Network Analysis

Applications of networks in Psychology and beyond

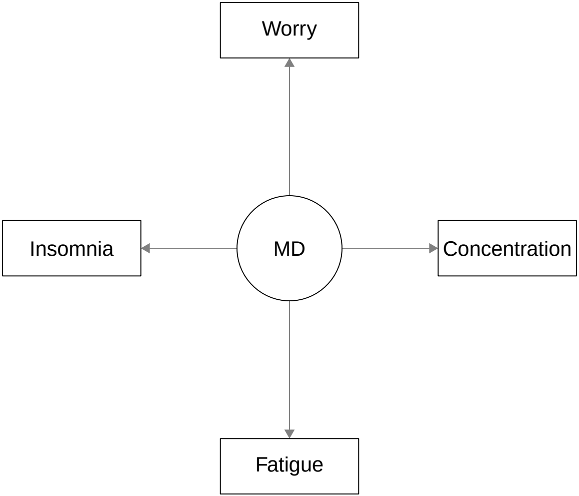
Sacha Epskamp

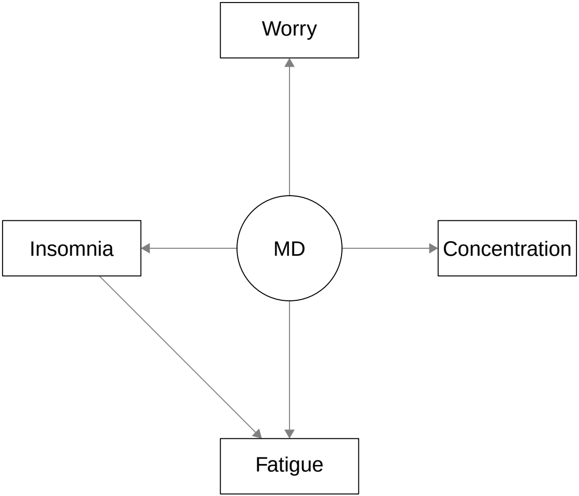
University of Amsterdam
Department of Psychological Methods

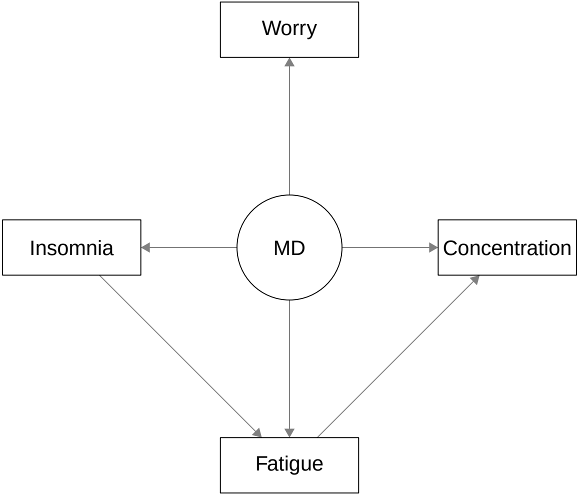
12-05-2014
TNO

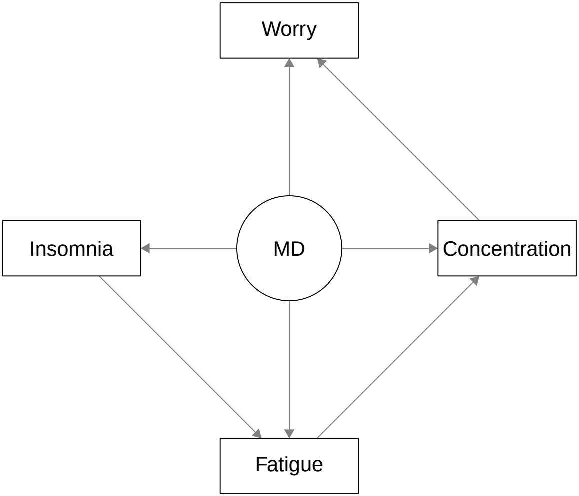
Outline

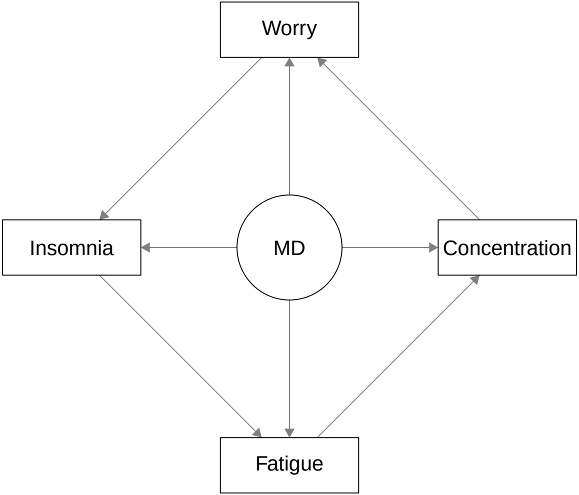
- What is a network?
- What can we do with networks?
- How can we obtain a network structure?
- Example of network analysis on radicalization data

