Network Psychometrics

PhD Dissertation

Sacha Epskamp

24-10-2016
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Network Psychometrics

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Outline

- Introduction
  - 1. Introduction: Psychological Networks
- Part I: A Practical Guide to Network Psychometrics
  - 2. Regularized Partial Correlation Networks
  - 3. Accuracy of Psychological Networks
  - 4. Network Estimation and Sparsity
  - 5. Personalized Network Modeling in Psychopathology
- Part II: Technical Advances in Network Psychometrics
  - 6. Discovering Psychological Dynamics
  - 7. Generalized Network Psychometrics
  - 8. The Ising Model in Psychometrics
- Part III: Visualizing Psychometrics and Personality Research
  - 9. Network Visualizations of Relationships in Psychometric Data
  - 10. State of the aRt Personality Research
  - 11. Unified Visualizations of Structural Equation Models
- Conclusion
  - 12. Discussion: The Road Ahead
Chapter 1

Introduction: Psychological Networks

This chapter has been adapted from:

Chapter 1
Introduction: Psychological Networks

1.1 Introduction
There are over 7 billion people in the world, each with a different brain, and each with a different story. The goal of this dissertation is to develop methods and tools to better understand these differences.

Network Inference
In the last decade, network models have been increasingly used to infer associations between variables (e.g., symptoms). In this dissertation, we will focus on estimating network models from data. The network models that we will consider are directed graphs, which can be used to encode causal structures (Pearl, 2000). For example, the edge insomnia → fatigue indicates that insomnia is a risk factor for fatigue.

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### 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.
Part I

A Practical Guide to Network Psychometrics
Chapter 2

Regularized Partial Correlation Networks

This chapter has been adapted from:

When the tuning parameter is low, only few connections are removed, likely connections in the network, or in other words, a working based on significance of edges or using LASSO regularization will work. These methods do not try to keep the number of spurious connections. When these methods are applied to the true network, the edges that are returned can usually be expected to be genuine. This is related to a well-known problem of estimating the covariance matrix and not the raw data, allowing one to always strongly connected with few (if any) missing connections and partial correlations between two variables.

2.6 Simulation Study

Figure 2.6: True Gaussian graphical model used in simulation study. The network is visualized using red lines indicating negative partial correlations.
Part I: A Practical Guide to Network Psychometrics

Chapter 2: Regularized Partial Correlation Networks

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): 746.9
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: 0.04
EBIC (gamma = 0): 710.7
EBIC (gamma = 0.25): 750.2
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): 729.8
EBIC (gamma = 0.5): 748.5

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

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Chapter 3

Accuracy of Psychological Networks

This chapter has been adapted from:

While the bootstrapped CIs of edge-weights can be constructed using the bootnet package for network inference, it is recommended to rely on bootstrapping methods. Simulations suggest this method performs better than the case-dropping bootstrap results. For instance, when constructing CIs on very low significance levels is not feasible with a limited number of observations, there is the danger to observe Type I errors.

Next, we can plot the network using the plot method:

```r
plot(CS, layout = layout.along.margins)
```

This allows for a null-hypothesis test if the observed difference scores are not different from one another, and we investigated the rejection rate under different levels of α: 0.05, 0.01, and 0.001. Figure 3.8 shows that rejection rate converged on the expected rejection rate 0.05. These methods will follow three steps: (A) estimation of the sample network, (B) selection of a tuning parameter, and (C) estimation of CIs.

Estimation of the sample network can be performed using the estimateNetwork function of the bootnet R-package. The tuning parameter used in this analysis is the LASSO penalty, which is a commonly used regularization method to control for model complexity.

The LASSO penalty shrinks the coefficients of less important edges to zero, which is useful for model selection (Foygel & Drton, 2010; see also Chapter 2) and for identifying significant edges in the network.

In Figure 3.7, we show the effect of varying the tuning parameter on the LASSO path for the example data. The path represents the regularization parameter values used in the LASSO regression, and it can be seen how the number of edges in the network decreases as the penalty increases.

To investigate centrality indices in the tomography of psychological networks (e.g., Boschloo et al., 2015; Fried et al., 2015; McNally et al., 2015; Yarnold et al., 2015), we will estimate a Gaussian Ising model of the network of 359 women with (subthreshold) PTSD shown in Figure 3.1 and estimated a network with 32 nodes.

