Striding Towards Multidimensional Place and Social Space

Zachary Roman Ph.D.

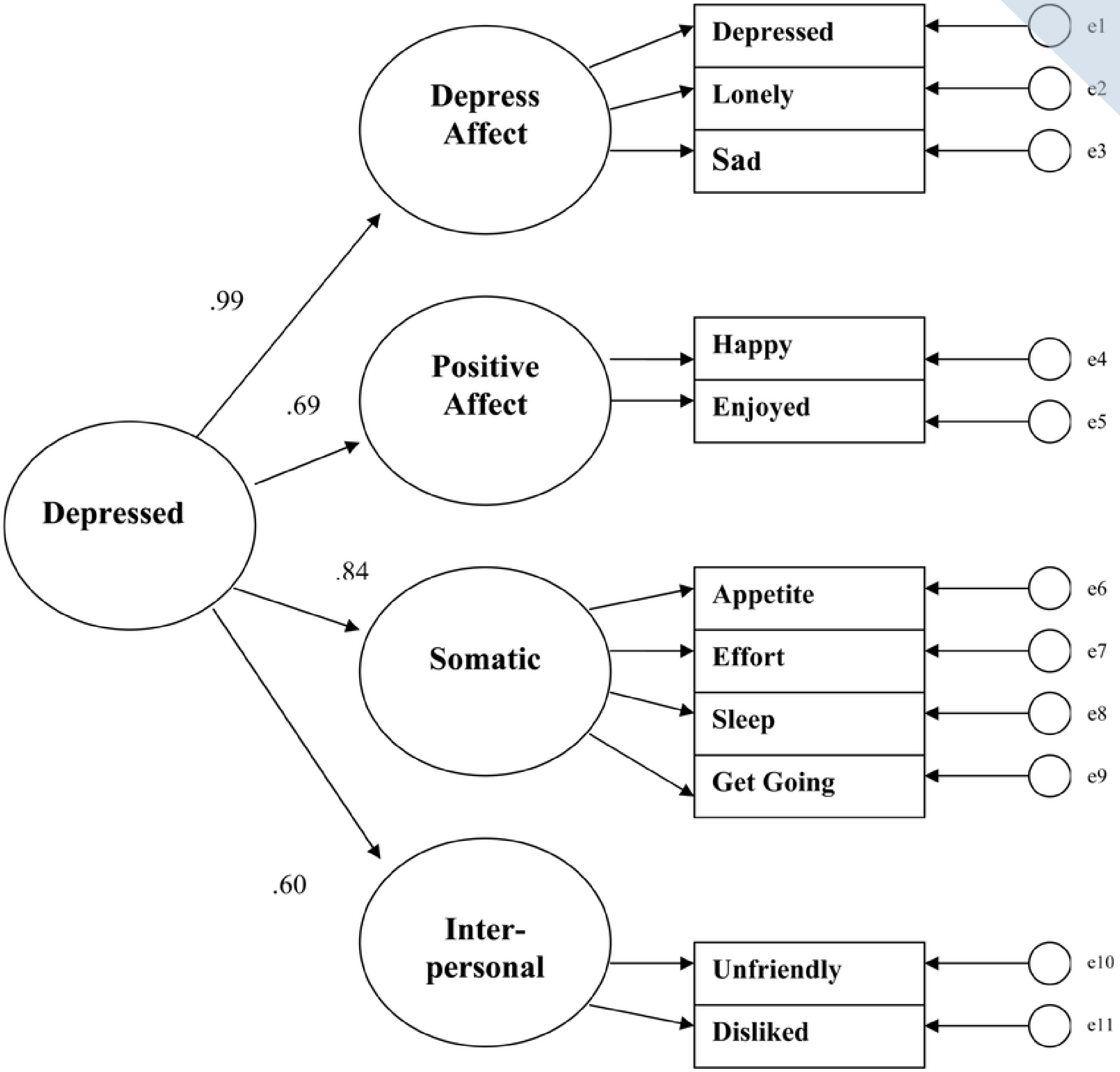
Department of Psychology
University of Zurich

Personal Background

- 2023 - Current Post-doc Informatics
  - Social Computing Group
  - University of Zurich
- 2020 - Current Post-doc Psychology
  - Quantitative Methods of Intervention & Evaluation
  - University of Zurich
- 2019 Ph.D. Quantitative Psychology
  - Minor in Computer Science
  - University of Kansas
- 2016 M.S. Quantitative Psychology
  - Illinois State University
- 2014 B.A. Psychology
  - Ohio University

Latent Variable Models

- Best practice
- Multivariate constructs
- Widely used



Latent Variable Models

- Best practice
- Multivariate constructs
- Widely used

[BOOK] Structural equations with latent variables

KA Bollen - 1989 - books.google.com

Analysis of Ordinal Categorical Data Alan Agresti Statistical Science Now has its first coordinated manual of methods for analyzing ordered categorical data. This book discusses ...

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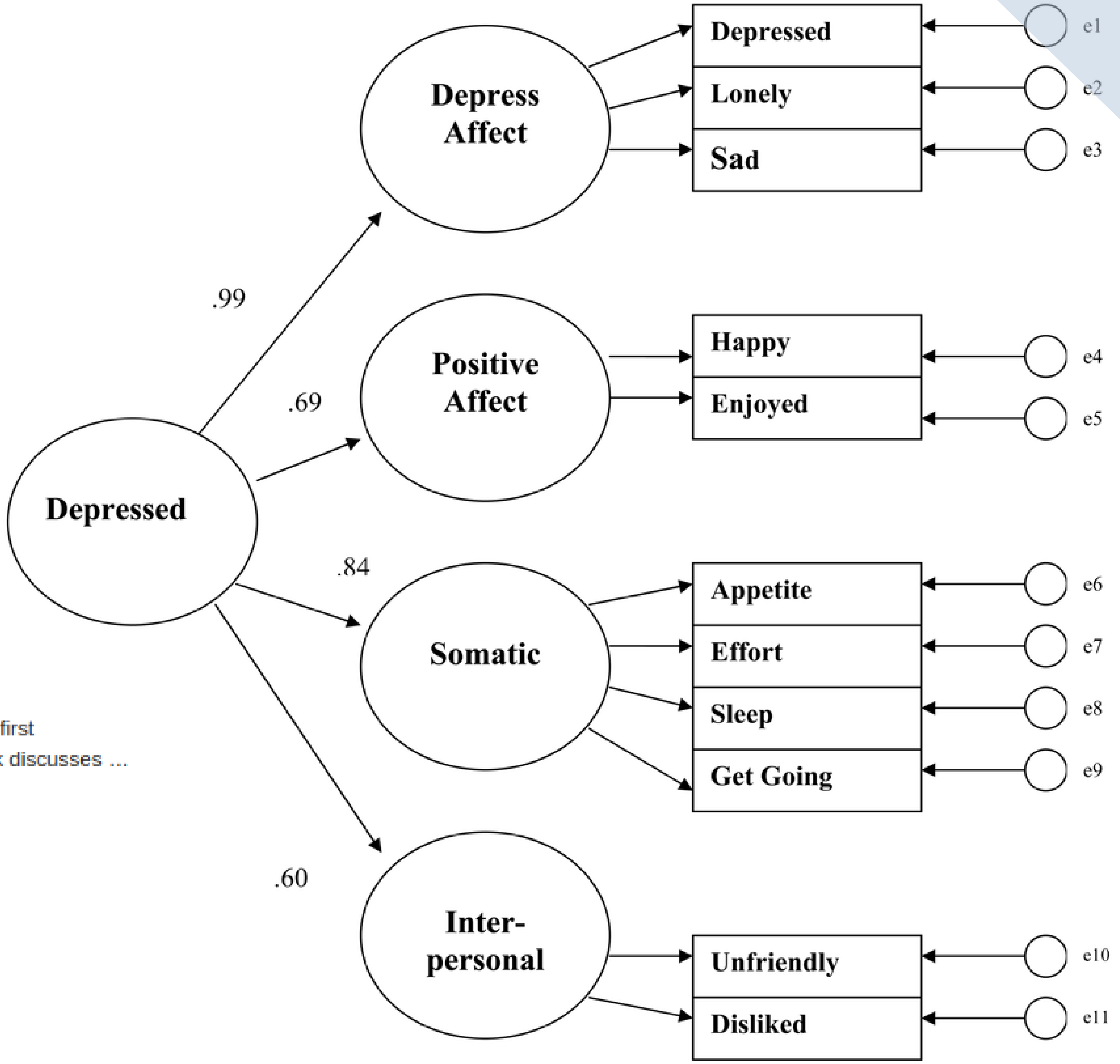
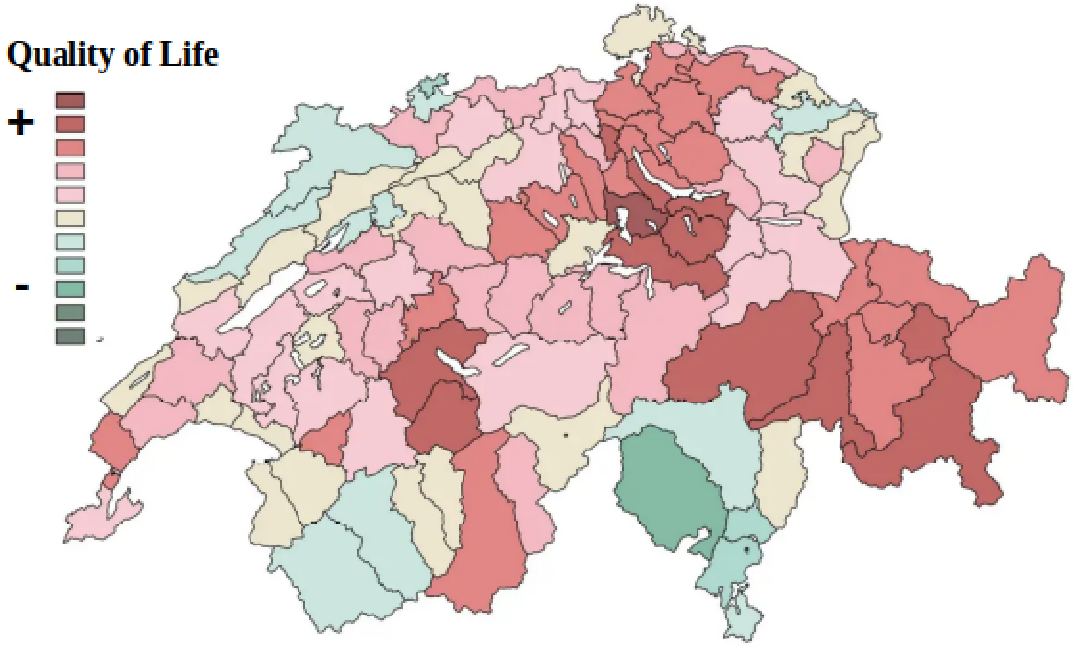
- Notable Limitation
  - Dependence