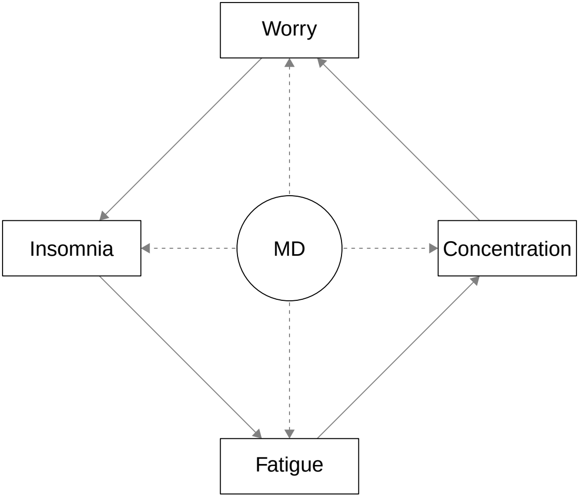

Worry
Insomnia
MD
Concentration
Fatigue


Worry
Insomnia
MD
Concentration
Fatigue

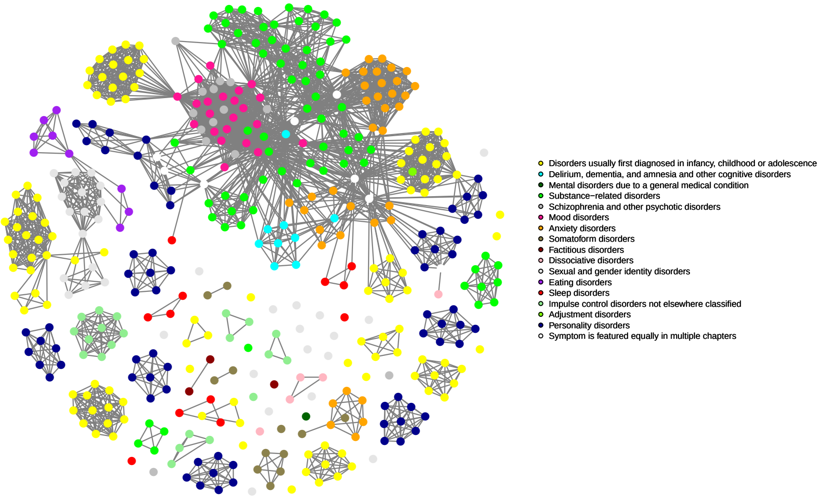

Worry
Insomnia
MD
Concentration
Fatigue


Worry
Insomnia
MD
Concentration
Fatigue


Worry
Insomnia
MD
Concentration
Fatigue


Worry
Insomnia
MD
Concentration
Fatigue

Psychology as a complex system



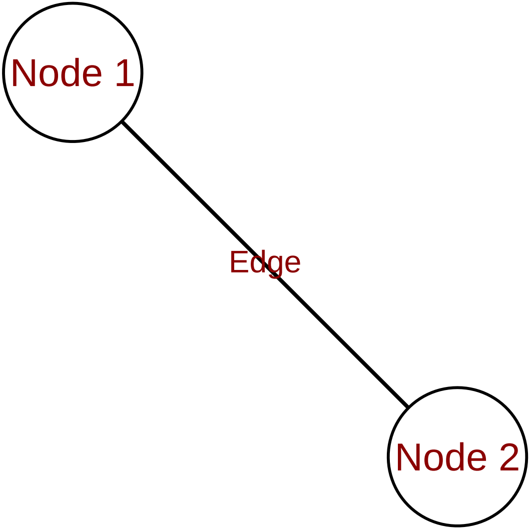
The Psych Systems Project

http://www.psychosystems.org/

What is a network?

What is a network?

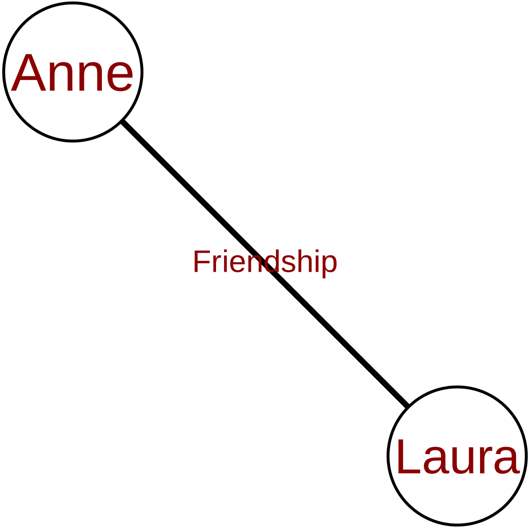
- A network is a set of *nodes* connected by a set of *edges*


Node 1
Edge
Node 2

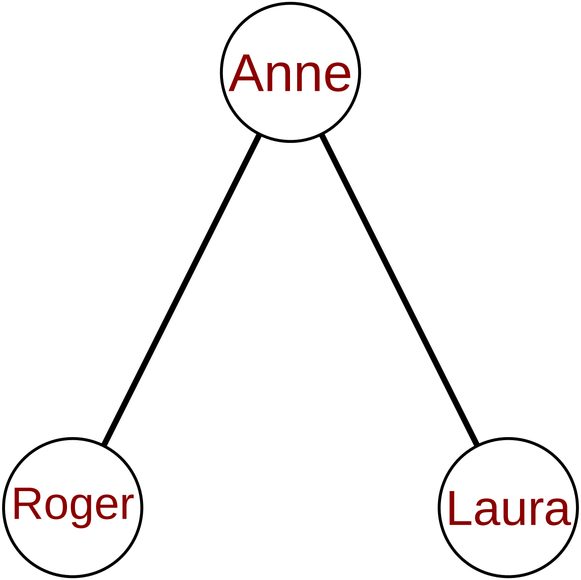
What is a network?

- A network is a set of *nodes* connected by a set of *edges*
  - A node represents an entity, this can be anything:
    - People
    - Cities
    - Symptoms
  - An edge represents some connection between two nodes. Again, this can be anything:
    - Friendship / contact
    - Distance
    - Comorbidity

Anne is friends with Laura:

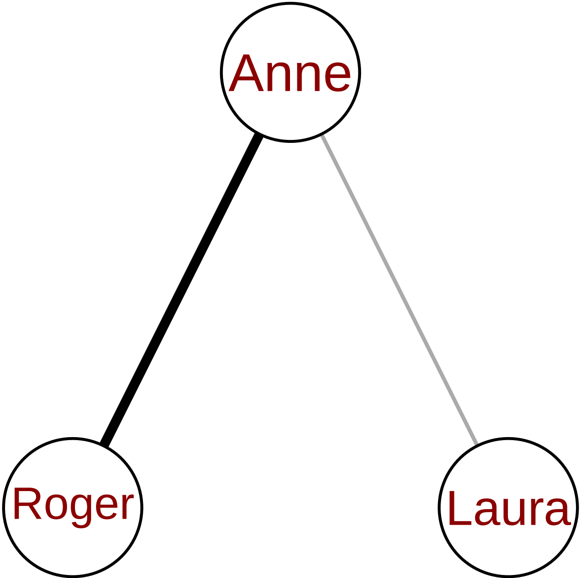


Anne is friends with Laura and Roger, but Laura is not friends with Roger:



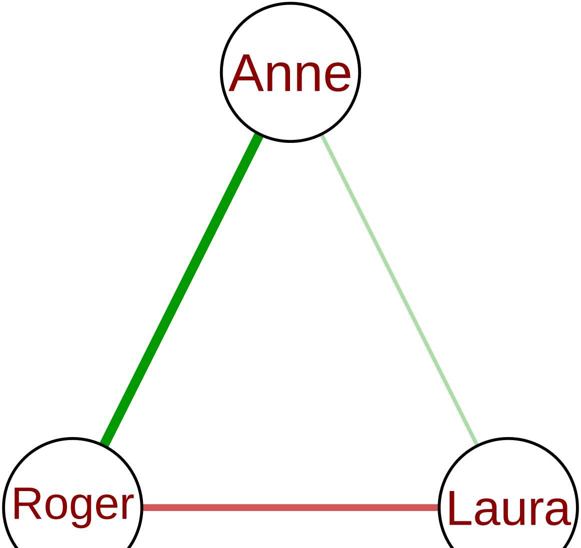
Networks can be weighted

Anne is better friends with met Roger than Laura:



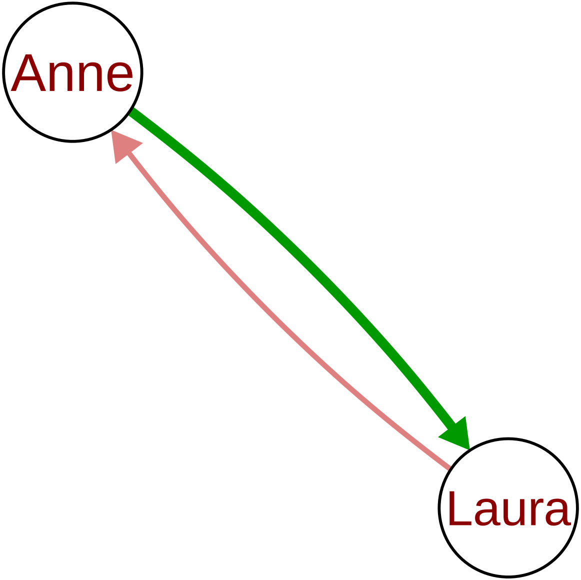
Weights can be signed

Anne is friends with Roger and Laura, but Roger and Laura don’t like each other at all!