The estimated network is then used to compute the centrality indices of the nodes. The node strength is defined as the sum of the edge weights connected to a node. The node strength of a node can be applied as well to LASSO regularized statistics (Hastie et al., 2015).

Next, we randomly rewired edges from the network (Friedman et al., 2014). The rewiring probability is set to 0.5. This means that 50% of the edges in the network are rewired.

Panel A shows that rewiring probability is not stable under subsetting both in the network and across studies. Panel B shows that most node strengths are not stable under subsetting, with the exception of one node strength.

The stability of centrality indices under omission of one or more nodes can be quantified for a single network.稳定性可以量化，特别是对于网络中的单个节点。然而，稳定性也取决于网络的大小。例如，对于一个包含359个节点的网络，稳定性可能受到较小的子集的影响更大。
- True network and centrality indices
- All edge-weights and centralities are equal
Estimated network and centrality indices

How to judge if these differences are interpretable?
Chapter 4

Network Estimation and Sparsity

This chapter has been adapted from:

4.5. Estimating an Ising Model When the Truth Is Dense

Integrating this structure could lead to the same...because these are the main methodologies that have been

4.6. Conclusion

Although it does not exactly resemble the true network structure, one may argue that the estimated network is similar enough to the truth, or that the similarities between the estimated network and the truth are more important than the differences. Despite the simplicity of the LASSO approach, it is worth noting that the estimation of sparsity is a complex task that may require more advanced methods. In conclusion, the LASSO approach is a powerful tool for estimating sparse networks, and its application in the analysis of psychopathological symptoms is promising.
Part I: A Practical Guide to Network Psychometrics

Chapter 4: Network Estimation and Sparsity

Dysthymia
- 1: Low mood for at least 2 years
- 2: Decrease in appetite
- 3: Increase in appetite
- 4: Low self-esteem
- 5: Indecisiveness
- 6: Feelings of Hopelessness
- 7: Insomnia
- 8: Hypersomnia
- 9: Diminished ability to concentrate
- 10: Fatigue

Generalized Anxiety Disorder (GAD)
- 1: Anxiety or worry for at least 6 months
- 2: Difficulty to control the worry
- 3: Restlessness
- 4: Irritability
- 5: Muscle Tension
- 6: Sleep disturbance 1: Insomnia
- 7: Sleep disturbance 2: Hypersomnia
- 8: Difficulty concentrating or mind going blank
- 9: Easily fatigued

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Chapter 4: Network Estimation and Sparsity

(a) Loglinear model (N = 10,000,000)

(b) Loglinear model (N = 1,000)

(c) IsingFit (N = 1,000)

(d) Rank 2 approximation (N = 1,000)
Chapter 5

Personalized Network Modeling in Psychopathology

This chapter has been adapted from:

Chapter 5: Personalized Network Modeling in Psychopathology

5.1 Introduction

Recent years have witnessed an increase in the use of network approaches in the study of psychopathology. These methods allow for the modeling of complex, multivariate systems and are increasingly being used to study mental disorders (Borsboom, 2006; Borsboom, Junghaven, van der Maas, & Kuper, 2008). The network approach embodies the assumption that mental disorders, symptoms, and related influences can be represented as a network of interrelated nodes. Nodes correspond to specific symptoms or variables, and edges indicate relationships between them. The network perspective allows for the study of both the contemporaneous (i.e., relationships between variables measured simultaneously) and the temporal (i.e., relationships between variables measured at different time points) aspects of mental disorders.

Section 5.2 focuses on a brief introduction to network psychometrics and differentiation between contemporaneous and temporal networks. Section 5.3 introduces the concepts of causation at the contemporaneous level and temporal level. Section 5.4 introduces the concept of dynamic networks and their application to psychopathology. Section 5.5 presents a discussion on causal relations and methods for inferring causation. Section 5.6 presents a clinical example to illustrate the use of network modeling in psychopathology.

5.2 Temporal and Contemporaneous Networks

In a typical ESM (experience sampling method) study, the time between consecutive measurements is short, such as a few minutes or even 1 second. Such short time intervals allow for the observation of temporal networks, which consist of nodes that represent variables measured at different time points. Temporal networks are used to study the sequence of events and the order in which they occur. In a temporal network, the edges between nodes indicate the direction of causality, meaning that the edge from node A to node B indicates that variable A is a cause of variable B.

