Mplus

rijksuniversiteit groningen
Assistant Professor
University of Groningen

Laura F. Bringmann

8th M*plus* Users Meeting:

Modeling change in psychopathological networks with DSEM

ICPE

Outline

Networks in psychology

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Comorbidity: A network perspective

Angélique O. J. Cramer
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
A.O.J.Cramer@uva.nl
www.aojcramer.com

Lourens J. Waldorp
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
L.J.Waldorp@uva.nl
http://users.fmg.uva.nl/lwaldorp

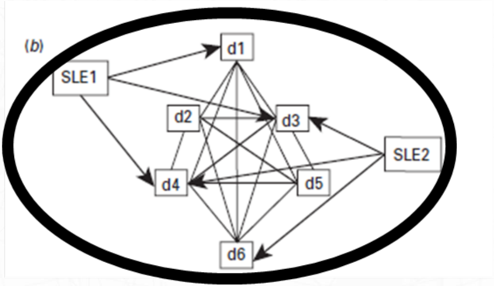
Han L. J. van der Maas
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
H.L.J.vanderMaas@uva.nl
http://users.fmg.uva.nl/hvandermaas/

Denny Borsboom
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
D.Borsboom@uva.nl
http://sites.google.com/site/borsboomdenny/dennyborsboom

Abstract: The pivotal problem of comorbidity research lies in the psychometric foundation it rests on, that is, *latent variable theory*, in which a mental disorder is viewed as a latent variable that *causes* a constellation of symptoms. From this perspective, comorbidity is a (bi)directional relationship between multiple latent variables. We argue that such a latent variable perspective encounters serious problems in the study of comorbidity, and offer a radically different conceptualization in terms of a *network approach*, where comorbidity is hypothesized to arise from direct relations between symptoms of multiple disorders. We propose a method to visualize comorbidity networks and, based on an empirical network for major depression and generalized anxiety, we argue that this approach generates realistic hypotheses about pathways to comorbidity, overlapping symptoms, and diagnostic boundaries, that are not naturally accommodated by latent variable models: Some pathways to comorbidity through the *symptom space* are more likely than others; those pathways generally have the same direction (i.e., from symptoms of one disorder to symptoms of the other); overlapping symptoms play an important role in comorbidity; and boundaries between diagnostic categories are necessarily fuzzy.

Keywords: comorbidity; complex networks; generalized anxiety; latent variable models; major depression

Why do symptoms tend to co-vary?



- Symptoms directly (causally) influence each other
- Focus on symptom level
- Depression is its symptoms[1]

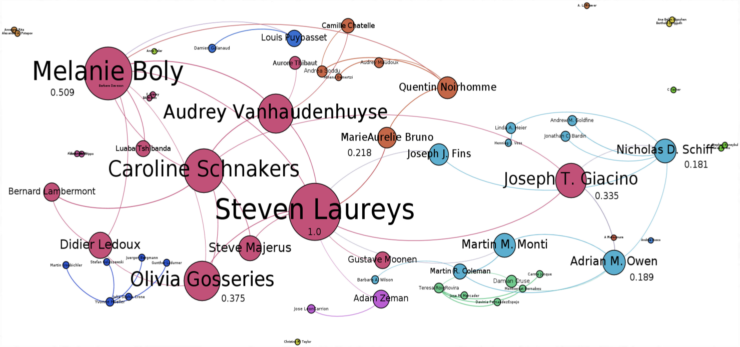
[1] Figure of [Cramer et al., 2012]

How to infer a network in psychology?