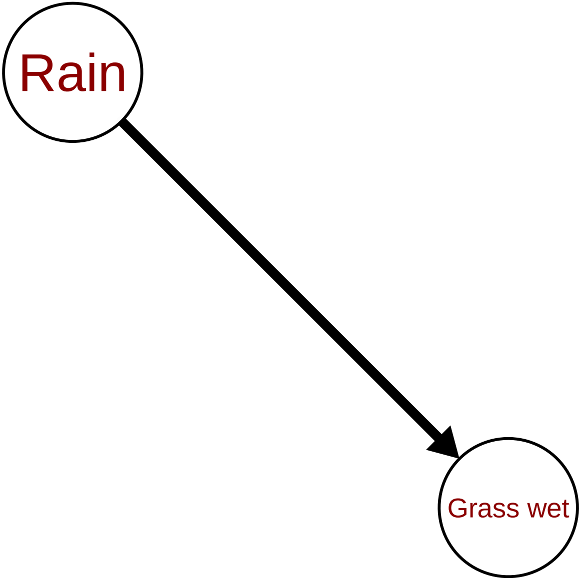
Networks can be directed

Anne likes Laura, but Laura doesn't like Anne:

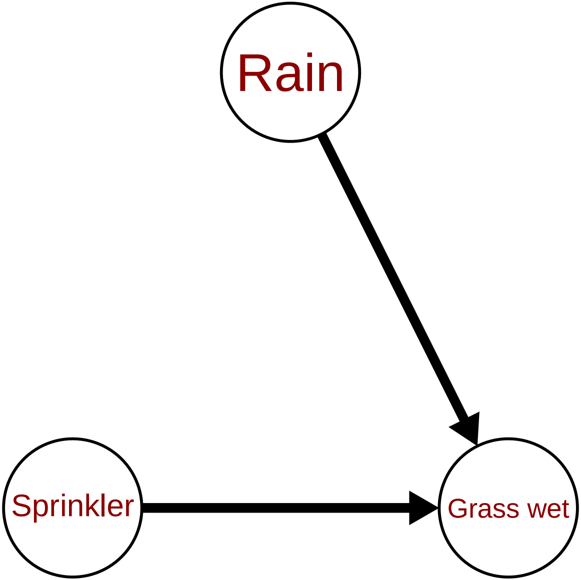


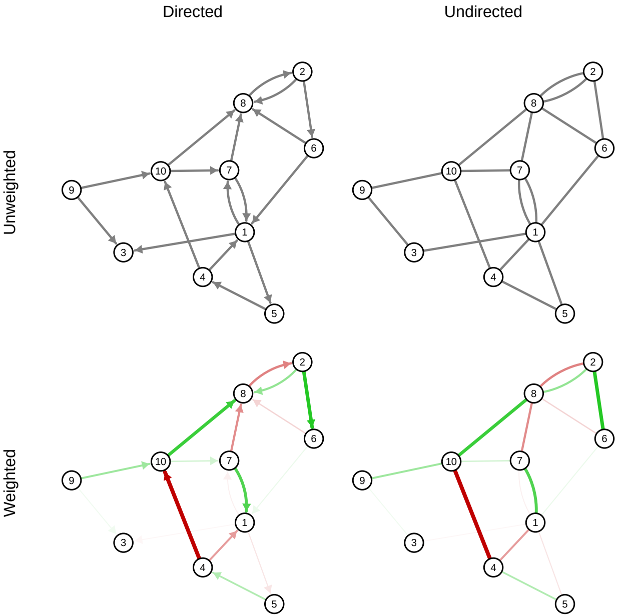
Networks can model causality

If it rains the grass becomes wet:



If the sprinkler is on the grass also becomes wet:




Directed
Undirected
Unweighted
Weighted
1
2
3
4
5
6
7
8
9
10

What can we do with networks?

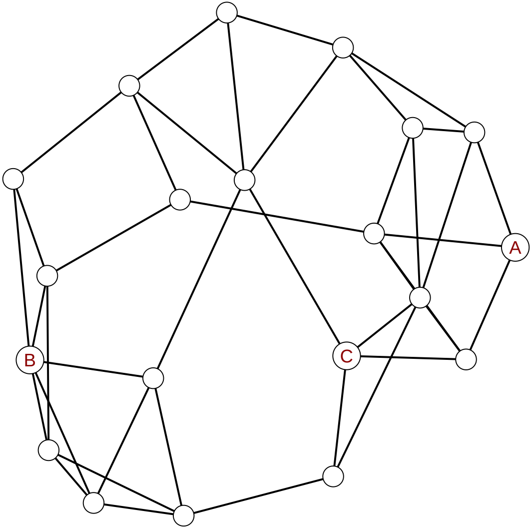
What can we do with networks?

Besides providing a interpretable structure of a complex system, we can also use networks to compute unique measures such as:

- Distance
  - How fast can symptom A influence symptom B?
- Centrality
  - Which symptom is the most important?
- Connectivity?
  - How well are symptoms connected?

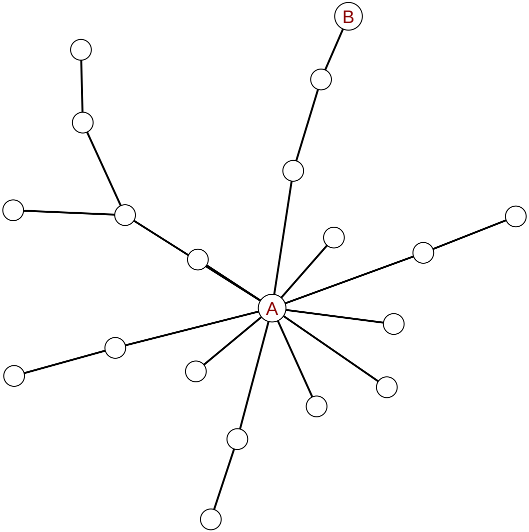
Distance

Node A is much further away from node B than node C:



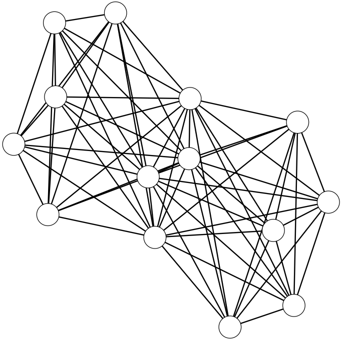
Centrality

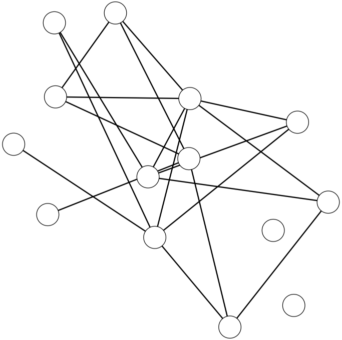
Node A is much more influential than node B:



