Stability of Psychological Network Models

ECR Retreat DYNAMIC 2026

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Björn Siepe



Postdoc at Philipps University and Goethe University (soon)

- Time series modeling (incl. dynamic networks), open software (`openESM`), metascience
- Dynamic networks: particularly Bayesian estimation



Kai Jannik Nehler

Postdoc at Goethe University and Justus Liebig University

- (Cross-sectional) Network estimation under challenging data conditions
- Specifically ordinal and missing values (`mantar`)

Outline

1 Terminology and Motivation

2 Cross-sectional Networks

3 Longitudinal networks

4 Conclusion

Two perspectives on network stability



Schematic network.

Definition

Core question

Related concepts

(Borsboom et al., 2018; Epskamp et al., 2018; Haslbeck et al., 2021a)

Two perspectives on network stability



Schematic network.

	Stability of estimation
Definition	Sensitivity of estimated network features to sampling variation.
Core question	Would another sample from the same population support similar conclusions?
Related concepts	precision, robustness

(Borsboom et al., 2018; Epskamp et al., 2018; Haslbeck et al., 2021a)

Two perspectives on network stability



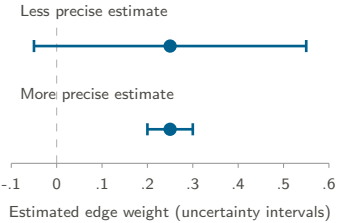
Schematic network.

	Stability of estimation	**Stability across time and groups**
Definition	Sensitivity of estimated network features to sampling variation.	Similarity of underlying network parameters across occasions or populations.
Core question	Would another sample from the same population support similar conclusions?	Do the same parameters hold at another time or in another population?
Related concepts	precision, robustness	invariance, generalizability

(Borsboom et al., 2018; Epskamp et al., 2018; Haslbeck et al., 2021a)

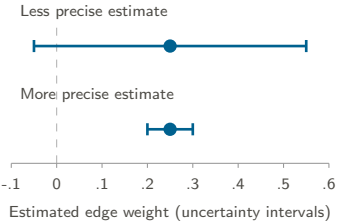
Why does stability of estimation matter?

- Network connections are estimated rather than directly observed **(Epskamp et al., 2018)**



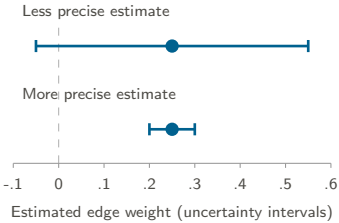
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- Substantive interpretations often concern specific network features **(Borsboom et al., 2018)**



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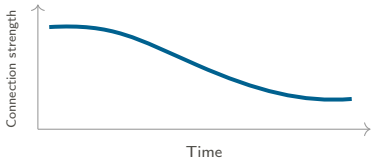


Interpret substantive conclusions in light of estimation precision.

Why is stability across time and groups interesting?

Across time (Haslbeck et al., 2021a)

- Interventions may aim to change relationships between symptoms
- Development and life events may strengthen or weaken these relationships

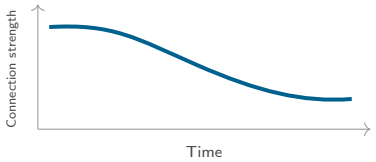


Does the insomnia–fatigue connection change over time?

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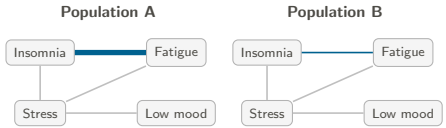
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Across groups (Borsboom et al., 2018)

- Findings often used to explain symptoms beyond the original population
- Group comparisons help distinguish shared from population-specific relationships

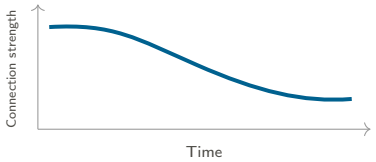


Is the insomnia–fatigue connection similar across populations?

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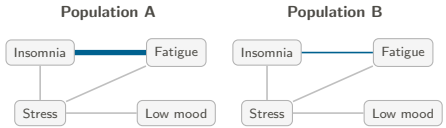
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Is the insomnia–fatigue connection similar across populations?

Stability across time and groups is often the substantive research question.

Different estimated networks: evidence of different underlying relationships?



(Borsboom et al., 2018; Epskamp et al., 2018; Haslbeck et al., 2021a)

Different estimated networks: evidence of different underlying relationships?



Substantive perspective

- Network differences may be meaningful.

Statistical perspective

- Estimated networks may differ even when underlying relationships are identical.

(Borsboom et al., 2018; Epskamp et al., 2018; Haslbeck et al., 2021a)

Different estimated networks: evidence of different underlying relationships?



