Centrality and Interventions in Continuous-Time Dynamical Networks

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Summary

Dynamic networks are appealing because they offer the promise of discovering **targets for intervention** using **centrality** measures

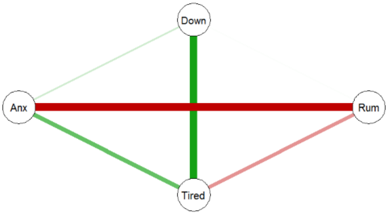
Current approaches may fall short because they focus more on the **network structure** and less on the **dynamic model**

Improvements could be made by:

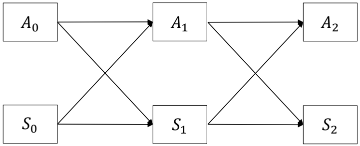
- Using a dynamic model which better fits substantive ideas
- Grounding the rationale of “interventions” in the dynamics of the model

Networks and Dynamics in Psychology

- **Network approach** to psychopathology
  - System of interacting symptoms
  - Large, multivariate
  - Borsboom & Cramer (2013), Epskamp et al (2016)

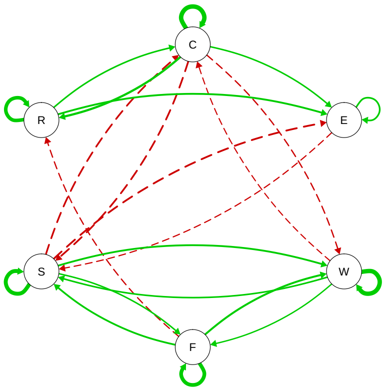


- **Intra-individual dynamics**
  - Within-person processes
  - Unfolding over time
  - Molenaar (2004), Hamaker et al. (2005), Kuppens et al (2010)



Dynamical Network approach to psychology

- Network of symptoms which influence one another over time
  - Bringmann et al (2013)
  - Effect of **W**orry now on **C**heerfulness later
- Intensive Longitudinal (ESM) Data
- Multilevel VAR(1) model
  - $\boldsymbol{Z}_{i,\tau} = \boldsymbol{c}_i + \boldsymbol{\Phi}_i \boldsymbol{Z}_{i,\tau-1} + \boldsymbol{e}_{i,\tau}$



Advantages of the Dynamical Network Approach

1. Combines appealing aspects of network and intraindividual approaches to psychology

2. Widely applicable, including analysis of
   - Depression (Bringmann et al. 2013, 2015; Dejonckheere et al. 2017)
   - Psychosis (Bak et al. 2016)
   - Anhedonia (van Roekel et al. pre-print)

3. Allows us to use the **network analysis toolbox**

Centrality Measures and Interventions

Centrality measures measure the effect of one variable on the network **as a whole**

Used to identify **targets for interventions** (Valente, 2012)

- In-strength: direct in
- Out-strength: direct out
- Betweenness: “indirect”
- Closeness: “indirect”

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Network	**Variable**	**Centrality**
Depression	Worry	Betweenness
	Suicidal Thoughts	Out-strength
	Social Pressure	Out-strength
Psychosis	Paranoia	Betweeneness
Anehdonia	Cheerfulness	Out-strength

What's the problem?

While centrality measures are appealing, and the general idea is sound, this application is problematic in two ways

1. The Time-Interval Problem
   - The VAR(1) **model** used to estimate the network structure
2. Centrality-Intervention matching
   - Which centrality measure to choose? For which intervention?

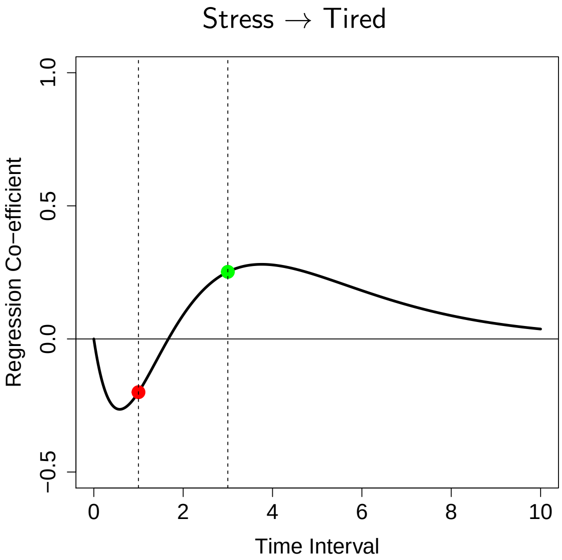
Both of these problems have solutions which involve a greater focus on the **dynamic** aspect of dynamical networks

The time-interval problem

The effect of one variable on another is likely to change depending on how those variables are spaced in time

- We may come to very different conclusions about "the effect" of X on Y using a different time-interval
- This is referred to as **time-interval dependency** and has been long observed in the social sciences (Gollob & Reichardt, 1987)
- Psychological processes are likely to influence one another continuously over time (Boker, 2002)

The time-interval problem



The time-interval problem

Current VAR(1) models do not take account of this

- More variables in our system: more possibility for effects changing in sign/relative strength (Kuiper & Ryan, 2018)
- Implications for centrality

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Solution: **Continuous-time** VAR(1) models

- Try to explicitly model effects as a function of the time interval
- See Boker (2002), Voelkle et al (2012), Driver & Voelkle (2016), Ryan, Kuiper & Hamaker (in press)