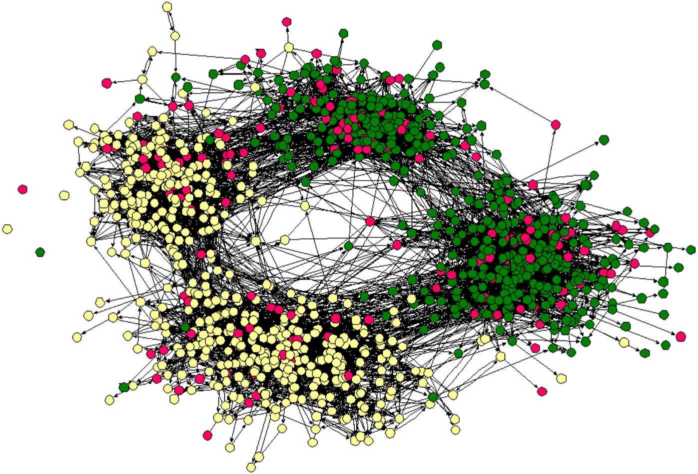
Connectivity

The left network is much denser connected than the right one:



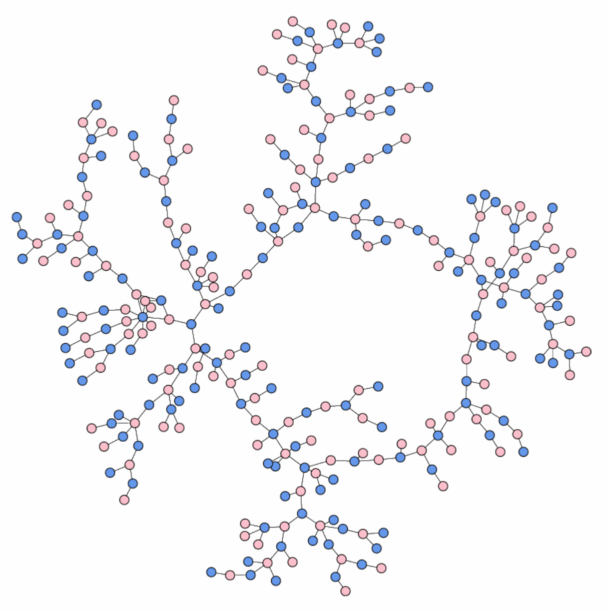


Friendship

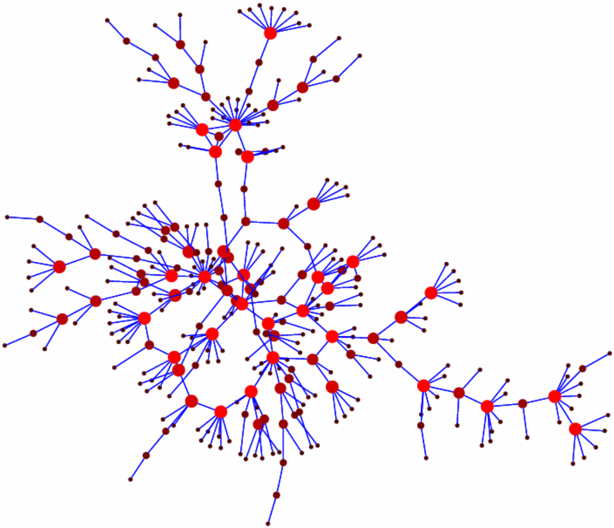



facebook
December 2010

Relationships

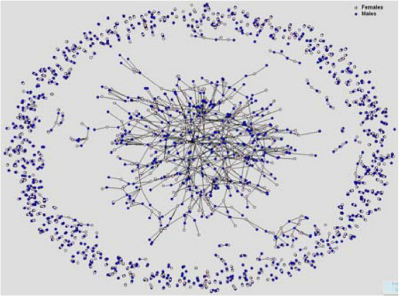


Sexual contacts

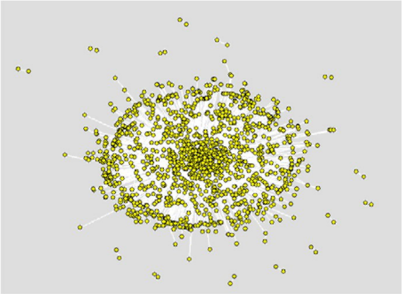


Networks can be simulated given sufficient information about a population:

(a)



(b)



Psychopathology as a virus...

How to get a network?

Journal of Statistical Software

May 2012, Volume 48, Issue 4. http://www.jstatsoft.org/

qgraph: Network Visualizations of Relationships in Psychometric Data

Sacha Epskamp
University of Amsterdam

Angélique O. J. Cramer
University of Amsterdam

Lourens J. Waldorp
University of Amsterdam

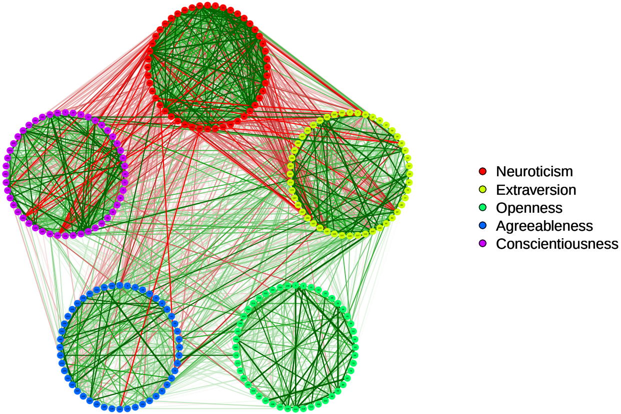
Verena D. Schmittmann
University of Amsterdam

Denny Borsboom
University of Amsterdam

Abstract

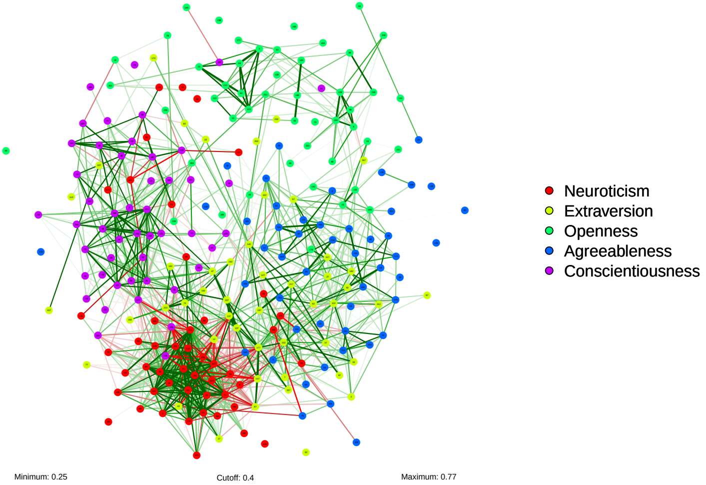
We present the **qgraph** package for R, which provides an interface to visualize data through network modeling techniques. For instance, a correlation matrix can be represented as a network in which each variable is a node and each correlation an edge; by

qgraph



Epskamp, Cramer, Waldorp, Schmittmann, and Borsboom (2012)