Spatial & Social Dependence

Spatial:

- Observations **physically closer** are more similar on a construct



Spatial & Social Dependence

Spatial:

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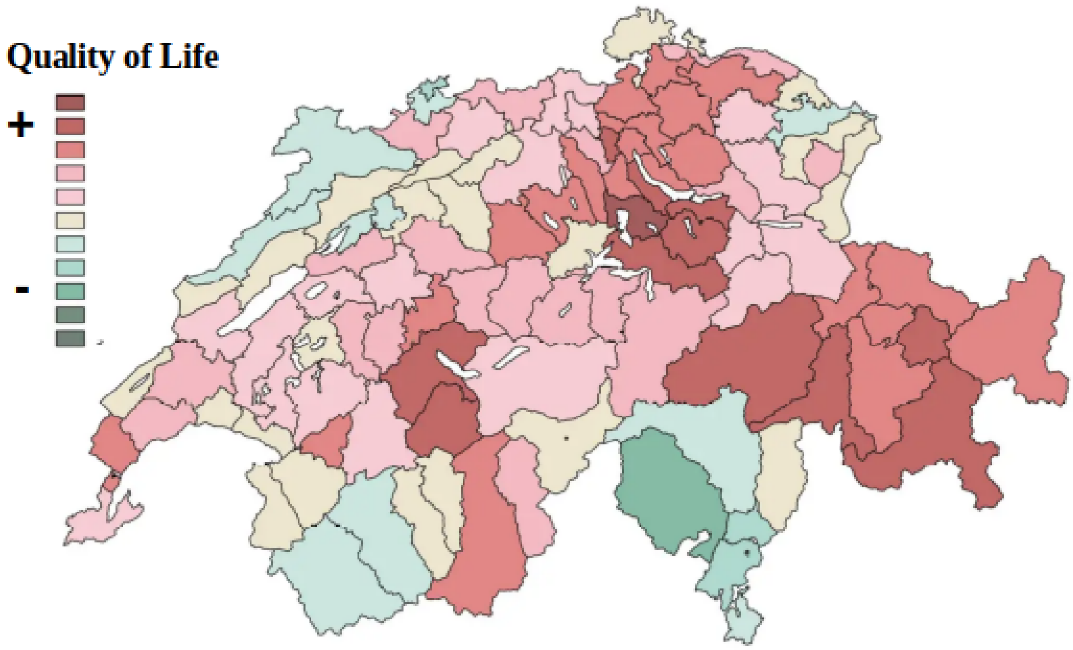
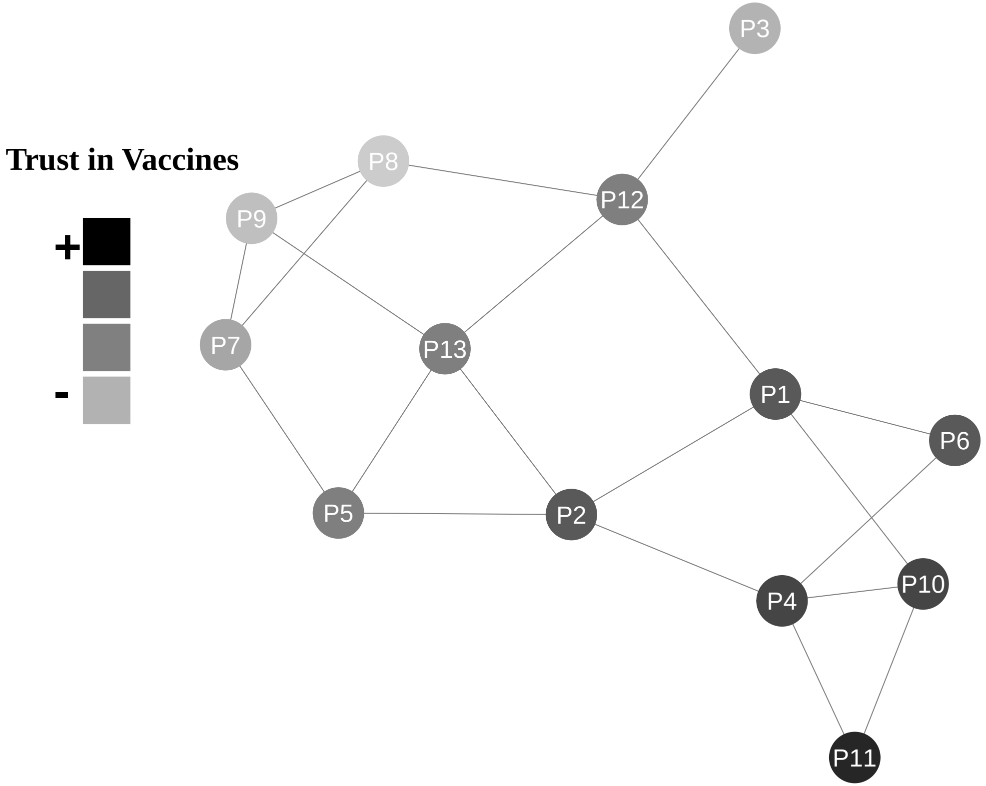
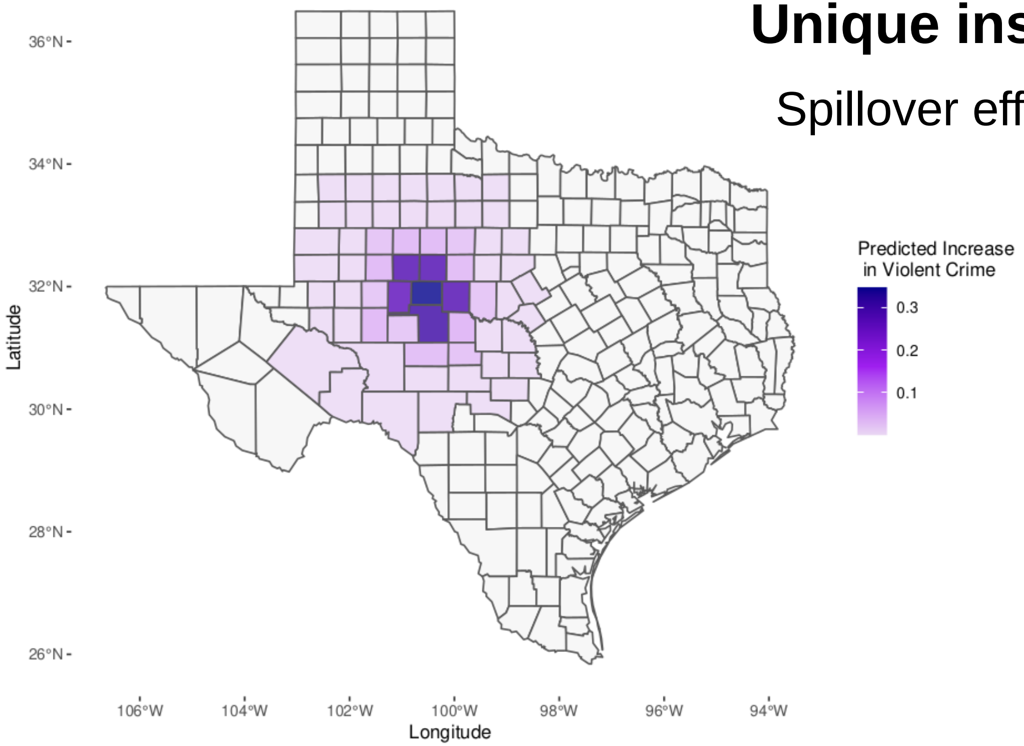


