



**Marburg
University**

Using Features of Dynamic Networks to Guide Treatment Selection and Outcome Prediction: The Central Role of Uncertainty

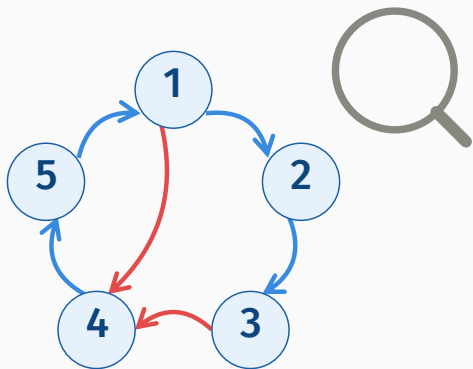
APS · May 2026

Björn Siepe

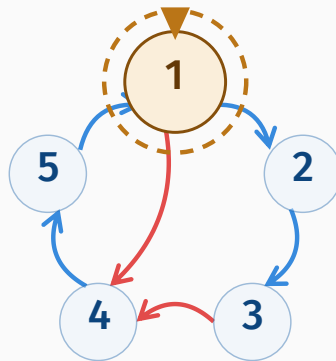
Psychological Methods Lab, Department of Psychology, Marburg University

How can we use Dynamic Networks?