Correlations



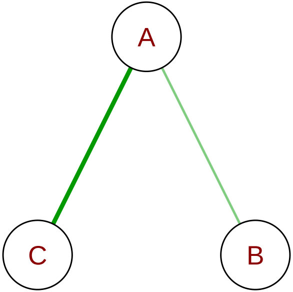
Correlation networks

- Correlation networks are useful as a visualization tool
- But correlations are not easily interpreted as networks due to many *spurious* connections
- A partial correlation network, in which you display the correlations conditional on all other variables in the network, is easier interpretable:
  - Two nodes are connected if and only if there is covariance between those nodes that can not be explained by any other variable in the network
- Such a network is called a Markov Random Field

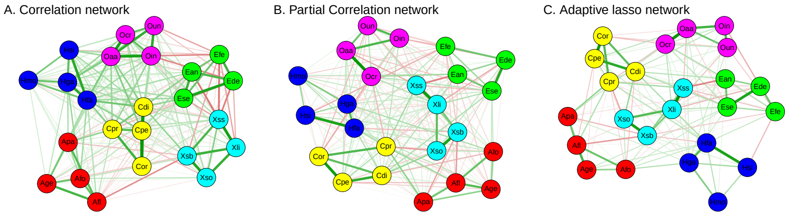
Markov Random Fields

- A specific type of network is called a Markov Random Field
- Undirected networks with the property that a node is independent of all other nodes given its neighbors (connected nodes)
- Interpretable
- High predictive power
- If data is assumed normal these are called Gaussian random fields or Partial correlation matrices
- If the data is binary these are called the *Ising model*
- Typically we want to estimate a *sparse* structure, which we can do using a LASSO penalty

Markov Random Fields



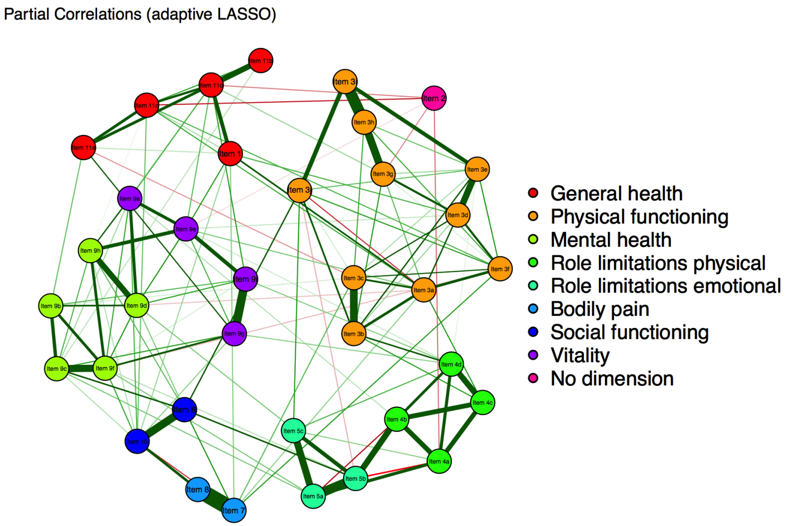
- A predicts C and B, but C better
- C predicts A, and B via A
- B predicts A, and C via A
- B and C are *independent given A*



Paper by Giulio Costantini, Sacha Epskamp, Denny Borsboom, Marco Perugini, René Mõttus, Lourens J. Waldorp & Angelique O. J. Cramer submitted

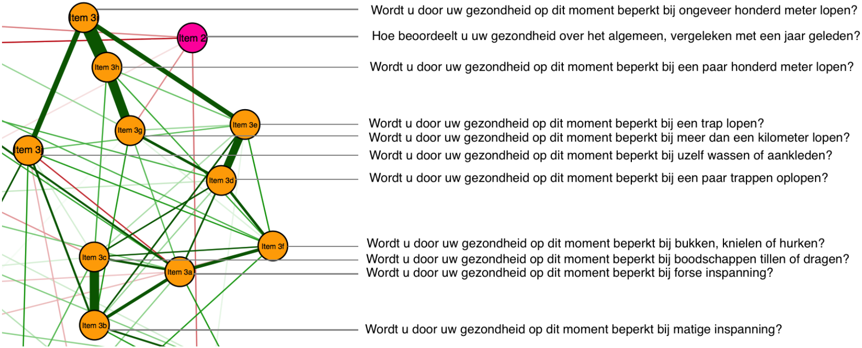
```r
# Load packages:
library("qgraph")
library("parcor")

# Read data:
Data <- read.csv("HEXACOfacet.csv")

# Plot correlations:
qgraph(cor(Data), layout = "spring")

# Plot partial correlations:
qgraph(cor(Data), layout = "spring", graph = "concentration")

# Plot LASSO network:
adls <- adalasso.net(Data)
network <- as.matrix(forceSymmetric(adls$pcor.adalasso))
qgraph(network, layout = "spring")
```

Partial correlations (using adaptive lasso)



Paper by Jolanda J. Kossakowski, Jacobien M. Kieffer, Sacha Epskamp & Denny Borsboom in preparation

Zooming in: Physical Functioning en Item 2



Three datasets

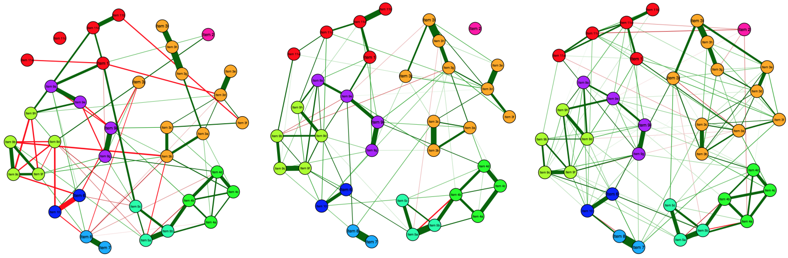
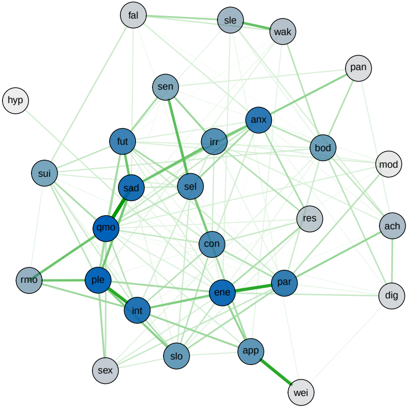


Figure: Left: AMC cancer. Middle: NKI cancer. Right: NKI healthy.

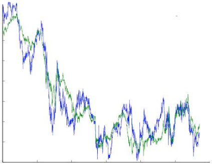
- General health
- Physical functioning
- Mental health
- Role limitations physical
- Role limitations emotional
- Bodily pain
- Social functioning
- Vitality
- No dimension

Ising Network

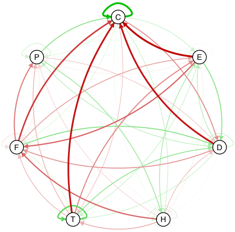


Paper by Claudia D. van Borkulo, Denny Borsboom, Sacha Epskamp Tessa F. Blanken, Lynn Boschloo, Robert A. Schoevers & Lourens J. Waldorp submitted

Individual networks



$$Y_{ijt} = \alpha + \beta_1 X_{1,t-1} + \beta_2 X_{2,t-1} + \ldots + \varepsilon$$



Bringmann, L., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., & Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PLoS ONE*.

A subject over time...