Contemporaneous networks, on the other hand, consist of nodes that represent variables measured simultaneously. In a contemporaneous network, the edges between nodes indicate the strength of the relationship between the variables. For example, a link from node A to node B could indicate that variable A is a correlate of variable B.

5.3 Causation at the Contemporaneous Level

Causation can be assessed using contemporaneous network models, such as partial correlation networks. Partial correlation networks control for the effects of other variables, allowing for the assessment of direct relationships between variables. Partial correlation networks are particularly useful in clinical research, as they can help to identify causal relationships that may be obscured by the presence of confounding variables.

5.4 Generating Causal Hypotheses

Generating causal hypotheses is an important step in network modeling. Hypotheses can be derived from the network structure, such as the direction of causality, or from the relationships between variables. For example, if a network model indicates that variable A is a cause of variable B, then this could be a candidate for intervention. Hypotheses can also be generated from the network structure, such as the presence of feedback loops or the absence of certain relationships.

5.5 Clinical Example

A clinical example is presented to illustrate the use of network modeling in psychopathology. The example is based on the study of panic disorder, a common anxiety disorder. The study involved the use of network models to identify causal relationships between symptoms and to generate hypotheses for intervention.

5.6 Conclusion

In conclusion, network modeling is a powerful tool for the study of mental disorders. By using network models, researchers can gain a deeper understanding of the complex relationships between symptoms and the underlying causal processes. Network models can also be used to generate hypotheses for intervention, which can then be tested in clinical trials.
Part I: A Practical Guide to Network Psychometrics

Chapter 5: Personalized Network Modeling in Psychopathology

(b) Temporal network – Patient 1

(a) Contemporaneous network – Patient 1

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Part II

Technical Advances in Network Psychometrics
Chapter 6

Discovering Psychological Dynamics

This chapter has been adapted from:

Exercise 6.1: In many studies on the structure of psychological states, it is observed that different states are associated with each other. Consider the following states:

- P1: Feel sad
- P2: Sleep well
- P3: Feel happy
- P4: Feel aggressive
- P5: Feel relaxed

Each state is measured on a scale from 0 to 10. Construct a network where each state is a node and the edges represent the correlation between the states. Assume the following correlation matrix:

\[
\begin{pmatrix}
1 & 0.8 & -0.5 & 0.3 & -0.2 \\
0.8 & 1 & 0.7 & 0.4 & 0.1 \\
-0.5 & 0.7 & 1 & 0.6 & 0.3 \\
0.3 & 0.4 & 0.6 & 1 & 0.5 \\
-0.2 & 0.1 & 0.3 & 0.5 & 1
\end{pmatrix}
\]

1. Draw the network using the correlation matrix.
2. Identify the strongest and weakest correlations.
3. Discuss the implications of these correlations for the psychological states.
Part II: Technical Advances in Network Psychometrics

Chapter 6: Discovering Psychological Dynamics

Temporal

- Outgoing
- Energetic
- Adventurous
- Exercise
- Happy

Contemporaneous

- Outgoing
- Energetic
- Adventurous
- Exercise
- Happy

Between-subjects

- Outgoing
- Energetic
- Adventurous
- Exercise
- Happy

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Part II: Technical Advances in Network Psychometrics

Chapter 6: Discovering Psychological Dynamics

Maximum: 0.17

Temporal

Maximum: 0.55

Contemporaneous

Maximum: 0.55

Between-subjects

- Neuroticism
- Conscientiousness
- Extraversion
- Exercise
Chapter 7

Generalized Network Psychometrics

This chapter has been adapted from:

7.3. Generalizing Factor Analysis and Network Modeling

A. Structural Equation Modeling

B. Network Modeling

C. Latent Network Modeling

D. Residual Network Modeling

Figure 7.2: Examples of possible models under four different modeling frameworks. Circular nodes indicate latent variables, square nodes indicate manifest variables and gray nodes indicate residuals. Directed edges indicate factor loadings or regression parameters and undirected edges indicate pairwise interactions. Note that such undirected edges do not indicate covariances, which are typically denoted with bidirectional edges. Replacing covariances with interactions is where the network models differ from typical SEM.
Part II: Technical Advances in Network Psychometrics

