

- Multiple people measured once: *cross-sectional analysis*

Psychological Data

Thoughts of ending your life

0 1 2 3 4

Crying easily

0 1 2 3 4

Feelings of being trapped or caught

0 1 2 3 4

Blaming yourself for things

0 1 2 3 4

Subject	Time	Item 1	Item 2	Item 3
Subject 1	Time 1	2	2	4
Subject 1	Time 2	2	4	4
Subject 1	Time 3	1	4	3

- Multiple people measured once: *cross-sectional analysis*
- One person measured multiple times: $N = 1$ *time-series*

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Thoughts of ending your life

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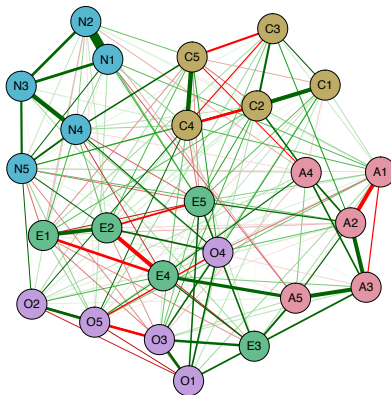
Blaming yourself for things

0 1 2 3 4

Subject	Time	Item 1	Item 2	Item 3
Subject 1	Time 1	2	2	4
Subject 1	Time 2	2	4	4
Subject 1	Time 3	1	4	3
Subject 2	Time 1	4	1	2
Subject 2	Time 2	3	1	2
Subject 2	Time 3	3	2	1
Subject 3	Time 1	1	3	0
Subject 3	Time 2	4	0	1
Subject 3	Time 3	0	3	3

- Multiple people measured once: *cross-sectional analysis*
- One person measured multiple times: $N = 1$ *time-series*
- Multiple people measured multiple times: $N > 1$ *time-series*

Cross-sectional Analysis



Agreeableness

- A1: Am indifferent to the feelings of others.
- A2: Inquire about others' well-being.
- A3: Know how to comfort others.
- A4: Love children.
- A5: Make people feel at ease.

Conscientiousness

- C1: Am exacting in my work.
- C2: Continue until everything is perfect.
- C3: Do things according to a plan.
- C4: Do things in a half-way manner.
- C5: Waste my time.

Extraversion

- E1: Don't talk a lot.
- E2: Find it difficult to approach others.
- E3: Know how to captivate people.
- E4: Make friends easily.
- E5: Take charge.

Neuroticism

- N1: Get angry easily.
- N2: Get irritated easily.
- N3: Have frequent mood swings.
- N4: Often feel blue.
- N5: Panic easily.

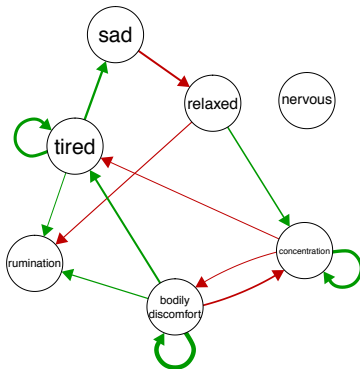
Openness

- O1: Am full of ideas.
- O2: Avoid difficult reading material.
- O3: Carry the conversation to a higher level.
- O4: Spend time reflecting on things.
- O5: Will not probe deeply into a subject.

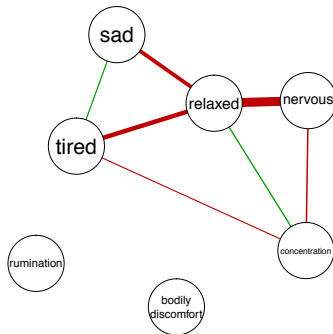
- Concentration network: unique variance between two variables