Substantive perspective

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Statistical perspective

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Implications for this talk

- Investigating substantive stability and change
- Quantifying and communicating statistical uncertainty

(Borsboom et al., 2018; Epskamp et al., 2018; Haslbeck et al., 2021a)

Outline

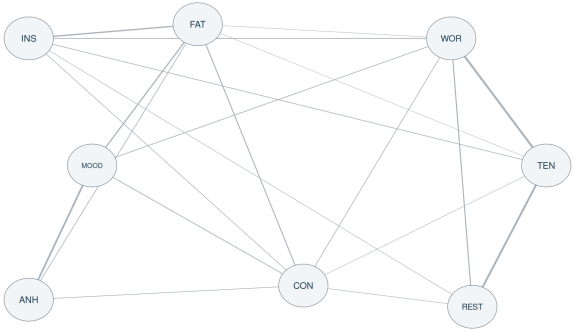
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From estimated networks to substantive conclusions

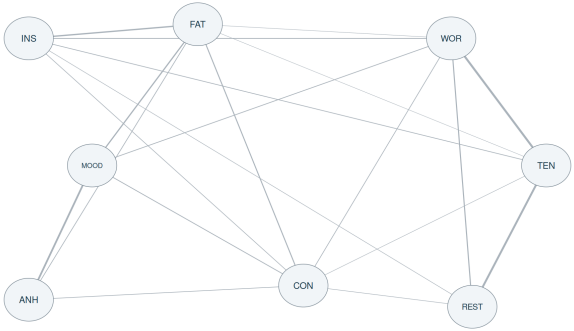


Simulated data; regularized partial correlations.

Gaussian graphical models **(Epskamp & Fried, 2018)**

- different claims about associations require different kinds of statistical support
- always including uncertainty due to sampling variability

From estimated networks to substantive conclusions



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What do we want to learn from this network?

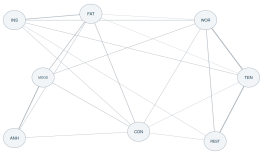
- Which conditional associations characterize the symptom pattern?
- How large are these associations?
- Which associations are supported as present or absent?

The familiar workflow: What can we conclude?

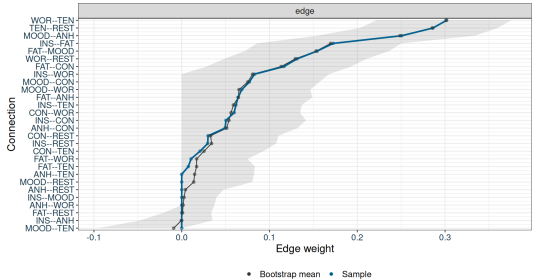
Which associations characterize the pattern? **(Epskamp & Fried, 2018; Epskamp et al., 2018)**

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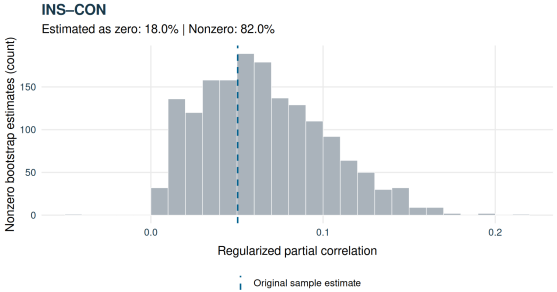


Simulated data; regularized partial correlations.



Original estimates, bootstrap means, and central 95% bootstrap regions.
2,000 resamples; EBICglasso ($\gamma = .5$).

Interpreting bootstrap results – a cofidence interval?



Histogram: nonzero bootstrap estimates only.
Dashed blue line: original sample estimate.

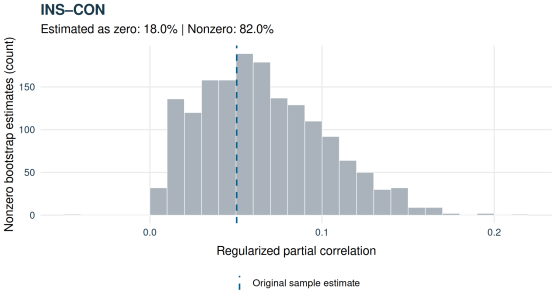
Interpreting bootstrap results – a cofidence interval?

What should a 95% confidence interval provide?

