Discovering Psychological Dynamics

Part 2: Time-series Analysis

Sacha Epskamp

11-10-2016
Three Types of Psychological Networks

- 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

- **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

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

\[ Y_t \mid y_{t-1} \sim N(\mu + B(y_{t-1} - \mu), \Theta) \]

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

Time-series: $n = 1$

$\begin{align*}
\text{Exercising} & \rightarrow \text{Energetic} \\
& \quad ^{-0.25}
\end{align*}$

$\begin{align*}
\text{Temporal network}
\end{align*}$

$\begin{align*}
\text{Contemporaneous network}
\end{align*}$

$\begin{align*}
\text{Exercising} & \rightarrow \text{Energetic} \\
& \quad ^{0.3}
\end{align*}$
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
- Estimation via LASSO regularization, using EBIC to select optimal tuning parameter
- 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\textsuperscript{1}, Claudia D. van Borkulo\textsuperscript{1}, Date C. van der Veen\textsuperscript{2}, Michelle N. Servaas\textsuperscript{2}, Adela-Maria Isvoranu\textsuperscript{1}, Harriëtte Riese\textsuperscript{2}, Angelique O.J. Cramer\textsuperscript{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
Recap

Time-series: $n = 1$

Conclusion

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
Feeling worthless interacts with feeling helpless
Feeling stressed interacts with feeling the need to do things
Central node: Feeling sad

1: I feel anxious
2: I feel stressed
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Recap

Time-series: $n = 1$

Time-series: $n > 1$

Conclusion

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18: I was physically active
Recap

Time-series: $n = 1$

Time-series: $n > 1$

Conclusion

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

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

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:

$$Y_t^{(p)} \mid y_t^{(p)} = \mathcal{N} \left( \mu^{(p)} + B^{(p)} y_{t-1}^{(p)}, \Theta^{(p)} \right)$$

Level 2 model:

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

$f$ encodes fixed effects and $\Omega$ the distribution of random effects.
Recap

Time-series: $n = 1$

Conclusion

Time-series: $n > 1$
Each Parameter has a Distribution
Recap

Time-series: \( n = 1 \)

Time-series: \( n > 1 \)

Conclusion

Individual Networks

Bob

\[
\begin{align*}
Y_1 & \rightarrow Y_2 & 0.15 \\
Y_2 & \rightarrow Y_1 & 0.16 \\
Y_1 & \rightarrow Y_1 & -0.58 \\
Y_2 & \rightarrow Y_2 & 0.2 \\
Y_1 & \rightarrow Y_2 & 0.15 \\
Y_2 & \rightarrow Y_1 & 0.28 \\
\end{align*}
\]

Alice

\[
\begin{align*}
Y_1 & \rightarrow Y_2 & 0.06 \\
Y_2 & \rightarrow Y_1 & -0.1 \\
Y_1 & \rightarrow Y_1 & -0.54 \\
Y_2 & \rightarrow Y_2 & 0.22 \\
Y_1 & \rightarrow Y_2 & 0.07 \\
Y_2 & \rightarrow Y_1 & 0.29 \\
\end{align*}
\]
Random Effects

Recap

Time-series: $n = 1$

Conclusion

$\overbrace{\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\
Fixed Effects

Recap

Time-series: \( n = 1 \)

Conclusion

Time-series: \( n > 1 \)
**Fixed Effects**

Recap

Time-series: \( n = 1 \)

Conclusion

Time-series: \( n > 1 \)
**Individual Differences**

- **Recap**
  - Time-series: $n = 1$
  - Conclusion

- **Time-series: $n > 1$**

```r
x <- dnorm(x, means[i], SDs[i])
```

95% interval

- **Conclusion**
Recap

Time-series: $n = 1$

Conclusion

Parameter correlation Matrix
## Parameter Correlation Matrix

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**Connectivity**

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<th>Time-series: $n &gt; 1$</th>
<th>Conclusion</th>
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**Diagram:**

- **Recap Diagram**
- **Time-series Diagrams**
- **Conclusion Diagram**
Emotion-Network Density in Major Depressive Disorder

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

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

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Recap

Conclusion
Between-subjects Network

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

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

- Block \( \Omega_\mu \) encodes the between-subject relationships between means
- These can be used to estimate a GGM
  - Between-subjects network of partial correlations
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
- \texttt{lme4} packages implements univariate multi-level regression
    doi:10.18637/jss.v067.i01
  - \texttt{lmer} function
- A multi-level VAR model can be estimated by sequentially estimating univariate models
  - Estimate all incoming edges per node
Recap

Time-series: $n = 1$

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Time-series: $n > 1$

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Conclusion
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

- 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
Recap

Time-series: \( n = 1 \)

Conclusion

Time series: \( N > 1 \)

![Diagram of relationships between outgoing, energetic, adventurous, happy, and exercise over temporal, contemporaneous, and between-subjects contexts.](image-url)
Individual Differences

Temporal

Outgoing
Energetic
Exercise
Happy

Contemporaneous

Outgoing
Energetic
Exercise
Happy
### Recap

#### Time-series: $n = 1$

<table>
<thead>
<tr>
<th>Measurements per subject:</th>
<th>25</th>
<th>50</th>
<th>75</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation (fixed)</td>
<td><img src="image1.png" alt="Graph" /></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity (fixed)</td>
<td><img src="image2.png" alt="Graph" /></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specificity (fixed)</td>
<td><img src="image3.png" alt="Graph" /></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation (random)</td>
<td><img src="image4.png" alt="Graph" /></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Time-series: $n > 1$

**Conclusion**

- Correlation (fixed)
- Sensitivity (fixed)
- Specificity (fixed)
- Correlation (random)

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

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

Recap

- Time-series: $n = 1$
- Time-series: $n > 1$

Conclusion

The Psychosystems Ecosystem

- mlVAR
  - Multiple persons?
    - Yes
      - Longitudinal
      - Cross-sectional
    - No
      - Mixed
  - Type of data
    - Continuous
    - Binary
    - Ordinal
    - Yes
    - No

- mgm
  - Enough observations?
    - Yes
    - No

- Graphical VAR

-/bootnet
  - Binarize
  - Gaussian?
    - Yes
    - No
  - Scale of measurement
    - Ordinal
    - Continuous
    - Binary
    - Enough observations?
      - Yes
      - No

- lvnet
  - qgraph: cor_auto()
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Thank you for your attention!