Social:

- Observations **socially closer** are more similar on a construct



Modeling Spatial & Social Dependence



Unique insight

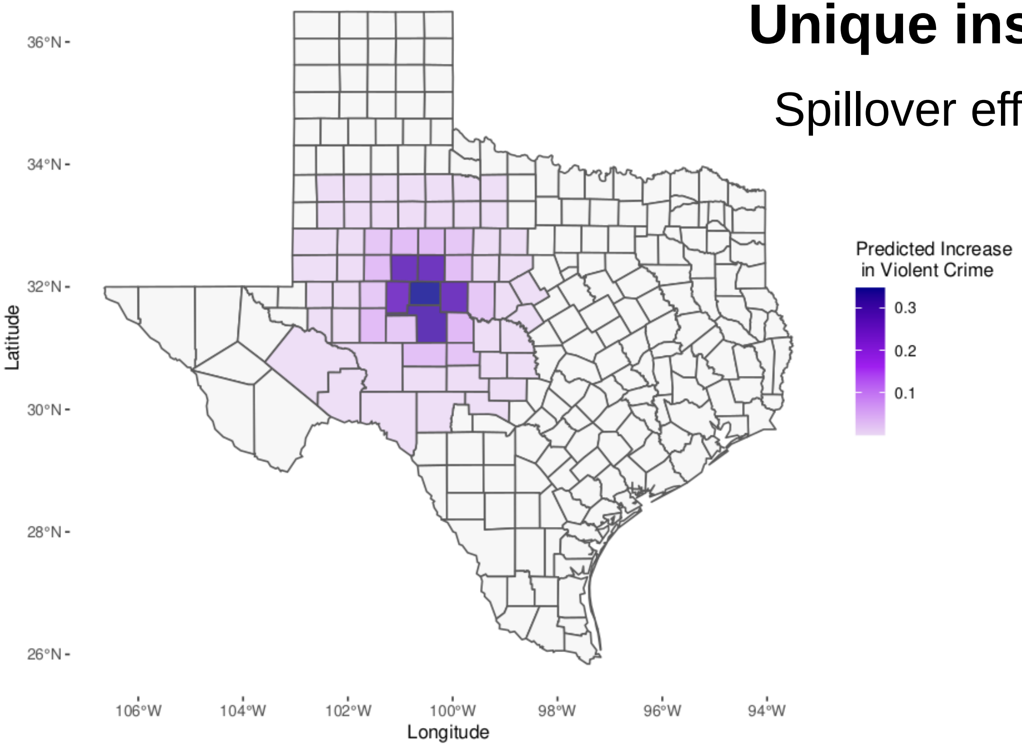
Spillover effects

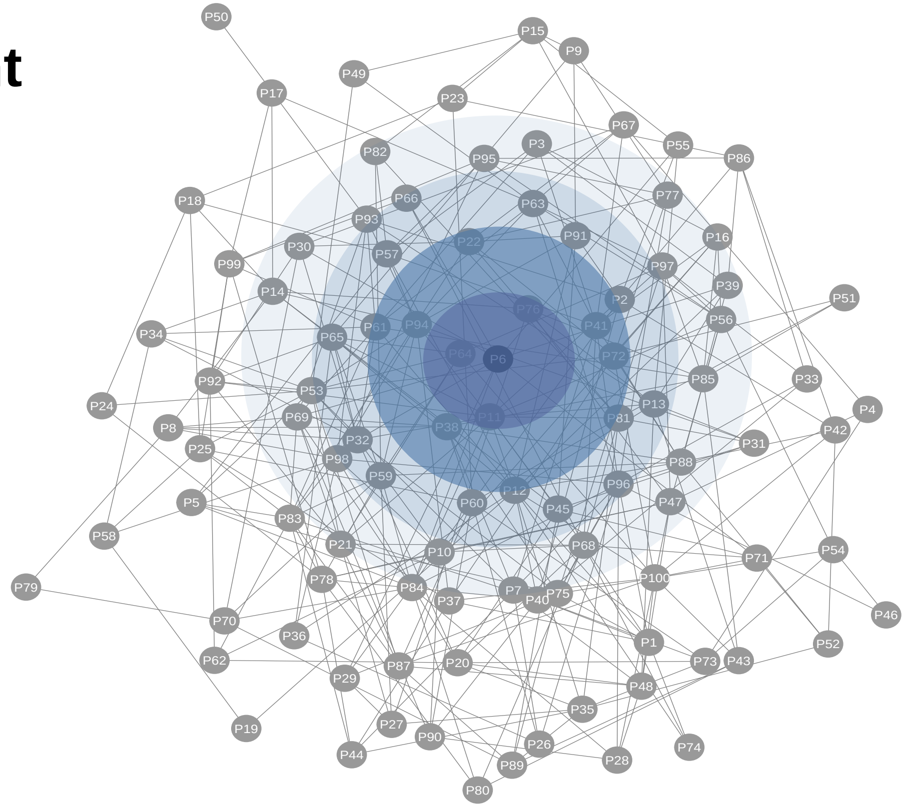
Example from:
Roman, Z. J. & Brandt, H. (2021). A latent auto-regressive approach for Bayesian structural equation modeling of spatially or socially dependent data. *Multivariate Behavioral Research*, 1-25.