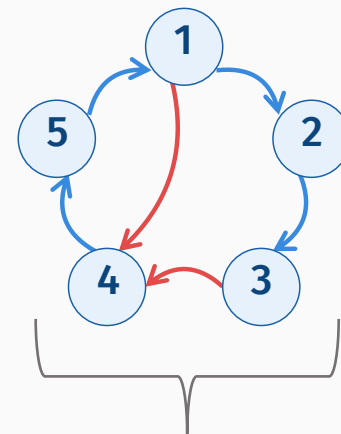
Description



Treatment selection



Prediction

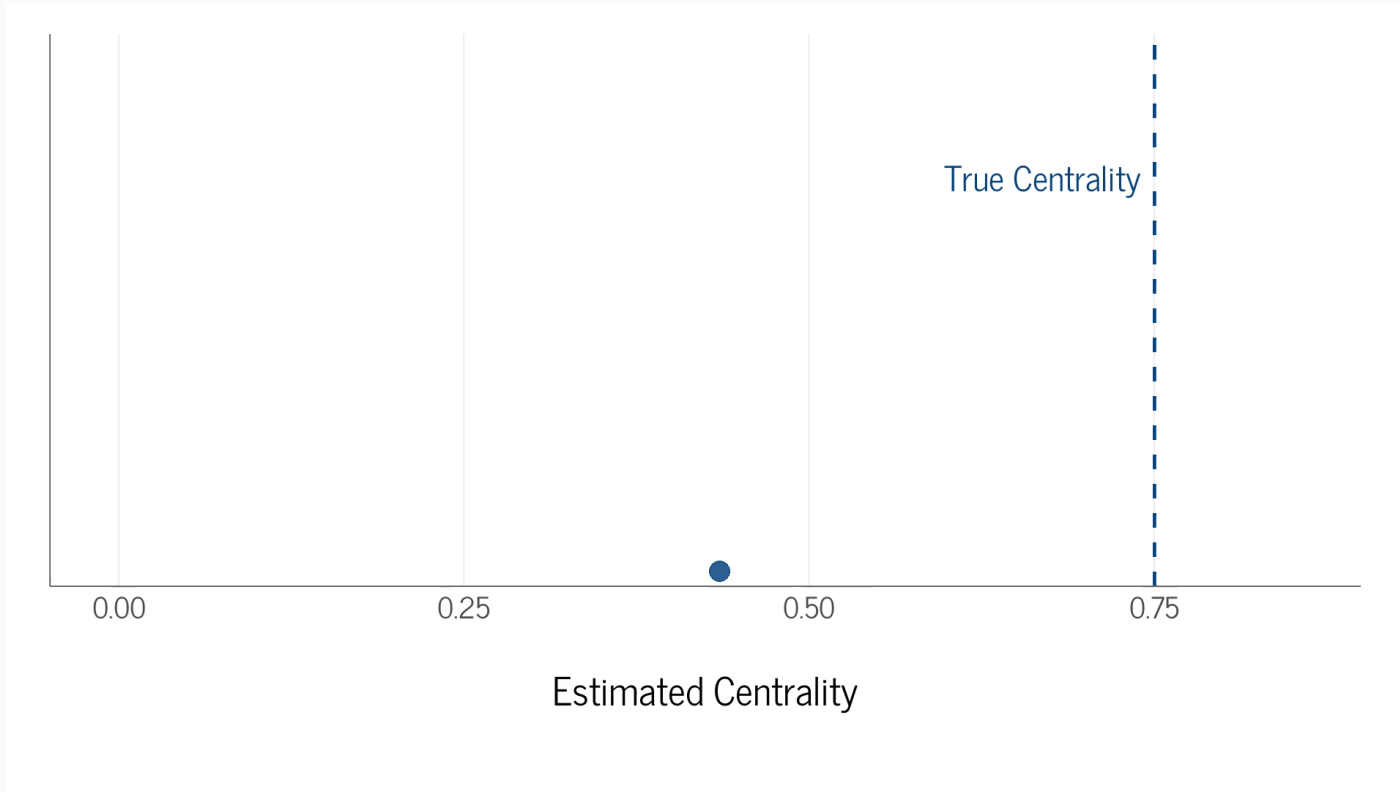


Network Feature

Outcome

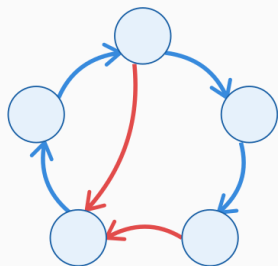
Theoretical issues aside: Are these use cases realistic?

Issue: Uncertainty about central node

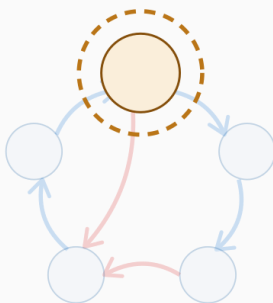


Bayesian One-Step Approach (BmlVAR)

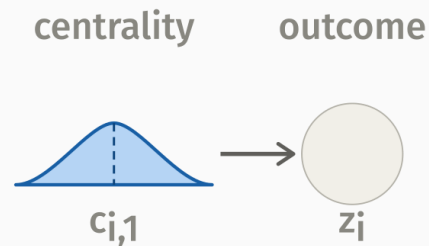
Multilevel VAR



Network Feature



Outcome Regression



Simulation Setup

Data Generation

- Data from multilevel VAR model
- Timepoints
- Individuals
- Heterogeneity
- Relation to outcome