Emotion or symptom networks differ from social networks

- Edges are not given

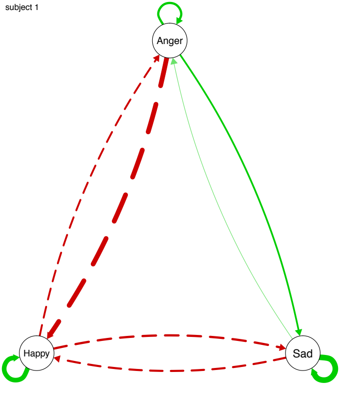
Co-author network



An example with 3 variables

VAR model

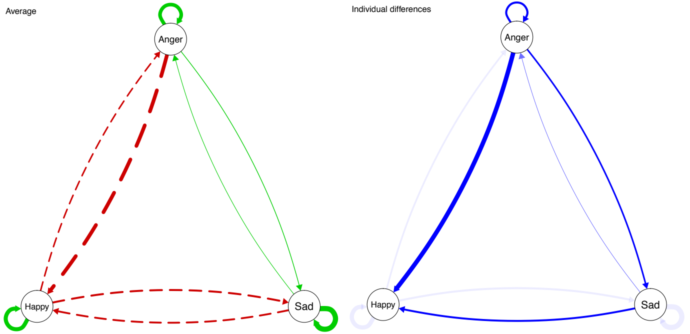
$$
\begin{aligned}
Happy_t &= \beta_{10} + \beta_{11} Happy_{t-1} + \beta_{12} Sad_{t-1} + \beta_{13} Anger_{t-1} + e_{1,t} \\
Sad_t &= \beta_{20} + \beta_{21} Happy_{t-1} + \beta_{12} Sad_{t-1} + \beta_{23} Anger_{t-1} + e_{2,t} \\
Anger_t &= \beta_{30} + \beta_{31} Happy_{t-1} + \beta_{32} Sad_{t-1} + \beta_{33} Anger_{t-1} + e_{3,t}
\end{aligned}
$$



Networks inferred by multilevel-VAR

Multilevel-VAR model

$$
\begin{aligned}
Happy_{i,t} = \beta_{10} + b_{10i} + (\beta_{11} + b_{11i})Happy_{i,t-1} + \\
(\beta_{12} + b_{12i})Anger_{i,t-1} + \\
(\beta_{13} + b_{13i})Sad_{i,t-1} + \\
e_{1i,t}
\end{aligned}
$$



Estimation limitations until now

- Multilevel VAR is not yet well implemented in open source software

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  - Not all parameters together in the same model

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- Does not estimate all parameter covariances
  - Not all parameters together in the same model
- You have to center the lagged predictor in order to get the mean instead of the intercept
- Unequal distance/missingess is problematic

The data

Analyzing ESM data [Geschwind et al., 2011]

- Subjects having residual depressive symptoms
- Mindfulness therapy/control group

- Per study period
- 6 days
- 10 beeps per day

- 4 items: Happy Relaxed Sad Worry

Mplus code: comparing networks

Pre Post -> zeros and ones

Lets focus on the between level:

$$Happy_{pre_i} = \gamma_{00} + \gamma_{01} Group + e_{it}$$

$$Happy_{post_i} = \gamma_{10} + 1 * Happy_{pre_i} + \gamma_{11} Group + e_{it}$$

$$Happy_{post_i} - Happy_{pre_i} = \gamma_{10} + \gamma_{11} Group + e_{it}$$

```
%BETWEEN%
  Happre Worpre Sadpre Relpre phi111-phi144
  WITH Happre Worpre Sadpre Relpre phi111-phi144;

  Happre Worpre Sadpre Relpre phi111-phi144 ON Group;
  Happos ON Happre@1 Group;
  Worpos ON Worpre@1 Group;
  Sadpos ON Sadpre@1 Group;
  Relpos ON Relpre@1 Group;


  Phi211 ON phi111@1 Group;
  Phi222 ON phi122@1 Group;
  Phi233 ON phi133@1 Group;
  Phi212 ON phi112@1 Group;
  Phi213 ON phi113@1 Group;
  Phi214 ON phi114@1 Group;
  Phi221 ON phi121@1 Group;
  Phi223 ON phi123@1 Group;
  Phi224 ON phi124@1 Group;
  Phi231 ON phi131@1 Group;
  Phi232 ON phi132@1 Group;
  Phi234 ON phi134@1 Group;
  Phi241 ON phi141@1 Group;
  Phi242 ON phi142@1 Group;
  Phi243 ON phi143@1 Group;
  Phi244 ON phi144@1 Group;

OUTPUT: TECH1 TECH8 STANDARDIZED (CLUSTER);
PLOT:   TYPE = PLOT3;
```