Modeling Spatial & Social Dependence

Unique insight

Spillover effects





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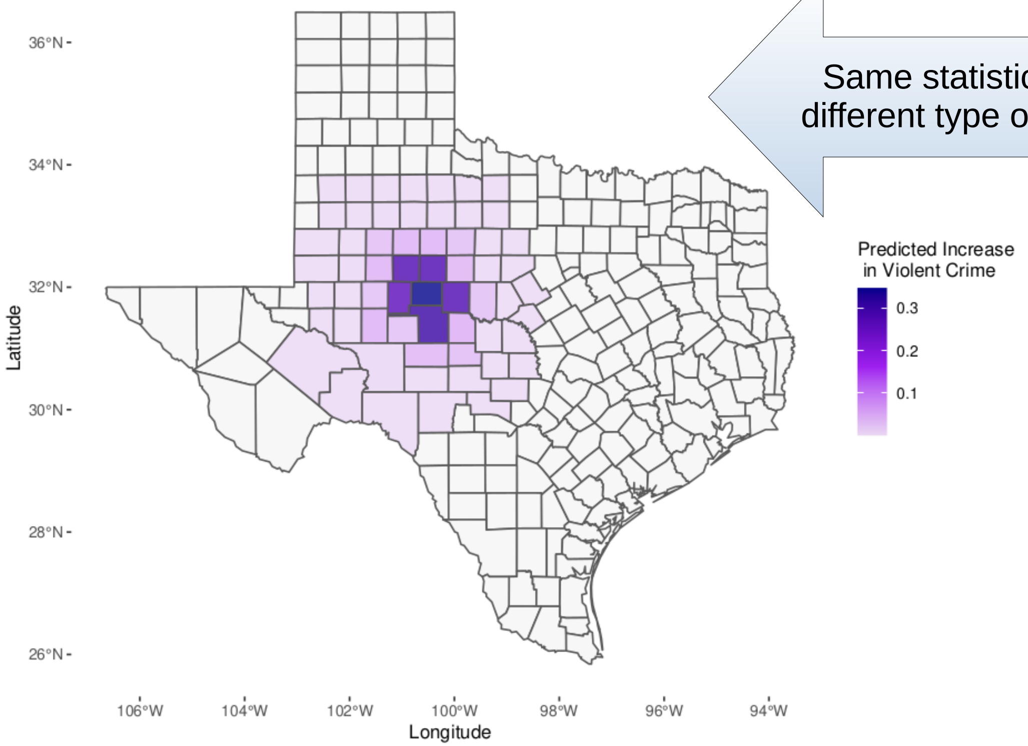
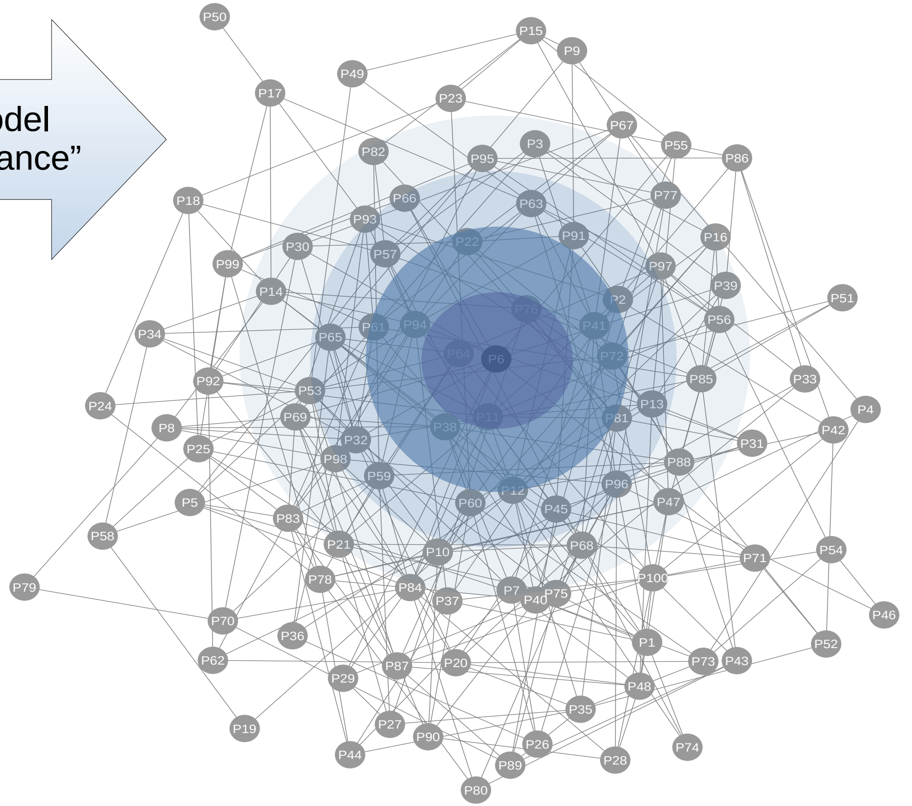
Example adapted from:
Roman, Z. J. (2021). Spatial and Social Network Auto-regressive Structural Equation Modeling **[Conference oral presentation]**. *15th Conference of Fachgruppe Methoden und Evaluation (FGME) annual meeting, University of Mannheim.*

Modeling Spatial & Social Dependence



Same statistical model
different type of “distance”



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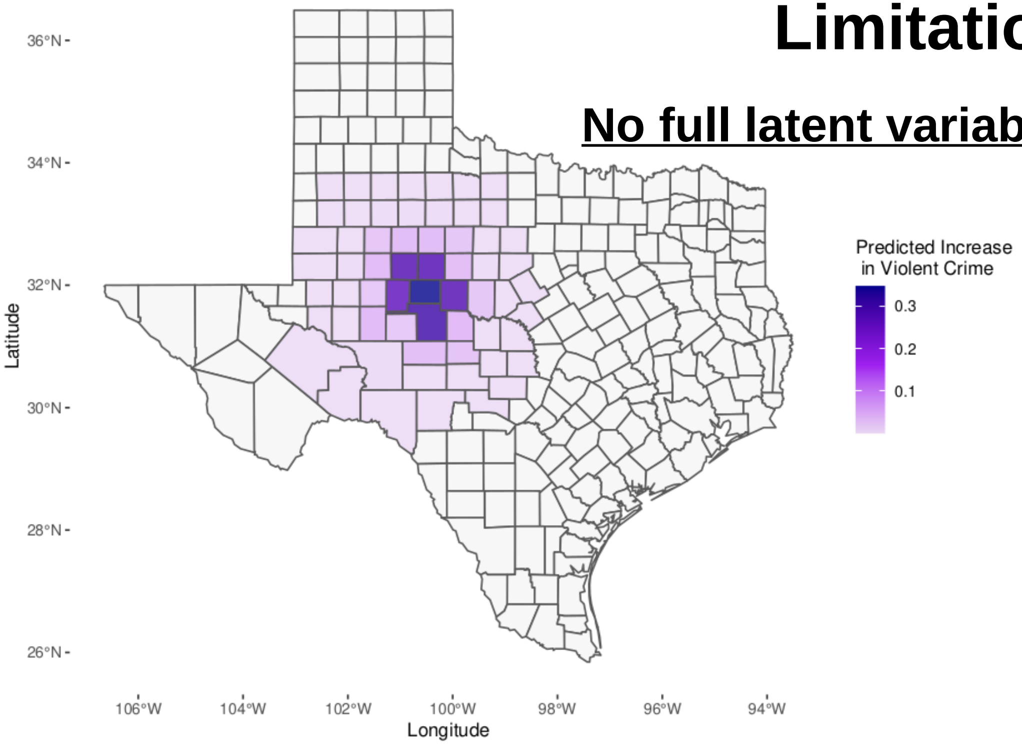
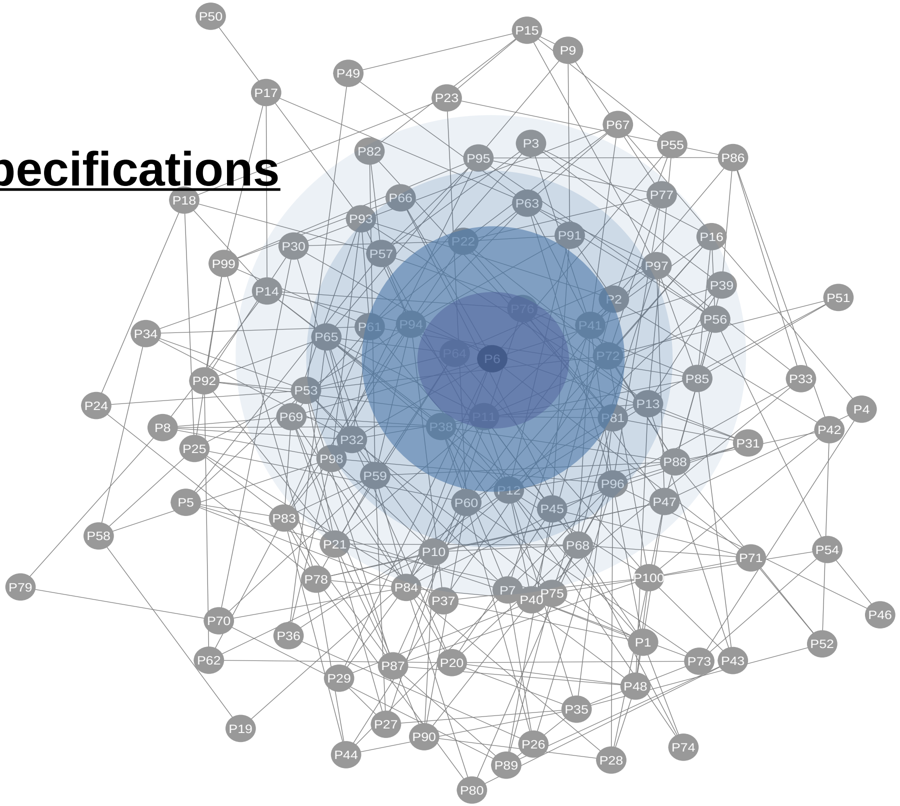
Modeling Spatial & Social Dependence