- Approximately 95% coverage of the population edge weight across repeated samples

Why is regularization problematic? **(Waldorp & Haslbeck, 2024)**

- Bootstrap estimates inherit shrinkage and selection
- Central 95% regions need not achieve 95% coverage



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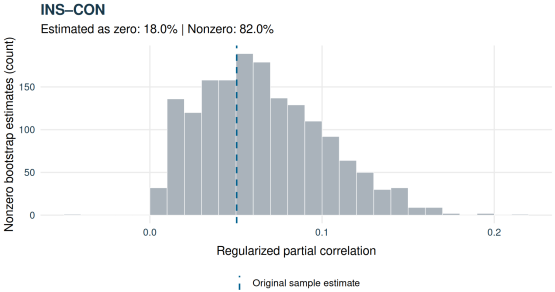
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Why is regularization problematic? **(Waldorp & Haslbeck, 2024)**

- Bootstrap estimates inherit shrinkage and selection
- Central 95% regions need not achieve 95% coverage

What does this limit?

- Bootstrap regions are not automatically valid confidence intervals or tests against zero
- The proportion of zero estimates is not the probability that the population edge is absent



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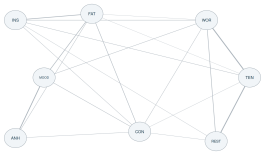
The familiar workflow: What can we conclude?

Which associations characterize the pattern? **(Epskamp & Fried, 2018; Epskamp et al., 2018)**

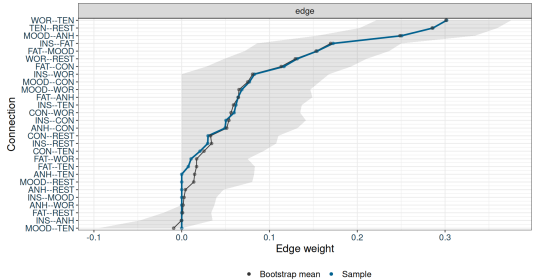
- Regularization selects a sparse pattern of conditional associations

How large are these associations? **(Epskamp et al., 2018; Waldorp & Haslbeck, 2024)**

Which are supported as present or absent? **(Epskamp et al., 2018)**



Simulated data; regularized partial correlations.



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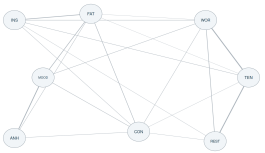
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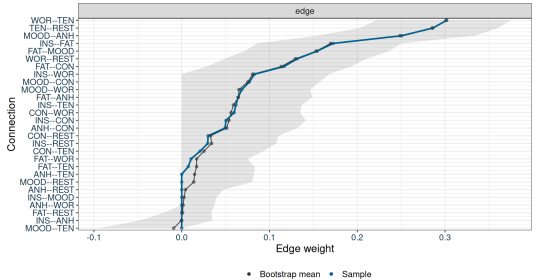
How large are these associations? (Epskamp et al., 2018; Waldorp & Haslbeck, 2024)

- Shrinkage biases estimated magnitudes towards zero
- Bootstrap intervals help compare different edge weights

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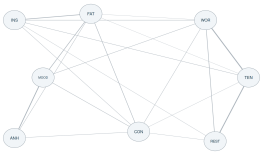
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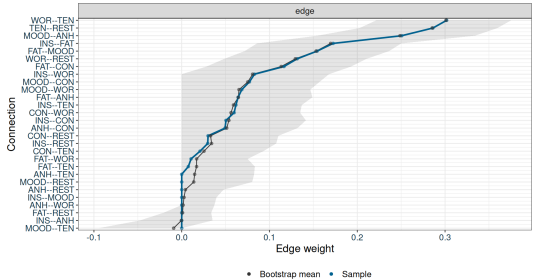
- Shrinkage biases estimated magnitudes towards zero
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Which are supported as present or absent? (Epskamp et al., 2018)

- Bootstrap intervals are not intended as significance tests against zero
- Omitted edges do not establish population absence



Simulated data; regularized partial correlations.



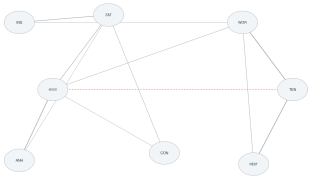
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Unregularized estimation with GGMnonreg (Williams, 2021)

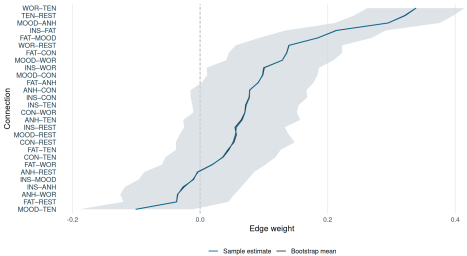
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Reduced network: edges retained when their pointwise 95% interval excludes zero.



All edge estimates and pointwise 95% bootstrap confidence intervals.

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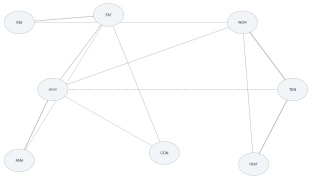
- Estimate all conditional associations without lasso shrinkage

How large are these associations?