Mplus code

Pre Post -> zeros and ones

```
MODEL:   %WITHIN%
  phi111 | Happre ON Happre&1;
  phi122 | Worpre ON Worpre&1;
  phi133 | Sadpre ON Sadpre&1;
  phi112 | Happre ON Worpre&1;
  phi113 | Happre ON Sadpre&1;
  phi114 | Happre ON Relpre&1;
  phi121 | Worpre ON Happre&1;
  phi123 | Worpre ON Sadpre&1;
  phi124 | Worpre ON Relpre&1;
  phi131 | Sadpre ON Happre&1;
  phi132 | Sadpre ON Worpre&1;
  phi134 | Sadpre ON Relpre&1;
  phi141 | Relpre ON Happre&1;
  phi142 | Relpre ON Worpre&1;
  phi143 | Relpre ON Sadpre&1;
  phi144 | Relpre ON Relpre&1;


  phi211 | Happos ON Happos&1;
  phi222 | Worpos ON Worpos&1;
  phi233 | Sadpos ON Sadpos&1;
  phi212 | Happos ON Worpos&1;
  phi213 | Happos ON Sadpos&1;
  phi214 | Happos ON Relpos&1;
  phi221 | Worpos ON Happos&1;
  phi223 | Worpos ON Sadpos&1;
  phi224 | Worpos ON Relpos&1;
  phi231 | Sadpos ON Happos&1;
  phi232 | Sadpos ON Worpos&1;
  phi234 | Sadpos ON Relpos&1;
  phi241 | Relpos ON Happos&1;
  phi242 | Relpos ON Worpos&1;
  phi243 | Relpos ON Sadpos&1;
  phi244 | Relpos ON Relpos&1;

  Happre WITH Happos@0;
  Worpre WITH Worpos@0;
  Sadpre WITH Sadpos@0;
  Relpre WITH Relpos@0;
  Happre WITH Worpos@0;
  Worpre WITH Sadpos@0;
```

Results I

MODEL RESULTS

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within Level						
HAPPRE WITH						
HAPPOS	0.000	0.000	1.000	0.000	0.000	
WORPOS	0.000	0.000	1.000	0.000	0.000	
SADPOS	0.000	0.000	1.000	0.000	0.000	
RELPOS	0.000	0.000	1.000	0.000	0.000	
WORPRE WITH						
WORPOS	0.000	0.000	1.000	0.000	0.000	
SADPOS	0.000	0.000	1.000	0.000	0.000	
RELPOS	0.000	0.000	1.000	0.000	0.000	
HAPPOS	0.000	0.000	1.000	0.000	0.000	
HAPPRE	-0.782	0.024	0.000	-0.818	-0.724	*
SADPRE WITH						
SADPOS	0.000	0.000	1.000	0.000	0.000	
WORPOS	0.000	0.000	1.000	0.000	0.000	
RELPOS	0.000	0.000	1.000	0.000	0.000	
HAPPOS	0.000	0.000	1.000	0.000	0.000	
HAPPRE	-0.743	0.021	0.000	-0.778	-0.694	*
WORPRE	0.747	0.023	0.000	0.703	0.787	*
RELPRE WITH						
RELPOS	0.000	0.000	1.000	0.000	0.000	
WORPOS	0.000	0.000	1.000	0.000	0.000	
SADPOS	0.000	0.000	1.000	0.000	0.000	
HAPPOS	0.000	0.000	1.000	0.000	0.000	
HAPPRE	0.848	0.026	0.000	0.797	0.896	*
WORPRE	-0.782	0.028	0.000	-0.832	-0.733	*
SADPRE	-0.630	0.022	0.000	-0.669	-0.586	*
WORPOS WITH						
HAPPOS	-0.493	0.019	0.000	-0.534	-0.463	*
SADPOS WITH						
HAPPOS	-0.520	0.014	0.000	-0.549	-0.495	*
WORPOS	0.514	0.018	0.000	0.473	0.542	*
RELPOS WITH						
HAPPOS	0.647	0.014	0.000	0.623	0.675	*
WORPOS	-0.511	0.019	0.000	-0.552	-0.477	*
SADPOS	-0.436	0.017	0.000	-0.467	-0.394	*
Between Level						
RELPOS ON						
RELPRE	1.000	0.000	0.000	1.000	1.000	
GROUP	0.444	0.150	0.001	0.143	0.741	*
PHI211 ON						
PHI111	1.000	0.000	0.000	1.000	1.000	