Limitation

No full latent variable specifications





Example from:
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Project Overview

Goals

Create spatial & social dependence latent variable modeling framework

Create open source software package

Milestone	Completion Goal
I Develop observed multi-group model	
II Develop unobserved multi-group model (Latent classification)	
III Develop clustered group multi-level model	
IV Develop Longitudinal multi-level model	
V Create Open source software (R-package)	
VI Author framework tutorial paper	

Project Overview

Goals	Milestone	Completion Goal
Create spatial & social dependence latent variable modeling framework	**I** Develop observed multi-group model	Month 8
	II Develop unobserved multi-group model (Latent classification)	
	III Develop clustered group multi-level model	
Create open source software package	**IV** Develop Longitudinal multi-level model	
	V Create Open source software (R-package)	
	VI Author framework tutorial paper	

Project Overview

Goals

Create spatial & social dependence latent variable modeling framework

Create open source software package

Milestone	Completion Goal
I Develop observed multi-group model	Month 8
II Develop unobserved multi-group model (Latent classification)	Month 16
III Develop clustered group multi-level model	
IV Develop Longitudinal multi-level model	
V Create Open source software (R-package)	
VI Author framework tutorial paper	

Project Overview

Goals

Create spatial & social dependence latent variable modeling framework

Create open source software package

Milestone	Completion Goal
I Develop observed multi-group model	Month 8
II Develop unobserved multi-group model (Latent classification)	Month 16
III Develop clustered group multi-level model	Month 24
IV Develop Longitudinal multi-level model	
V Create Open source software (R-package)	
VI Author framework tutorial paper	

Project Overview

Goals

Create spatial & social dependence latent variable modeling framework

Create open source software package

Milestone	Completion Goal
I Develop observed multi-group model	Month 8
II Develop unobserved multi-group model (Latent classification)	Month 16
III Develop clustered group multi-level model	Month 24
IV Develop Longitudinal multi-level model	Month 32
V Create Open source software (R-package)	
VI Author framework tutorial paper	

-Model developments were selected to maximize scientific impact and accessibility

Project Overview

Goals

Create spatial & social dependence latent variable modeling framework

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Milestone	**Completion Goal**
I Develop observed multi-group model	Month 8
II Develop unobserved multi-group model (Latent classification)	Month 16
III Develop clustered group multi-level model	Month 24
IV Develop Longitudinal multi-level model	Month 32
V Create Open source software (R-package)	Month 40
VI Author framework tutorial paper	

Reproducible Research

Project Overview

Goals

Create spatial & social dependence latent variable modeling framework

Create open source software package

Milestone	**Completion Goal**
I Develop observed multi-group model	Month 8
II Develop unobserved multi-group model (Latent classification)	Month 16
III Develop clustered group multi-level model	Month 24
IV Develop Longitudinal multi-level model	Month 32
V Create Open source software (R-package)	Month 40
VI Author framework tutorial paper	Month 48

Reproducible Research

Network of Project Collaborators

Methodological
Application
Software

Prof. Arkady Konovalov
University of Birmingham - UK

Prof. Holger Brandt
Prof. Augustin Kelava
University of Tuebingen - DE

Prof. Carolin Strobl
Prof. Birgit Kleim
Prof. Aniko Hannak
Prof. Urte Scholz
Prof. Nicolas Langer
University of Zurich - CH

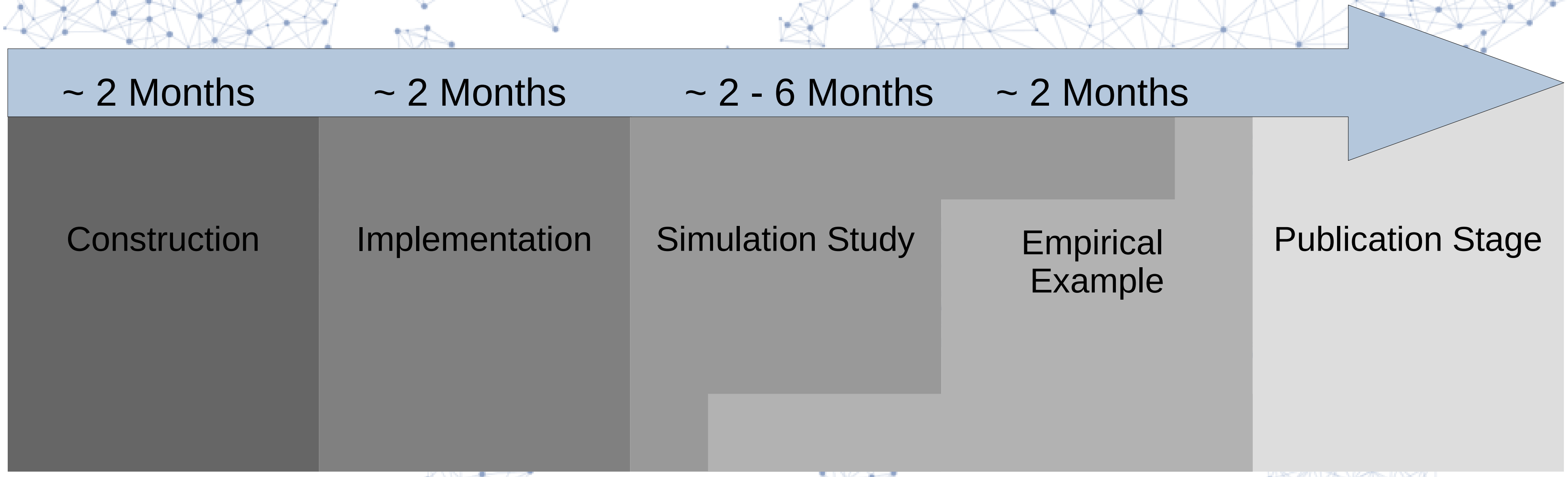
Prof. Jörg Müller
Open University of Catalonia - ES