Example of network analysis in Radicalization

Determinants of Radicalization of Islamic Youth in the Netherlands: Personal Uncertainty, Perceived Injustice, and Perceived Group Threat

Bertjan Doosje*
University of Amsterdam

Annemarie Loseman and Kees van den Bos
Utrecht University

In this study among Dutch Muslim youth ($N = 131$), we focus on the process of radicalization. We hypothesize that this process is driven by three main factors: (a) personal uncertainty, (b) perceived injustice, and (c) perceived group threat. Using structural equation modeling, we demonstrate that personal uncertainty, perceived injustice, and group-threat factors are important determinants of a radical belief system (e.g., perceived superiority of Muslims, perceived illegitimacy of Dutch authorities, perceived distance to others, and a feeling of being disconnected from society). This radical belief system in turn predicts attitudes toward violence by other Muslims, which is a determinant of own violent intentions. Results are discussed in terms of the role of individual and group-based determinants of radicalization.

Radicalization example

Doosje, Loseman, and Bos (2013) investigated the process of radicalization of Dutch youth. They looked at possible determinants for adopting a radical beliefs system, which in turn can cause the basis for violent attitudes. An oversimplified version of their model is:

Determinants $\rightarrow$ Radical beliefs system $\rightarrow$ Violent attitudes

To test this model they measured several constructs in 131 Islamic youths in the Netherlands.

Radical belief system:

- Perceived illegitimacy of authorities
- Perceived in-group superiority
- Perceived distance to other people
- Perceived societal disconnectedness

Determinants:

- Personal uncertainty
- Perceived injustice
- Perceived group threat

Background variables:

- In-group identification
- individualistic relative deprivation
- collective relative deprivation

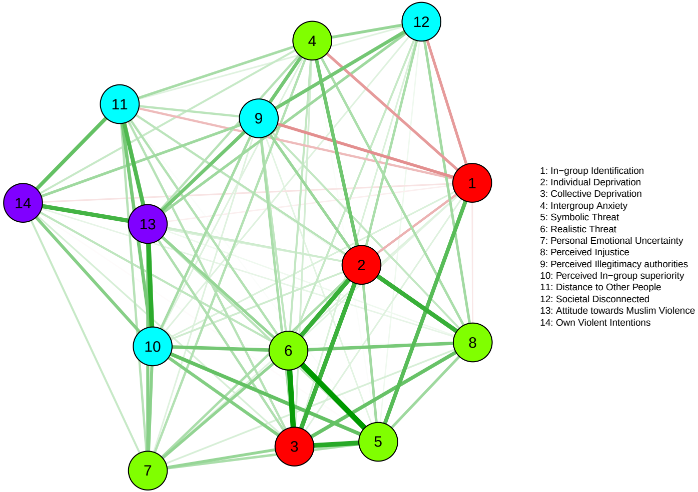
Table 1. The Means, Standard Deviations, and Inter-Correlations of All the Constructs

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Identification	4.56	0.85	–	−.19*	.08	−.25*	.42*	.07	.08	−.06	−.28*	.09	−.17	−.25*	−.04	−.07
2. Ind. Rel. Depri.	2.39	0.81		–	.49*	.36*	.23*	.50*	.21*	.50*	.25*	.12	.17	.21*	.12	.09
3. Col. Rel. Depri.	3.31	0.92			–	.11	.54*	.62*	.26*	.38*	.21	.31*	.18*	.09	.20*	.10
4. Int. Anxiety	−0.20	0.17				–	.01	.15	.19*	.21*	.35*	.08	.22*	.26*	.18*	.14
5. Symbolic Threat	3.46	0.76					–	.64*	.21*	.24*	.07	.39*	.01	.04	.17	−.01
6. Realistic Threat	3.10	0.88						–	.27*	.34*	.16	.35*	.19*	.14	.26*	.16
7. Per. Em. Uncertain.	2.84	0.67							–	.10	.08	.29*	.18	.00	.30*	.14
8. Perc. Proc. Injustice	2.38	0.68								–	.15	.01	.03	.23*	.04	.06
9. Perc. Illegitimacy	2.37	0.02									–	.22*	.17*	.35*	.35*	.24*
10. Perc. Ingr. Super.	3.26	0.93										–	.34*	.08	.53*	.30*
11. Distance	2.32	0.66											–	.08	.44*	.39*
12. Disconnected	2.79	0.96												–	.24*	.00
13. Moslim Violence	2.89	1.06													–	.47*
14. Violent Intentions	2.08	0.91														–

Note. 2 = *Individual Relative Deprivation*, 3 = *Collective Relative Deprivation*, 4 = *Intergroup Anxiety*, 5 = *Symbolic Threat*, 6 = *Realistic Threat*, 7 = *Personal Emotional Uncertainty*, 8 = *Perceived Procedural Injustice*, 9 = *Perceived Illegitimacy*, 10 = *Perceived Ingroup Superiority*. $^*p < .05$.

Correlations

The qgraph package can be used to visualize correlations as a network (Epskamp et al., 2012):



To test the hypothesized model, Doosje et al. (2013) used Structural Equation Modelling (SEM). SEM is a powerful modeling framework that has been one of the main focuses of Psychometrics for decades. In essence, it can be seen as confirmatory testing a network of observed and unobserved variables where typically is assumed that:

- All paths are directed and indicate linear effects
- All variables are assumed normally distributed
- The network is *acyclic*

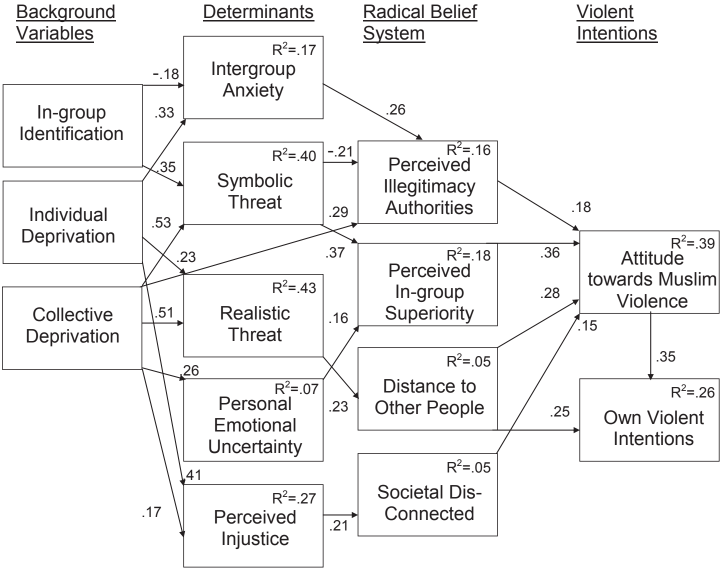


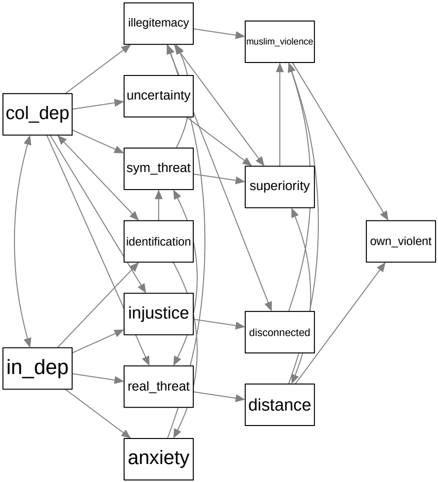
Fig. 1. Final structural equation model. All paths are significant. $R^2 = \%$ variance explained.