Results II

Between Level

Intercepts

HAPPRE	4.043	0.092	0.000	3.864	4.222	*
HAPPOS	-0.021	0.106	0.419	-0.224	0.194	
WORPRE	2.939	0.119	0.000	2.698	3.171	*
WORPOS	-0.195	0.124	0.063	-0.444	0.040	
SADPRE	2.521	0.103	0.000	2.309	2.723	*
SADPOS	-0.195	0.097	0.021	-0.388	-0.009	*
RELPRE	4.215	0.082	0.000	4.054	4.376	*
RELPOS	0.008	0.102	0.474	-0.194	0.209	
PHI111	0.288	0.034	0.000	0.227	0.363	*
PHI122	0.220	0.034	0.000	0.159	0.288	*
PHI133	0.249	0.034	0.000	0.183	0.321	*
PHI112	-0.018	0.022	0.216	-0.057	0.027	
PHI113	-0.106	0.030	0.000	-0.164	-0.045	*
PHI114	0.071	0.025	0.002	0.023	0.119	*
PHI121	-0.085	0.035	0.007	-0.150	-0.018	*
PHI123	0.123	0.034	0.000	0.056	0.191	*
PHI124	-0.070	0.031	0.011	-0.135	-0.009	*
PHI131	-0.144	0.030	0.000	-0.204	-0.089	*
PHI132	0.070	0.022	0.006	0.016	0.106	*
PHI134	-0.031	0.022	0.062	-0.077	0.009	
PHI141	0.154	0.032	0.000	0.092	0.217	*
PHI142	-0.017	0.026	0.298	-0.061	0.035	
PHI143	-0.066	0.030	0.015	-0.125	-0.004	*
PHI144	0.203	0.030	0.000	0.139	0.260	*
PHI211	0.043	0.043	0.153	-0.037	0.133	
PHI222	0.016	0.044	0.369	-0.068	0.103	
PHI233	-0.049	0.043	0.105	-0.144	0.024	
PHI212	-0.014	0.037	0.347	-0.098	0.052	
PHI213	0.076	0.036	0.010	0.014	0.155	*
PHI214	0.000	0.039	0.498	-0.077	0.075	
PHI221	-0.061	0.043	0.038	-0.160	0.005	
PHI223	-0.115	0.049	0.004	-0.215	-0.021	*
PHI224	0.037	0.041	0.186	-0.051	0.119	
PHI231	-0.016	0.038	0.340	-0.096	0.054	
PHI232	-0.031	0.037	0.221	-0.096	0.046	
PHI234	-0.014	0.030	0.269	-0.079	0.039	
PHI241	0.028	0.043	0.259	-0.054	0.112	
PHI242	-0.014	0.047	0.408	-0.103	0.056	
PHI243	0.066	0.048	0.086	-0.024	0.166	
PHI244	-0.014	0.043	0.387	-0.091	0.067	