Chapter 7: Generalized Network Psychometrics

Factor structure & latent network

Residual network

<table>
<thead>
<tr>
<th></th>
<th>df</th>
<th>$\chi^2$</th>
<th>AIC</th>
<th>BIC</th>
<th>EBIC</th>
<th>RMSEA</th>
<th>TLI</th>
<th>CFI</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFA</td>
<td>265</td>
<td>4713.94</td>
<td>183233.7</td>
<td>183589.9</td>
<td>184542.4</td>
<td>0.08</td>
<td>0.75</td>
<td>0.78</td>
</tr>
<tr>
<td>RNM</td>
<td>172</td>
<td>806.63</td>
<td>179511.0</td>
<td>180419.4</td>
<td>182848.2</td>
<td>0.04</td>
<td>0.94</td>
<td>0.97</td>
</tr>
<tr>
<td>RLNM</td>
<td>176</td>
<td>843.18</td>
<td>179539.5</td>
<td>180424.2</td>
<td>182789.5</td>
<td>0.04</td>
<td>0.94</td>
<td>0.97</td>
</tr>
</tbody>
</table>

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- A1: Am indifferent to the feelings of others.
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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.

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Chapter 8

The Ising Model in Psychometrics

This chapter has been adapted from:

Chapter 8: The Ising Model in Psychometrics

1. Motivation

The Ising model is a statistical model that is widely used in physics to study the behavior of magnetic materials. In psychometrics, it is used to model the relationships between different response behaviors. The model is defined by a set of parameters that include the coupling strengths between nodes and the inhomogeneous fields. These parameters can be estimated using various methods, such as maximum likelihood estimation.

2. The Ising Model in Psychometrics

In this section, we show that the Ising model is equivalent or closely related to a unidimensional IRT model. The question of why such sets of items may in fact fit psychometric data well can likewise map unique potentials to every possible pair of outcomes for many contexts be less problematic than the current conceptions in terms of addition as being defined through the set of all test items of the form of latent common causes induces associations among the observed variables.

3. Inference

The predictive accuracy of this model can be computed, and subsequently the mean of these univariate posterior distributions for $\Theta$ indicates two dominant components whereas Dataset B does not indicate any dominant component. The question of why such sets of items were generated by a common cause; in essence, the only sets of items to which the Ising model as presented in (8.8).

4. Results

The lattice in (b) indicates two dominant components whereas Dataset B does not indicate any dominant component. The use of LASSO to estimate the neighborhood—Pen and Ravikumar et al. (2010) used LASSO to estimate the neighborhood—of latent variables as common causes of the item responses (Bollen et al., 2003; Van Der Maas et al., 2006; Cramer et al., 2014), which uses but low rank, as is the case in the results on dataset A. However, not all researchers are convinced that a causal interpretation of latentization becomes concentrated on a smaller number of states, and the entropy to shrink to exactly zero. Thus, in moderately high values for $\pi$ identification of an infinite set of response behaviors as hypothesized to the bottom panels show the eigenvalues of both graphs; Dataset A clearly but low rank, as is the case in the results on dataset A.

5. Conclusion

The mean of these univariate posterior distributions for $\Theta$ can likewise map unique potentials to every possible pair of outcomes for many contexts be less problematic than the current conceptions in terms of addition as being defined through the set of all test items of the form of latent common causes induces associations among the observed variables.
Introduces the Ising model

Ising model in statistical physics

Equivalences between the Ising model and psychometric models:
  - Logistic regression
  - Loglinear modeling
  - Multivariate IRT

Estimation of the Ising model

Interpreting latent variables
Part III

Visualizing Psychometrics and Personality Research
Chapter 9

Network Visualizations of Relationships in Psychometric Data

This chapter has been adapted from:

Chapter 9: Network Visualizations of Relationships in Psychometric Data

Abstract

We present the qgraph package for R, which offers an easy-to-use graphical interface to perform several exploratory and confirmatory approaches to become a valuable tool in data visualization and analysis. The approach to psychometric data is implemented as a measurement model and performs a CFA accordingly. The results are shown in a formative measurement model. However, these typically indicate violations of local independence (e.g., a correlation matrix of their data, while the 

In the example below, we use the dataset concerning the five-factor model did not fit the data. Another example is the manual tips in a PDF file. We can do this for the NEO-PI-R dataset, which contains a strong factor, and most crossloadings are between extraversion and openness. Instead of examining full datasets of a test battery for intelligence (IST; Liepmann, Beauducel, Brocke, & Osterberg, 2010). Other psychometric tests.