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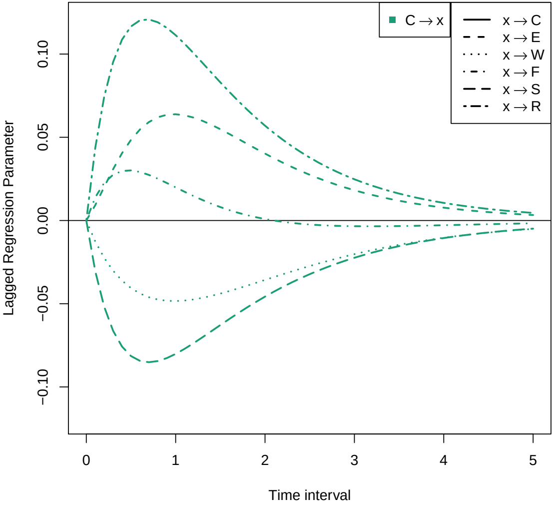
We can illustrate this by re-analysis Bringmann et al (2013)

CT analysis of Bringmann et al (2013)



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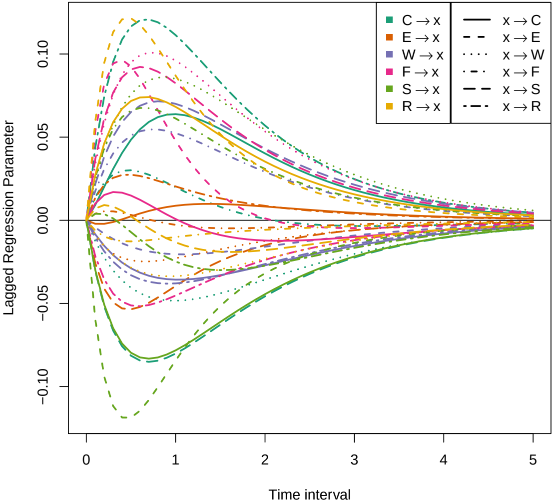

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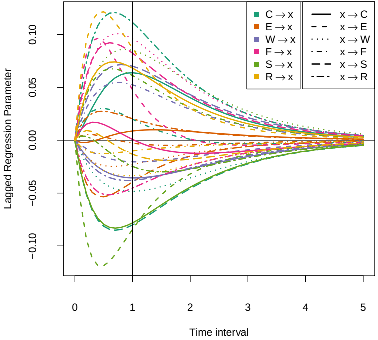

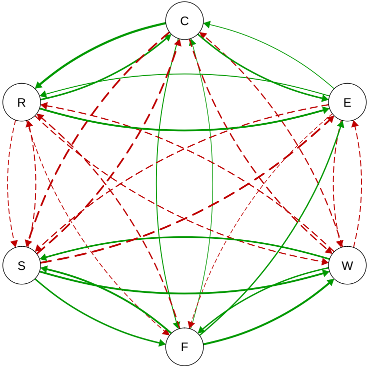

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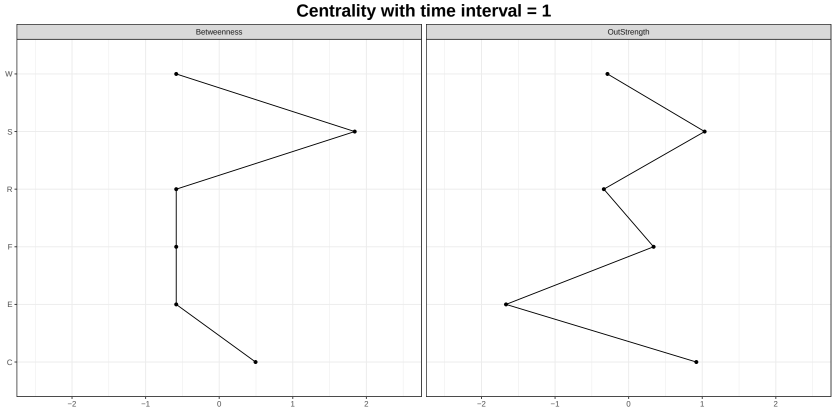

Centrality-Intervention matching

- Centrality measures change depending on the time-interval: now what?
  - We could use this information to get, for example, centrality averaged over time-intervals

- More importantly: **which** centrality measure, if any, should I use?
  - Centrality measures are **context dependent** (Borgatti, 2002)
  - The most popular out-of-the-box measures may be too general for this **dynamic setting**
  - Typical measures ignore the passage of time, auto-regressive effects, use absolute values

Centrality-Intervention matching

Solution: Back to the drawing board

1. Translate substantive/clinical intervention into model terms
   - Momentary prompts: intervene on value of worry at **one moment in time**
   - Mindfulness meditation: intervene on value of worry over **an interval of time** (Ryan, under review)
2. Specify the type of effect we want to achieve
   - Regulatory weakness is theoretically linked to psychological disorder (Kuppens et al 2010; Koval et al 2014)
   - Given a shock, the system returns to baseline quicker
3. Use our model to make predictions
4. Test those predictions empirically

Example

Let's again evaluate the network(s) of Bringmann et al. (2013)

- **Intervention**: set a variable to its average value for a period of time
  - Stop that variable from affecting other variables
- **Desired Outcome**: Given a shock, the system returns to baseline quick than before the intervention
  - Change in time it takes for all variables to return below some cut-off value after a shock (averaged over different shocks)
- **Advice**: intervene on the variable which gives the biggest reduction in 'time to decay'

Visualisation

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Visualisation

Using the subject-specific parameters estimated by Bringmnn et al (2013)

- Betweenness suggests the same node for intervention in around 44 percent of cases
- Out-Strength in 57 percent of cases

Summary

The dynamic network approach is an exciting and appealing way to investigate psychological phenomena

The general idea to use centrality measures to determine interventions is a good starting point

However these types of conclusion must be grounded in our substantive ideas about the underlying dynamics

To move more efficiently from description to intervention, we must

- Evaluate the models we use to estimate networks
- Use our data to make specific predictions about interventions

Thank you for listening!

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