The hypothesized model had a good fit: Chi-square (65) = 76.58, p = .154, CFI = .98, NFI = .87, GFI = .93, SRMR = .082, and RMSEA = .037. La Grange Multiplier Test suggested including two direct paths: from collective deprivation to perceived illegitimacy of Dutch authorities, and from perceived distance to own violent intentions. When we included these paths, the fit became better. Our final model is presented in Figure 1. It has a very good fit: Chi-square (62) = 58.13, p = .650, CFI = 1.00, NFI = .90, GFI = .94, SRMR = .070, and RMSEA = .000. All paths included in the model are significant. We discuss this model in steps from left to right.

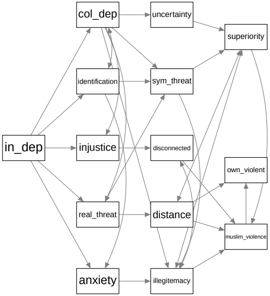
Interpreting SEM results

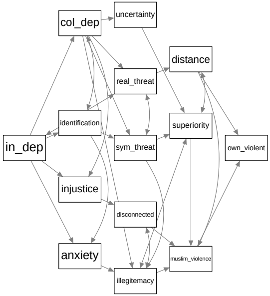
SEM can be used to test if the data rejects a theorized model. But care should be taken in that a fitting SEM model *does not mean the model is correct*. Many equivalent models could fit the data just as well.