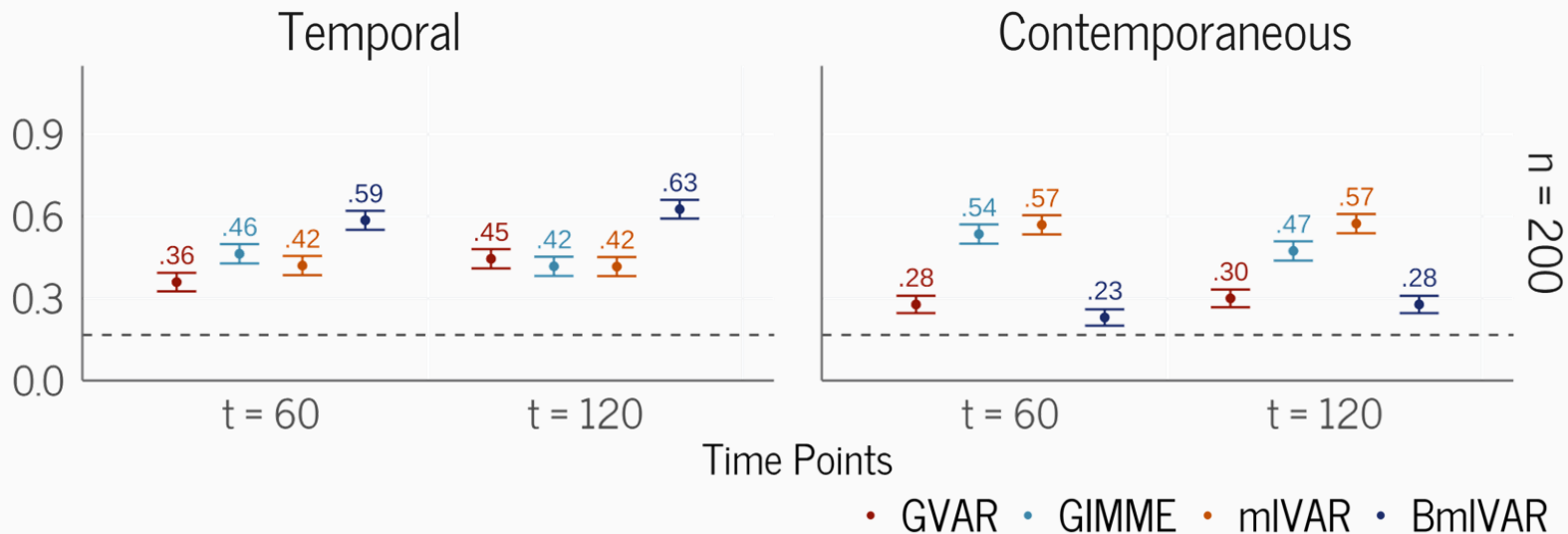
Methods

- graphicalVAR
- mlVAR
- GIMME
- BmlVAR

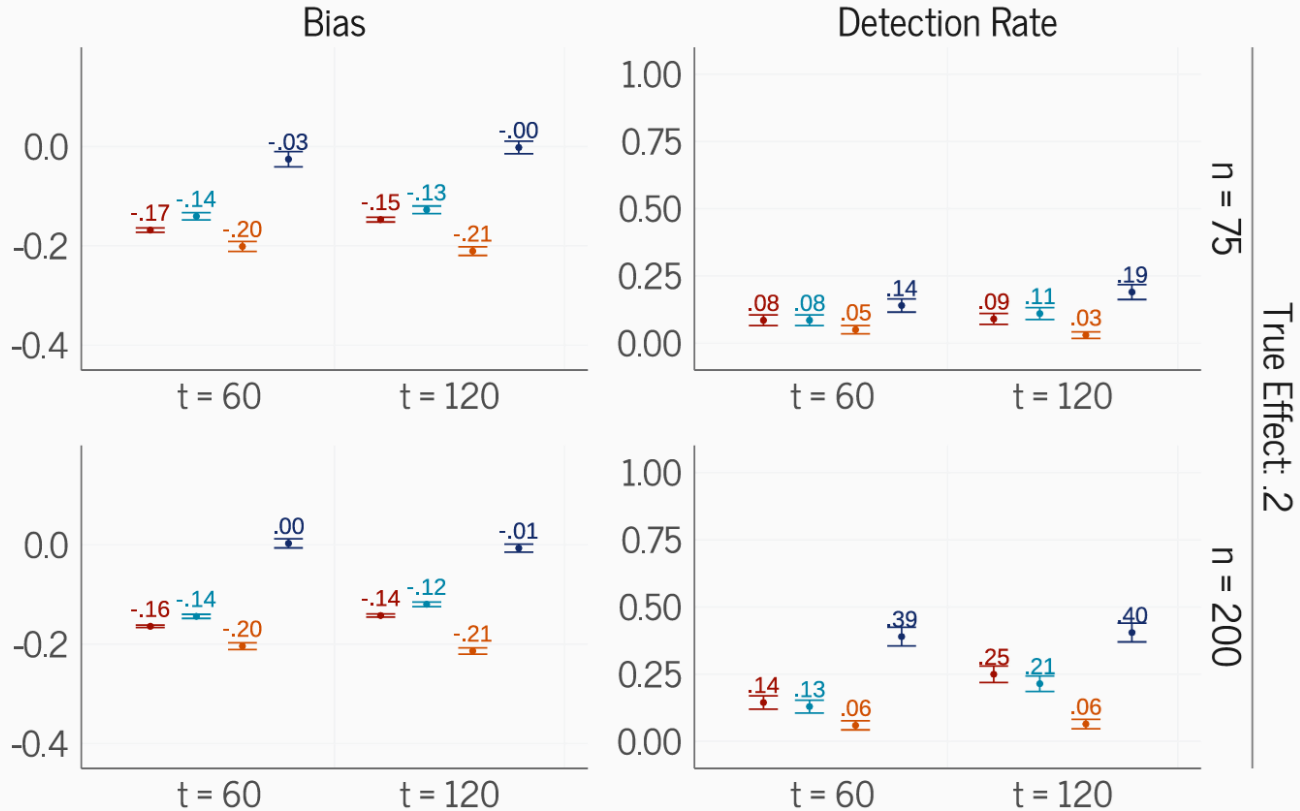
Performance

- Identification of most central node
- Estimation of centrality → outcome association

Proportion of correctly identified central nodes



Estimating Centrality-Outcome Association



• GVAR • GIMME • mIVAR • BmIVAR

Article

Assessing Temporal Emotion Dynamics Using Networks

Assessment
2016, Vol. 23(4) 425–435
© The Author(s) 2016
Reprints and permissions:
sagepub.com/journalsPermissions.nav
DOI: 10.1177/1073191116645909
asm.sagepub.com