Prof. Ed Merkle
University of Missouri

Prof. Christian Crandall
University of Kansas

Prof. Dan Bauer
Dr. Chris Urban
University of North Carolina

Work Package Timeline



Work Package Timeline

~ 2 Months

~ 2 Months

~ 2 - 6 Months

~ 2 Months

Construction

Implementation

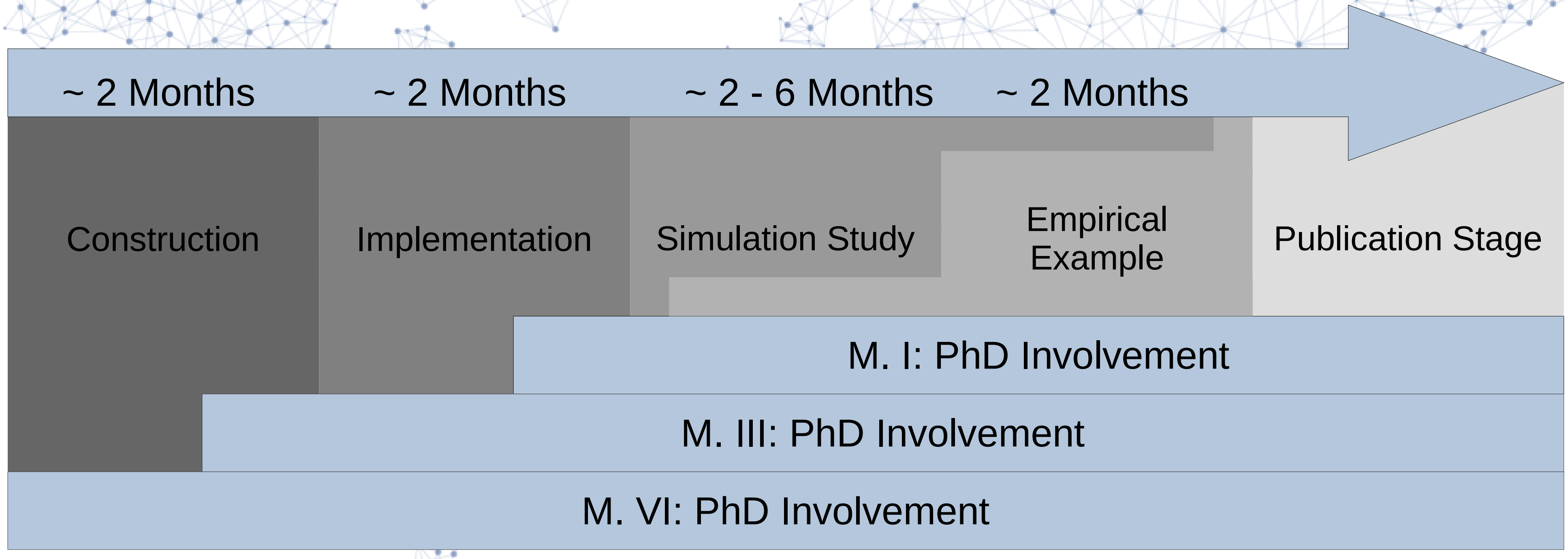
Simulation Study

Empirical Example

- Collaborators

Publication Stage

Work Package Timeline: PHD



Project Outcome

- Full latent variable dependence modeling framework
  - Old theories new perspectives
  - New theories
  - Novel and unique insights
    - Combined approach is more than the sum of its parts

Beyond Ambizione

- Impact to many discplines
  - Psychology, sociology, political science, economics, public policy, epidemiology, biology etc.

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  - Psychology, sociology, political science, economics, public policy, epidemiology, biology etc.
- Many more directions
  - Methodological
  - Neuropsychology

Beyond Ambizione

- Impact to many discplines
  - Psychology, sociology, political science, economics, public policy, epidemiology, biology etc.
- Many more directions
  - Methodological
  - Neuropsychology
- Professorship
  - Eccellenza
  - Tenure Track

Thank You!

Content related publications:

Roman, Z. J., Schmidt, P., Miller, J. M., & Brandt, H. (2023). Identifying dynamic shifts to non-compliant behavior in questionnaire responses; A novel approach and experimental validation. *[Pre-print available, under review]*

Roman, Z. J., Brandt, H., & Miller, J. M. (2022). Automated bot detection using Bayesian latent class models in online surveys. *Frontiers in Psychology*, 1947.

Roman, Z. J. & Brandt, H. (2021). A latent auto-regressive approach for Bayesian structural equation modeling of spatially or socially dependent data. *Multivariate Behavioral Research*, 1-25.

Roman, Z. J. (2019). Auto-regressive latent variable modeling: A general framework for Bayesian spatial structural equation models (Doctoral dissertation, University of Kansas).

Appendix

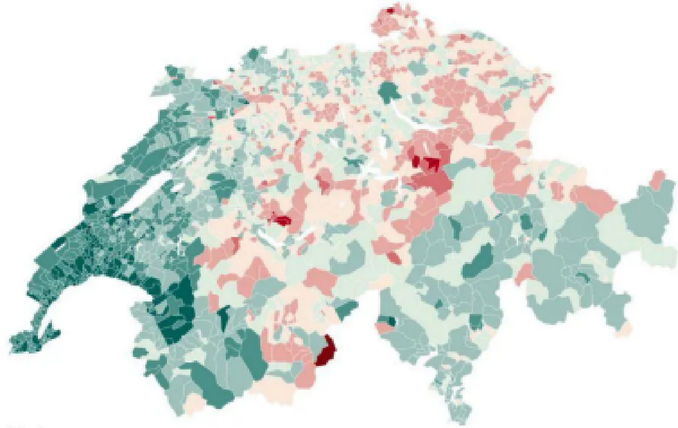
Milestone I: Multi-group Model

Bayesian auto-regressive dependence multi-group structural equation model

- Full latent variables
- Spillover interactions compared across groups
- Experimental & quasi-experimental applications

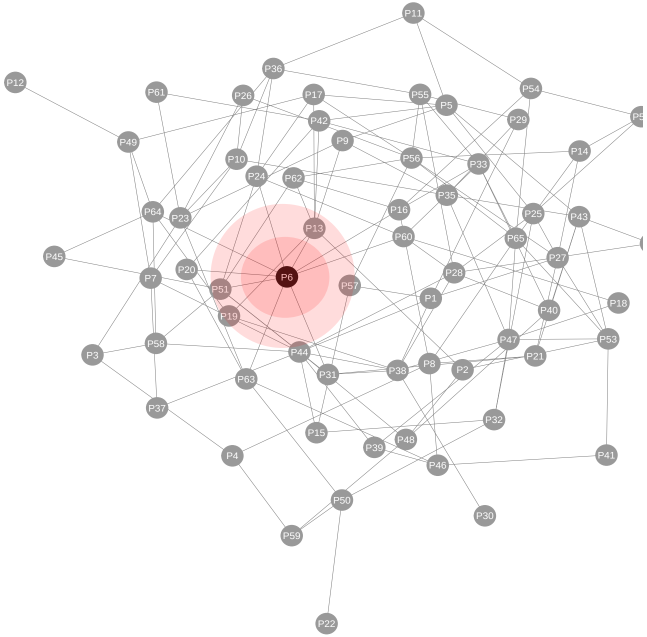
<u>Quality of Life</u>

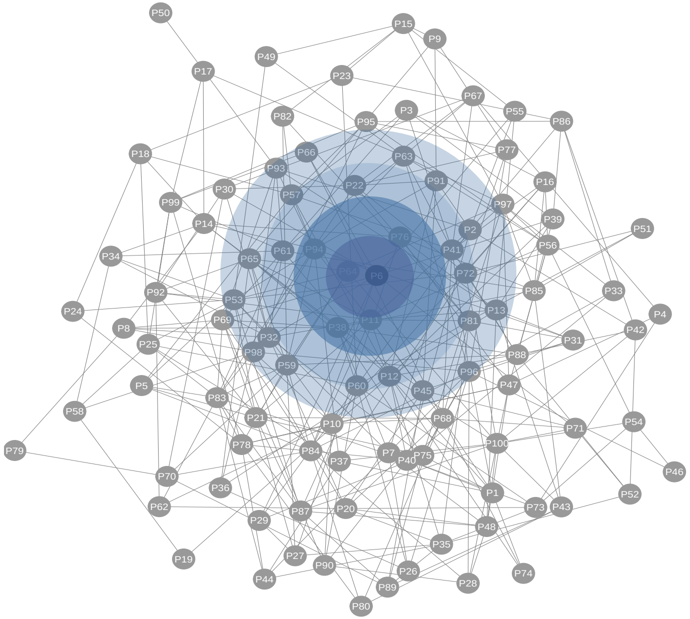
Romande **German**



<u>Misinformation</u>

Political Leftists **Political Rightist**





Work Package Timeline: Data

Empirical Example

- Gender Diversity Impact Study (GEDII)
  - Prof. Jörg Müller
- Temporal Dynamics of Health Behavior Change*
  - Prof. Urte Scholz
- Optimising Outcomes in Psychotherapy for Anxiety Disorders (OPTIMX) **
  - Prof. Birgit Kleim
- Social Media Scraping
  - Prof. Aniko Hannak