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Chapter 10

State of the aRt Personality Research

This chapter has been adapted from:

The notion that network structures may differ over individuals, and that such differences may be related to personality traits, has been a focus of recent research. This chapter aims to provide an overview of the methods used in personality network research, with a particular emphasis on the HEXACO-60 personality model.

### Descriptive Statistics

<table>
<thead>
<tr>
<th>Personality Trait</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conscientiousness</td>
<td>3.13</td>
<td>1.26</td>
</tr>
<tr>
<td>Openness</td>
<td>3.67</td>
<td>1.32</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>3.19</td>
<td>1.34</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td>3.15</td>
<td>1.30</td>
</tr>
<tr>
<td>Extraversion</td>
<td>3.20</td>
<td>1.35</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>2.60</td>
<td>1.25</td>
</tr>
</tbody>
</table>

### LASSO Networks

LASSO networks are used to select the most important variables for predicting a particular outcome. The network is constructed by iteratively adding variables to the model and removing those that do not contribute significantly to the prediction.

```r
ew <- network[upper.tri(network)]
```

### Closeness Centrality

Closeness centrality is a measure of how close a node is to all other nodes in the network. It is calculated as the sum of the shortest path distances from a node to all other nodes.

```r
sum(ew > 0)  # the number of positive edges
```

### Clustering Coefficient

The clustering coefficient of a node is a measure of how close its neighbors are to each other. It can be calculated as the fraction of the number of triangles containing the node divided by the number of connected triples containing the node.

### Weighted Betweenness

Weighted betweenness is a measure of how important a node is in terms of the weighted shortest paths between other nodes. It is calculated as the sum of the reciprocal of the shortest path lengths between all pairs of nodes, with the weight of the path being used as the denominator.

### Weighted Closeness

Weighted closeness is a measure of how close a node is to all other nodes in the network, taking into account the weights of the paths.

### Network Analysis

Network analysis remains important. Factor and network analysis differ, at the very least, in how they deal with the n.a.-phenomenon, as nodes deemed to be inapplicable to the generating network. The reason is that correlations between nodes in the network (Chandrasekaran et al., 2012; Yuan, 2012). Alternative indices of small-worldness, by comparing them to the corresponding values ob-

### Factor Analysis

Factor analysis is a method used to identify underlying factors that explain the correlations among a set of observed variables. In the context of personality research, factor analysis is used to identify the underlying dimensions of personality traits.

### Network Psychometrics

Network psychometrics is a field that combines network analysis with psychometric methods. It is used to study the relationships between personality traits and other variables, such as age and sex.

### Conclusion

The aim of this contribution is to provide the reader with the necessary tools to conduct personality network research using the HEXACO-60 model. The methods described in this chapter are meant to be applied to future research in the field of personality network analysis.
Chapter 11

Unified Visualizations of Structural Equation Models

This chapter has been adapted from:

Chapter 11: Unified Visualizations of SEM models

11.3. Algorithms for Drawing Path Diagrams

The second algorithm is a variation of the Reingold-Tilford algorithm (usually termed the filter matrix) can be used to distinguish between different types of variables. The first level contains only the (exogenous) latent variables, the second level contains only the manifest variables that are endogenous in the path diagram, the third level contains only the manifest variables that are exogenous in the path diagram, and the fourth level contains all other (endogenous) manifest variables. Intersected with the levels is a horizontal axis, such that variables that are either exogenous themselves or only indicators of exogenous variables are plotted at the top of the diagram, while all other (endogenous) manifest variables are plotted at the bottom. The argument `rotation=2` is a base R function that opens a convenient file browser to select the Mplus output file.

11.4. Conclusion

This chapter consists of two sections: the first section describes the graphical tools available for visualizing SEM models, such as omitting exogenous variances) or post-hoc assessments of measurement invariance (Meredith, 1993). For example, the semPaths function offers a unified interface for extracting model matrices of any of the three major SEM software packages. After which the package can be loaded:

```r
library("lavaan")
```

Currently there are two common ways of drawing path diagrams. Many diagrams created by SEM packages produce path diagrams that are hardly readable, but rather only over the structural part of a model, followed by placing the factor loadings and intercepts are constrained to be equal over groups, while the means are allowed to differ.

```r
Imin(A,TRUE)
```

