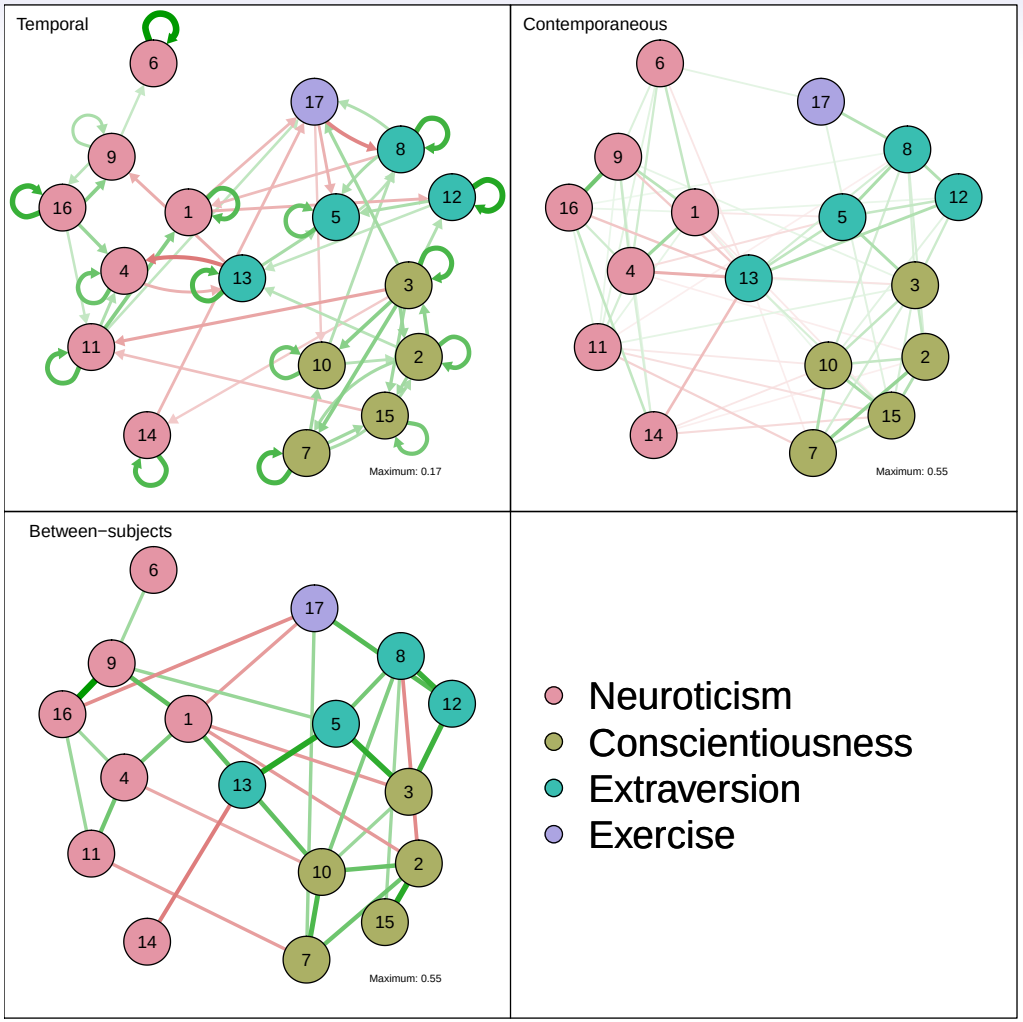
- Two datasets
  - Original: 26 subjects, 51 measurements on average, 1323 total observations
  - Replication: 65 subjects, 35.5 measurements on average, 2309 total observations
- 16 indicators of neuroticism, extroversion, conscientiousness
- Orthogonal estimation of temporal and contemporaneous effects
- Only significant effects shown
  - Alpha = 0.05 and using the "or" rule