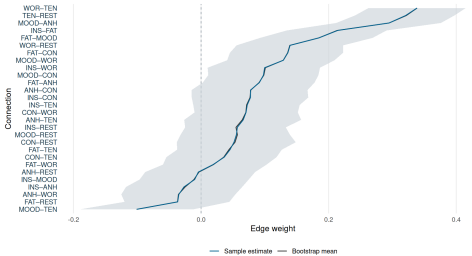
- Estimate magnitudes without shrinkage towards zero
- Approximate confidence intervals quantify estimation precision

Which are supported as present or absent?

- Intervals excluding zero provide evidence against a zero association
- Intervals containing zero do not establish absence



Reduced network: edges retained when their pointwise 95% interval excludes zero.



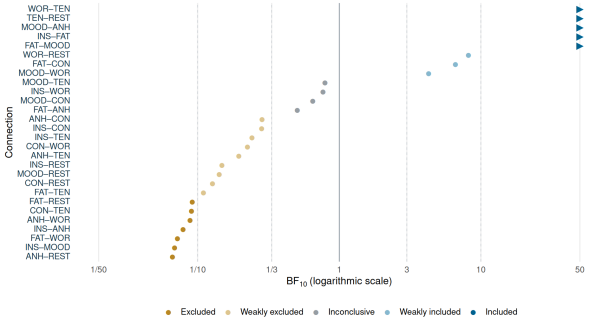
All edge estimates and pointwise 95% bootstrap confidence intervals.

A Bayesian extension: Evidence for inclusion and exclusion (Williams & Mulder, 2020)

What remains unresolved?

- An interval containing zero does not establish an absent association

What can Bayesian analysis add?



Edgewise Bayes factors; evidence categories as in Huth et al. (2026). Triangles indicate values below 1/50 or above 50.

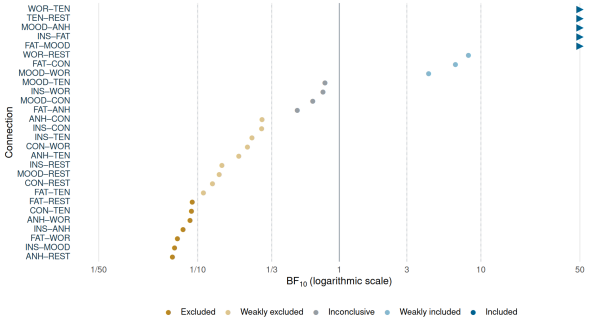
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What can Bayesian analysis add?

- Compare evidence for a nonzero association versus an absent edge
- Quantify support for either explanation, or identify inconclusive evidence
- so distinguish evidence favouring exclusion and insufficient evidence for conclusion



Edgewise Bayes factors; evidence categories as in Huth et al. (2026). Triangles indicate values below 1/50 or above 50.

Research questions overview

	Regularization + bootstrap	Unregularized + intervals	Bayesian estimation + Bayes factors
Characterize the association pattern	✓	✓	✓
Estimate association magnitudes and their uncertainty	△ Shrinkage; CI limitations	✓	✓
Evaluate evidence for presence **and** absence	–	△ Tests against zero only	✓

✓ Can address the question under suitable assumptions △ Partial answer / limitations – Not provided by this workflow

(Epskamp & Fried, 2018; Waldorp & Haslbeck, 2024; Williams, 2021; Williams & Mulder, 2020)

Research questions overview

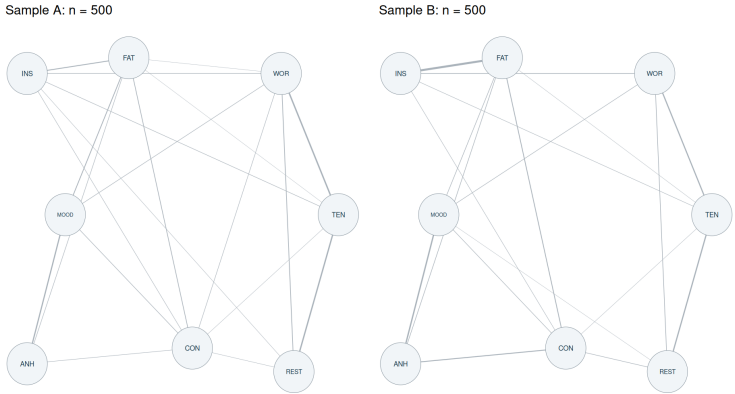
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(Epskamp & Fried, 2018; Waldorp & Haslbeck, 2024; Williams, 2021; Williams & Mulder, 2020)

- A method can support estimation without supporting every intended claim
- All approaches address estimation uncertainty, but differ in the conclusions they support

Are these networks different beyond estimation variability?