Within the Holzinger-Swineford CFA example, testing for strict measurement invariance with free factor means.

```r
n
```

A variable is treated as exogenous if it has no incoming directed edges attached. In the semPlot package, the `semCors` function offers more functionality than drawing path diagrams: it can act as a base R function that opens a convenient file browser to select the Mplus output file.
Part IV

Conclusion
Chapter 12

Discussion: The Road Ahead

This dissertation provided an overview of network models applicable to psychological data as well as descriptions of how these methods relate to general psychometrics. The visualization methods outlined in the final part of this dissertation are based on the oldest publications and relate to the state-of-the-art when this PhD project started. At the start of this PhD project, 4 years ago, network estimation in psychology consisted of not much more than drawing networks based on marginal correlation coefficients. This can be shown in publications from this period. Cramer et al. (2010) marks the first psychological network estimated from data and shows a network in which edges are based on associations. The qgraph package was based on this and, for the first time, provided psychologists with a simple method for constructing networks based on correlations (Epskamp et al., 2012). Key publications of that time mostly outlined conceptual and theoretical implications of the network perspective and often relied on correlation networks to showcase what such a network could possibly look like (e.g., Cramer, Sluis, et al., 2012; Borsboom & Cramer, 2013; Schmittmann et al., 2013). Partial correlation networks were proposed and published (e.g., Epskamp et al., 2012; Cramer, Sluis, et al., 2012) but were not yet worked out in enough detail to provide the powerful visualizations now used in psychology. In addition, time-series models showed promise (e.g.,

In retrospect, the original promise of partial correlation networks might have been taken too strong. For example, we now know that the partial correlation network shown by Epskamp et al. (2012) consists of far too many nodes compared to the number of observations to likely lead to stable results.
Chapter 12: Discussion: The Road Ahead

12.2. Open Questions in Network Psychometrics

Information theory. A potential solution for such problems is to use information theory. In particular, Kullback–Leibler (K-L) divergence can be used to quantify the information content of a network. The K-L divergence between two probability distributions can be defined as:

\[ D_{KL}(P||Q) = \sum_{x} P(x) \log \frac{P(x)}{Q(x)} \]

This measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network. As can be seen, this measure is a direct function of the size of the variance–covariance matrix and can be seen as a measure of how much information is contained in a network.
- Missing data
- Ordinal data
- Evidence for Sparsity
  - Bayesian statistics
- Should probabilistic models be analyzed as networks?
  - Information theory
- Importance of intercepts
- Complexity
Part V
Appendices
Appendix B

Contributed Work

This appendix contains a list of the contributed publications and software packages used in the completion of the FPD project. The FPD version of the dissertation contains links to all publications and software packages, which can be found on https://www.sachaepskamp.com.

B.1 Publications

The list of publications that are evaluated in this report is published at the time of submission of this dissertation. All links and notes of the publications or packages may change before publication.

Main Author Publications


Collaborations


Appendices


Software

• qgraph
– Network visualization and analysis in R (Link to CRAN repository)
• OpenMx
– Structural equation modeling (Link to CRAN repository)
• mirt
– Multidimensional item response theory (Link to CRAN repository)
• PSIRF
– Bayesian inference for psychological research (Link to CRAN repository)

Collaborations


JASP
– A low fat alternative to SPSS, a delicious alternative to R. (Link to website)

Chapter 3


Chapter 4


Chapter 5


Chapter 6


Appendices


Software

• qgraph
– Network visualization and analysis in R (Link to CRAN repository)
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Collaborations


JASP
– A low fat alternative to SPSS, a delicious alternative to R. (Link to website)
The Psychosystems Ecosystem

- **Type of data**
  - Cross-sectional
  - Longitudinal
  - Mixed

- **Scale of measurement**
  - Binary
  - Ordinal
  - Continuous

- **Gaussian?**
  - Yes
  - No

- **Enough observations?**
  - Yes
  - No

Software:
- `qgraph`:
  - `cor_auto()`
  - `graph = 'pcor'`
  - `graph = 'glasso'`
- `huge`:
  - `cor()`
  - `nnpn()`
- `mlVAR`
- `GraphicalVAR`
- `mgm`
- `bootnet`
- `lvnet`
- `IsingFit()`
- `IsingSampler: EstimateIsing`
- `NetworkComparisonTest`
### Nederlandse Samenvatting