$N = 1$ Time-series Analysis

(b) Temporal network – Patient 1

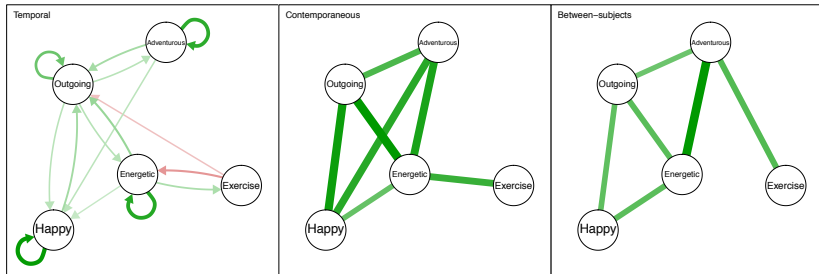


(a) Contemporaneous network – Patient 1



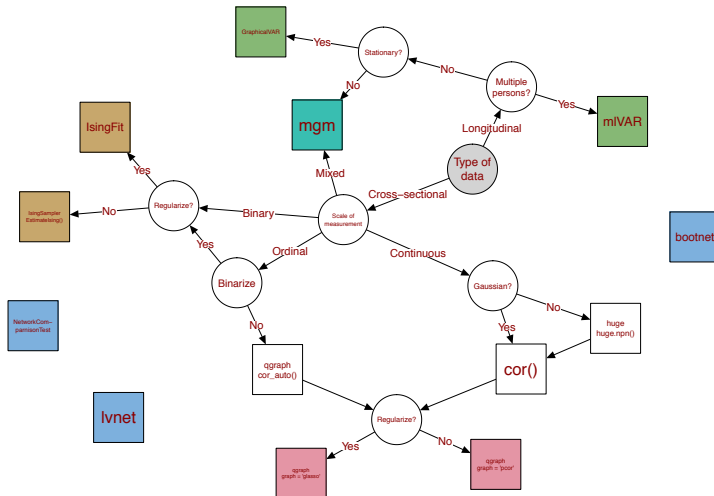
- Contemporaneous network: conditional concentration given $t - 1$
- Temporal network: regression coefficients between $t - 1$ and t

$N > 1$ Time-series Analysis



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

The Psychosystems Ecosystem



$N = 1$: Graphical VAR

Graphical Vector Auto-regression (VAR)

$$\mathbf{Y}_t \mid \mathbf{y}_{t-1} \sim N(\mathbf{B}\mathbf{y}_{t-1}, \mathbf{\Theta})$$

- Variables assumed centered
- \mathbf{B} encodes the *temporal network*
 - Temporal prediction
- $\mathbf{\Theta}^{-1}$ encodes the *contemporaneous network*
 - GGM
- Graphical VAR model
 - Wild, B., Eichler, M., Friederich, H. C., Hartmann, M., Zipfel, S., & Herzog, W. (2010). A graphical vector autoregressive modelling approach to the analysis of electronic diary data. BMC medical research methodology, 10(1), 28.

Temporal effects

	relaxed	sad	nervous	concentration	tired	rumination	bodily.discomfort	time
31	5	6	4	5	6	4	4	2014-05-01 10:15:00
32	3	5	4	5	6	4	5	2014-05-01 13:15:00
33	NA	NA	NA	NA	NA	NA	NA	2014-05-01 16:15:00
34	3	5	4	5	6	4	4	2014-05-01 19:15:00
35	4	6	4	4	7	5	4	2014-05-01 22:15:00
36	4	3	3	5	5	2	3	2014-05-02 10:15:00
37	4	3	4	5	5	3	2	2014-05-02 13:15:00

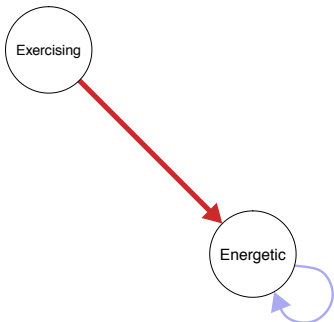
- The temporal network shows that one variable predicts another variable in the *next* measurement occasion
- *Granger causality*
- Only temporal network from (graphical) VAR needed in *predicting* new responses