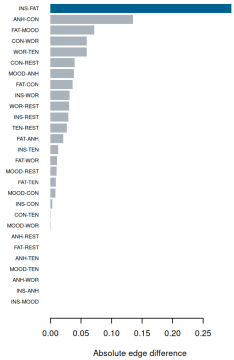


- Same eight symptoms; two independent samples of 500 participants
- Visible differences can reflect population differences, sampling variability, or both

Three possible questions about stability in our symptom networks

Network structure

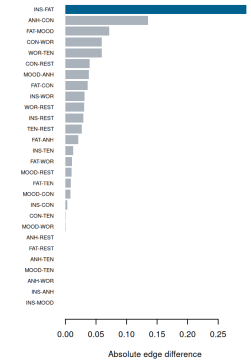
Does any symptom association differ?



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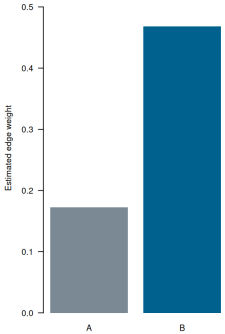
Network structure

Does any symptom association differ?



Specific edge

Does the INS–FAT association differ?

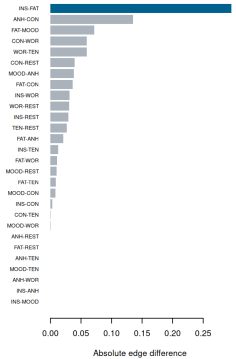


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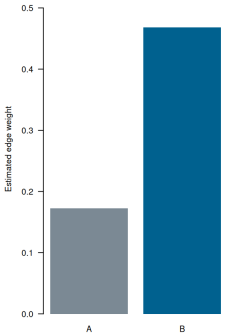
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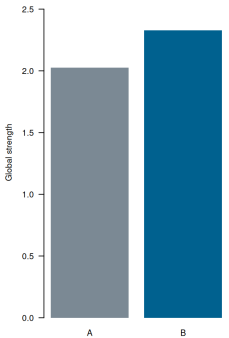
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Global strength

Does overall connectivity differ?

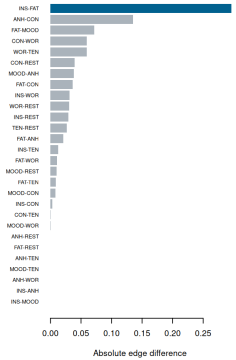


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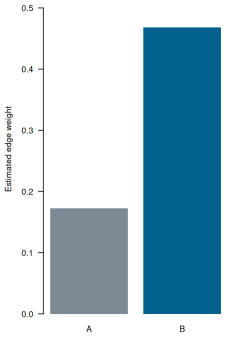
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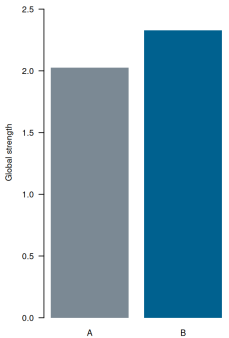
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Global strength

Does overall connectivity differ?

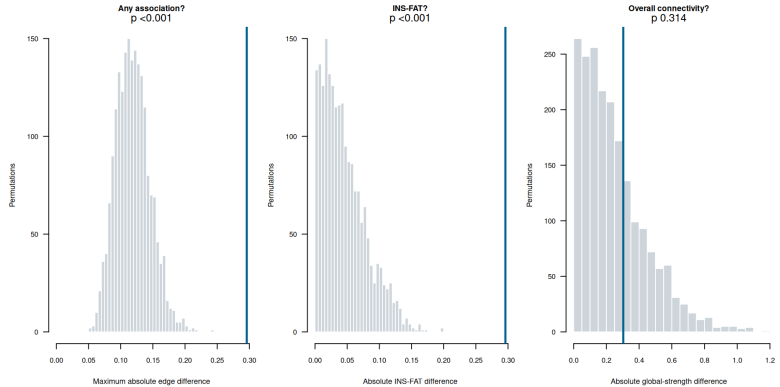


Are the observed differences larger than we would expect from sampling variation alone?

Network Comparison Test: Are the observed differences unusual?

