Discovering Psychological Dynamics

Tilburg Social Psychology Colloquium

Sacha Epskamp

03-03-2017
Outline

- Independent cases (e.g., cross-sectional data)
  - The Gaussian Graphical model
  - Interpreting network structures
- Temporally ordered data (e.g., $N = 1$)
  - The VAR model
  - Temporal and contemporaneous networks and causation
- Temporally ordered data of multiple subjects ($N > 1$)
  - The multi-level VAR model
  - Between-subjects networks and causation
- Conclusion
Network Psychometrics

- What is the structure of psychology?
- *Psychological Networks*
Psychological Data

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

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

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

Concentration

Cross-sectional

$n = 1$

$n > 1$ Time-series

Conclusion

---

Psychological Data

- **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*

<table>
<thead>
<tr>
<th>Subject</th>
<th>Time</th>
<th>Item 1</th>
<th>Item 2</th>
<th>Item 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>Time 1</td>
<td>2</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Subject 1</td>
<td>Time 2</td>
<td>2</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Subject 1</td>
<td>Time 3</td>
<td>1</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Subject 2</td>
<td>Time 1</td>
<td>4</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Subject 2</td>
<td>Time 2</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Subject 2</td>
<td>Time 3</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Subject 3</td>
<td>Time 1</td>
<td>1</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Subject 3</td>
<td>Time 2</td>
<td>4</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Subject 3</td>
<td>Time 3</td>
<td>0</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>
$N > 1$ Time-series Analysis

- Between-subjects network: concentration network between stationary means
- Two-step multilevel VAR
Concentration Networks
Concentration Networks (Markov Random Fields)

- $B$ separates $A$ and $C$
- $A \perp C \mid B$
Different kinds of Concentration Networks

- Multivariate normal data: Gaussian graphical models (partial correlation networks)
- Binary data: Ising model
  - [http://www.nature.com/articles/srep05918](http://www.nature.com/articles/srep05918)
- Mixed data: Mixed graphical models
  - [https://arxiv.org/abs/1510.05677](https://arxiv.org/abs/1510.05677)
Edge-weights encode conditional association between two variables after conditioning on all other variables in the network.

In the multivariate normal case: partial correlation coefficients.
The MRF model:

- Concentration – Fatigue – Insomnia

Is equivalent to three causal structures:

1. Concentration → Fatigue → Insomnia
2. Concentration ← Fatigue → Insomnia
3. Concentration ← Fatigue ← Insomnia

Thus, MRF highlights potential causal pathways
Data generating structure

- If we could *not* condition on $\eta$

**Equivalent models**
- Data generated as a cluster of interacting components can fit a factor model perfectly!
Cross-sectional Data
Cross-sectional Data

- These slides assume multivariate normality
- Every person measured only once
- Cases can reasonably be assumed to be independent
  - Given IQ has a mean of 100 and SD of 15, does knowing that Peter has an IQ of 90 help us predict better that Sarah had an IQ of 110?
- Because of this assumption, likelihood reduces to a product
  - \( Y \sim N(\mu, \Sigma) \)
  - \( f(y | \mu, \Sigma) = \prod_{p=1}^{N} f(y^{(p)} | \mu, \Sigma) \)
The Gaussian Graphical Model

- $\Sigma$, the variance-covariance matrix, encodes *all* information how variables relate to one-another
- Because of the Schur complement, it also encodes *all* conditional relationships
- We will focus on its inverse, $K$:
  - $K = \Sigma^{-1}$
- The inverse variance-covariance matrix is called a Gaussian graphical model (GGM)
  - Encodes an undirected network
- GGM is a network of partial correlation coefficients:
  - \( \text{Cor} \left( Y_i, Y_j \mid Y^{-(i,j)} \right) = -\frac{k_{ij}}{\sqrt{k_{ii}} \sqrt{k_{jj}}} \)
GGM and Multiple Regressions
GGM and Multiple Regressions

\[ y_1 = \tau_1 + \gamma_{12}y_2 + \gamma_{13}y_3 + \gamma_{14}y_4 + \varepsilon_1 \]
$$\gamma_2 = \tau_2 + \gamma_{21}Y_1 + \gamma_{23}Y_3 + \gamma_{24}Y_4 + \varepsilon_2$$
GGM and Multiple Regressions

\[ y_3 = \tau_3 + \gamma_{31}y_1 + \gamma_{32}y_2 + \gamma_{34}y_4 + \varepsilon_3 \]
GGM and Multiple Regressions

\[ y_4 = \tau_4 + \gamma_{41} y_1 + \gamma_{42} y_2 + \gamma_{43} y_3 + \varepsilon_4 \]
GGM and Multiple Regressions
GGM and Multiple Regressions

\[ \rho_{ij} = \frac{\gamma_{ij} \text{Var}(\varepsilon_j)}{\text{Var}(\varepsilon_i)} = \frac{\gamma_{ji} \text{Var}(\varepsilon_i)}{\text{Var}(\varepsilon_j)} = -\frac{\kappa_{ij}}{\sqrt{\kappa_{ii}} \sqrt{\kappa_{jj}}} \]
- How to select the best model?
A Tutorial on Regularized Partial Correlation Networks

Sacha Epskamp, Eiko I. Fried

(Submitted on 5 Jul 2016 (v1), last revised 3 Oct 2016 (this version, v4))

Recent years have seen an emergence of network modeling applied to moods, attitudes, and problems in the realm of psychology. In this framework, psychological variables are understood to directly interact with each other rather than being caused by an unobserved latent entity. In this tutorial, we introduce the reader to estimating the most popularly used network model for psychological data: the partial correlation network. We describe how regularization techniques can be used to efficiently estimate a parsimonious and interpretable network structure on cross-sectional data. We show how to perform these analyses in R and demonstrate the method in an empirical example on post-traumatic stress disorder data. In addition, we discuss the effect of the hyperparameter that needs to be manually set by the researcher and provide a checklist with potential solutions for problems often arise when estimating regularized partial correlation networks.