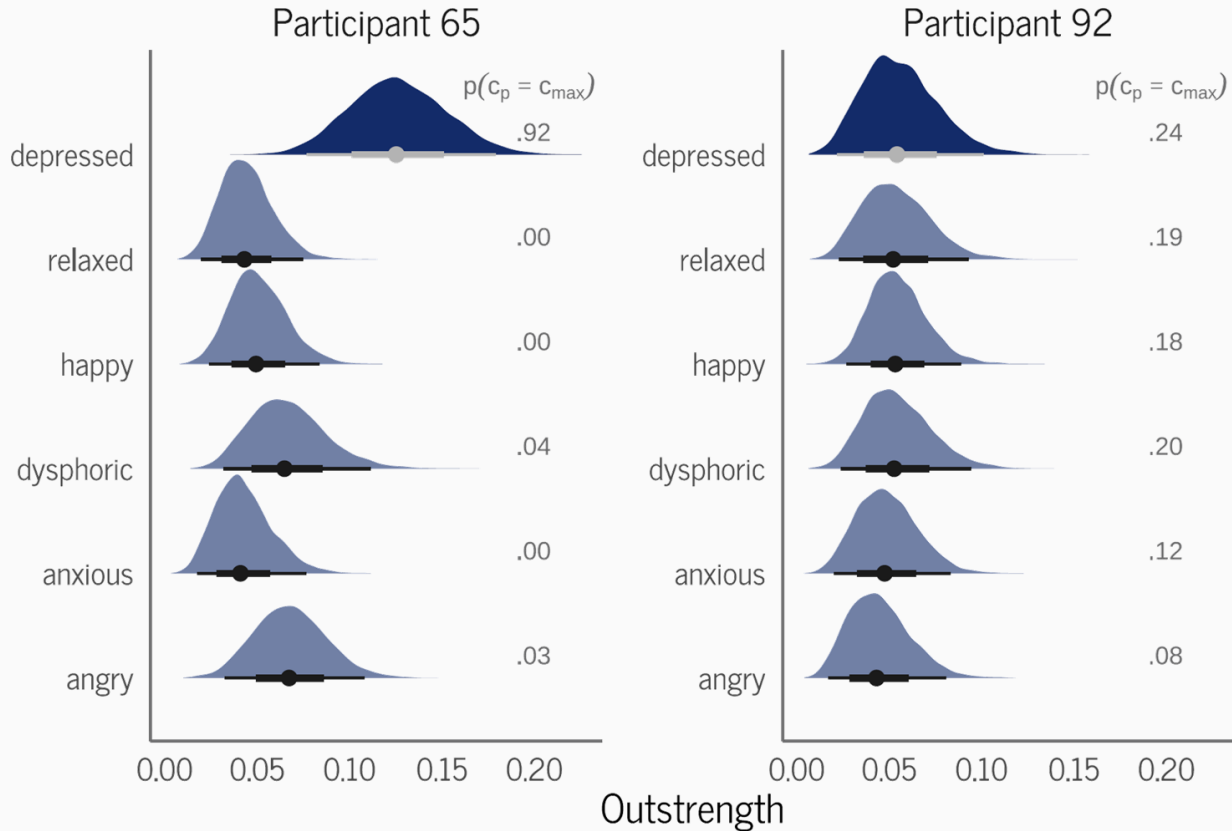


**Laura F. Bringmann¹, Madeline L. Pe¹, Nathalie Vissers¹, Eva Ceulemans¹,
Denny Borsboom², Wolf Vanpaemel¹, Francis Tuerlinckx¹, and Peter Kuppens¹**

Empirical Example

	Density			Outstrength		
	Point Est.	95% Low	95% High	Point Est.	95% Low	95% High
GVAR	0.08	-0.12	0.29	-0.04	-0.25	0.16
GIMME	0.36*	0.18	0.54	0.22*	0.03	0.42
mlVAR	0.33*	0.15	0.52	0.03	-0.18	0.24
BmlVAR	0.03	-0.04	0.20	0.01	-0.09	0.14

Uncertainty Quantification





Conceptualization

- Discuss why a network feature should be relevant for a given treatment or outcome
- Consider plausible effect size and sample size needed to detect an association with a distal outcome

Recommendations



Conceptualization

- Discuss why a network feature should be relevant for a given treatment or outcome
- Consider plausible effect size and sample size needed to detect an association with a distal outcome



Estimation

- Carefully choose preprocessing and network estimation methods
- Follow good practices for predictive models (e.g., cross-validation, out-of-sample validation)

Recommendations



Conceptualization

- Discuss why a network feature should be relevant for a given treatment or outcome
- Consider plausible effect size and sample size needed to detect an association with a distal outcome



Estimation

- Carefully choose preprocessing and network estimation methods
- Follow good practices for predictive models (e.g., cross-validation, out-of-sample validation)



Interpretation

- Consider uncertainty in node selection and network feature regression
- Compare network features with simpler time series features (e.g., person-specific mean or SD)

Collaborators



Matthias Kloft



Yong Zhang



Fridtjof Petersen



Laura Bringmann



Daniel Heck

Thank You!