Contemporaneous effects

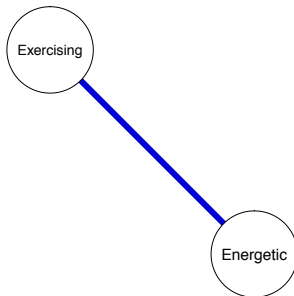
	relaxed [↑]	sad [↓]	nervous [↑]	concentration [↑]	tired [↓]	rumination [↑]	bodily.discomfort [↑]	time [↕]
31	5	6	4	5	6	4	4	2014-05-01 10:15:00
32	3	5	4	5	6	4	5	2014-05-01 13:15:00
33	NA	NA	NA	NA	NA	NA	NA	2014-05-01 16:15:00
34	3	5	4	5	6	4	4	2014-05-01 19:15:00
35	4	6	4	4	7	5	4	2014-05-01 22:15:00
36	4	3	3	5	5	2	3	2014-05-02 10:15:00
37	4	3	4	5	5	3	2	2014-05-02 13:15:00

- The contemporaneous network shows that two variables predict one-another after taking temporal information into account
- Contains effects faster than the time-window of measurement
 - Somatic arousal → anticipation of panic attack → anxiety
- The temporal network can be seen as a correction for dependent measurements in estimating the GGM

Temporal network



Contemporaneous network



- 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

Assumptions

- Stationarity
 - Plausible when data is obtained in short time-span, less plausible if data is obtained in longer time-span
 - Stationary means
 - Can be assessed by regressing each time-series on time itself as predictor
 - Detrending is possible: for example one can remove a linear trend (see practical)
 - Stationary network model(s)
 - Jonas will talk about time-varying models this afternoon!
- Equidistant measurements
 - With multiple measurements per day, by default violated due to nights
 - Remove nights, or model nights as missing observations
 - Oisín Ryan will give a presentation on Friday on continuous time modeling

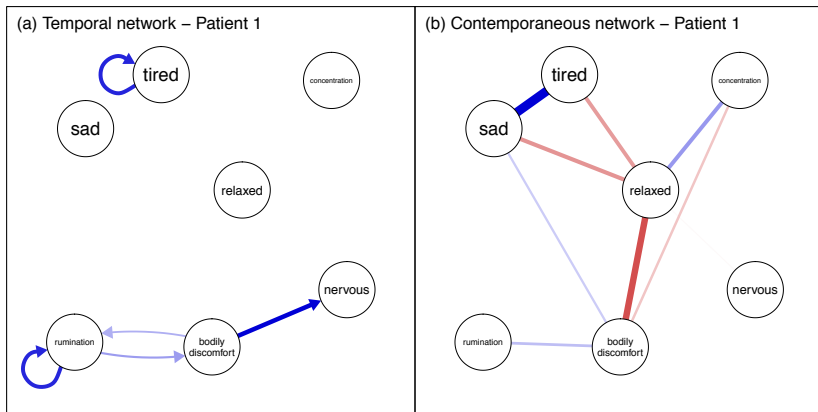
Personalized Network Modeling in Psychopathology: The Importance of Contemporaneous and Temporal Connections

Sacha Epskamp¹, Claudia D. van Borkulo¹, Date C. van der Veen²,
Michelle N. Servaas², Adela-Maria Isvoranu¹, Harriëtte Riese²,
Angelique O.J. Cramer¹

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

$N > 1$: 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
- Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., ... & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one*, 8(4), e60188.

Brief Empirical Report

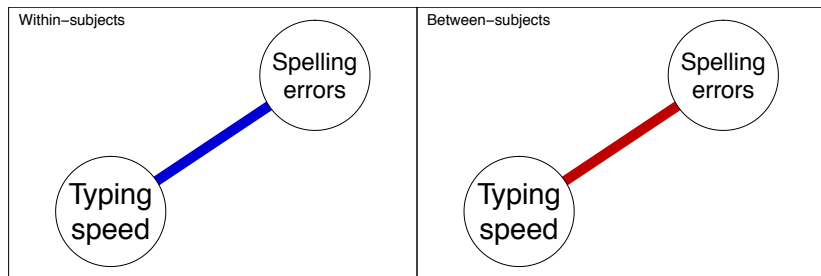


Emotion-Network Density in Major Depressive Disorder

**Madeline Lee Pe¹, Katharina Kircanski², Renee J. Thompson³,
Laura F. Bringmann¹, Francis Tuerlinckx¹, Merijn Mestdagh¹,
Jutta Mata⁴, Susanne M. Jaeggi⁵, Martin Buschkuehl⁶,
John Jonides⁷, Peter Kuppens¹, and Ian H. Gotlib²**

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

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DOI: 10.1177/2167702614540645
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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.