https://arxiv.org/abs/1607.01367
Lambda: 0.005
EBIC (gamma = 0): 746.4
EBIC (gamma = 0.25): 804.7
EBIC (gamma = 0.5): 862.9

Lambda: 0.009
EBIC (gamma = 0): 749.9
EBIC (gamma = 0.25): 805.1
EBIC (gamma = 0.5): 863.3

Lambda: 0.015
EBIC (gamma = 0): 733.9
EBIC (gamma = 0.25): 785.9
EBIC (gamma = 0.5): 837.9

Lambda: 0.024
EBIC (gamma = 0): 712.3
EBIC (gamma = 0.25): 753.9
EBIC (gamma = 0.5): 795.4

Lambda: 0.067
EBIC (gamma = 0): 703.5
EBIC (gamma = 0.25): 736.7
EBIC (gamma = 0.5): 770

Lambda: 0.113
EBIC (gamma = 0): 702.8
EBIC (gamma = 0.25): 729.8
EBIC (gamma = 0.5): 748.5

Lambda: 0.188
EBIC (gamma = 0): 711.1
EBIC (gamma = 0.25): 762.8
EBIC (gamma = 0.5): 796

Lambda: 0.313
EBIC (gamma = 0): 762.8
EBIC (gamma = 0.25): 779.4
EBIC (gamma = 0.5): 796

Lambda: 0.522
EBIC (gamma = 0): 800
EBIC (gamma = 0.25): 800
EBIC (gamma = 0.5): 800

Lambda: 0.04
EBIC (gamma = 0): 710.7
EBIC (gamma = 0.25): 750.2
EBIC (gamma = 0.5): 795.4
Estimation

- GGM can be computed using *qgraph*
- Ordinal data
  - Use polychoric correlations (*cor_auto* in *qgraph*) as input
- Non-normal continuous data
  - Transform variables first (*huge.npn* in *huge*)
- Binary data
  - Use *IsingFit*
- Mixed variables
  - Use *mgm*
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.
Time-series: \( n = 1 \)
Vector Auto-regression

In time-series data, we can take temporal ordering into account:

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

- \( B \) 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
**Introduction**

Concentration

Cross-sectional

$n = 1$

$n > 1$ Time-series

**Conclusion**
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 Epskamp¹, Claudia D. van Borkulo¹, Dale 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 $t$
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
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
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
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
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: $n > 1$
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
- Recently extended to incorporate contemporaneous and between subject effects.
  - mlVAR R package
Multi-level VAR

Adding superscript $p$ for subject. Level 1 model:

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

Level 2 model:

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

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

Concentration

Cross-sectional

\[ n = 1 \]

\[ n > 1 \text{ Time-series} \]

Conclusion

\[ \beta_{11} \]

\[ \beta_{12} \]

\[ \beta_{21} \]

\[ \beta_{22} \]

\[ \mu_1 \]

\[ \mu_2 \]
Each Parameter has a Distribution
Individual Networks

Bob

\[ Y_1 \]

0.15

1

\[ Y_2 \]

0.15

1

\[ Y_1 \]

0.15

1

\[ Y_2 \]

0.15

1

Alice

\[ Y_1 \]

0.06

1

\[ Y_2 \]

0.29

1

\[ Y_1 \]

0.07

1

\[ Y_2 \]

0.22

1

\[ Y_1 \]

0.22

1

\[ Y_2 \]

0.22

1
Random Effects

\[
\text{dnorm}(x, \text{means}[i], \text{SDs}[i])
\]
Fixed Effects

\[
\begin{align*}
Y_1 & \rightarrow Y_2 \\
X & \rightarrow Y_2
\end{align*}
\]

\[
\begin{align*}
Y_1 & \rightarrow Y_2 \\
X & \rightarrow Y_2
\end{align*}
\]

\[
\begin{align*}
Y_1 & \rightarrow Y_2 \\
X & \rightarrow Y_2
\end{align*}
\]

\[
\begin{align*}
Y_1 & \rightarrow Y_2 \\
X & \rightarrow Y_2
\end{align*}
\]

\[
\begin{align*}
Y_1 & \rightarrow Y_2 \\
X & \rightarrow Y_2
\end{align*}
\]

\[
\begin{align*}
Y_1 & \rightarrow Y_2 \\
X & \rightarrow Y_2
\end{align*}
\]
Fixed Effects

\[
\begin{align*}
Y_1 & \quad 0.07 \quad -0.14 \quad 0.17 \quad 0.18 \quad 0.34 \quad -0.6 \\
Y_2 & \quad 0.07 \\
1 & \quad 1
\end{align*}
\]
Individual Differences

\begin{align*}
\text{Y}_1 & \rightarrow \text{Y}_2 \\
\text{Y}_1 & \leftarrow \text{Y}_2
\end{align*}

\[ \text{dnorm}(x, \text{means}[i], \text{SDs}[i]) \]

95% interval
The random effects variance-covariance matrix can be divided into four blocks:

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

- 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
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: \( N > 1 \)
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.

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)
The Psychosystems Ecosystem

Introduction

Concentration

Cross-sectional

\( n = 1 \)

\( n > 1 \) Time-series

Conclusion
http://sachaepskamp.com/Dissertation
Follow the Discussion on Facebook

facebook.com/groups/PsychologicalDynamics/
Acknowledgements

Special thanks to Hariëtte Riesse, Laura Bringmann, Noémi Schuurman and Ellen Hamaker for collaboration, helpful tips, and invigorating discussion.
Thank you for your attention!