(van Borkulo et al., 2023)

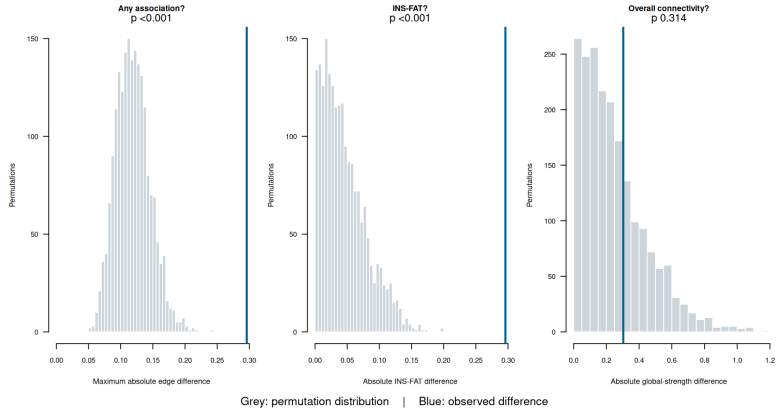
- Permute group labels → re-estimate both networks → recalculate all three comparison statistics.



Network Comparison Test: Are the observed differences unusual?

(van Borkulo et al., 2023)

- Permute group labels → re-estimate both networks → recalculate all three comparison statistics.



- Observed difference in the upper tail → larger than typically expected from sampling variability under the null hypothesis

Outline

1 Terminology and Motivation

2 Cross-sectional Networks

3 Longitudinal networks

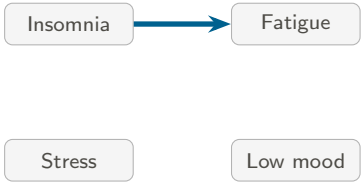
4 Conclusion

From cross-sectional to dynamic networks

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Repeated measurements within persons (Epskamp, 2020)

- Temporal network: does insomnia at $t-1$ predict fatigue at t?



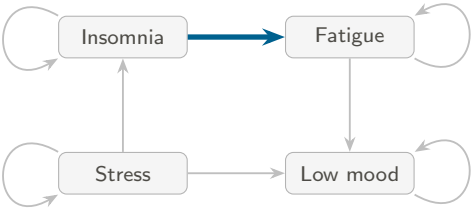
Schematic temporal network.

From cross-sectional to dynamic networks

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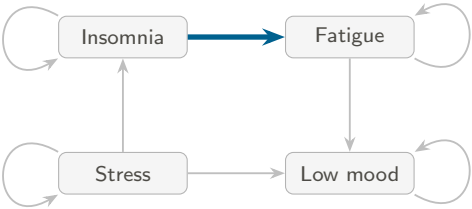
Schematic temporal network.
Arrows: lagged effects ($t-1 \rightarrow t$); loops: autoregressive effects.

From cross-sectional to dynamic networks

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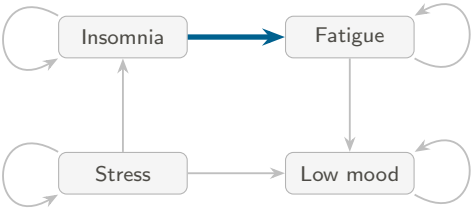
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Repeated measurements within persons (Epskamp, 2020)

- Temporal network: does insomnia at $t-1$ predict fatigue at t?
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Many models, one representation

- VAR, graphicalVAR, mlVAR, DSEM (Asparouhov et al., 2018)
- Parameters of many dynamic models can be displayed as a network

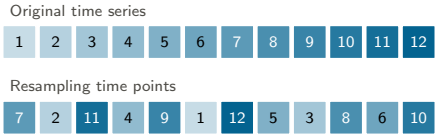


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Estimation uncertainty: bootstrapping time series

Resampling single time points

- Re-estimating on shuffled occasions removes the serial dependence the model is about



Numbers: measurement occasions.

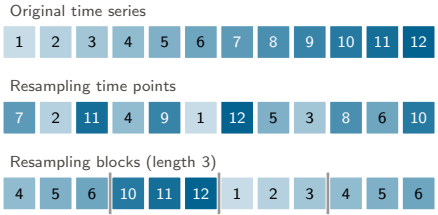
Estimation uncertainty: bootstrapping time series

Resampling single time points

- Re-estimating on shuffled occasions removes the serial dependence the model is about

Block bootstrap

- Resample contiguous blocks instead of single time points
- Block length must be chosen; gaps (e.g., nights) complicate block construction



Numbers: measurement occasions.
Blocks keep short-term dependence intact.

Estimation uncertainty: Bayesian estimation

Limits of common approaches

- Regularized estimation (e.g., graphicalVAR): same shrinkage and selection issues as in the cross-sectional case
- Several implementations report no intervals for some or all parameters

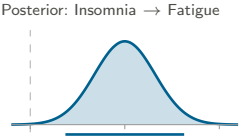
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Bayesian estimation **(Siepe et al., 2024)**

- Posterior distribution for every parameter



Schematic posteriors with 95% credible intervals.