* SNF grant number 197471
** SNF grant number 169827

Bayesian Auto-regressive Dependence Latent Variable Modeling Technical Details

Spatial Auto-regression

Traditional Linear Regression

$$y_i = \alpha + x\beta_1 + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma I_N) \tag{1}$$

Spatial Auto-Regression (SAR)

$$y_i = \underbrace{\rho \boldsymbol{W} y_i}_{\text{Spatial Lag}} + \alpha + x\beta_1 + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma I_N) \tag{2}$$

Where:

- ρ summarizes the spatial auto-correlation in the dependent variable.[a]
- $\boldsymbol{W}$ is an $N \times N$ matrix summarizing the dependence of the cases

[a] When $\rho = 0$ traditional regression and spatial regression are equivilent

BARDSEM (Roman & Brandt, 2021)

Measurement Model

$$y_j = \tau_{yj} + \lambda_{yj}\eta + \epsilon_j, \quad \epsilon_j \sim N(0, \sigma^2_\epsilon) \tag{4}$$

$$x_k = \tau_{xk} + \boldsymbol{\lambda}_{xk}\boldsymbol{\xi} + \delta_k, \quad \delta_j \sim N(0, \sigma^2_\delta) \tag{5}$$

Structural Model

$$\eta = \alpha + \underbrace{\rho_\eta \mathbf{W}\eta}_{\text{Spatial Lag}} + \gamma_1\xi_1 + \gamma_2\xi_2 + \gamma_3 h(\boldsymbol{\xi}) + \zeta, \quad \zeta \sim N(0, \sigma_\zeta) \tag{6}$$

Error Distributions

- $\epsilon_j \sim N(0, \sigma^2_{\epsilon j})$, for $j = 1 \dots J$
- $\delta_k \sim N(0, \sigma^2_{\delta k})$, for $k = 1 \dots K$
- $\zeta \sim N(0, \sigma^2_\zeta)$

BARDSEM Priors

Priors

- $\rho_\eta \sim U[1 - min(\lambda_{\mathbf{w}}), 1 - max(\lambda_{\mathbf{w}})]$
- $\gamma, \lambda, \alpha, \tau \sim N(0, 1)$
- $\sigma_* \sim \text{Cauchy}(0, 2.5)^+$
- $\boldsymbol{\Phi} \sim \text{LK}_j(I_2, 2)$

Spillover Computation

Computing $\partial_\eta / \partial_\xi^{p\prime}$

$$\partial_\eta / \partial_\xi^{p\prime} = (\boldsymbol{I}_n - \rho \mathbf{W})^{-1} \boldsymbol{I}_n \gamma_p \tag{3}$$

Where:

$p = 1 \ldots P$ indicates the respective exogenous latent variable

I_n is an identity matrix of length n

Interpreting $\partial_\eta / \partial_\xi^{p\prime}$

- Cell i, j of $\partial_\eta / \partial_\xi^{p\prime}$, provides the anticipated impact of case j on case i
- Direct interpretation of $\partial_\eta / \partial_\xi^{p\prime}$ is possible but potentially burdensome
- Impact measures summarize the matrix to ease interpretation

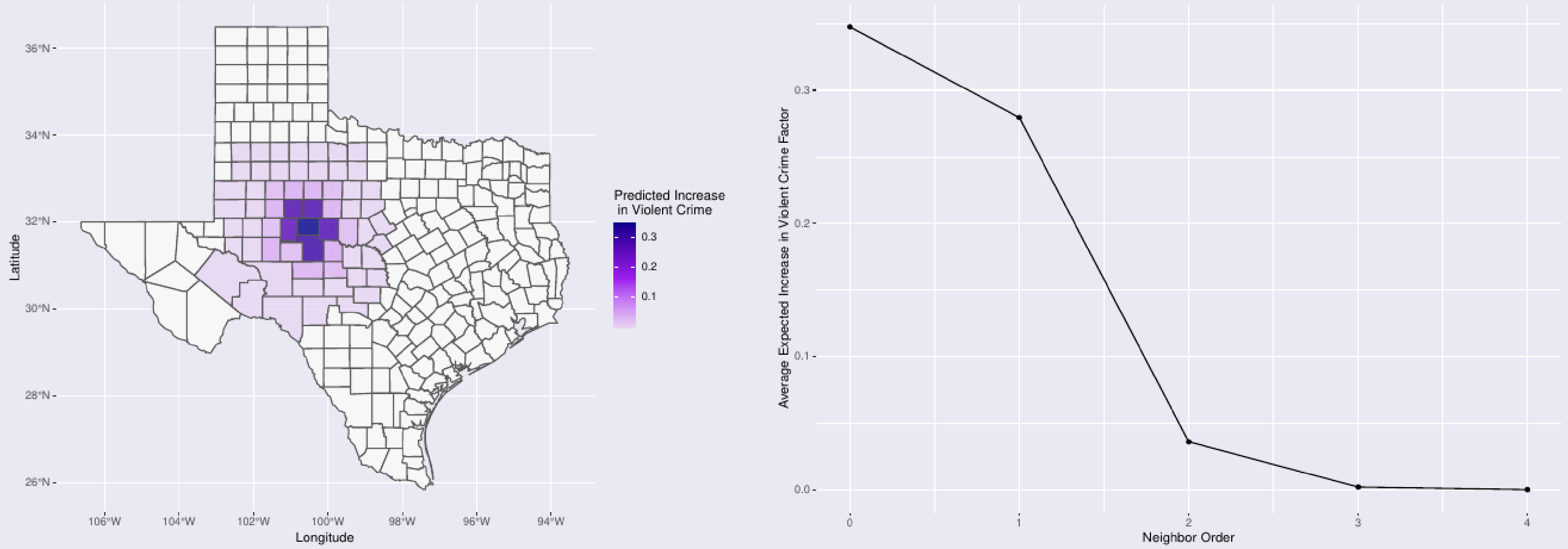
Summarizing Spillover

Summarize $\partial_\eta / \partial_\xi^{p\prime}$

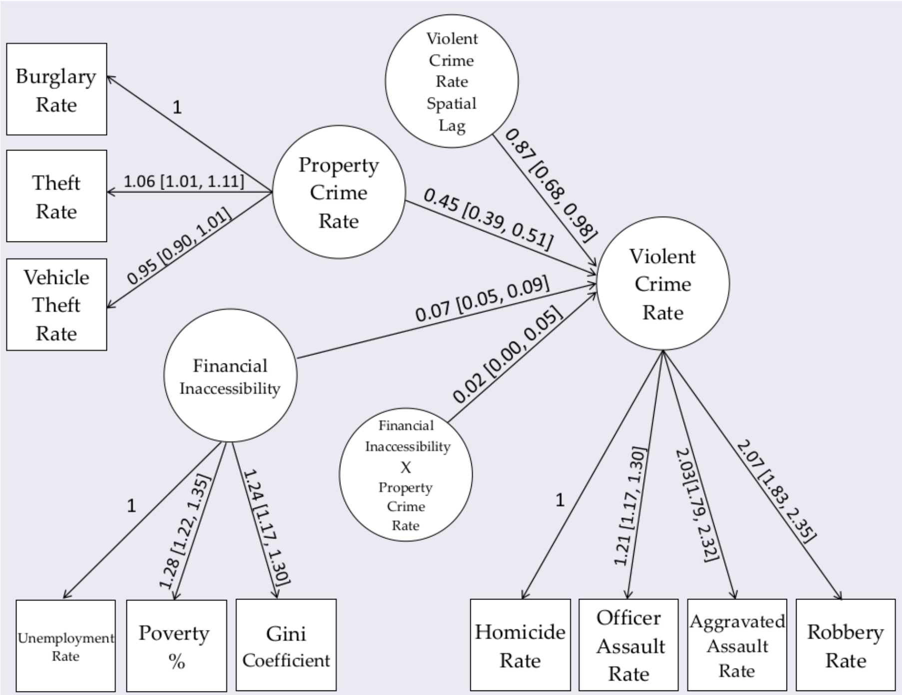
- Direct
  - Mean of diagonal
  - Expected mean change in the outcome of case $\neq i$ for a 1 unit increase in predictor p in case i
- Indirect
  - Mean of off diagonal
  - Expected mean change in the outcome of case i for a 1 unit increase in predictor p in all $\neq i$ cases.
- Total
  - Mean of matrix
  - Expected mean change in case i for a 1 unit increase in all cases (Including case i)