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.

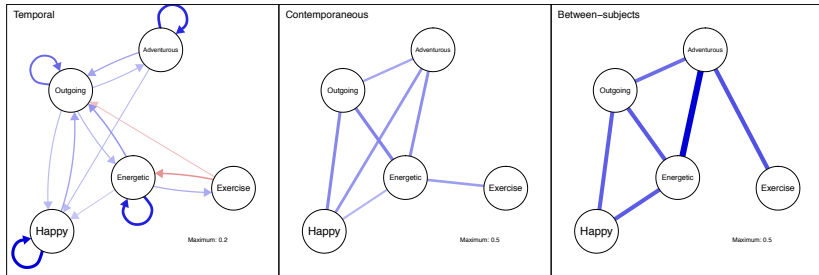
Mplus

- Mplus 8 contains *dynamic structural equation models*
 - statmodel.com/download/DSEM.pdf
- Multi-level VAR is a special case
 - statmodel.com/download/usersguide/Chapter9.pdf, example 9.32
- Contemporaneous and between-subject networks are not obtained by default, can be computed from the Bayesian samples (BPARAMETERS option)
- Automated wrapper to come in *m/VAR* (implemented in devel version)

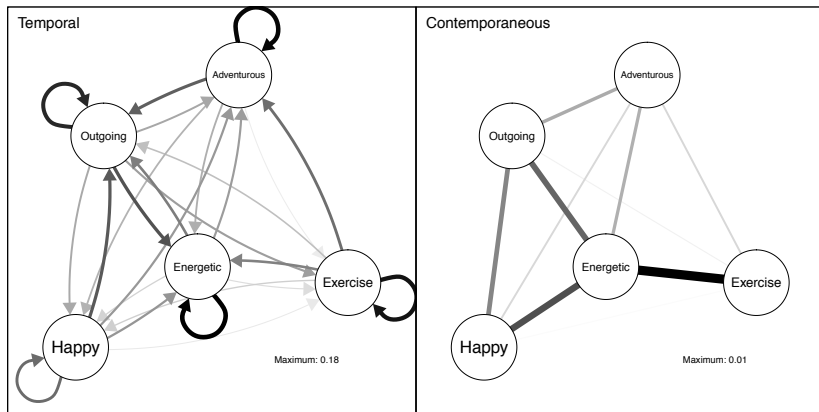
Empirical Example 1

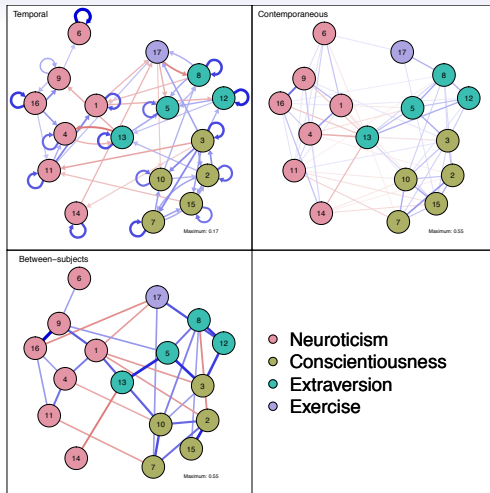
- Two datasets
 - Original: 26 subjects, 51 measurements on average, 1323 total observations
 - Replication: 65 subjects, 35.5 measurements on average, 2309 total observations
- 16 indicators of neuroticism, extroversion, conscientiousness
- Orthogonal estimation of temporal and contemporaneous effects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