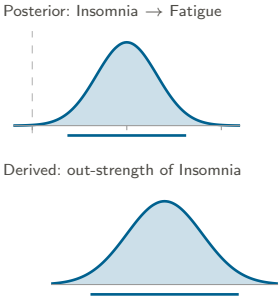
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Schematic posteriors with 95% credible intervals.
Same draws, any function of the parameters.

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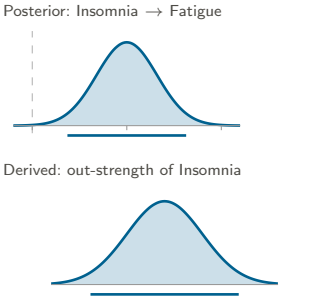
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Bayesian estimation **(Siepe et al., 2024)**

- Posterior distribution for every parameter
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Carrying uncertainty forward **(Siepe et al., 2026)**

- Network features are often used in later analyses, e.g., predicting outcomes from centrality
- Taking their uncertainty into account leads to more realistic conclusions

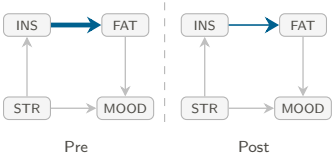


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Different dynamic networks: beyond estimation variability?

Two time series ($n = 1$)

Is my insomnia → fatigue effect weaker after therapy?



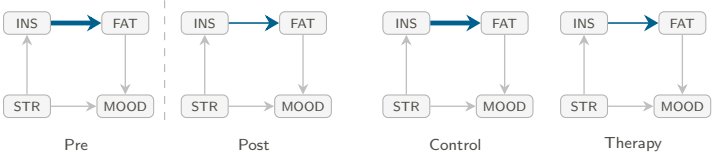
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Two groups ($n > 1$)

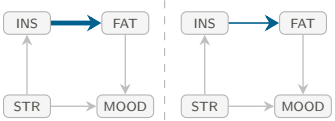
Does the average effect differ between therapy and control group?



Different dynamic networks: beyond estimation variability?

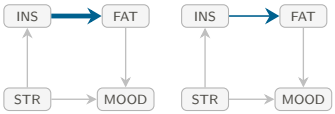
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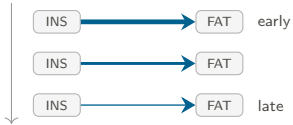
Two groups ($n > 1$)

Does the average effect differ between therapy and control group?



Gradual change

Does the effect change continuously over time?



Comparing person-specific networks ($n = 1$)

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Typical questions

- Is my insomnia $\rightarrow$ fatigue effect weaker after therapy than before?
- Does my network differ from Kai's?

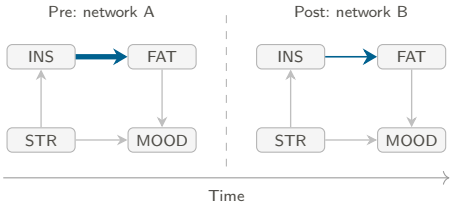
Comparing person-specific networks ($n = 1$)

Typical questions

- Is my insomnia → fatigue effect weaker after therapy than before?
- Does my network differ from Kai's?

Data

- Two separate time series: two phases of one person, or two persons
- Each long enough for a person-specific model; often 100+ time points, depending on number of variables, effect sizes, and estimator **(Mansueto et al., 2023; Siepe et al., 2024; Zhang et al., 2025)**



One person, two phases; each phase modeled separately.

Comparing person-specific networks ($n = 1$)

Typical questions

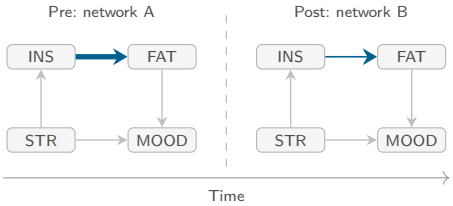
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Assumption

- Parameters are constant within each series



One person, two phases; each phase modeled separately.

Comparing person-specific networks: available tests

Method	Approach	Answers
INIT (Hoekstra et al., 2024)	Compare model with equality constraints to unconstrained model (AIC/BIC)	Do the networks differ overall?
Bayesian comparison (Siepe et al., 2024)	Posterior distance between networks vs. reference distribution of sampling variability	Do the networks differ overall?
IVPP (Du et al., 2025)	Global test, then stepwise partial pruning of equality constraints	Do the networks differ, and which parameters differ?
Permutation / parametric test (Haslbeck et al., 2025)	Compare estimated VAR parameters against a no-difference reference	Which parameters differ?

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Permutation / parametric test (Haslbeck et al., 2025)	Compare estimated VAR parameters against a no-difference reference	Which parameters differ?