Equivalent model

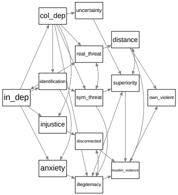


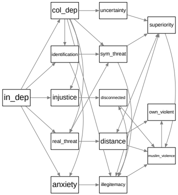
Equivalent models

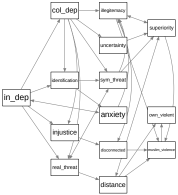


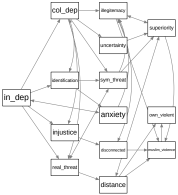


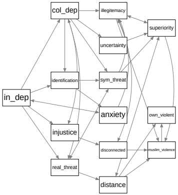
Equivalent models

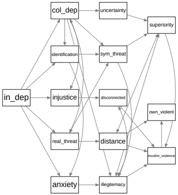




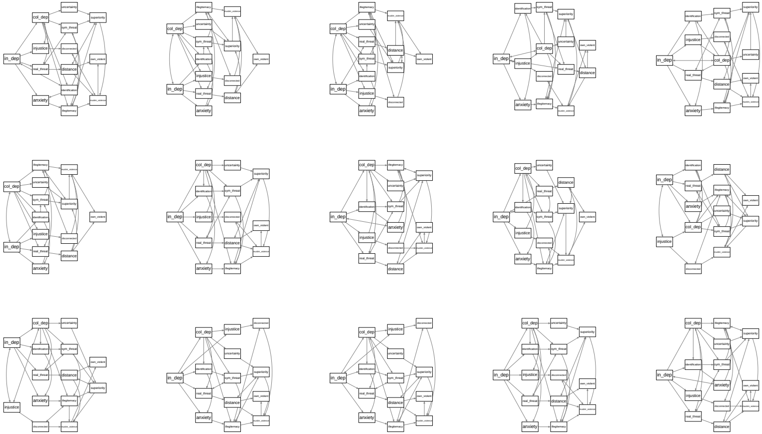




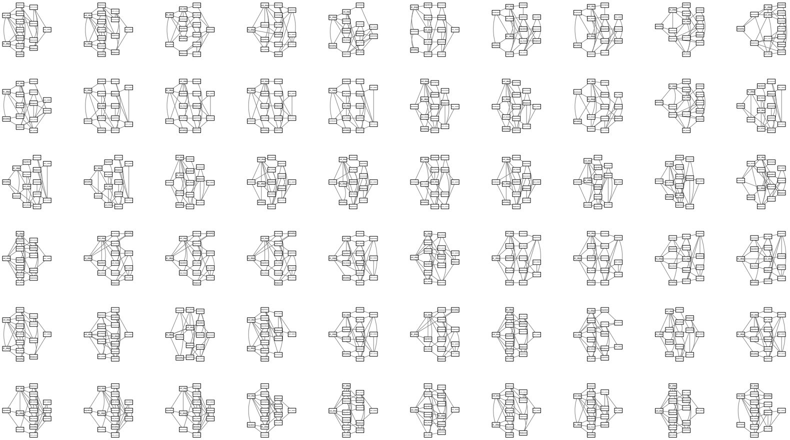




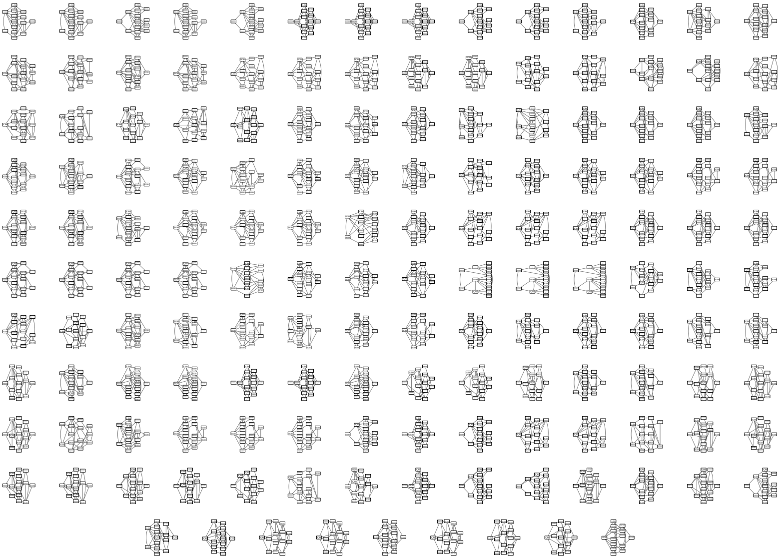
Equivalent models



Equivalent models



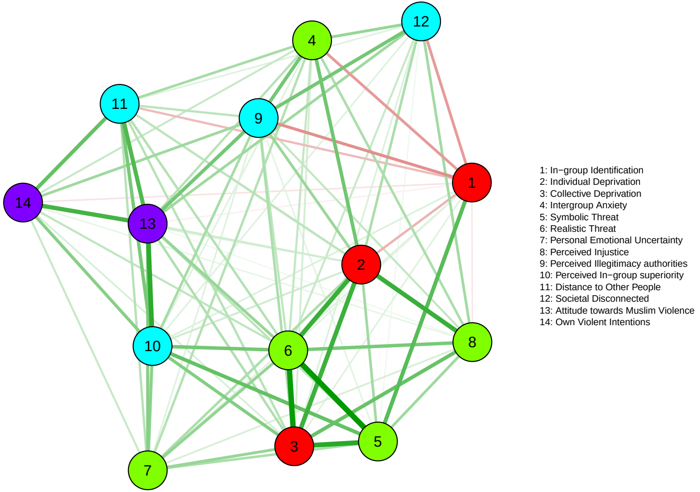
Equivalent models



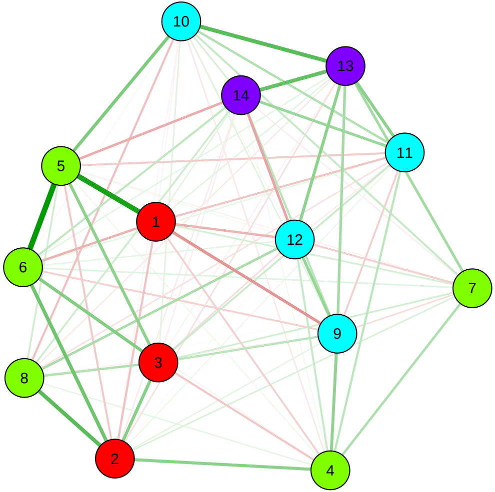
Interpreting SEM results

- Direction of causation can often not be inferred
- Assumption of no cycles is very strict and in psychology often not tenable
- SEM is very powerful in testing strict theories where the acyclic assumption is met. In more exploratory settings however, using partial correlation networks can be preferred:
  - Shows relationships present in the data
  - No equivalent models
  - Naturally cyclic
  - Optimally predicts each node given all others

Correlation network



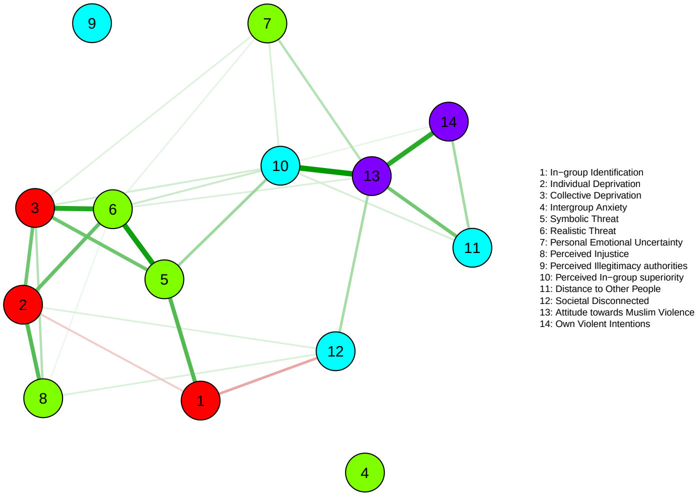
Partial correlation network



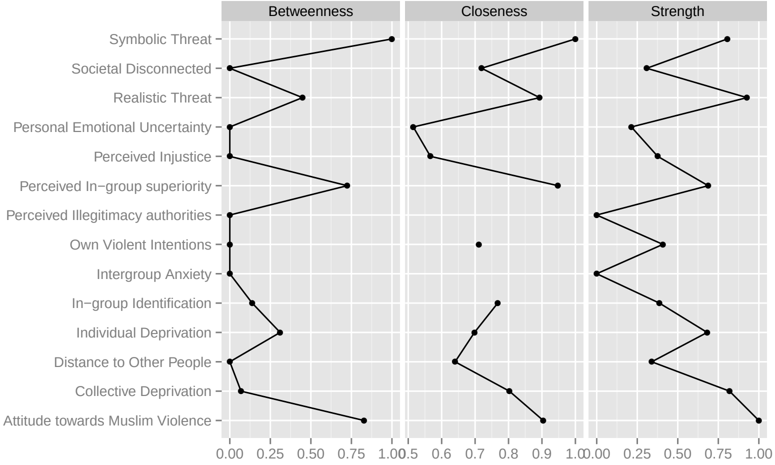
1: In−group Identification
2: Individual Deprivation
3: Collective Deprivation
4: Intergroup Anxiety
5: Symbolic Threat
6: Realistic Threat
7: Personal Emotional Uncertainty
8: Perceived Injustice
9: Perceived Illegitimacy authorities
10: Perceived In−group superiority
11: Distance to Other People
12: Societal Disconnected
13: Attitude towards Muslim Violence
14: Own Violent Intentions

Partial correlation network

After glasso (Friedman, Hastie, & Tibshirani, 2011):



Centrality



Betweenness
Closeness
Strength
Symbolic Threat
Societal Disconnected
Realistic Threat
Personal Emotional Uncertainty
Perceived Injustice
Perceived In−group superiority
Perceived Illegitimacy authorities
Own Violent Intentions
Intergroup Anxiety
In−group Identification
Individual Deprivation
Distance to Other People
Collective Deprivation
Attitude towards Muslim Violence
0.00 0.25 0.50 0.75 1.00
0.5 0.6 0.7 0.8 0.9 1.0
0.00 0.25 0.50 0.75 1.00

Shortest path length

	Muslim Violence	Violent Intentions
In-group Identification	16.12	19.89
Individual Deprivation	20.10	23.87
Collective Deprivation	17.05	20.82
Intergroup Anxiety	Inf	Inf
Symbolic Threat	11.44	15.21
Realistic Threat	14.81	18.58
Personal Emotional Uncertainty	10.73	14.50
Perceived Injustice	24.83	28.60
Perceived Illegitimacy authorities	Inf	Inf
Perceived In-group superiority	3.16	6.93
Distance to Other People	5.70	8.81
Societal Disconnected	9.15	12.92
Attitude towards Muslim Violence	0.00	3.77
Own Violent Intentions	3.77	0.00

Shortest path length

	Muslim Violence	Violent Intentions
In-group Identification	16.12	19.89
Individual Deprivation	20.10	23.87
Collective Deprivation	17.05	20.82
Intergroup Anxiety	Inf	Inf
Symbolic Threat	11.44	15.21
Realistic Threat	14.81	18.58
Personal Emotional Uncertainty	10.73	14.50
Perceived Injustice	24.83	28.60
Perceived Illegitimacy authorities	Inf	Inf
Perceived In-group superiority	3.16	6.93
Distance to Other People	5.70	8.81
Societal Disconnected	9.15	12.92
Attitude towards Muslim Violence	0.00	3.77
Own Violent Intentions	3.77	0.00

Conclusion

Preliminary network analysis agrees with Doosje et al. (2013) that Perceived In-group superiority, Distance to Other People and to a lesser extent Societal Disconnected are strong predictors for attitudes towards Muslim violence which in turn predicts own violent intents. The fourth element of the radical beliefs system, Perceived Illegitimacy authorities, plays a lesser role in the network.
Personal Emotional Uncertainty is the only variable whose predictive power on the violent variables is not mediated by the radical beliefs system.

Thank you for your attention!

References I

Doosje, B., Loseman, A., & Bos, K. (2013). Determinants of radicalization of islamic youth in the netherlands: Personal uncertainty, perceived injustice, and perceived group threat. *Journal of Social Issues*, *69*(3), 586–604.

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*(4), 1–18. Retrieved from `http://www.jstatsoft.org/v48/i04/`

Friedman, J., Hastie, T., & Tibshirani, R. (2011). glasso: Graphical lasso- estimation of gaussian graphical models [Computer software manual]. Retrieved from `http://CRAN.R-project.org/package=glasso` (R package version 1.7)