Fixed effects



Individual Differences

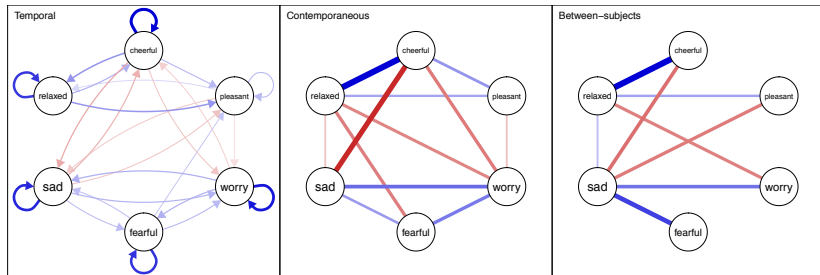




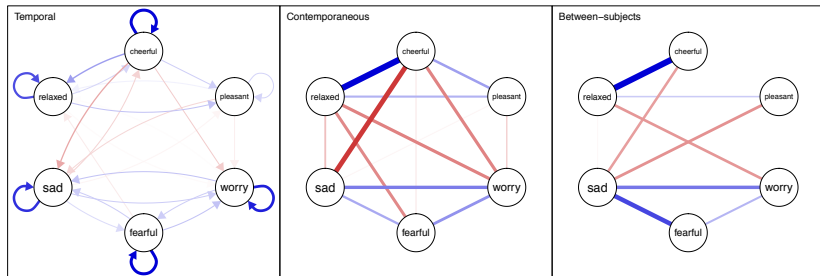
1 = "Worried"; 2 = "Organized"; 3 = "Ambitious"; 4 = "Depressed"; 5 = "Outgoing"; 6 = "Self-Conscious"; 7 = "Self-Disciplined"; 8 = "Energetic"; 9 = "Frustrated"; 10 = "Focused"; 11 = "Guilty"; 12 = "Adventurous"; 13 = "Happy"; 14 = "Control"; 15 = "Achieved"; 16 = "Angry"; 17 = "Exercise."

Empirical Example 2

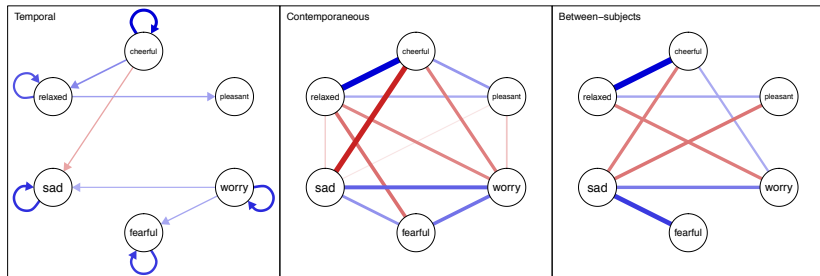
- Re-analysis of original Bringmann example
 - Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one*, 8(4), e60188.
 - Geschwind, N., Peeters, F., Drukker, M., van Os, J., & Wichers, M. (2011). Mindfulness training increases momentary positive emotions and reward experience in adults vulnerable to depression: a randomized controlled trial. *Journal of consulting and clinical psychology*, 79(5), 618-628.
- Re-analysis using three software packages
 - Two-step multi-level VAR (*mIVAR*)
 - LASSO regularization (*graphicalVAR*)
 - Bayesian multivariate estimation (*Mlus 8*, generated by *mIVAR*)
- arxiv.org/abs/1609.04156



m/VAR estimation



graphicalVAR estimation



Mplus estimation

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 Möttus, 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 mIVAR. The paper presents a simulation study to show the performance of mIVAR and showcases the method in an empirical example on personality inventory items and physical exercise.

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References & Citations

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Pre-print online at <http://arxiv.org/abs/1609.04156>

Limitations and Future Directions

- A lot of problems with VAR models
 - Multivariate normality
 - Stationarity
 - Lag interval
 - Model complexity (lag-2, day effects, etcetera)
- 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?

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