Spillover is a nonlinear function over space

Property Crime Spillover



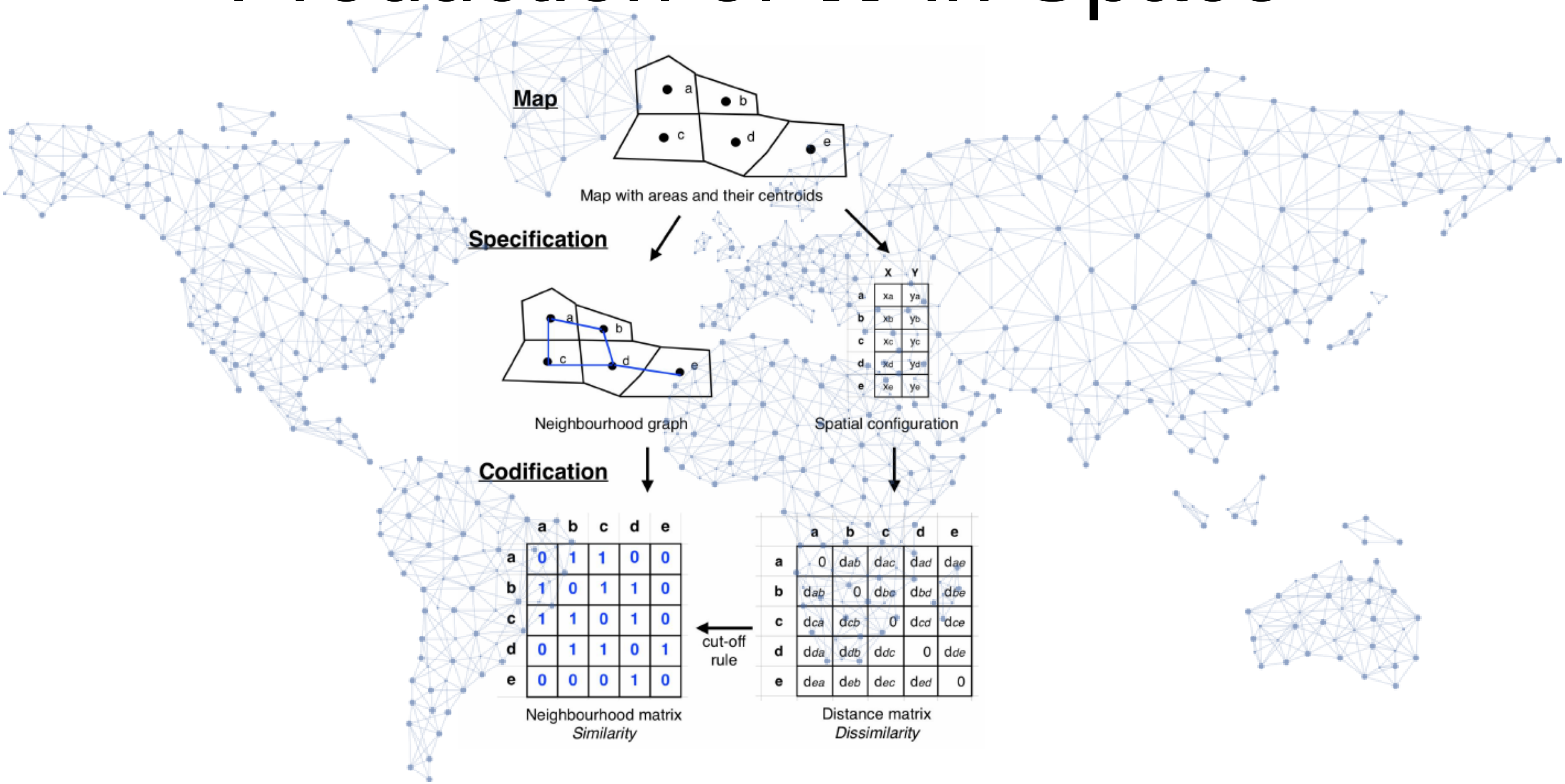
Spatial Spillover Example: Latent Variables



Simple Slopes Spillover Effects

	Direct Impact (2.5%, 97.5%)	Indirect Impact (2.5%, 97.5%)	Total Impact (2.5%, 97.5%)
$\gamma_{\text{Property}} \mid \xi_{\text{Fin. Inac.}} = -2$	0.55 (0.47, 0.60)	2.60 (2.22, 2.86)	3.15 (2.69, 3.46)
$\gamma_{\text{Property}} \mid \xi_{\text{Fin. Inac.}} = -1$	0.58 (0.50, 0.64)	2.73 (2.35, 3.05)	3.31 (2.85, 3.69)
$\gamma_{\text{Property}} \mid \xi_{\text{Fin. Inac.}} = 0$	0.60 (0.52, 0.68)	2.86 (2.48, 3.24)	3.46 (3.01, 3.92)
$\gamma_{\text{Property}} \mid \xi_{\text{Fin. Inac.}} = 1$	0.63 (0.55, 0.72)	2.98 (2.60, 3.43)	3.62 (3.15, 4.15)
$\gamma_{\text{Property}} \mid \xi_{\text{Fin. Inac.}} = 2$	0.66 (0.58, 0.76)	3.11 (2.73, 3.62)	3.77 (3.31, 4.38)

Production of **W** in Space



Simulation Study Designs

Milestone I

- Conditions follow those of Roman & Brandt (2021)
- Simulation Conditions
  - # of observed groups
  - Magnitude of connectivity matrix **W**
    - High, medium, low
  - Connectivity structure
    - Social or spatial representation
  - Sample size
    - High, medium, low, very low
  - Effect sizes
    - Auto-regressive Coef.
    - Difference in auto-reg. Coef. By group
  - Complexity of Measurement model
    - 3 – 10 observed items per indicator

- Measuring model performance
  - Bias
  - Coverage + Error Rates
  - Convergence

Milestone II

- Conditions follow those of Roman & Brandt (2021)
- Simulation Conditions
  - **# of unobserved groups**
  - Magnitude of connectivity matrix **W**
    - High, medium, low
  - Connectivity structure
    - Social or spatial representation
  - Sample size
    - High, medium, low, very low
  - Effect sizes
    - Auto-regressive Coef.
    - Difference in auto-reg. Coef. By group
  - Complexity of Measurement model
    - 3 – 10 observed items per indicator

- Measuring model performance
  - Bias
  - Coverage + Error Rates
  - Convergence

Milestone III

- Conditions follow those of Roman & Brandt (2021)
- Simulation Conditions
  - **# of Level 2 clusters**
  - Magnitude of connectivity matrix **W**
    - High, medium, low
  - Connectivity structure
    - Social or spatial representation
  - Sample size
    - High, medium, low, very low
  - Effect sizes
    - Auto-regressive Coef.
    - Difference in auto-reg. Coef. By group
  - Complexity of Measurement model
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- Measuring model performance
  - Bias
  - Coverage + Error Rates
  - Convergence

Milestone IV

- Conditions follow those of Roman & Brandt (2021)
- Simulation Conditions
  - **# of measurement occasions**
  - Magnitude of connectivity matrix **W**
    - High, medium, low
  - Connectivity structure
    - Social or spatial representation
  - Sample size
    - High, medium, low, very low
  - Effect sizes
    - Auto-regressive Coef.
    - Difference in auto-reg. Coef. By group
  - Complexity of Measurement model
    - 3 – 10 observed items per indicator

- Measuring model performance
  - Bias
  - Coverage + Error Rates
  - Convergence

R packages

lavaan: An R **package** for structural equation modeling [PDF] jstatsoft.org

Y Rosseel - Journal of statistical software, 2012 - jstatsoft.org

… paper describes **package lavaan**, a **package** for structural equation modeling implemented in the R system for statistical computing (R Development Core Team 2012). The **package** is …

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blavaan: Bayesian structural equation models via parameter expansion 243 2018

EC Merkle, Y Rosseel

Journal of Statistical Software 85 (4), 1-30

- Accessible user experience
- Highly citable tools
- Guidance in documentation
- Working examples