Time series: $N > 1$

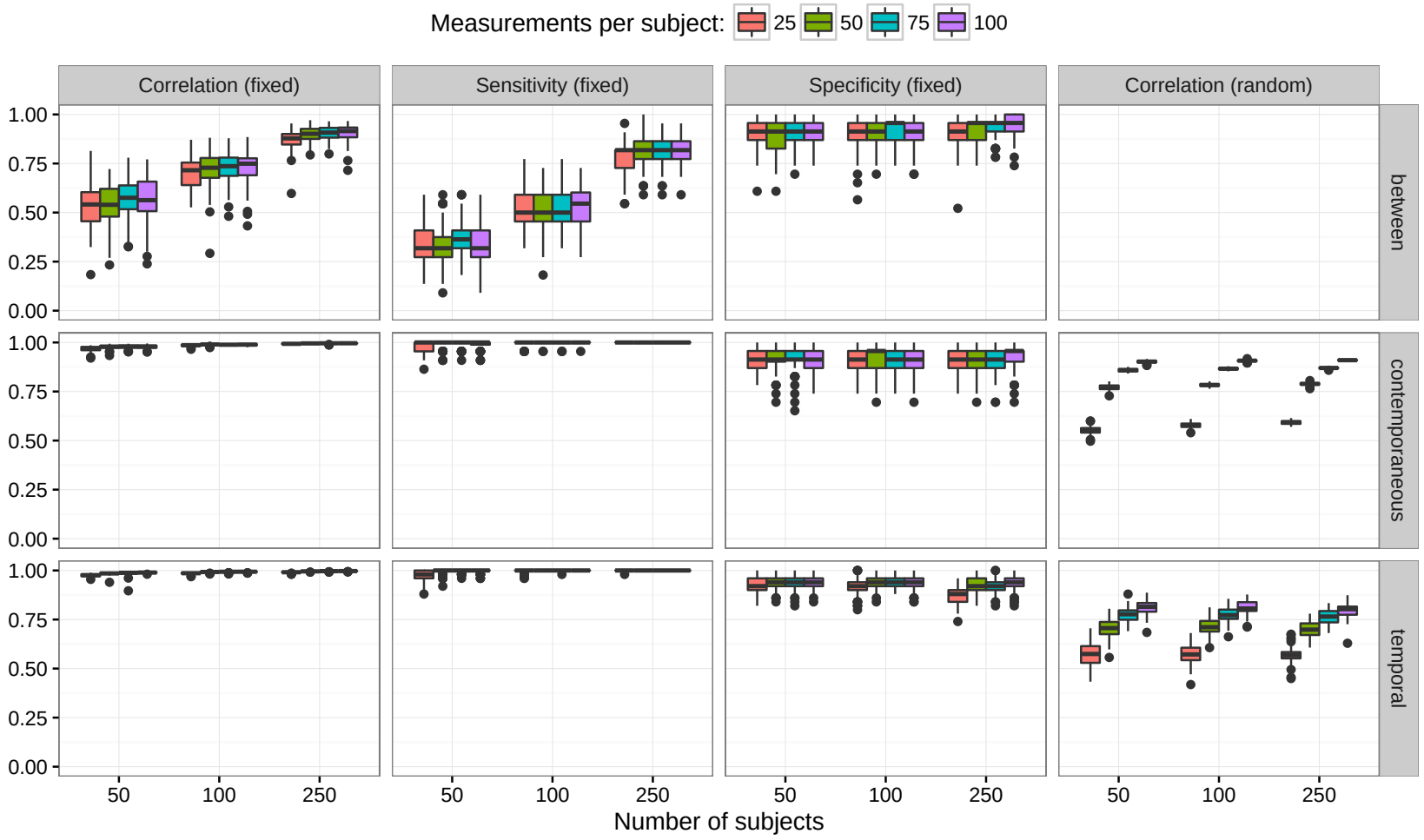


Individual Differences





1 = "Worried"; 2 = "Organized"; 3 = "Ambitious"; 4 = "Depressed"; 5 = "Outgoing"; 6 = "Self-Conscious"; 7 = "Self-Disciplined"; 8 = "Energetic"; 9 = "Frustrated"; 10 = "Focused"; 11 = "Guilty"; 12 = "Adventurous"; 13 = "Happy"; 14 = "Control"; 15 = "Achieved"; 16 = "Angry"; 17 = "Exercise."