- Global tests answer "does anything differ?", not "does insomnia $\rightarrow$ fatigue differ?"
- For a single effect: posterior (or block bootstrap distribution) of the difference

Comparing groups of individuals ($n > 1$)

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Typical questions

- Does the average insomnia $\rightarrow$ fatigue effect differ between therapy and control group?
- Do individuals differ more from each other in one group?

Comparing groups of individuals ($n > 1$)

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- Many persons, fewer time points per person (often 50–100), information pooled within groups
- Enough persons per group to estimate group differences

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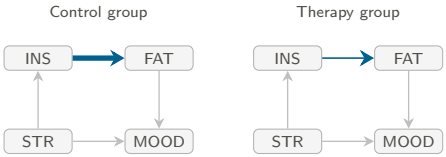
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- Enough persons per group to estimate group differences

What can differ?

- Fixed effects, random-effect variances, contemporaneous and between-person networks



Average (fixed-effect) temporal networks; individual networks vary around them.

Comparing groups: available approaches

Permutation test for mlVAR **(Haslbeck et al., 2025)**

- Permute group labels, re-estimate, recompute differences

Observed labels

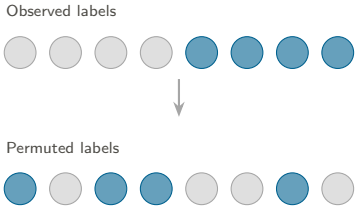


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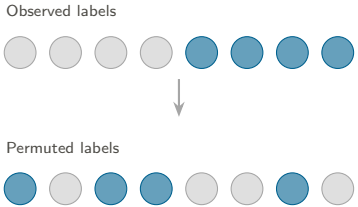
Re-estimate both groups;
repeat many times → reference distribution

Comparing groups: available approaches

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Permutation test for mlVAR **(Haslbeck et al., 2025)**

- Permute group labels, re-estimate, recompute differences
- The dynamic counterpart of the NCT



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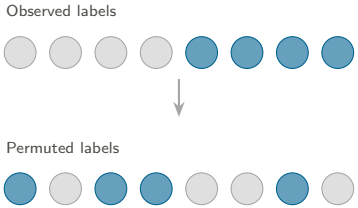
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- Permute group labels, re-estimate, recompute differences
- The dynamic counterpart of the NCT

Multilevel models with group predictors **(Asparouhov et al., 2018)**

- DSEM or Bayesian mlVAR: group membership predicts person-specific parameters
- Posterior of the group difference for any parameter or derived quantity



Re-estimate both groups;
repeat many times → reference distribution

Gradual change: time-varying networks

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Typical questions

- Does the insomnia → fatigue effect weaken gradually during therapy?
- Does insomnia become less central over time?

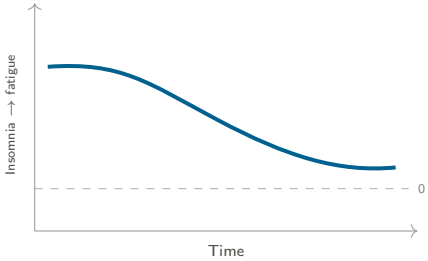
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Approaches **(Bringmann et al., 2024; Haslbeck et al., 2021b)**

- Time-varying VAR: let parameters change smoothly
- Moderation: parameters as a function of a measured variable (e.g., treatment phase)



Schematic time-varying effect.

Gradual change: time-varying networks

Typical questions

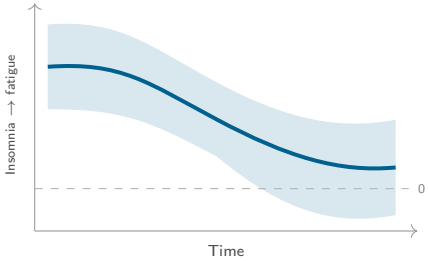
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Approaches **(Bringmann et al., 2024; Haslbeck et al., 2021b)**

- Time-varying VAR: let parameters change smoothly
- Moderation: parameters as a function of a measured variable (e.g., treatment phase)

Caveats

- Requires long time series; flexibility trades off against precision
- Moderation requires specific hypotheses



Schematic time-varying effect.
Band: pointwise uncertainty.

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Take-home messages

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Stability of estimation

- Quantify uncertainty for the quantity you interpret: an edge, a centrality index, a difference
- Methods support different claims: bootstrap regions, confidence intervals, and Bayes factors are not interchangeable
- Time series need dependence-aware methods, e.g., block bootstrap or Bayesian estimation

Take-home messages

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- Estimated networks differ even when the underlying networks do not
- Test whether differences exceed sampling variability; the design determines the method
- Global and edge-specific tests answer different questions

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Start from the research question: which part of the network should be (in)stable, and why does it matter?

DYNAMIC Methods Consultation

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