Results III

etween Level

PHI111 ON GROUP	-0.020	0.044	0.327	-0.108	0.064	
PHI122 ON GROUP	0.089	0.053	0.054	-0.023	0.185	
PHI133 ON GROUP	0.031	0.043	0.238	-0.059	0.116	
PHI112 ON GROUP	-0.058	0.036	0.042	-0.126	0.008	
PHI113 ON GROUP	-0.001	0.044	0.489	-0.095	0.085	
PHI144 ON GROUP	0.022	0.040	0.275	-0.053	0.105	
PHI211 ON GROUP	-0.053	0.067	0.259	-0.159	0.096	
PHI222 ON GROUP	-0.076	0.071	0.146	-0.213	0.057	
PHI233 ON GROUP	0.025	0.059	0.339	-0.087	0.142	
PHI212 ON GROUP	0.069	0.050	0.066	-0.025	0.169	
PHI213 ON GROUP	-0.145	0.067	0.030	-0.264	0.007	
PHI214 ON GROUP	-0.047	0.049	0.162	-0.147	0.042	
PHI221 ON GROUP	0.115	0.062	0.017	0.011	0.242	*
PHI223 ON GROUP	0.069	0.062	0.125	-0.053	0.194	
PHI224 ON GROUP	-0.019	0.065	0.380	-0.167	0.086	
PHI231 ON GROUP	0.053	0.058	0.182	-0.049	0.175	
PHI234 ON GROUP	0.035	0.050	0.184	-0.043	0.163	
PHI244 ON GROUP	-0.041	0.060	0.238	-0.168	0.069	

Results IV

HAPPRE ON						
GROUP	-0.220	0.134	0.047	-0.476	0.044	
WORPRE ON						
GROUP	-0.061	0.174	0.358	-0.398	0.284	
SADPRE ON						
GROUP	-0.134	0.151	0.183	-0.434	0.161	
RELPRE ON						
GROUP	-0.284	0.119	0.009	-0.514	-0.053	*
HAPPOS ON						
HAPPRE	1.000	0.000	0.000	1.000	1.000	
GROUP	0.558	0.156	0.001	0.247	0.855	*
WORPOS ON						
WORPRE	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.595	0.188	0.001	-0.964	-0.228	*
SADPOS ON						
SADPRE	1.000	0.000	0.000	1.000	1.000	
GROUP	-0.342	0.148	0.013	-0.639	-0.052	*
RELPOS ON						
RELPRE	1.000	0.000	0.000	1.000	1.000	
GROUP	0.444	0.150	0.001	0.143	0.741	*

In line with previous research

[Bringmann et al., 2013] [Snippe et al., 2017]

Challenges

```
*** WARNING
  One or more individual-level variables have no variation within a
  cluster for the following clusters.

     Variable   Cluster IDs with no within-cluster variation

      HAPPOS      10778 10725 10763 10846 10799 10744 10777 10828 10775
      WORPOS      10778 10725 10763 10846 10799 10744 10777 10828 10775 10754 10755
      SADPRE      10812 10755 10843
      SADPOS      10778 10725 10763 10846 10799 10744 10777 10828 10775 10812 10797
      RELPOS      10778 10725 10763 10846 10799 10744 10777 10828 10775
      WORPOS&1    10754 10755
      SADPRE&1    10812 10755 10843
      SADPOS&1    10812 10797

   1 WARNING(S) FOUND IN THE INPUT INSTRUCTIONS
```

```
WARNING: PROBLEMS OCCURRED IN SEVERAL ITERATIONS IN THE COMPUTATION OF THE STANDARDIZED ESTIMATES FOR SEVERAL
CLUSTERS. THIS IS MOST LIKELY DUE TO AR COEFFICIENTS GREATER THAN 1 OR PARAMETERS GIVING NON-STATIONARY MODELS.
SUCH POSTERIOR DRAWS ARE REMOVED. THE FOLLOWING CLUSTERS HAD SUCH PROBLEMS:
     10778 10763 10846 10799 10744 10773 10791 10781 10722 10851 10812 10793 10732 10808 10726 10802
     10772 10813 10755 10822 10783 10832 10792 10844
```

```
Number of Free Parameters                              146
```

Challenges II

- Robustness
- Multiple testing
- Time variable

Acknowledgments

Many thanks to Ellen Hamaker for discussing and helping with clarifying the topics discussed here!

Citations I

Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., and Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PloS One*, 8(4):e60188.

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Thank you!

L.F.Bringmann@rug.nl