8 variables; 50% sparse; 100 replications in each condition.

arXiv.org > stat > arXiv:1609.04156

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Statistics > Methodology

Discovering Psychological Dynamics: The Gaussian Graphical Model in Cross-sectional and Time-series Data

Sacha Epskamp, Lourens J. Waldorp, René Mõttus, Denny Borsboom

(Submitted on 14 Sep 2016 (v1), last revised 5 Oct 2016 (this version, v2))

This paper outlines statistical network models in cross-sectional and time-series data, that attempt to highlight potential causal relationships between observed variables. The paper describes three kinds of datasets. In cross-sectional data (1), one can estimate a Gaussian graphical model (GGM; a network of partial correlation coefficients). In single-subject time-series analysis (2), networks are typically constructed through the use of (multilevel) vector autoregression (VAR). VAR estimates a directed network that encodes temporal predictive effects---the temporal network. We show that GGM and VAR models are closely related: VAR generalizes the GGM by taking violations of independence between consecutive cases into account. VAR analyses can also return a GGM that encodes relationships within the same window of measurement---the contemporaneous network. When multiple subjects are measured (3), multilevel VAR estimates fixed and random temporal networks. We show that between-subject effects can also be obtained in a GGM network---the between-subjects network. We propose a novel two-step multilevel estimation procedure to obtain fixed and random effects for contemporaneous network structures. This procedure is implemented in the R package mlVAR. The paper presents a simulation study to show the performance of mlVAR and showcases the method in an empirical example on personality inventory items and physical exercise.

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Conclusion

Conclusion

- Network structures are useful in discovering potential causal relationships
- Cross-sectional data:
  - Gaussian graphical model (GGM)
- Time-series data:
  - Contemporaneous network (GGM)
  - Temporal network (VAR)
  - Between-subjects network (GGM)