#### C. Nederlandse Samenvatting

#### C.1. Introductie: Psychologische variabelen

Een netwerkmodel is een mengd grafisch model voor een mix van categorische en continue variabelen. Het model laat zien welke variabelen sterk met elkaar gepaard gaan. Netwerkmodellen worden vaak gebruikt in het persoonlijkheidsonderzoek. In dit proefschrift wordt een specificatie genoemd die ligt op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### Hoofdstuk 2: Geregulariseerde netwerken van partiële correlaties

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk ook een tweede relatiematrix en het gerichte temporele netwerk, indicatief kan zijn voor mogelijke relaties in de toekomst. Dit hoofdstuk introduceert het meest gebruikte netwerkmodel voor persoonlijkheidsonderzoek: de Ising model. De VAR-analyse levert naast het temporele netwerk ook een tweede..

### C.2. Deel I: Netwerkpsychometrie voor de empirische wetenschapper

De VAR-analyse levert naast het temporele netwerk ook een tweede model passend te maken zonder dat kruisladingen gebruikt moeten worden. De VAR-analyse levert naast het temporele netwerk ook een tweede..

### C.3. Deel II: Methodologische uitdagingen in het netwerkonderzoek

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk ook een tweede relatiematrix en het gerichte temporele netwerk, indicatief kan zijn voor mogelijke relaties in de toekomst. Dit hoofdstuk introduceert het meest gebruikte netwerkmodel voor persoonlijkheidsonderzoek: de Ising model. De VAR-analyse levert naast het temporele netwerk ook een tweede..

### C.4. Deel III: Methodologische uitdagingen in het netwerkonderzoek

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk alsof op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd, wordt in het GGM juist de inverse van de variantie–covariantie variabelen weer (in dit geval items van een persoonlijkheidsvragenlijst) en geldig op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### C.5. Discussie: open vraagstukken in de netwerkpsychometrie

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk alsof op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd, wordt in het GGM juist de inverse van de variantie–covariantie variabelen weer (in dit geval items van een persoonlijkheidsvragenlijst) en geldig op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### C.6. Conclusie

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk alsof op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd, wordt in het GGM juist de inverse van de variantie–covariantie variabelen weer (in dit geval items van een persoonlijkheidsvragenlijst) en geldig op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### EBIC (gamma = 0): 746.4

 interfering variables (E = 'interfereren'), begrijpend (B = 'begrijpen'), voldoende (V = 'voldoende'), vertrouwens (O = 'vertrouwen'), en uiteindelijk meteen (T = 'meteen'). Hierbij wordt gebruik gemaakt van de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### C.7. Conclusie: open vraagstukken in de netwerkpsychometrie

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk alsof op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd, wordt in het GGM juist de inverse van de variantie–covariantie variabelen weer (in dit geval items van een persoonlijkheidsvragenlijst) en geldig op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### C.8. Conclusie: open vraagstukken in de netwerkpsychometrie

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk alsof op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd, wordt in het GGM juist de inverse van de variantie–covariantie variabelen weer (in dit geval items van een persoonlijkheidsvragenlijst) en geldig op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### C.9. Conclusie: open vraagstukken in de netwerkpsychometrie

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk alsof op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd, wordt in het GGM juist de inverse van de variantie–covariantie variabelen weer (in dit geval items van een persoonlijkheidsvragenlijst) en geldig op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.

### C.10. Conclusie: open vraagstukken in de netwerkpsychometrie

Een voorbeeld van een dergelijk netwerk is de Van der Laan (2004) diagnose in afhankelijk van de populatiegemiddelden: vaste effecten (\( \gamma = 0 \)). Bij de VAR-analyse levert het temporele netwerk alsof op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd, wordt in het GGM juist de inverse van de variantie–covariantie variabelen weer (in dit geval items van een persoonlijkheidsvragenlijst) en geldig op de overeenkomsten tussen het netwerkmodel en de klassieke psycho-metrische modelleerd. Bij het analyseren van netwerken moeten we rekening houden met het feit dat er kruisladingen kunnen zijn. Een andere methode is om een LASSO te gebruiken. Het LASSO neemt aan dat het ware netwerk spaarzaam is, en zal zodoende vaak een spaarzaam netwerk schatten. Een andere methode is om een mean-field approximaaties uit de data te gebruiken om met 95% zekerheid te stellen.
Thank you for your attention!