<https://openesmdata.org>



bjoernsiepe+openesm@gmail.com

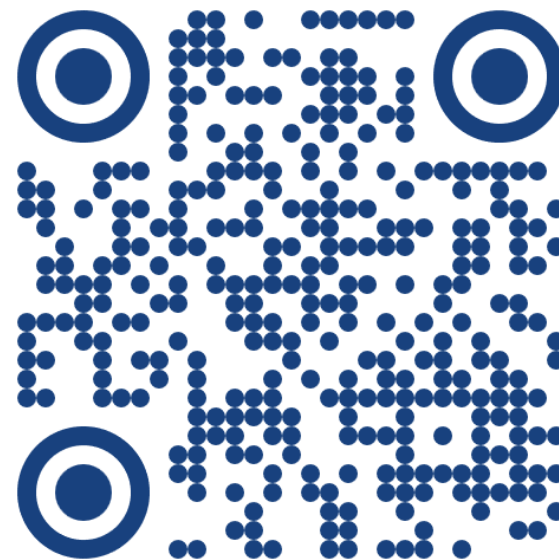


<https://bsiepe.github.io>



bsiepe.bsky.social

Slides & Preprint



Resources

- All icons either from PowerPoint or fontawesome
 - <https://fontawesome.com/icons/bluesky>
 - <https://fontawesome.com/icons/glasses>
 - <https://fontawesome.com/icons/code>
 - <https://fontawesome.com/icons/dna>
- Python Software Foundation. (n.d.). *The Python logo*. <https://www.python.org/community/logos/> (PSF Trademark Policy)
- Rob Hyndman - <https://robjhyndman.com/hyndsight/m4comp/>
- Steni Sebastian - <https://medium.com/@ssteni/imagenet-what-why-and-how-e5ebed04abb5>
- R Foundation for Statistical Computing. (2016). *R logo*. <https://www.r-project.org/logo/> (CC-BY SA 4.0)
- James Grellier – Own Work, CC BY-SA 3.0, <https://commons.wikimedia.org/w/index.php?curid=10253357>
- Marcin Wichary from San Francisco, U.S.A. - [1]Uploaded by Partyzan_XXI, CC BY 2.0, <https://commons.wikimedia.org/w/index.php?curid=8198235>
- Carbon (<https://carbon.now.sh/>) for pretty code screenshots

Appendix: Bayesian One-Step Approach

1. Step: Multilevel VAR model

Observations for i at time t

$$y_{t,i} \sim \text{MVN}\left(\underbrace{\mu_i}_{\text{Person-specific intercept}} + \underbrace{B_i}_{\text{Coefficient matrix}} \left(\underbrace{y_{t-1,i} - \mu_i}_{\text{Lagged deviations from } \mu_i}\right), \underbrace{\Sigma_i}_{\text{Innovation covariance}}\right)$$

$$B_i = \begin{bmatrix} 0.2 & \dots & \dots \\ 0.1 & \dots & \dots \\ 0.3 & \dots & \dots \end{bmatrix}$$

$$c_{i,1} = 0.6$$

2. Step: Centrality feature regression

Distal outcome

Centrality predictor

$$z_i \sim \mathcal{N}\left(\underbrace{\alpha}_{\text{Intercept}} + \underbrace{\gamma}_{\text{Slope}} \cdot \underbrace{c_{i,1}}_{\text{Residual variance}}, \sigma_\epsilon^2\right)$$

Intercept

Slope

Residual variance

Appendix: Model Specifics

We specified a normal distribution of person-specific network parameters at level 2:

$$\mathbf{B}_{i,jk} \sim \mathcal{N}(\mu_{jk}^B, \sigma_{jk}^B) \quad (3)$$

We assumed the following prior distributions:

$$\begin{aligned} \mu_{jk}^B &\sim \mathcal{C}(0, 0.05) \\ \sigma_{jk}^B &\sim t_{df=3}(0, 0.2) \in (0, \infty] \\ \Omega_i^L &\sim \text{LKJ-Cholesky}(df = 3) \\ \sigma_{i,j}^\Sigma &\sim t_{df=3}(0, 1) \in (0, \infty] \end{aligned} \quad (4)$$

$$\alpha \sim t_{df=3}(0, 2)$$

$$\gamma \sim t_{df=3}(0, 2)$$

$$\sigma_\epsilon \sim t_{df=3}(0, 1) \in (0, \infty]$$

Appendix: Estimation Variability