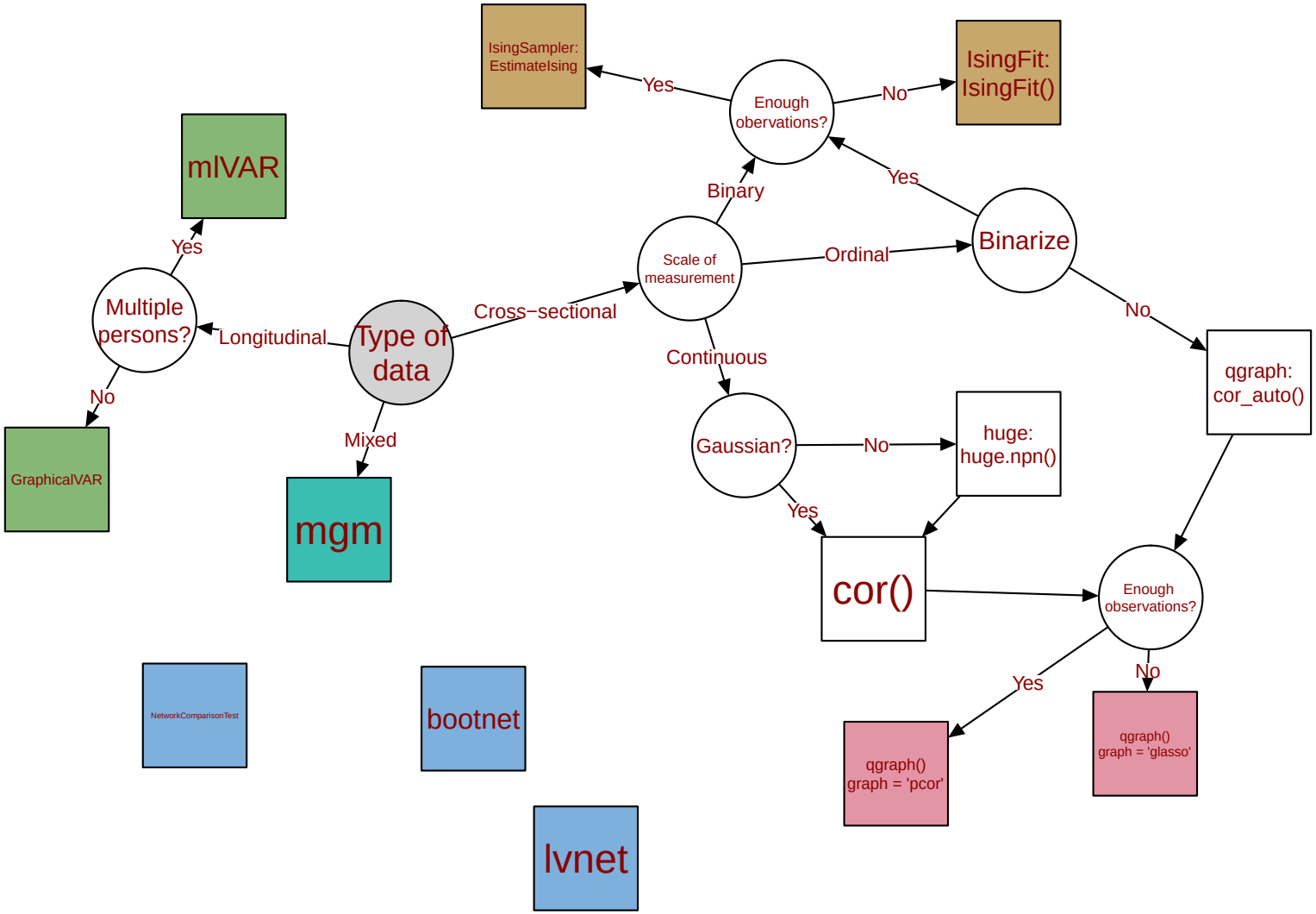
Limitations and Future Directions

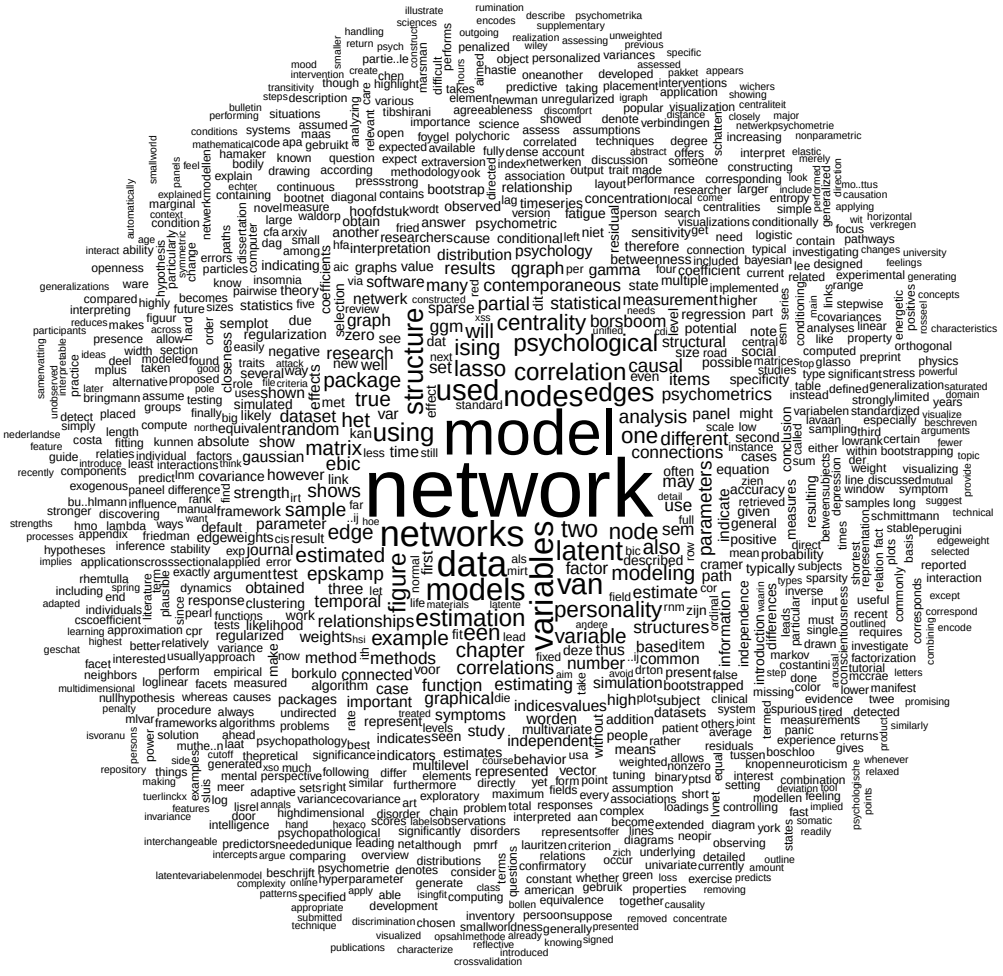
- A lot of potential problems with multi-level estimation
  - Multivariate estimation
  - Modeling random contemporaneous effects
  - Parameter variance-covariances
  - Model selection
- Possibly move away from multi-level
  - LASSO variants?
- Lag-interval

The Limit of Observational Data

- Network structures are only hypothesis generating
  - Highlighting potential causal pathways
- Observational data can *never* confirm causality
  - Mixture of experimental and observational data needed
- We need to completely rethink the modeling framework to do so

The Psychosystems Ecosystem





http://sachaepskamp.com/ and http://psychosystems.org/

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Thank you for your attention!